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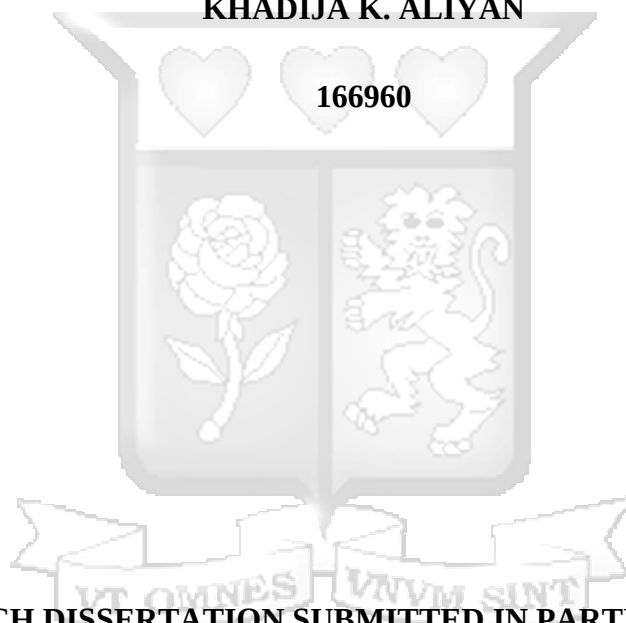
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**FACTORS INFLUENCING ADOPTION OF ELECTRONIC MEDICAL
RECORDS AMONGST PRIVATE DENTAL CLINICS IN NAIROBI AND
MOMBASA COUNTIES, KENYA.**

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166960



**A RESEARCH DISSERTATION SUBMITTED IN PARTIAL FULFILMENT
OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF BUSINESS
ADMINISTRATION IN HEALTHCARE MANAGEMENT AT
STRATHMORE UNIVERSITY**

JUNE 2026

DECLARATION

I hereby declare that this research project titled “Factors Influencing the Adoption of Electronic Medical Records (EMRs) in Private Dental Clinics in Kenyan Cities” is my original work and has not been presented for examination or award of any academic degree in any institution.

This research is undertaken as part of the requirements for the award of an MBA in Healthcare Management at Strathmore University. The information and data collected in this study will solely be for both academic and societal benefit. Adherence to ethical principles will be ensured, including obtaining informed consent from participants and ensuring confidentiality and data protection.

I also confirm that all sources used in this research have been properly acknowledged, and any work that is not my own has been appropriately cited.

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ABSTRACT

Despite the recognized benefits of Electronic Medical Records (EMRs) in improving healthcare efficiency, data management, and continuity of patient care, adoption within Kenya's private dental sector remains inconsistent and insufficiently understood. This study investigated the factors influencing EMR adoption among private dental clinics in Nairobi and Mombasa Counties, Kenya. Guided by the Diffusion of Innovations (DOI) theory and the Technology Acceptance Model (TAM), the study examined the association between system-related, organizational, and policy/environmental factors and EMR adoption and integration within routine dental practice. The study employed a quantitative analytical cross-sectional design among registered private dental clinics in Nairobi and Mombasa Counties. Data were collected using a structured online questionnaire administered to respondents involved in EMR implementation and management. Data were collected using a structured online questionnaire and analyzed using chi-square tests, Pearson correlation, multiple regression, and ordered logistic regression analysis. The findings demonstrated significant associations between EMR adoption and clinic location ($\chi^2 = 34.107$, $p < 0.001$), clinic size ($\chi^2 = 44.402$, $p < 0.001$), and clinic ownership ($\chi^2 = 22.337$, $p = 0.001$). Correlation analysis revealed that organizational factors had the strongest positive relationship with EMR adoption ($r = 0.385$, $p < 0.01$), followed by system-related factors ($r = 0.251$, $p < 0.01$), while policy and environmental factors demonstrated no statistically significant relationship with EMR adoption ($r = -0.054$, $p > 0.05$). Multiple regression analysis identified organizational readiness as the only statistically significant predictor of EMR adoption ($\beta = 0.278$, $p < 0.001$). Similarly, ordered logistic regression analysis showed that organizational readiness significantly increased the likelihood of higher levels of EMR adoption ($\beta = 1.411$, $p < 0.001$), while demographic and policy/environmental variables remained statistically insignificant. Qualitative responses suggested that EMR implementation was perceived to be more integrated in Nairobi than in Mombasa, although the contextual factors underlying these differences were beyond the scope of the present study. The study concludes that organizational readiness—including leadership support, workflow integration, resource availability, technical support, and staff training—was more strongly associated with EMR adoption than system-related or policy/environmental factors. The study recommends that private dental clinics in Kenya to strengthen organizational readiness through leadership engagement, continuous staff training, workflow integration, and structured technical support to promote sustainable EMR adoption.

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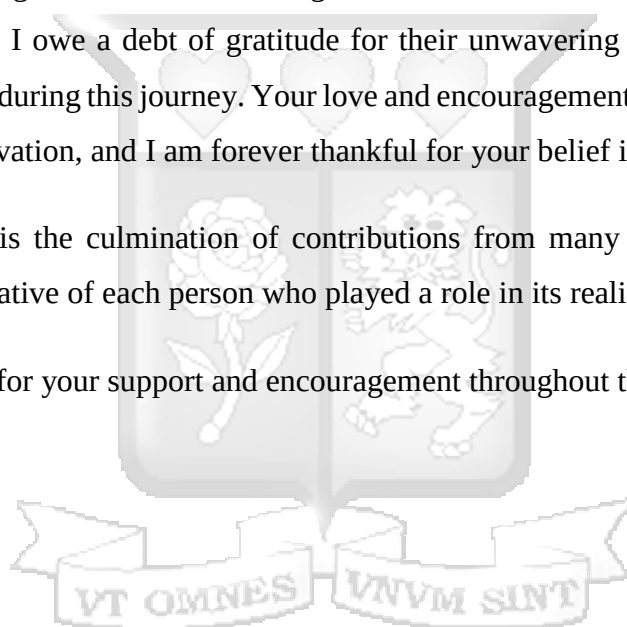
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LIST OF ABBREVIATIONS

CAF: Clinical Adoption Framework

EHR: Electronic Health Record

EMR: Electronic Medical Record

HIS: Health Information System

ICT: Information and Communication Technology

IRB: Institutional Review Board

KMPDC: Kenya Medical Practitioners and Dentists Council

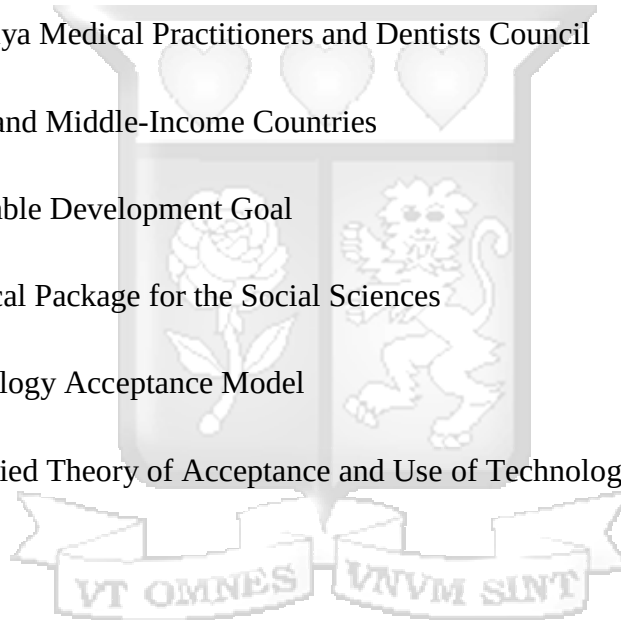
LMIC: Low- and Middle-Income Countries

SDG: Sustainable Development Goal

SPSS: Statistical Package for the Social Sciences

TAM: Technology Acceptance Model

UTAUT: Unified Theory of Acceptance and Use of Technology



KEY TERMS AND CONCEPTS:

Adoption: The process by which a new technology, such as EMRs, is accepted and integrated into routine practice.

Clinical Adoption Framework (CAF): A theoretical model used to analyze the factors influencing technology adoption in healthcare settings.

Electronic Medical Record (EMR): A digital version of a patient's medical chart used within a healthcare practice to improve record management and clinical workflows.

Health Information System (HIS): An integrated system designed to manage healthcare data and improve decision-making.

Macro-Level Factors: External influences such as government policies, funding mechanisms, and societal trends that affect technology adoption.

Meso-Level Factors: Organizational elements, including leadership, infrastructure, and culture, that influence the implementation of new technologies.

Micro-Level Factors: Individual or system-related aspects like user satisfaction, training, and system usability that affect technology use.

Private Dental Clinics: Privately-owned healthcare facilities specializing in dental services, often operating with distinct financial and operational challenges compared to public facilities.

Sustainable Development Goal (SDG) 3: A global objective aimed at ensuring healthy lives and promoting well-being for all at all ages.

Term	Definition	Source
Adoption	The process by which a new technology, such as Electronic Medical Records (EMRs), is accepted, implemented, and integrated into routine healthcare practice.	Rogers, E. M. (2003). <i>Diffusion of Innovations</i> (5th ed.). Free Press.
Clinical Adoption Framework (CAF)	A comprehensive model that organizes the factors influencing health technology adoption into micro-, meso-, and macro-level domains to guide implementation in clinical environments.	Lau, F., Price, M., & Boyd, J. (2011). <i>Clinical Adoption Framework: A framework for research on eHealth implementation. Healthcare Quarterly</i> , 14(Spec No): 44–53.
Electronic Medical Record (EMR)	A digital version of a patient's medical chart that stores medical history, diagnoses, medications, and treatment plans within a single healthcare provider's practice.	World Health Organization (WHO, 2016). <i>Classification of digital health interventions v1.0</i> .
Health Information System (HIS)	A system that collects, stores, manages, and transmits a patient's electronic medical information to support healthcare delivery and decision-making.	World Health Organization (WHO, 2010). <i>Health Systems Strengthening Glossary</i> .
Macro-Level Factors	External influences such as national policies, regulations, donor funding, and sociopolitical context that affect the adoption and sustainability of health technologies.	Lau et al. (2011); Kruse, C. S. et al. (2016). <i>Barriers to EMR adoption: a systematic review. JMIR Medical Informatics</i> , 4(2): 19.

Meso-Level Factors	Organizational-level elements such as leadership, workflow, infrastructure, and support systems that impact the implementation of health innovations.	Lau et al. (2011); Kuo, A. M. H. et al. (2013). <i>Factors affecting adoption of EMRs in developing countries. Health Informatics Journal</i> , 19(2): 59–76.
Micro-Level Factors	Individual and system-level attributes like user skills, attitudes, training, and system usability that affect daily interaction with EMRs.	Holden, R. J. & Karsh, B. T. (2010). <i>The Technology Acceptance Model: Its past and future in health care. Journal of Biomedical Informatics</i> , 43(1): 159–172.
Private Dental Clinics	Privately-owned healthcare facilities providing oral health services, typically operating independently from public health systems and often affected by unique financial and technological constraints.	Okumu, M., et al. (2022). <i>Geospatial disparities in dental healthcare access in Kenya. BMC Oral Health</i> , 22(1): 88.
Sustainable Development Goal (SDG) 3	A United Nations global objective aimed at ensuring healthy lives and promoting well-being for all at all ages, including strengthening health systems through technology.	United Nations (2015). <i>Transforming our world: The 2030 Agenda for Sustainable Development</i> .

CHAPTER ONE

INTRODUCTION

1.1 Background

In today's technology-driven world, industries across all sectors are increasingly adopting digital tools to enhance efficiency and accuracy in record-keeping (Sidek & Martins, 2017). From banking to education, businesses are leveraging digital systems to improve efficiency, data accuracy, and decision-making (Carmona et al., 2023). The healthcare sector is no exception, with Electronic Medical Records (EMRs) emerging as transformative solutions for managing patient information among various digital technologies existing (Yi, 2018). EMRs are digital versions of patients' paper charts, designed to streamline the storage and management of medical data. EMR systems serve as a central hub for transforming this data into meaningful information, knowledge, and wisdom within the healthcare sector. They enhance the efficiency of healthcare delivery by facilitating better data sharing, improving patient care, and supporting clinical decision-making, ultimately contributing to smarter healthcare solutions (Lederman et al., 2024).

Despite the transformative potential of EMRs across healthcare settings, their adoption in specialist private practice, particularly in dental clinics, remains poorly understood and critically under-researched. Unlike general outpatient or hospital settings, dental practices operate within a distinct clinical workflow: patient encounters are predominantly procedure-based rather than diagnosis-driven, records must capture highly specific data including periodontal charts, radiographs, treatment plans, and prosthetic histories, and clinics typically function as small, independently owned enterprises with limited administrative infrastructure (Kaur et al., 2021; Ho et al., 2024). These structural and operational peculiarities mean that EMR adoption barriers and facilitators in dental settings cannot simply be extrapolated from hospital-based studies. Consequently, evidence generated from hospital-based settings may not adequately explain the unique factors influencing EMR adoption within private dental clinics. This creates an important knowledge gap that the present study seeks to address.

Over the past decade, the global adoption of EMRs has gained significant momentum, reshaping how medical data is recorded, stored, and accessed (Li et al., 2019). A survey by the World Health Organization reveals that 114 countries are currently working on

developing national electronic medical record systems, driven by a growing recognition that stronger health information technology is crucial for providing high-quality healthcare while lowering costs (WHO, 2016). These systems are now important to streamline workflows, enhance communication among providers, and improve patient safety by reducing errors (Tchaiwe, 2021). Furthermore, they align with global objectives like Sustainable Development Goal (SDG) 3, which aims to ensure healthy lives and promote well-being for all ages (Cox, 2020).

Despite these advancements, the adoption of EMRs has been slow, particularly in low- and middle-income countries (LMICs) (Kariuki & Richard, 2024),(Owolabi et al., 2020). This has been as a result of persistent obstacles such as inadequate infrastructure, financial constraints, and limited technical expertise. Additionally, a lack of government subsidies and resistance to change among healthcare providers further exacerbates the slow adoption of EMRs (Jones-Esan et al., 2024).

In Kenya, the situation reflects this dual reality. Public hospitals have made commendable progress in digitizing patient records through initiatives like the Ministry of Health's partnership with Konza Technopolis, which introduced the tibERbu system for public hospital integration. These efforts form part of the government's broader Digital Superhighway initiative, which aims to digitize 80% of government services and establish a unified EMR system by extending broadband infrastructure nationwide (Mbego, 2023; Investment Promotion Authority, 2025). However, the private healthcare sector has not kept pace (Kang'a et al., 2017; Ngugi et al., 2021). Most private providers continue to rely on manual documentation, despite facing growing patient loads and rising demands for efficient, standardized care. This lag poses a significant challenge to improving healthcare efficiency, standardization of communication, credibility in patient data management and patient outcomes in these settings (Enahoro et al., 2023).

Dental clinics play a vital role in addressing oral health, a critical component of overall well-being (Igbinosa et al., 2023). However, most clinics still rely on manual record-keeping systems, which are prone to errors, inefficiencies, and data loss (Kaur et al., 2021). These outdated methods undermine the quality of patient care and clinic operations (Riaz et al., 2021; Ho et al., 2024). Modernizing these practices through the

adoption of EMRs has the potential to enhance service delivery and improve health outcomes (Razzano, 2024).

Incorporating the Digital Superhighway initiative underscores its relevance to private dental practices aiming to adopt EMRs. A unified EMR system, integrated nationwide, offers a framework for standardized healthcare records, reducing redundancies, and improving continuity of care. This alignment between national priorities and private practice digitalization underscores the potential for a cohesive healthcare ecosystem, where private providers can contribute to and benefit from shared digital resources. Such developments have critical implications for eHealth adoption, especially in resource-constrained settings, emphasizing the need for policies and incentives to support private sector integration (Investment Promotion Authority, 2025),(Kenya Ministry of Health, 2023).

Despite the growing need for digitized record management in private dental care, there is a noticeable gap in empirical research exploring how these clinics are integrating—or failing to integrate—EMRs into their operations. Little is known about the specific individual, organizational, and environmental factors that influence EMR adoption in this unique healthcare setting. Addressing this gap is vital for informing both health policy and private sector investment strategies aimed at strengthening Kenya’s digital health ecosystem.

Although Electronic Medical Records have been extensively studied in public hospitals and general healthcare settings, comparatively little evidence exists regarding their adoption within private dental clinics, particularly in low- and middle-income countries. Furthermore, existing studies have largely examined isolated technological or organizational determinants, with limited evidence integrating system-related, organizational, and policy/environmental factors within a single analytical framework. This study addresses these gaps by focusing on private dental clinics in Nairobi and Mombasa Counties, where digital health adoption remains underexplored despite increasing policy emphasis on healthcare digitization.

1.1.1 Adoption of EMR

Electronic Medical Record (EMR) is a digital version of a patient's medical chart, typically used within a single healthcare practice. It includes critical information such as medical history, medications, diagnoses, allergies, immunization records, and

treatment plans, all managed by healthcare providers to monitor patient care (Gopidasan et al., 2022). This technology not only streamlines workflows but also enhances communication among healthcare providers, ultimately leading to improved patient safety and quality of care.

While Electronic Health Records (EHRs) are often mentioned alongside EMRs, they are distinct in that EHRs encompass a more comprehensive, patient-centered record that integrates data from multiple healthcare providers (Anshari, 2019). However, this study focuses exclusively on EMRs, specifically within private dental clinics.

The use of EMRs began in the 1960s when healthcare providers started experimenting with computers to manage patient data (Klar, 2004). Early systems, developed in the 1970s and 1980s, had limited functionality and faced slow adoption. Advancements in computing during the 1990s paved the way for more widespread use of EMRs, as governments and healthcare organizations recognized the need for digitized health data (Malhotra & Lassiter, 2014). This led to a global increase in EMR adoption, particularly in developed countries where governments incentivized healthcare providers to implement these systems, aiming to improve patient care and operational efficiency (Sun et al., 2018).

Sub-Saharan Africa has yet to adopt Electronic Health Records (EHRs) despite their benefits, facing barriers like poor infrastructure and lack of management commitment (Adetoyi & Raji, 2020). However, healthcare providers' willingness and the evolving health information exchange infrastructure facilitate their adoption in the region (Woldemariam & Jimma, 2023).

In Kenya, the adoption of EMRs has progressed more slowly compared to high-income countries (Njoroge et al., 2017). The Kenyan government has introduced initiatives such as the Kenya eHealth Policy to encourage digital health solutions, and the Digital Health Act of 2023 was recently enacted to provide a legal framework for the development and implementation of digital health systems (Ministry of Health, Kenya, 2016) (Digital Health Act, 2023). These initiatives aim to enhance the management of patient data across the healthcare sector. While public hospitals have made progress in adopting EMRs, the private healthcare sector, especially dental clinics, faces barriers

such as high costs, limited infrastructure, and a lack of technical expertise (Ahmed et al., 2022).

Technology adoption in healthcare has been widely explained using models such as the Technology Acceptance Model (TAM), which emphasizes system-related perceptions including perceived usefulness and perceived ease of use, and the Diffusion of Innovations (DOI) theory, which explains how organizational and innovation characteristics influence technology adoption (Davis, 1989; Rogers, 2003). These complementary perspectives informed the conceptualization of EMR adoption in the present study.

Studies have emphasized the distinction between the availability and active use of electronic medical records (EMRs) in clinical workflows (Tandon, 2020; Chen et al., 2015). For instance, Chebole (2015) explored public health facilities in Nakuru County, Kenya, highlighting challenges in transitioning from system installation to meaningful use. Similarly, Janssen et al. (2021) examined barriers and enablers to EMR adoption in a cancer center, focusing on how infrastructure availability does not guarantee active utilization. Furthermore, Chepkwony (2015) investigated EMR adoption in Nairobi County, showcasing the importance of both the presence of a system and its routine use in clinical operations.

Informed by these studies, EMR adoption is operationalized in this research as the availability and actual use of an EMR system within a clinic's workflow. Availability refers to whether a clinic has installed an EMR system, regardless of its level of use, while use refers to the extent to which the EMR system is actively utilized for patient registration, clinical documentation, billing, reporting, and clinical decision-making. This operationalization reflects the nuanced reality of healthcare digitization in LMICs, where facilities may possess digital tools but lack the resources, motivation, or infrastructure to use them effectively. Focusing on both presence and actual utilization, this study provides a more accurate picture of EMR adoption in private dental clinics in Kenya.

It is important to note that the majority of existing EMR adoption literature draws on hospital-based or general outpatient settings, and findings from these contexts may not translate directly to dental practice environments. Dental clinics are characterized by

high patient throughput, procedure-specific documentation needs, and a predominantly small-practice ownership model — factors that create a distinct set of adoption challenges (Riaz et al., 2021; Razzano, 2024). In Kenya specifically, the private dental sector operates largely outside the formal public health information system, meaning that national EMR rollout initiatives have had limited reach into this segment of the healthcare workforce (Kang'a et al., 2017). The absence of dental-specific EMR adoption evidence in the Kenyan context is therefore not merely a literature gap — it is a policy and practice gap with direct implications for the quality and continuity of oral healthcare delivery in urban Kenya

1.1.2 Factors influencing adoption of EMR

The adoption of Electronic Medical Records (EMRs) in healthcare settings is a complex, multidimensional process shaped by a variety of interrelated factors — and in the context of private dental clinics, these factors take on particular significance given the sector's operational characteristics, resource constraints, and limited integration into national digital health frameworks. Theoretical frameworks such as the Technology Acceptance Model (TAM), the Diffusion of Innovations (DOI) theory, and the Clinical Adoption Framework (CAF) provide structured perspectives for understanding this process. TAM highlights the importance of perceived usefulness and ease of use in influencing user acceptance (Davis, 1989), while DOI explains how innovation characteristics, adopter traits, and communication channels affect the spread of new technologies (Rogers, 2003). CAF integrates these perspectives by categorizing adoption determinants across micro (individual), meso (organizational), and macro (system/policy) levels, which serves as the guiding lens for this study.

Technological factors are central to EMR adoption. The usability, interface design, and functionality of the system directly influence whether healthcare providers perceive EMRs as helpful or burdensome. High information quality is associated with greater satisfaction and usage (Tilahun & Fritz, 2015), while systems that deliver clinical and operational benefits are more likely to be embraced (Chen & Hsiao, 2021). On the other hand, poorly designed systems that lack critical features or are difficult to navigate can lead to frustration and resistance among users (Ngugi et al., 2021). Additionally, the

availability of reliable technical support including troubleshooting and regular updates is essential to ensure sustained adoption (Castillo et al., 2010; Thit et al., 2020).

Organizational factors also significantly influence the adoption process. Leadership commitment, management support, and resource availability create an environment conducive to digital transformation. When clinic leadership actively champions EMR implementation, it sends a strong message of institutional support (Akwaowo et al., 2022). Involving healthcare providers in decision-making and system customization fosters a sense of ownership, which has been shown to improve acceptance (Kruse et al., 2016). Furthermore, comprehensive training programs can help build users' digital competence, thereby reducing anxiety and resistance (Kuo et al., 2013). Experienced users often become internal advocates for EMRs, due to perceived improvements in patient care and safety (O'Donnell et al., 2018).

System-related factors are central to the adoption of EMRs. Characteristics such as system usability, ease of use, information quality, reliability, and perceived usefulness influence healthcare providers' acceptance and routine use of EMR systems (Davis, 1989; Chen & Hsiao, 2021). Systems that are intuitive, reliable, and capable of supporting clinical decision-making are more likely to be integrated into daily clinical workflows, whereas poorly designed systems may discourage routine use and reduce adoption (Ngugi et al., 2021).

The policy and environmental context further shapes adoption outcomes. National health ICT strategies, regulatory frameworks, and funding mechanisms either support or hinder adoption efforts. In high-income countries, initiatives like the U.S. HITECH Act have used financial incentives to accelerate EMR uptake across healthcare systems (Kruse et al., 2016; Trudel et al., 2017). In contrast, private providers in low- and middle-income countries often cite the lack of subsidies, unclear legal frameworks, and concerns about data security and compliance as major barriers to adoption (Singh et al., 2020; Vijayanthi & Vidhukumar, 2020). Strong policy environments that promote interoperability, standardization, and data protection can serve as powerful enablers of EMR adoption.

While some research explores the link between user satisfaction and continued EMR use, this study is concerned primarily with factors influencing adoption. Satisfaction

may contribute to early acceptance if systems align well with existing workflows and support clinical efficiency (Chen & Hsiao, 2021; Dubale et al., 2023). Conversely, rigid systems that disrupt established routines are more likely to provoke resistance (Aqleh et al., 2019; Singh et al., 2020). Successful implementation strategies must therefore consider how EMRs integrate with current practices and include feedback loops from frontline users.

This study focuses specifically on system-related, organizational, and policy/environmental factors influencing EMR adoption in private dental clinics. These three domains provide a comprehensive framework for examining technological, organizational, and contextual determinants of EMR adoption within the private dental sector. System-related factors in this study refer to users' perceptions of EMR usability, reliability, information quality, and perceived usefulness in supporting routine clinical and administrative functions. These factors influence the extent to which healthcare providers are able and willing to integrate EMR systems into routine clinical practice (Njoroge, 2014). Organizational factors involve internal clinic dynamics such as leadership support, workflow integration, and training systems (Masana & Muriithi, 2023). Policy and environmental factors refer to government regulations, national digital infrastructure, financial incentives, and broader system-level enablers or constraints (Chepkwony, 2015). Other variables such as technical readiness or patient engagement may influence adoption but are considered as sub-themes within these broader categories to maintain analytical clarity.

To guide the investigation of these multi-level factors, this study draws on three complementary theoretical frameworks. The Technology Acceptance Model (TAM) (Davis, 1989) provides a lens for understanding individual-level perceptions of EMR usability and usefulness. The Diffusion of Innovations (DOI) Theory (Rogers, 2003) explains how innovation characteristics and organizational dynamics shape the spread and adoption of new technologies. The Clinical Adoption Framework (CAF) extends these perspectives by categorizing adoption determinants across micro (individual), meso (organizational), and macro (policy/environmental) levels, making it particularly suited to the multi-level nature of this study. These frameworks are elaborated in Chapter Two and operationalized through the study's conceptual framework. Anchoring the analysis within these three dimensions, this study will adopt a structured lens that

captures the multifactorial nature of EMR adoption in private healthcare settings while remaining focused on the most influential and policy-relevant determinants.

1.1.3 Private Dental Clinics in Nairobi and Mombasa counties

Kenya's healthcare system operates under a mixed public-private model, with both sectors playing vital roles in delivering health services. The public sector is administered by the Ministry of Health (MoH) and devolved county governments and is structured into six tiers of service delivery: community health units, dispensaries, health centers, sub-county hospitals, county referral hospitals, and national referral hospitals (Kimathi, 2017). These levels provide a continuum of care, where lower tiers offer preventive and primary services and higher tiers provide specialized and referral services. Despite its broad reach, the public system faces persistent challenges including underfunding, staffing shortages, and supply chain inefficiencies, all of which undermine quality and access to care (Oyoo & Wagah, 2024).

To fill these gaps, the private health sector plays a complementary role, particularly in urban areas where demand for quality and efficient healthcare is high. This sector is diverse and fragmented, comprising large corporate hospital chains, faith-based organizations, non-governmental organizations (NGOs), private insurance-funded outpatient networks, and numerous independently owned clinics. These providers differ by ownership model (individual, corporate, faith-based), level of care (primary, secondary, tertiary), and specialization (e.g., dental, dermatology, imaging, ophthalmology). The diversity of the private sector enables differentiated service delivery, often catering to middle- and high-income populations seeking more personalized or faster care options (Owino, 2021).

Within this landscape, private dental clinics occupy a crucial niche by addressing Kenya's growing oral health burden—an area historically under-resourced in the public health system (Barnes et al., 2010). Oral health is now recognized as a key component of overall well-being, yet dental diseases remain among the most common non-communicable conditions globally (Hapsari & Mamun, 2024). According to the World Health Organization (WHO, 2022), nearly 50% of the global population suffers from oral diseases. In Kenya, oral health problems account for a significant share of

outpatient visits in urban centers, where demand for both preventive and specialized dental care is on the rise.

Dental services in Kenya are predominantly urban-centered, with Nairobi and Mombasa serving as major hubs for private dental care. These cities host a significant share of the country's dental professionals and infrastructure, owing to high population density, stronger economic activity, and better-developed health systems. A geospatial analysis by Okumu et al. (2022) found that 43% of Kenya's dental workforce is based in Nairobi, where the dentist-to-population ratio stands at 1:9,018—substantially better than rural counties like Wajir, which lack registered dental facilities entirely. Moreover, only 11% of Kenya's population resides within 2.5 km of a dental clinic, while 58% live over 20 km away, highlighting major geographical disparities in oral healthcare access.

Nairobi and Mombasa offer distinct but complementary healthcare landscapes. Nairobi, the capital city, is a leading hub for health technology, medical innovation, and private investment—making it an ideal context for examining EMR adoption trends (Chepkwony, 2015). Mombasa, Kenya's second-largest city and coastal commercial center, features a culturally diverse population and a healthcare system shaped by tourism, trade, and multicultural dynamics (Waronja & Mogote, 2024). Private dental clinics in both counties serve a cross-section of high-, middle-, and low-income groups and range from solo-owned practices to multi-specialty facilities.

According to the Kenya Medical Practitioners and Dentists Council (KMPDC, 2023), Nairobi is home to 230 private dental clinics, while Mombasa hosts 25. These facilities differ in size, scope of services, and digital maturity, making them ideal for assessing variations in EMR adoption. Together, these 255 registered private dental clinics formed the study population from which the study sample was derived. Owing to the relatively small number of clinics in Mombasa County, all eligible clinics were included, while sampling was undertaken in Nairobi County as described in Chapter Three.

Private dental clinics in urban areas face growing challenges such as overcrowding, resource constraints, and increasing demand for personalized and accurate patient data management. These operational pressures create a compelling rationale for adopting

Electronic Medical Record (EMR) systems, which can streamline workflows, enhance record accuracy, and support continuity of care (Chepkwony, 2015). Furthermore, Nairobi's status as a digitization hub and Mombasa's socio-cultural diversity make the two cities ideal for comparative analysis of EMR adoption drivers and constraints.

Regulation of the private dental sector is managed through a multi-agency framework aimed at safeguarding patient safety and professional standards. The Kenya Medical Practitioners and Dentists Council (KMPDC) oversees facility licensing and clinical governance. The Kenya Dental Association (KDA) focuses on advocacy, ethics, and continuing professional development. Clinics are also subject to National Health Insurance Fund (NHIF) accreditation standards, Kenya Revenue Authority (KRA) tax compliance, and data governance regulations under the Data Protection Act (2019). The adoption of EMR systems introduces new regulatory responsibilities, particularly regarding the ethical and secure management of personal health information and data protection.

Beyond clinical service provision, private dental clinics contribute meaningfully to Kenya's socio-economic development. They generate employment opportunities for dentists, dental technologists, administrative staff, and support workers. Many clinics operate on a fee-for-service or private insurance model, contributing to domestic revenue streams. Some high-end facilities in Nairobi and Mombasa also serve international patients, boosting Kenya's profile in medical tourism (Kenya Tourism Board, 2022). Additionally, clinics often engage in corporate social responsibility (CSR) efforts such as free dental camps, school outreach programs, and oral health awareness drives in underserved communities.

The decision to focus this study on Nairobi and Mombasa is guided by both strategic and practical factors. These cities not only host the highest concentration of private dental clinics in Kenya but also reflect diverse urban healthcare realities. Nairobi presents a more digitized and investment-ready environment, while Mombasa offers insight into EMR adoption in settings marked by cultural complexity and varied access levels. Studying both allows for a nuanced understanding of how contextual factors including infrastructure, regulation, provider characteristics, and patient demographics influence the adoption of EMRs in the private dental sector.

1.2 Problem Statement

The adoption of Electronic Medical Records (EMRs) has been recognized as a transformative solution to delivering effective and equitable healthcare services (Gatiti et al., 2021). EMRs have proven benefits such as improved patient safety, enhanced workflow efficiency, and timely access to patient data (Jawhari et al., 2016). Critically, the converse is equally well-evidenced: the absence or non-use of EMR systems is directly associated with fragmented, incoherent patient care, increased medical errors, and compromised patient safety (Price, 2017; Larsen et al., 2018). Reliance on paper-based records has been shown to hinder coherent clinical decision-making by creating information silos that prevent clinicians from accessing a patient's complete medical history across visits and providers (Price, 2017). Studies have further demonstrated that paper-based prescribing carries significantly higher medication error rates — as high as 35.7% — compared to just 2.5% for electronic prescriptions, representing a direct and quantifiable patient safety risk (Memon et al., 2024). Additionally, analysis of patient safety events during periods of EHR unavailability confirms that the absence of electronic records directly compromises care processes and patient safety outcomes (Larsen et al., 2018; Meeks et al., 2014).

Despite these well-documented risks of non-adoption, the global uptake of EMRs remains uneven (Shelke & Bagade, 2022). While developed countries have made significant strides, developing countries encounter barriers such as resistance to change, prohibitive implementation costs, inadequate infrastructure, and insufficient technical support (Progress on Implementing and Using Electronic Health Record Systems, 2023; Danso et al., 2024).

In sub-Saharan Africa, the situation mirrors global trends, with low EMR adoption rates exacerbated by financial and operational limitations in resource-limited settings (Kuffour, 2022). Most health facilities still rely on paper records, with only a few using recording software since 2011 (Gueye et al., 2021).

Evidence from the African context further illustrates the consequences: in Uganda, implementing EHRs during medical service trips increased patients served per physician per hour by 45% and prescriptions dispensed per hour by 38%, revealing that paper-based systems directly reduced care efficiency and delayed patient treatment

(Maarsingh et al., 2022). In Ethiopia, incomplete EMR integration in an antiretroviral therapy clinic led to dual documentation burdens, data quality failures, and disruptions to continuity of care — a scenario that mirrors the mixed paper-electronic environment prevalent in many private dental clinics in Kenya (Abiy et al., 2018).

In Kenya, government initiatives have supported the adoption of EMRs in public healthcare facilities, leading to notable progress in digitizing patient records (Ngwashi et al., 2023; Kang'a et al., 2016). However, private healthcare providers compared to their public counterparts, face additional constraints such as regulatory fees, equipment shortages, and low staffing levels (Montagu et al., 2022; Khondowe & Mpundu, 2024). Despite the growing demand for dental services and the critical role of oral health in overall well-being (Okumu et al., 2019), research on EMR adoption in private dental clinics remains limited. Such clinics, which are critical in providing specialized care, remain heavily reliant on manual, paper-based systems that are inefficient, prone to errors, and delay access to accurate patient records, thereby undermining workflow efficiency and quality of care (Ho et al., 2024). Local studies have primarily focused on public healthcare institutions, offering limited insight into the specific needs and constraints of private clinics in urban areas like Nairobi and Mombasa.

Existing research has primarily examined isolated technological, organizational, or policy determinants of EMR adoption, with limited studies simultaneously examining system-related, organizational, and policy/environmental factors within private dental clinics (Wolverton & Lanier, 2019; Danso et al., 2024).

Given that dental clinics serve a significant portion of Kenya's urban oral health needs, the persistence of paper-based record-keeping in this sector is not merely a technological gap — it represents an ongoing patient safety and care quality risk. Without targeted evidence on the specific factors hindering EMR adoption in private dental clinics, policymakers and clinic managers lack the actionable insights needed to address this gap and protect patient care outcomes in this growing sector.

According to the Kenya Medical Practitioners and Dentists Council (KMPDC, 2024), there are over 255 licensed private dental clinics in Nairobi and Mombasa Counties alone. These two counties represent Kenya's two largest urban centres and together account for the highest concentration of private health facilities in the country, with

national data confirming that private facility distribution is skewed toward urban counties (Moturi et al., 2022). However, beyond their shared urban status, Nairobi and Mombasa present meaningfully distinct digital health contexts that make their comparison analytically valuable. Nairobi, as the capital city and economic hub, has been the focal point of Kenya's eHealth investment, hosting the largest share of digital health projects and demonstrating comparatively advanced private-sector adoption of health information systems (Njoroge et al., 2017; Muema, 2014). Mombasa, while equally urban, has a different digital health trajectory — EMR implementation studies in the county have focused primarily on public comprehensive care clinics, with limited evidence on private specialist facilities, and cost and infrastructure barriers have been more prominently documented (Waronja & Mogote, 2024). These contextual differences mean that factors influencing EMR adoption are unlikely to be uniform across the two counties, and that findings from one county cannot be assumed to represent the other. Examining both counties together therefore enables a more nuanced and nationally relevant understanding of EMR adoption barriers and facilitators within Kenya's private dental sector, and provides an evidence base that can inform county-specific digital health strategies rather than a one-size-fits-all policy response.

This study therefore aimed to address these gaps by identifying factors influencing EMR adoption in private dental clinics in Nairobi and Mombasa Counties. Drawing on system-related, organizational, and policy/environmental factors, this study provides a multidimensional analysis of EMR adoption within private dental clinics.

1.3 Research Objectives

1.3.1 Broad objective

To evaluate factors influencing the adoption of Electronic Medical Records (EMRs) in private dental clinics in Nairobi & Mombasa Counties.

1.3.2 Specific objectives

1. To analyze how clinic size, location, and Healthcare worker sociodemographics influence EMR adoption in Nairobi and Mombasa private dental clinics.
2. To identify system- related, organizational, and policy/environmental factors affecting EMR adoption in the target clinics.

3. To compare EMR adoption and implementation experiences between Nairobi and Mombasa private dental clinics.

1.4 Research Questions

1. How do clinic size, location, and healthcare worker sociodemographic characteristics influence the adoption of Electronic Medical Records (EMRs) in private dental clinics in Nairobi and Mombasa?
2. What system-related, organizational, and policy/environmental factors affect the adoption of EMRs in private dental clinics in Nairobi and Mombasa?
3. How does EMR adoption and implementation differ between private dental clinics in Nairobi and those in Mombasa?

1.5 Scope of the Study

This study was delimited by four key dimensions; conceptual, contextual, methodological, and temporal scope. Conceptually, the study focused on the adoption of Electronic Medical Records (EMRs) in private dental clinics. Specifically, it examined three core categories of factors influencing adoption: individual and system-related factors (e.g., system usability, ease of use, reliability, information quality, and perceived usefulness), organizational-level factors (e.g., leadership support, resource availability, workflow integration, and staff training), and policy/environmental-level factors (e.g., regulatory frameworks, digital infrastructure, financial incentives, and data protection requirements). EMR adoption is operationalized as both the availability of an EMR system and its active use in routine clinical and administrative functions such as registration, documentation, billing, and reporting.

Contextually, the study was confined to private dental clinics located in Nairobi and Mombasa Counties. The exclusion of public dental units is justified by the fundamentally different operational, financial, and regulatory environments governing public health institutions in Kenya — including government-mandated EMR systems, centralized IT support, and different funding mechanisms — which would introduce confounding variables beyond the scope of this study. Rural settings were excluded due to significant disparities in ICT infrastructure, clinic density, and resource availability that would require a distinct analytical framework and separate study design. These exclusions are acknowledged as limiting the generalizability of findings to urban

private dental clinics specifically, and future research is recommended to extend this investigation to public facilities and rural settings.

Methodologically, the study employed a Methodologically, the study employed an analytical cross-sectional quantitative design. A sample of private dental clinics was drawn from the 255 registered clinics in Nairobi and Mombasa Counties. The two counties constituted the primary strata. Due to the relatively small number of clinics in Mombasa County, all eligible clinics were included through a census approach, while clinics in Nairobi County were selected using a sampling approach described in Chapter Three. Descriptive and inferential statistical analyses were conducted to examine factors associated with EMR adoption.

As for the time scope, the study covered data collected within the year 2026, reflecting the state of EMR adoption and associated influencing factors during this period. The research also reviewed relevant policy and technological developments up to 2024 to contextualize current practices and inform future projections.

1.6 Significance of the Study

This study is expected to generate valuable insights for policymakers, industry stakeholders, and academic scholars, particularly in the domains of digital health and health systems strengthening.

From a policy perspective, the findings will inform national and county-level health authorities, including the Ministry of Health and regulatory bodies such as the Kenya Medical Practitioners and Dentists Council (KMPDC). By identifying the key barriers and enablers of Electronic Medical Records (EMR) adoption in the private sector, the research can support the formulation of inclusive digital health policies. The evidence gathered may also guide the creation of targeted incentives and regulatory reforms designed to accelerate EMR uptake among private urban clinics, particularly within the oral health sector, which has historically been underprioritized in national health planning.

For the healthcare industry, the study offers practical value to private dental practitioners, medical associations such as the Kenya Dental Association (KDA), and health information technology vendors. Through examining the organizational and

infrastructural determinants of EMR adoption, the findings can support better strategic choices for allocating resources, designing systems, training, and implementation strategies. These insights are likely to enhance digital transformation efforts and improve the efficiency, accuracy, and quality of care within private dental settings.

Academically, the study contributes to the growing body of literature on EMR adoption in low- and middle-income countries (LMICs), particularly in specialized but under-researched areas such as private dental care. It addresses existing conceptual and methodological gaps by adopting a multi-level framework that integrates individual, organizational, and policy or environmental factors. The study's approach and findings may serve as a valuable foundation for future research, including comparative or longitudinal studies focusing on health information systems in resource-constrained settings.

1.7 Chapter Summary

This chapter introduced the study by providing the background, problem statement, research objectives and questions, justification, and scope. It highlights the growing relevance of EMR systems in healthcare, the uneven progress in their adoption across public and private sectors, and the limited research focused on private dental clinics in Kenya. The chapter established the need for examining clinic characteristics together with system-related, organizational, and policy/environmental factors associated with EMR adoption among private dental clinics in Nairobi and Mombasa Counties.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter provides a comprehensive review of the existing literature relevant to the study's focus on understanding the factors influencing the adoption of EMRs in private dental clinics within Nairobi and Mombasa counties, Kenya. It establishes the conceptual and empirical foundation for the research by examining key theories of technology adoption, relevant global and regional studies, and the specific dynamics of EMR integration in private healthcare settings.

Drawing on both the Diffusion of Innovations Theory (DOI) and the Technology Acceptance Model (TAM), the chapter presents a theoretically grounded analysis of how EMR systems are perceived, adopted, and utilized in dental care environments. It also explores empirical evidence from high-income and low- and middle-income countries (LMICs), identifying both generalizable trends and context-specific insights. Special attention is given to the Kenyan private health sector, which, despite its significant role in service delivery, remains underrepresented in digital health research. Key gaps in the current literature are highlighted that underscore the relevance of the current study and help justify its methodological approach, which seeks to generate insights that are both locally grounded and theoretically informed.

2.2 Theoretical Review

The adoption of Electronic Medical Records (EMRs) in private dental clinics is influenced by various theoretical perspectives that explain technology acceptance and diffusion. To this end, this study draws on two complementary theories: the Diffusion of Innovations Theory (DOI) and the Technology Acceptance Model (TAM). While DOI offers a broad explanation of how innovations like EMRs are adopted across social systems, TAM provides insight into the psychological and perceptual dimensions of technology use. Using both frameworks provides a more comprehensive lens through which to analyze EMR adoption in the distinct context of Kenya's private dental sector.

2.2.1 Diffusion of Innovations Theory

The Diffusion of Innovations Theory (DOI), first developed by Everett Rogers in 1962 and later refined (Rogers, 2003), posits that the adoption of a new technology is

influenced by five core attributes: relative advantage, compatibility, complexity, trialability, and observability. These factors affect the speed and likelihood of adoption by individuals or organizations. DOI is especially relevant in healthcare settings where new technologies like EMRs must be integrated into complex clinical workflows and institutional cultures.

In the context of private dental clinics in urban Kenya, DOI helps to conceptualize how adoption decisions are made and diffused through professional networks. For instance, relative advantage is evident in the perceived benefits of EMRs, such as improved record-keeping, enhanced clinical decision-making, and better administrative coordination (Ngugi et al., 2021). Compatibility plays a role in how well EMRs align with existing practices, especially in clinics already using digital tools for billing or appointments (Kariuki & Richard, 2024). However, complexity remains a barrier, particularly when systems are perceived as difficult to use or require substantial technical training (Owolabi et al., 2020).

Despite its strengths, DOI is often critiqued for its limited attention to individual psychological factors and its assumption that all adopters are rational actors influenced solely by innovation characteristics. The theory tends to underplay how crucial it is for users to perceive a technology as useful and easy to use, as these are often central to user engagement in technology adoption. This limitation is particularly salient in clinical contexts, where personal experiences, attitudes, and resistance to change can heavily influence adoption outcomes.

2.2.2 Technology Acceptance Model

To address the limitations of DOI, this study incorporates the Technology Acceptance Model (TAM), introduced by Davis (1989). TAM focuses on two principal factors: perceived usefulness (PU) and perceived ease of use (PEOU). These factors aim to predict an individual's intention to use a technology based on their cognitive evaluations. TAM has been widely applied in health informatics studies to understand the psychological drivers behind EMR adoption, especially among clinicians.

In private dental clinics, TAM provides a valuable perspective on how individual dentists and their staff perceive EMR systems. For example, even when systems offer

clear functional advantages (as described in DOI), they may be rejected if users perceive them as difficult to use or irrelevant to their daily tasks. This is particularly relevant in resource-constrained clinics, where staff are often overburdened and less inclined to adopt technologies that increase workload without clear personal benefit (Dwivedi et al., 2019).

However, TAM also has notable limitations. It underestimates the impact of organizational and social influences, which are crucial in healthcare settings where adoption is often shaped by institutional policies, leadership, and peer norms (Owolabi et al., 2020). Furthermore, TAM does not fully account for external factors such as financial incentives, legal mandates, or infrastructural readiness, all of which are highly relevant in the Kenyan context (Ngugi et al., 2021). This makes TAM insufficient as a standalone framework for understanding EMR adoption at the organizational level.

2.2.3 Integration of DOI and TAM Theories

Given the complementary limitations of DOI and TAM, this study adopts a dual-theory approach that uses each framework to compensate for the other's documented weaknesses. This integration is not merely additive, it is structured so that each model's explanatory gap is directly addressed by the other's strength.

DOI's primary limitation is its insufficient attention to individual psychological factors. It assumes that adoption decisions are driven primarily by innovation characteristics (relative advantage, compatibility, complexity, trialability, observability) without accounting for how individual perceptions, attitudes, and cognitive evaluations shape those decisions. TAM complements DOI by explaining how users' perceptions of system usefulness, ease of use, and functionality influence acceptance and utilization of EMR systems. (Davis, 1989).

Conversely, TAM's primary limitation is its underestimation of organizational, social, and environmental influences. TAM treats adoption as an individual decision but does not account for how institutional policies, leadership support, workflow constraints, financial incentives, or regulatory environments shape whether individuals ever encounter, evaluate, or have the opportunity to adopt a technology. DOI's innovation-diffusion perspective directly addresses this gap by explaining how adoption spreads through social systems and is shaped by organizational and environmental context (Rogers, 2003).

This mutual compensation has empirical precedent. Wiedenbeck et al. (2008) integrated DOI and TAM into a unified EHR Acceptance Model and demonstrated that the combined framework explained over 73% of variance in EHR acceptance attitudes — substantially more than either model alone. Abdekhoda (2025), in a hybrid TAM and DOI study among 330 physicians, found that DOI constructs (relative advantage, compatibility, trainability) and TAM constructs (perceived usefulness, perceived ease of use) each independently contributed to adoption attitudes, confirming that both sets of predictors are necessary for a complete explanation. Ouheda et al. (2024) further demonstrated that integrating TAM with DOI and organizational frameworks revealed temporal and organizational dynamics invisible to single-model approaches.

In the context of private dental clinics in Nairobi and Mombasa, this integration is especially appropriate. The variation in clinic size, staffing, infrastructure, and professional culture means that some clinics may face primarily organizational barriers (addressed by DOI) while others face primarily perceptual barriers (addressed by TAM). By integrating both frameworks, the study is positioned to provide a more comprehensive understanding of EMR adoption and identify the relative contribution of system-related, organizational, and policy/environmental factors.

2.2.4 Critical Synthesis: Contradictions and Debates in EMR Adoption Research

While DOI and TAM provide complementary theoretical lenses, the empirical literature applying these frameworks reveals persistent contradictions that caution against treating either model as universally predictive. A critical reading of this evidence is essential for understanding why a multi-dimensional, context-sensitive approach is warranted for the current study.

One of the most debated questions concerns the relative predictive power of perceived usefulness (PU) versus perceived ease of use (PEOU). Several studies in high-income settings report PU as the dominant predictor of adoption intention (Moeinedin, 2011), while others find that PEOU independently drives behavioral intention when usability barriers are high (Listiowati et al., 2025). Critically, Moukoumbi Lipenguet et al. (2022), studying health professionals in Gabon, found that perceived ease of use and computer familiarity were not significantly associated with intention to use EMRs, despite being central TAM constructs — suggesting that in African contexts, social norms and perceived usefulness may outweigh ease of use as drivers of adoption.

A second area of disagreement concerns whether individual or organizational factors are the primary drivers of adoption. TAM privileges individual cognition, yet Wiedenbeck et al. (2008), in an integrated DOI-TAM study, found that sociotechnical and organizational factors — including management support, physician involvement, and workflow concerns — accounted for more variance in EHR acceptance than individual characteristics alone. This finding directly challenges the individual-centric assumptions embedded in standard TAM applications.

The inconsistencies within the existing literature indicate that EMR adoption cannot be adequately explained by a single theoretical perspective. Consequently, the present study therefore integrates DOI and TAM as complementary explanatory theories, while the Clinical Adoption Framework provides an organizing structure for classifying determinants into system-related, organizational, and policy/environmental domains, to examine the relative contribution of the factors influencing EMR adoption among private dental clinics in Nairobi and Mombasa Counties.

2.3 Empirical Review

This empirical review synthesizes findings from global, regional, and local studies to identify the key factors that influence EMR adoption, with a specific focus on the applicability of these insights to private dental clinics in urban Kenya. The section is structured thematically around three key areas. First, it explores how clinic-level characteristics such as size, ownership, location, specialty, and ICT infrastructure influence the likelihood and quality of EMR implementation. Second, it examines the influence of individual, organizational, and environmental factors, including staff attitudes, leadership engagement, policy context, and resource availability. Finally, the review turns to inter-county comparisons, focusing on Nairobi and Mombasa to explore how regional disparities in infrastructure, regulation, and market dynamics affect EMR adoption.

Each subsection provides an overview of relevant empirical studies, highlighting the methodologies employed, populations studied, and major findings. Particular attention is paid to the contextual relevance of these studies to the Kenyan setting and the dental health sector specifically. The review concludes with a critical synthesis of the literature gaps, pointing to the need for localized, sector-specific, and theory-informed research that can guide digital health strategy in Kenya's private dental clinics. Through this

structure, the section aims to build a robust foundation for the current study by situating it within existing scholarship and identifying areas where new empirical evidence is most needed.

2.3.1 Clinic Characteristics and EMR Adoption

Clinic characteristics refer to the structural and operational attributes that define a healthcare facility's configuration, including its size, location, type of ownership, availability of specialty services, information and communication technology (ICT) infrastructure, and staffing profile (Chauhan et al., 2018; Tsagaankhuu et al., 2021; Majid et al., 2023). These factors are widely recognized as influential determinants in the adoption of electronic medical records (EMRs), as they shape a clinic's resource capacity, technological readiness, and ability to implement innovations. Larger clinics, for instance, often possess more robust financial and human resources, making it easier to invest in EMR systems, while clinics situated in urban areas may benefit from better ICT infrastructure and closer proximity to technical support services (Chauhan et al., 2018; Tsagaankhuu et al., 2021). Likewise, clinics that provide specialized services, such as dental care, may have unique record-keeping requirements that necessitate tailored digital systems (Majid et al., 2023).

Several empirical studies conducted in high-income countries have explored the relationship between clinic characteristics and EMR adoption. Kawaguchi (2019), in a longitudinal observational study in Japan, analyzed EMR use trends between 2011 and 2014. The study found that larger clinics with higher patient volumes were significantly more likely to adopt EMRs, attributing this to economies of scale that allow such clinics to absorb the high implementation costs. While the study provides valuable evidence linking clinic size and adoption, it is situated in a high-income context with strong ICT infrastructure and government incentives—factors not consistently present in developing countries. Furthermore, it does not address how adoption varies by medical specialty, thereby limiting its relevance to specific sectors such as dentistry.

Boonstra and Broekhuis (2010) conducted a systematic review of physician practices in North America and Europe, identifying clinic size, financial capacity, and practice type as key predictors of EMR adoption. Their analysis revealed that smaller, independently owned clinics experienced greater challenges due to capital constraints

and limited administrative resources. However, the study is largely descriptive and lacks empirical differentiation across clinical specialties. Moreover, the review primarily synthesizes data from large healthcare systems, which may not reflect the conditions under which small, private dental clinics operate in low-resource settings like Kenya.

In low- and middle-income countries (LMICs), comparable patterns have emerged. Thu et al. (2017), in a cross-sectional study of 245 dental professionals in Myanmar, found that small and poorly resourced clinics were significantly less likely to adopt EMRs, citing cost, inadequate ICT infrastructure, and insufficient training as major barriers. This study is notable for its focus on the dental sector, which is often underrepresented in EMR literature. However, its single-country focus and narrow scope on urban centers limit its generalizability to other LMIC contexts. Furthermore, the study does not explore inter-regional comparisons or policy-level influences that may affect adoption.

Within Sub-Saharan Africa, Owolabi et al. (2020) examined EMR adoption using the Unified Theory of Acceptance and Use of Technology (UTAUT) in South African clinics. The study found that urban-based facilities had higher adoption rates due to stronger infrastructure, digital training programs, and alignment with national eHealth initiatives. While insightful, the study focused on general outpatient clinics and did not account for specialty-specific needs or challenges. Its generalizability to dental clinics, which often operate independently and under different regulatory frameworks, remains unclear.

In the Kenyan context, Chepkwony (2015) studied EMR implementation in public health institutions in Nairobi. The study identified leadership commitment, staff training, and infrastructure availability as key enablers. However, it lacked attention to clinic size, location variation, or private sector dynamics. Its exclusive focus on the public sector omits the unique operational models of private dental clinics, where decision-making is often individualized and resources are limited.

Similarly, Njoroge (2014) investigated small private clinics in Ruiru Sub-County and found that limited ICT infrastructure and financial barriers were major hindrances to EMR use. While this study aligns more closely with the current research context, it does not differentiate between types of clinical services offered and therefore overlooks the

unique demands of dental care provision. Additionally, it focuses on a peri-urban setting and does not offer comparative insights across counties or urban centers.

From this review, it becomes evident that although clinic characteristics significantly influence EMR adoption, existing studies often focus on general healthcare facilities and are limited in geographic or specialty scope. There is a noticeable lack of research that specifically examines how factors such as clinic size, urban location, and dental-specific operational structures affect EMR uptake in the private sector. This gap is particularly apparent in Kenya, where private dental clinics form a growing segment of urban healthcare provision. The present study addresses this shortfall by exploring these variables within the context of Nairobi and Mombasa counties—two distinct yet representative urban settings.

2.3.2 System-related, Organizational, and Environmental Factors Influencing EMR Adoption

The adoption of Electronic Medical Records (EMRs) in healthcare settings is often shaped by a complex interplay of individual, organizational, and policy or environmental factors. System related factors include the usability, information quality and ease of use, all of which can influence acceptance of new technologies (Gagnon et al., 2014). Organizational factors encompass leadership support, resource availability, staff training, and internal communication processes, which determine whether institutions are structurally and culturally prepared to adopt EMRs (Boonstra & Versluis, 2014). At the environmental or policy level, government incentives, legal frameworks, and alignment with national eHealth strategies can create enabling or constraining conditions for adoption (Ajami & Bagheri-Tadi, 2013).

In high-income countries, extensive empirical research has emphasized the role of these factors. Gagnon et al. (2014) conducted a large-scale cross-sectional study in Canada to evaluate determinants of EMR acceptance among physicians using an integrated theoretical model. The study found that physicians' perception of ease of use and usefulness, along with previous exposure to technology, significantly influenced behavioral intention. Although methodologically rigorous, the study was conducted in a context of high digital literacy, strong technical support, and structured health systems—conditions that differ from resource-constrained settings like Kenya.

Additionally, the study did not disaggregate findings by type of clinic or specialization, thereby overlooking variations in adoption across different healthcare sectors such as dentistry.

In the United Kingdom, Cresswell and Sheikh (2013) conducted an interpretative review exploring organizational-level issues in EMR implementation. The study identified poor workflow integration, inadequate change management, and resistance from clinical staff as major barriers. The findings reinforce the importance of organizational readiness, yet the study was limited by its secondary nature and absence of primary data from outpatient or private clinic settings. Furthermore, the research focused largely on public sector reforms, failing to address the specific challenges of independently operated private clinics, where adoption decisions are decentralized and resource constraints may be more pronounced.

In Sub-Saharan Africa, Adu et al. (2018) examined EMR readiness in private health facilities in Ghana. The study found that digital literacy, professional training, and openness to innovation significantly predicted adoption intention among clinicians. While this study is useful for drawing parallels with private health settings in Kenya, it focused predominantly on general health facilities and did not explore specialty contexts such as dental clinics. Additionally, it lacked comparative regional analysis that might uncover variations in policy enforcement or infrastructural support between cities or counties.

Mahomed et al. (2019) investigated EMR challenges in South Africa's primary healthcare system. Their findings emphasized that national eHealth strategies, while ambitious, were insufficient to guarantee adoption at the clinic level without accompanying investments in staff training, change management, and IT infrastructure. Although the study addressed both policy and organizational variables, it was conducted in the public sector and relied heavily on qualitative reports from policy actors, with minimal input from clinicians directly involved in EMR use. This limits the generalizability of findings to the small-scale private dental clinics in Kenya where providers also serve as system implementers.

In Kenya, Omollo and Were (2020) explored EMR adoption barriers among private healthcare providers in Nairobi. Their study revealed that inadequate training, limited

IT support, and clinician resistance were major barriers at the individual and organizational levels. While this study provides important insight into private practice dynamics, it did not distinguish between different medical specialties or examine inter-county differences. Moreover, it relied solely on qualitative interviews, which, although rich in detail, may lack the generalizability and statistical robustness needed for broad application across urban centers like Nairobi and Mombasa.

Kimani et al. (2022) studied organizational enablers of EMR adoption in Nairobi private clinics. They found that strong leadership, internal IT support, and institutional culture that promotes innovation were key drivers of EMR implementation. However, the study was limited to general outpatient facilities and did not explore whether these same enablers apply in specialized or dental settings. Additionally, no comparative analysis was done across urban locations, which could have provided valuable insight into regional variations in organizational capacity.

From this review, it is evident that individual, organizational, and policy factors significantly influence EMR adoption. However, a substantial gap exists in the literature with regard to specialty-specific analyses, especially within the private dental sector. Furthermore, most Kenyan studies are centered on Nairobi, leaving out other urban centers like Mombasa that may differ in infrastructure, leadership models, and policy uptake. This study addresses these gaps by using an urban comparative approach and applying the UTAUT model to assess how individual, institutional, and policy-level factors intersect to shape EMR adoption in private dental clinics.

2.3.3 EMR Adoption in LMIC and African Contexts: Divergent Realities

While the theoretical foundations of TAM and DOI were developed and validated primarily in high-income contexts, a growing body of evidence from LMICs demonstrates that adoption dynamics differ in important ways. Understanding these differences is essential for contextualizing the current study's findings within the Kenyan private dental sector.

Odekunle et al. (2017) conducted a systematic review of EHR adoption in sub-Saharan Africa and identified that the region lags significantly behind high-income countries, not primarily due to user attitudes or perceived usefulness, but due to infrastructural constraints, including unreliable power supply, poor internet connectivity, and

inadequate technical support, that are largely absent from TAM and DOI frameworks. This finding suggests that structural barriers, rather than individual perceptions, may be the primary adoption bottleneck in African contexts.

In Kenya specifically, Kumar et al. (2016) found that while mobile penetration is high, scaled successes in digital health remain limited, constrained by human resources shortages, political factors, ethical concerns around data privacy, and financial barriers that are not captured by standard TAM constructs. The national KenyaEMR deployment study (Science Journal of Public Health, 2023) similarly documented that implementation costs and infrastructure requirements were the dominant challenges in rollout, rather than clinician resistance or usability concerns.

In the dental sector, Farajollahi et al. (2024) examined barriers and facilitators for implementing electronic dental record (EDR) systems in a developing-country context and found that clinician-perceived barriers included system reliability, cost, and lack of technical support, factors that align more closely with DOI's complexity and trialability attributes than with TAM's psychological constructs. This finding is directly relevant to the current study's focus on private dental clinics, where resource constraints and system reliability are likely to be significant adoption barriers.

Ngusie et al. (2022), in a cross-sectional study in Ethiopia, found that only 52.8% of healthcare providers were ready for EHR adoption, with readiness associated with age, computer literacy, access to computers, attitude, perceived benefit, and self-efficacy. This multi-factor readiness profile differs substantially from high-income country studies where infrastructure readiness is typically assumed, underscoring the need for context-sensitive frameworks like the CAF's micro-meso-macro categorization.

Taken together, this evidence demonstrates that LMIC and African contexts present a distinct adoption landscape where infrastructural, financial, and systemic barriers operate alongside, and sometimes dominate the individual perceptual factors emphasized in TAM. The current study's integration of DOI, TAM, and CAF is specifically designed to capture this multi-level complexity in the Kenyan private dental context.

2.3.4 Inter-County Comparison of EMR Adoption Between Nairobi and Mombasa

Geographic location plays a crucial role in influencing health technology adoption, especially in decentralized health systems. Differences in infrastructure, administrative capacity, workforce skills, and local governance between urban centers can result in significant variations in electronic medical record (EMR) implementation outcomes (Rahurkar et al., 2015). In the Kenyan context, Nairobi and Mombasa represent two major urban counties with diverse socio-economic and institutional profiles, making them ideal for comparative analysis of EMR adoption in private dental clinics.

Internationally, Rahurkar et al. (2015) conducted a comparative study on health information exchange adoption across urban and rural settings in the United States. The study reported that urban healthcare facilities had higher EMR adoption rates, largely due to better funding, more technical expertise, and pressure to meet regulatory standards. While this study provides valuable insights into location-based disparities, it focused on the broader concept of health information exchange rather than EMRs alone. Moreover, its findings are situated within a high-income context with nationwide interoperability mandates, which limits its applicability to lower-resource settings such as Kenya.

Cowie et al. (2017), examining urban versus rural practices in Australia, found that EMR adoption was more prevalent in urban clinics due to improved access to vendor support and a higher demand for digital services among urban populations. Although this study offers useful parallels, it centered on general medical practices and did not consider the influence of administrative policies at the sub-national level, which are highly relevant in Kenya's devolved healthcare system. Furthermore, the study did not address the private sector or dental specialty practices, which often operate under different logistical and professional conditions.

In the African context, Abubakar et al. (2021) carried out a comparative study between Abuja and Lagos in Nigeria, reporting that Lagos-based private hospitals had significantly higher EMR adoption rates. The authors attributed this to more active investment in ICT infrastructure, a more competitive private health sector, and greater support from local government initiatives. While informative, the study did not include

dental practices and focused solely on large private hospitals, potentially missing the nuanced challenges of smaller, independently managed clinics.

Nyandoro et al. (2020), in a South African study comparing urban and peri-urban health facilities, found that infrastructural reliability—especially electricity and internet availability—played a determining role in EMR adoption. Although the study highlights critical operational variables, it does not account for county-level administrative differences or variations in policy enforcement, which are central to the Kenyan devolved health model. Additionally, the study focused only on public sector clinics, limiting its relevance to privately run dental facilities.

In Kenya, Mugo and Otieno (2021) compared EMR adoption between Nairobi and Kisumu counties, concluding that Nairobi clinics had higher adoption rates due to better access to training, more exposure to digital systems, and existing public-private partnerships that encouraged uptake. However, the study did not include Mombasa, leaving a gap in understanding inter-county differences among the country's major urban hubs. Moreover, the research emphasized general outpatient services without disaggregating findings by clinical specialty.

A more recent study by Hassan et al. (2022) explored EMR use in Mombasa-based private clinics and observed that while there was growing interest in digital health solutions, actual adoption remained low. Barriers identified included lack of peer benchmarking, insufficient access to EMR vendors, and low engagement with county-level digital health strategies. However, the study was limited in scope and did not include a comparative analysis with Nairobi or other counties, making it difficult to isolate location-specific challenges or best practices.

From this discussion, it is clear that while geographic disparities in EMR adoption are well-documented globally and regionally, comparative studies within Kenya—especially between Nairobi and Mombasa—are extremely limited. Existing research tends to focus on public facilities, lacks specialty-specific data, or omits key counties such as Mombasa altogether. Moreover, the private dental sector remains underrepresented despite its growing role in urban healthcare delivery. This study seeks to fill this gap by directly comparing EMR adoption experiences in Nairobi and

Mombasa’s private dental clinics, with a focus on identifying location-specific barriers and enablers within the framework of Kenya’s devolved health system.

2.4 Gaps in Literature

The review of empirical literature reveals several important gaps that this study seeks to address. First, although clinic characteristics have been shown to influence EMR adoption globally, most studies focus on general medical practices and rarely consider specialty clinics such as dental facilities. Second, while individual, organizational, and policy factors are recognized as key determinants of EMR use, there is a limited understanding of how these operate within the unique context of small, privately owned dental clinics in developing countries. Finally, comparative studies between counties in Kenya, particularly Nairobi and Mombasa, are sparse. Most studies are Nairobi-centric, with Mombasa often excluded or underrepresented. The table below summarizes these gaps based on conceptual, contextual, and methodological dimensions:

Table 2.1 Summary of Gaps in Literature and Implications for Current Study

Identified Research Gap	Definition / Nature of the Gap	Source(s)	Relevance to Current Study
Limited focus on EMR adoption in private dental clinics	Most EMR studies in Kenya focus on public hospitals or general outpatient departments, not on specialized private practices like dental clinics	Chepkwony (2015); Kang’a et al. (2016); Ahmed et al. (2022)	Fills sector-specific gap by focusing on EMR adoption in private dental clinics, a neglected but important healthcare segment
Limited evidence simultaneously examines clinic characteristics, system-related, organizational, and policy/environmental factors influencing EMR adoption among private dental clinics in Kenya.	Previous studies primarily examined isolated technological, organizational, or policy factors influencing EMR adoption.	Wolverton & Lanier (2019); Danso et al. (2024); Njoroge (2014)	This study examined the association between clinic characteristics and multiple domains of factors within a single analytical framework.
Absence of comparative data between urban counties in Kenya	No known peer-reviewed studies directly compare EMR adoption in Nairobi vs. Mombasa , despite their distinct urban health environments	Okumu et al. (2022); Waronja & Mogote (2024)	Provides first cross-county comparison on EMR adoption dynamics in Kenya’s urban private dental clinics

Limited evidence examining policy and environmental determinants of EMR adoption within private dental clinics in LMICs.	Environmental influences such as regulation, data protection, and infrastructure are frequently underrepresented in EMR adoption studies, especially in LMICs	Kruse et al. (2016); Musabi & Kipkebut (2024); Vijayanthi & Vidhukumar (2020)	Incorporates policy and regulatory environment to explore broader systemic enablers or barriers to EMR adoption in private practice
Outdated or generalized data on EMR adoption trends	Earlier studies are dated or too general to guide current practice in the rapidly evolving digital health landscape	Tchaiwe (2021); Malhotra & Lassiter (2014)	Generates updated, context-specific evidence reflecting 2025 realities in Nairobi and Mombasa

2.5 Conceptual Framework:

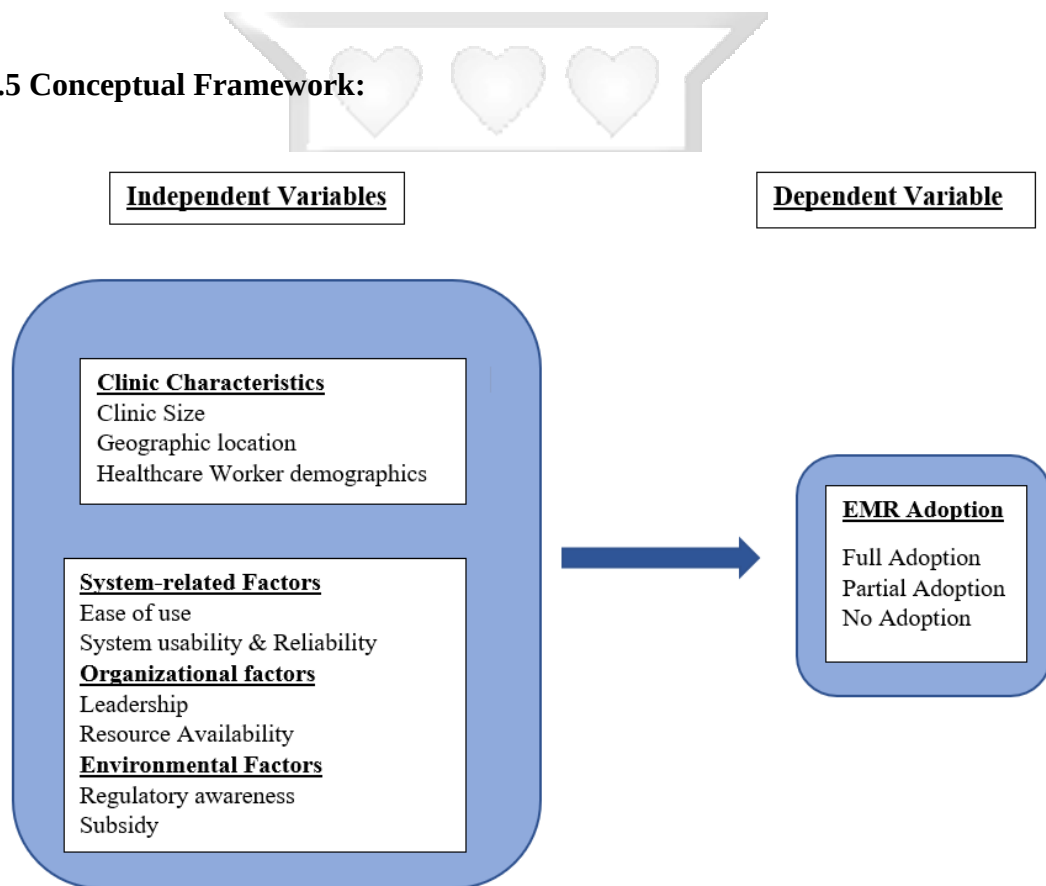


Figure 2.1: Conceptual Framework

The conceptual framework presented above illustrates the relationship between the independent variables—clinic characteristics, individual factors, organizational factors, and environmental factors—and the dependent variable, EMR adoption.

Table 2.2: Mapping of Study Variables to Theoretical Constructs

Study Variable	Theoretical Construct	Source Theory
System usability, information quality, ease of use	Perceived usefulness & perceived ease of use	TAM
Leadership support, workflow integration, resource availability	Organizational readiness	DOI / CAF
Government support, regulation, infrastructure	Policy and environmental context	CAF
Clinic size, ownership, location	Clinic structural characteristics	CAF

The conceptual framework presented in Figure 2.1 integrates constructs drawn from the Technology Acceptance Model (TAM), the Diffusion of Innovations (DOI) theory, and the Clinical Adoption Framework (CAF), as mapped in Table 2.3 above. Within the System-related Factors domain, the variables measuring system usability, reliability, ease of learning, and information quality correspond to TAM's core constructs of Perceived Ease of Use (PEOU) and Perceived Usefulness (PU), respectively (Davis, 1989). The perceived benefits of EMR over paper-based systems, including improved record-keeping, clinical decision support, and workflow efficiency, operationalize DOI's construct of Relative Advantage, while the alignment of EMR systems with existing clinic workflows reflects DOI's Compatibility construct (Rogers, 2003).

The Organizational Factors domain, encompassing leadership support, resource availability, workflow integration, and staff training, corresponds to the meso-level determinants of the Clinical Adoption Framework, which positions organizational readiness as an important determinant of technology adoption in healthcare settings (Gagnon et al., 2012). Environmental and policy factors map onto CAF's macro-level enablers, including regulatory frameworks, government incentives, and national digital health infrastructure. This study grounds each domain of the conceptual framework in its corresponding theoretical construct.

Clinic characteristics, including clinic size, geographical location, ownership type, and healthcare worker demographics, provide the contextual setting within which EMR adoption occurs. System-related factors, including system usability, ease of use, reliability, information quality, and perceived usefulness, are derived from the Technology Acceptance Model and represent users' perceptions of the EMR system. Organizational factors, including leadership support, resource availability, workflow integration, and staff training, reflect the organizational readiness required to support successful EMR implementation, consistent with the Diffusion of Innovations Theory and the Clinical Adoption Framework. Policy and environmental factors, such as regulatory support, government incentives, and digital infrastructure, represent the broader external environment within which clinics operate. Together, these domains provide the theoretical basis for examining factors associated with EMR adoption among private dental clinics in Nairobi and Mombasa Counties.

The dependent variable, EMR adoption, is operationalized into three categories: full adoption, partial adoption, and no adoption, which together capture both dimensions of the study's definition of EMR adoption. Specifically, 'no adoption' reflects the absence of both system availability and active use; 'partial adoption' reflects availability with limited active use across selected functions, such as billing only; and 'full adoption' reflects availability combined with active, routine use across most clinical and administrative operations. The framework guides the study in examining how these multidimensional factors are associated with varying levels of EMR adoption among private dental clinics.

Table 2.3 Operationalization of Study Variables

Domain	Subdomain	Operational Description (Indicators)
EMR Adoption Level (<i>Dependent Variable</i>)	Extent of Adoption	- No adoption - Partial adoption (limited use, e.g., billing only) - Full adoption (used across clinical workflows)
Individual/System Factors (<i>Independent Variable</i>)	Familiarity	- Self-reported familiarity with EMRs
	System Usability	- Ease of learning - Ease of mastering functions - Perceived user-friendliness

Domain	Subdomain	Operational Description (Indicators)
	Performance & Reliability	- Speed of system - Reliability during use
	Information Quality	- Accuracy and comprehensiveness of patient data - Sufficiency for clinical documentation
	Service Support	- Responsiveness of technical support - Quality of vendor customer service
	Usage Behavior	- Frequency of EMR use - Dependence on EMR for daily tasks
Organizational Factors (Independent Variable)	Leadership Support	- Perception of management's support for EMR use - Encouragement of digital solutions in the clinic
	Resource Availability	- Availability of infrastructure (computers, internet, electricity)
	Workflow Integration	- Degree to which EMR is integrated into clinic operations
	Training Support	- Availability of ongoing EMR training opportunities
Policy/Environmental Factors (Independent Variable)	Government & Policy Support	- Awareness of incentives or subsidies - Perceived impact of national health policies
	Regulatory Challenges	- Barriers related to compliance, licensing, and data protection
	External Funding	- Influence of donor or external funding support
Outcome Perceptions (Additional Exploratory Data)	Perceived Benefits	- Improved patient care - Operational efficiency - Data security - Decision-making support
	Perceived Challenges	- Cost barriers - Staff resistance - Technical issues - Privacy concerns

It is important to note, however, that the literature reviewed in this chapter does not converge on a single, universally applicable explanation for EMR adoption. Existing

evidence demonstrates important inconsistencies regarding the factors influencing adoption across different healthcare settings. For example, perceived ease of use a core construct of the Technology Acceptance Model was found to be non-significant in an African healthcare context (Moukoubi Lipenguet et al., 2022), while other studies reported organizational factors such as leadership support and workflow integration to exert a greater influence than individual system perceptions (Wiedenbeck et al., 2008).

Similarly, studies conducted in low- and middle-income countries have shown that infrastructural limitations, financial constraints, and organizational readiness frequently outweigh technological perceptions that are more influential in high-income settings (Odekunle et al., 2017; Ngusie et al., 2022). These contrasting findings suggest that EMR adoption is highly context-dependent and cannot be adequately explained by a single theoretical perspective. Consequently, the present study adopts an integrated theoretical approach, drawing on the Technology Acceptance Model, the Diffusion of Innovations Theory, and the Clinical Adoption Framework to examine the association between system-related, organizational, and policy/environmental factors and EMR adoption among private dental clinics in Nairobi and Mombasa Counties. By generating context-specific evidence from Kenya's private dental sector, the study contributes to the growing body of knowledge on digital health adoption and provides evidence to inform future research, policy, and practice.

2.6 Chapter Summary

This chapter has reviewed both theoretical and empirical literature related to the adoption of EMRs, with a particular focus on individual, organizational, and policy/environmental factors. Theoretical frameworks such as the TAM and DOI were explored to provide a conceptual foundation for understanding the dynamics of EMR uptake. Empirical studies from global, regional, and local contexts highlighted key trends, challenges, and gaps in existing research, particularly the limited focus on private dental clinics in urban settings within low- and middle-income countries like Kenya. The chapter also highlighted important conceptual, contextual, and empirical gaps within the existing literature, thereby justifying the need for the present study. These insights have informed the development of the study's conceptual framework and justified the need for a multidimensional investigation into the factors influencing EMR adoption in private dental clinics in Nairobi and Mombasa Counties.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the methodology employed to investigate the factors influencing the adoption of Electronic Medical Records (EMR) among private dental clinics in Kenyan cities. A cross-sectional quantitative research design was adopted to enable the systematic data collection and analysis, allowing for the identification of patterns and relationships among key variables. The methodology section outlines the research design, the population, sampling, data collection tools, data analysis methods, measures for research quality, and ethical considerations.

3.2 Research Philosophy

This study on the factors influencing the adoption of Electronic Medical Records (EMRs) in private dental clinics in Kenyan cities adopted a positivist research philosophy with a quantitative approach. Positivism is grounded in the belief that knowledge is derived from observable phenomena and measurable facts, emphasizing objectivity, rigor, and empirical evidence (Khanday et al., 2024). In the context of healthcare informatics, this philosophy is particularly relevant as it facilitates the systematic exploration of factors at the micro (system-related), meso (organizational), and macro (policy/environmental) levels that influence EMR adoption through measurable variables.

Under the positivist paradigm, the study focused on the collection of standardized data from a representative sample of private dental clinics in Nairobi and Mombasa. This data was obtained through structured tools, such as surveys, to ensure consistency, reliability, and validity in capturing key factors such as system quality, leadership support, resource availability, and the impact of policy incentives. The reliance on quantifiable data enabled statistical analysis, which was instrumental in identifying relationships, trends, and patterns relevant to EMR adoption.

Through adhering to a positivist approach, the study aimed to produce objective, evidence-based insights that can guide healthcare policy, inform best practices, and identify effective strategies for improving EMR adoption in resource-constrained settings. This approach aligned with the study's objective of contributing to the

modernization of healthcare delivery systems, enhancing operational efficiency in private dental clinics, and ultimately improving patient care through evidence-driven solutions.

3.3 Research Design

According to Vijayanthi & Vidhukumar (2020), a research design is a systematic plan to study a scientific problem, providing an appropriate framework for a study. It integrates different components coherently to effectively address the research problem. The choice of research design is indeed crucial as it dictates the methods and techniques used to collect evidence pertinent to the research problem. It ensures that the insights gained are accurate and unbiased, facilitating the evaluation of problems, testing of theories, or description of phenomena (Nichols & Edlund, 2023).

This study adopted a quantitative analytical cross-sectional research design, which involves collecting data at a single point in time to provide a snapshot of the variables of interest within a defined population (Wang & Cheng, 2020). Descriptive research focuses on identifying and describing patterns, relationships, or characteristics of a population without manipulating any variables (Omair, 2015). This design is particularly suited for exploring the "*what*," "*when*," "*who*," and "*where*" aspects of EMR adoption in private dental clinics, as it allows researchers to characterize distributions and answer practical descriptive questions by measuring population attributes at a single timepoint (Omair, 2015). It aligned with the study's aim, which was to assess the prevalence and influencing factors of EMR adoption without attempting to establish causal relationships — a recognized limitation of cross-sectional designs, given that simultaneous measurement of variables produces temporal ambiguity that prevents firm causal conclusions (Wang & Cheng, 2020).

Even though the selected design did not permit the establishment of definitive causal relationships, methodological measures were adopted to strengthen the robustness of the findings. These included the collection of data from multiple respondent categories within participating clinics to reduce single-source bias, and the inclusion of open-ended questions complemented the quantitative findings by providing contextual explanations for observed quantitative patterns and strengthening interpretation. While causality could not be inferred, these measures enhanced the credibility of observed

associations and provided a stronger basis for understanding factors associated with EMR adoption.

3.4 Population and Sampling

3.4.1 Target Population

Target population in research refers to specific subsets within a larger population, delineated by predefined criteria that align with the research objectives (Willie, 2024). The target population for this study comprised licensed private dental clinics operating in Nairobi and Mombasa Counties. According to the Kenya Medical Practitioners and Dentists Council (KMPDC, 2024), as of January 23, 2024, there were 230 private dental clinics in Nairobi and 25 in Mombasa, totaling 255 clinics. These urban centers were selected because they represented the highest concentration of private dental practices in the country and have contrasting healthcare environments. The study targeted clinic owners, lead dentists, dental assistants and administrators who are directly involved in EMR-related decisions and operations.

3.4.2. Inclusion and Exclusion Criteria

Inclusion Criteria:

Licensed private dental clinics registered with the Kenya Medical Practitioners and Dentists Council (KMPDC).

Clinics that have been in continuous operation for at least 12 months.

Clinics located within Nairobi or Mombasa Counties.

Exclusion Criteria:

Public or faith-based dental clinics.

Hospital-based dental clinics.

Clinics that are temporarily closed or undergoing renovation.

Locum and visiting staff whose engagement with the clinic was temporary and who were not directly involved in routine EMR implementation, system administration, policy development, or strategic decision-making.

The exclusion of the above respondents was intended to ensure that responses reflected institutional experiences and organizational practices rather than intermittent exposure to clinic operations.

3.4.3 Sample Size Estimation:

The study targeted registered private dental clinics in Nairobi and Mombasa Counties. Sample size estimation was informed by the total population of 255 licensed private dental clinics identified through the Kenya Medical Practitioners and Dentists Council (KMPDC, 2024) database. The two counties formed the primary study strata due to their differing numbers of registered private dental clinics and contrasting healthcare environments. A random sampling technique was applied to select the sample number of clinics using the Yamane (1967) formula as computed below

$$n = \frac{N}{1 + N(e)^2}$$

Where:

n = Sample Size.

N = Whole population under study.

e = Sampling Error of 0.05

A sampling error (e) of 0.05 was established to ensure acceptable accuracy in the results.

$$n = \frac{255}{1 + 255(0.05)^2} \approx 156$$

The calculated sample size was approximately 156 clinics.

To obtain multidimensional perspectives on EMR adoption, data was collected from at least two knowledgeable respondents from each participating clinic where feasible. These included one clinical respondent, such as a dentist, dental assistant, or community oral health officer, and one administrative or technical respondent, such as a practice manager, receptionist, or ICT personnel. This resulted in a target of 312 respondents for the study.

The unit of analysis for the study was the private dental clinic, as the study sought to examine EMR adoption at the facility level. However, the unit of observation comprised individual respondents from whom information regarding EMR implementation, organizational readiness, and system use was obtained. This approach enhanced the depth, reliability, and internal validity of the findings while maintaining the clinic as the primary analytical focus.

3.5 Data Collection Methods

Data was collected using a structured online questionnaire developed using Google Forms. The questionnaire (Appendix B) comprised 36 items grouped into five sections: sociodemographic information, clinic characteristics, system-related factors, organizational-level factors, and policy/environmental-level factors influencing EMR adoption as well as EMR adoption outcomes. Questions included structured items and 5-point Likert scale statements to capture perceptions and experiences.

In addition to structured quantitative items, the questionnaire included open-ended questions designed to capture deeper contextual insights on EMR adoption. These questions elicited qualitative responses on barriers, facilitators, and user experiences that could not be fully captured through Likert-scale items. The inclusion of qualitative items was intended to enhance contextual understanding and support interpretation of quantitative findings through methodological triangulation within a predominantly quantitative study design.

The link to the online questionnaire was distributed through contact information obtained from the KMPDC facility registry and professional networks such as the Kenya Dental Association (KDA) and dental practitioners' WhatsApp groups. Before accessing the questionnaire, participants were required to review an informed consent form (Appendix A) that outlined the study purpose, procedures, voluntary nature of participation, and assurances of confidentiality.

Participants completed the questionnaire using any internet-enabled device. The form incorporated user-friendly features such as progress bars, tooltips, and automatic validation to ensure usability and data quality. Responses were automatically anonymized and securely stored on a password-protected platform accessible only to the research team. Support contact information was provided for participants requiring assistance.

3.6. Data Analysis

This section outlines the procedures for managing, processing, and analyzing the data collected to evaluate the factors influencing the adoption of Electronic Medical Records (EMRs) in private dental clinics in Kenyan cities. The analysis focused on establishing the socio-demographic profile of participants, examining responses to Likert scale items, and identifying relationships between dependent and independent variables. The

data analysis process ensured accuracy, reliability, and alignment with the research objectives.

3.6.1. Data Management

Collected data was securely stored and regularly reviewed for completeness. After initial data cleaning to address missing or inconsistent entries, the dataset was exported to SPSS for analysis. Identifiable information was removed to ensure anonymity. Data was stored securely for approximately 7 years before its eventual deletion.

3.6.2. Descriptive Statistics

Descriptive statistics were employed to summarize the data and provide an overview of the socio-demographic characteristics of the respondents as well as the distribution of responses to the study variables. Categorical variables such as gender, professional role, clinic size, clinic ownership, and clinic location were summarized using frequencies and percentages, while continuous variables such as years of practice were described using means and standard deviations. This provided a clear profile of the study participants and the context within which EMR adoption was assessed.

In addition to descriptive profiling, the study developed composite indices to operationalize the multi-item constructs measured using Likert-scale questions. These constructs represented the individual/system-level factors, organizational-level factors, and policy/environmental-level factors influencing the adoption of Electronic Medical Records (EMRs) in private dental clinics. Each construct was measured using multiple items rated on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

The construction of the composite indices followed a systematic procedure. First, questionnaire items were grouped according to their theoretical domains as guided by the Clinical Adoption Framework and previous studies on EMR adoption. The Individual/System Factors Index comprised items measuring training and EMR familiarity, system usability, system performance and reliability, information quality, service and technical support, and usage behavior. The Organizational Factors Index included items measuring leadership support, resource availability, workflow integration, technical support, and staff readiness. The Policy/Environmental Factors Index comprised items relating to government incentives, policy support, regulatory environment, institutional support, and external funding mechanisms.

All negatively worded items were reverse-coded to ensure consistency in interpretation, such that higher scores uniformly represented more favorable conditions for EMR adoption. Reverse coding was performed using the transformation formula ($6 - \text{original response}$) for all items measured on the five-point Likert scale.

Further, the dataset was examined for missing values before index construction. Cases with substantial missing data were excluded through listwise deletion. For isolated missing responses within retained cases, mean substitution was applied. This approach ensured data completeness while minimizing potential bias arising from missing information.

The internal consistency reliability was assessed using Cronbach's Alpha. A minimum threshold of 0.70 was adopted to indicate acceptable reliability. Item-total correlations and Cronbach's Alpha-if-Item-Deleted statistics were examined to identify items that weakened construct reliability. Where necessary, poorly performing items were removed, provided their exclusion was theoretically justified. Only constructs that achieved acceptable reliability levels were retained for index construction.

Lastly, composite indices were computed using the mean-score approach. For each respondent, the scores of all retained items within a construct were summed and divided by the number of items. This generated a standardized index score ranging from 1 to 5 and preserved the original measurement scale, thereby facilitating interpretation and comparison across constructs.

Finally, the resulting indices were interpreted such that higher mean scores indicated stronger enabling conditions for EMR adoption, while lower scores reflected weaker support for adoption. For descriptive purposes, mean scores below 2.5 were interpreted as low levels of support, scores between 2.5 and 3.5 as moderate levels of support, and scores above 3.5 as high levels of support. The three indices were subsequently used as independent variables in the correlation and regression analyses to examine their influence on EMR adoption among private dental clinics.

3.6.3. Analytical Approach

The analytical approach focused on examining the relationships between the dependent variable, Electronic Medical Records (EMR) adoption, and the independent variables derived from the study constructs. These constructs were operationalized as composite indices representing individual/system-level factors, organizational-level factors, and policy/environmental-level factors. The use of indices ensured that multi-item Likert-

scale responses were consolidated into reliable and valid continuous variables suitable for inferential statistical analysis.

Prior to analysis, the composite indices were computed and treated as continuous variables. This allowed the study to retain the richness of the Likert-scale data while ensuring statistical appropriateness for regression analysis. The indices formed the basis for examining the influence of different contextual factors on EMR adoption among private dental clinics.

Chi-square tests of independence were initially used to explore associations between categorical variables such as clinic characteristics (e.g., size, location, ownership type, gender, and age group) and EMR adoption status. Cross-tabulations were generated to present the distribution of responses in terms of frequencies and percentages, providing an initial descriptive understanding of patterns in the data.

Pearson correlation analysis was subsequently conducted to assess the direction and strength of relationships among the composite variables and EMR adoption. Correlation coefficients were used to determine whether statistically significant linear relationships existed between individual/system factors, organizational factors, policy/environmental factors, and EMR adoption.

For inferential analysis, both multiple linear regression and ordered logistic regression techniques were employed. Multiple linear regression was used to examine the influence of demographic characteristics, individual/system factors, organizational factors, and policy/environmental factors on EMR adoption. The regression models estimated the magnitude and direction of influence of each predictor variable on EMR adoption while controlling for other variables in the model. Regression coefficients, standard errors, p-values, R-squared values, F-statistics, and significance levels were reported. Statistical significance was assessed at the 0.05 level.

In addition, ordered logistic regression was employed because the dependent variable, EMR adoption, was ordinal in nature and categorized into ordered levels representing no adoption, partial adoption, and full adoption. Ordered logistic regression was considered appropriate because it accounts for the natural ordering of the outcome variable while estimating the likelihood of clinics progressing from lower to higher levels of EMR adoption.

The ordered logistic regression models included demographic variables, individual/system factors, organizational readiness, and policy/environmental factors

as predictor variables. The analysis estimated regression coefficients, standard errors, z-statistics, p-values, likelihood ratio chi-square statistics, and pseudo R-squared values. The ordered logistic regression approach enabled the study to determine the factors significantly associated with higher levels of EMR adoption among private dental clinics.

Qualitative data obtained from open-ended questions was analyzed using a structured thematic content analysis approach. Responses were first read repeatedly to ensure familiarity with the data. Initial codes were then generated inductively to capture key ideas related to EMR adoption experiences. These codes were subsequently grouped into broader themes reflecting individual/ system factors, organizational factors, and policy/environmental influencing adoption.

The identified themes were used to complement and interpret quantitative findings rather than to stand alone as a separate qualitative analysis. This approach enhanced explanatory depth by providing context to statistical relationships identified in the regression and correlation analyses. The integration of qualitative insights strengthened the overall interpretation of results by revealing underlying reasons behind observed patterns in EMR adoption.

Overall, the analytical framework ensured a robust and systematic examination of both descriptive patterns and inferential relationships, thereby providing evidence-based insights into the factors influencing EMR adoption among private dental clinics in Nairobi and Mombasa Counties.

3.6.4. Presentation of Findings

The study findings were presented using tables, graphs, and figures to enhance clarity and facilitate understanding. These presentations ensured that the data trends and relationships were easily interpretable, allowing for actionable insights to address the study objectives.

Employing robust statistical methods and clearly presenting the findings, the data analysis gave a detailed insight on the factors influencing the adoption of EMRs in private dental clinics in Kenyan cities.

The findings were used primarily for academic research as part of a Master's thesis at Strathmore University. In addition to fulfilling academic requirements, the findings will be shared with relevant health authorities, professional associations, and stakeholders

to help improve electronic medical record (EMR) adoption in private dental clinics and strengthen digital health policies in Kenya.

3.7. Research Quality

3.7.1. Validity

To ensure the validity of the research, multiple strategies were employed to verify that the data collected accurately reflected the constructs under investigation. Content validity was addressed by aligning the questionnaire items with the conceptual framework of the study, which focused on micro-level, meso-level, and macro-level factors influencing the adoption of EMRs. Expert review by the study supervisors and healthcare informatics professionals ensured that the items comprehensively cover the dimensions of interest.

Construct validity was ensured by piloting the questionnaire and analyzing the responses to verify that the items measure the intended constructs consistently. This step included factor analysis to confirm that the questions align with the theoretical domains identified in the Clinical Adoption Framework (CAF). Criterion-related validity was also evaluated by comparing responses on the Likert scale to existing benchmarks for EMR adoption, where applicable.

Cross-validation further enhanced the robustness of the findings. Through testing the questionnaire across a subset of private dental clinics with varying characteristics, the research ensured that the instrument captured differences related to clinic size, location, and EMR adoption status, reflecting the diversity of the study population.

3.7.2 Reliability

Reliability was ensured through standardized data collection procedures and thorough training of data collectors. The data collection team underwent a comprehensive training program to ensure consistency in administering the online questionnaire, handling participant queries, and addressing technical issues.

The reliability of the questionnaire was assessed during a pilot study. Internal consistency was measured using Cronbach's alpha, with a threshold of 0.7 or higher indicating acceptable reliability. Test-retest reliability was also evaluated by administering the questionnaire to a small subset of participants twice, at a two-week interval, to ensure stable responses over time. These methods ensured that the instrument produced consistent and dependable results. The reliability results are indicated in Table 3.1 below

Table 3.1 Reliability Test Results

Variables	Cronbach's Alpha	Critical Value	Conclusion
Individual/system characteristics	0.874	0.7	Reliable
Organizational Factors	0.832	0.7	Reliable
Policy & Environmental Factors	0.701	0.7	Reliable

The Cronbach's alpha coefficients ranged from 0.699 to 0.874, indicating acceptable internal consistency of the measurement scales since all values exceeded the recommended threshold of 0.7.

Further measures included regular monitoring of data collection processes and auditing responses to identify and address discrepancies or patterns of inconsistency promptly. By adhering to these practices, the study maintained a high level of reliability and generated trustworthy data.

3.7.3. Objectivity

The research prioritized objectivity by employing validated and reliable instruments to minimize measurement bias. The use of a standardized online questionnaire reduced variability in data collection and ensured that all participants received the same questions in a consistent format.

Data collectors adhered to uniform procedures to avoid introducing personal biases during participant interactions. Pilot testing of the questionnaire allowed for refinement of ambiguous or leading questions, ensuring that all items were clear and unbiased. Quantitative data collection, focusing on numerical and measurable responses, further enhanced objectivity by reducing reliance on subjective interpretations.

Statistical analysis followed established protocols, with independent variables being analyzed against the dependent variable using transparent and replicable methods. By grounding the study in observable, empirical evidence, the research upheld its commitment to objective and impartial findings.

3.8. Ethical Considerations

This study adhered to ethical guidelines for research involving human participants. Informed consent was obtained electronically before participation. Participant anonymity and data confidentiality was ensured through data anonymization, secure storage, and restricted access protocols.

Ethical approval was sought from the Strathmore University Institutional Ethics Review Board (SU-IERC) and the National Commission for Science, Technology and Innovation (NACOSTI) prior to data collection. The study complied with the Data Protection Act (2019), including data minimization, transparency, and security measures. Participants were informed of their rights, including the right to withdraw at any time without penalty.



CHAPTER FOUR

PRESENTATION OF RESEARCH FINDINGS

4.1 Introduction

The results are presented in this chapter based on the study's objective. The aim of the study was to investigate the factors influencing the adoption of Electronic Medical Records (EMR) among private dental clinics in Kenyan cities. It was to determine the influence of clinic characteristics, system-related factors, organizational factors and policy/environmental factors on EMR adoption among private dental clinics in Nairobi and Mombasa. The results from the data analysis are presented.

4.2 Response Rate

A total of 312 questionnaires were issued to the respondents from the clinics selected for the study. A total of 272 responses were obtained resulting in an 87% response rate since 272 of the 312 submitted responses were complete. The response rate was appropriate for concluding the information gathered. According to Kothari (2016), a response rate of more than 70% in an investigation is deemed sufficient for data analysis purposes. As a result, the study's questionnaire response rate fell within the permissible range for conclusions and suggestions. The response rate is in table 4.1 below

Table 4.1: Response Rate

Department	Number	Percentage
Complete Responses	272	87%
Incomplete Responses	40	13%
Total	312	100%

4.3 Socio-demographic Information

To provide context for the study findings, the sociodemographic characteristics of the respondents were analyzed across key variables, including gender, age, professional role, years in healthcare, clinic ownership type, years of experience, clinic location, clinic size, and EMR adoption level. The summarized distribution is presented in Table 4.2, which highlights the composition of the study sample.

The findings in Table 4.2 indicate that the majority of respondents were female (66%), compared to 34% male, suggesting that the workforce within the selected private dental

clinics is predominantly female. These findings indicate that the workforce in the participating private dental clinics is largely female. This demographic profile provides important context for interpreting the study findings but does not, on its own, imply any difference in EMR adoption between male and female healthcare workers.

On age distribution, the majority of respondents were relatively young, with 40.8% aged between 31-40 years and 39.1% aged between 20-30 years. Collectively, this means that approximately 80% of the respondents were within the early-to-mid career stage. Respondents aged above 50 years accounted for only 4.7% of the sample. The findings indicate that the workforce was predominantly young.

On professional roles, dentists formed the largest proportion of respondents at 43%, followed by administrative staff at 29%, dental assistants at 22.2%, and community oral health officers at 5.8%. This distribution demonstrates representation from both clinical and administrative personnel involved in clinic operations. The implication is that successful EMR adoption requires coordinated participation across all professional categories because both clinical and administrative staff play essential roles in data entry, patient management, and records utilization.

The study further examined respondents' years in healthcare. The findings revealed that 37.5% of respondents had worked in healthcare for between 5-10 years, while 37% had less than 5 years of experience. Respondents with more than 10 years of healthcare experience accounted for 25.5%. These findings suggest that the sampled clinics possess a moderately experienced workforce capable of adapting to technological changes while also benefiting from institutional knowledge accumulated over time.

On the clinic ownership demographic characteristic, the majority of clinics were sole proprietorships (59%), while partnership-owned and corporate-owned clinics each accounted for 20.5%. This indicates that private dental practice within Nairobi and Mombasa is predominantly characterized by individually owned establishments. Such ownership structures may experience financial and technical limitations that can constrain full-scale EMR implementation compared to corporate-owned facilities, which are more likely to possess structured systems, dedicated IT support, and stronger financial capacity.

The study also assessed respondents' years of experience within their current work settings. The findings showed that 38.2% had between 1–3 years of experience, 23.8% had less than 1 year, 20.2% had between 4–6 years, while 17.8% had more than 6 years of experience. This suggests that a considerable proportion of employees are relatively early in their professional practice, which may positively influence adaptability to digital systems and openness to technological change.

With regard to clinic location, most respondents were drawn from Nairobi County (82%), while 18% were from Mombasa County. This distribution indicates that the study largely captured experiences from urban-based private dental clinics, where technological infrastructure and internet accessibility are generally more developed, potentially influencing EMR adoption positively.

On clinic size, the majority of facilities were small clinics with between 1–5 staff members (59.5%), followed by medium-sized clinics with 6–15 staff members (30.8%). Only 9.7% of the clinics were classified as large facilities with more than 16 staff members. These findings suggest that the private dental sector is primarily dominated by small and medium enterprises. Smaller clinics may face constraints related to finances, technological infrastructure, and specialized personnel, which can hinder comprehensive EMR implementation. Conversely, larger clinics are more likely to possess sufficient operational capacity and resources necessary to support EMR systems effectively.

Finally, the study established that 39.3% of clinics had fully adopted EMR systems, while 37.8% reported partial adoption and 22.9% indicated no adoption at all. These findings suggest that although significant progress has been made toward digital transformation within private dental clinics, a substantial proportion of facilities are still either partially digitized or entirely reliant on manual systems. This indicates the need for continued investment in infrastructure, technical support, and capacity building to enhance full EMR adoption across the sector. The results of the socio-demographic information are summarized in Table 4.2 below

Table 4.2 Socio-Demographic Information

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	92	34
	Female	180	66
Age	20-30 years	106	39.1
	31-40 years	111	40.8
	41-50 years	42	15.4
	51+ years	13	4.7
Professional Role	Dentist	117	43
	Dental Assistant	60	22.2
	Community Oral Health Officer	16	5.8
	Administrative Staff	79	29
	Others	0	0
Years in Healthcare	< 5 years	101	37
	5-10 years	102	37.5
	> 10 years	69	25.5
Clinic Ownership	Sole Proprietorship	160	59
	Partnership	56	20.5
	Corporate-owned	56	20.5
Years of Experience	< 1 year	65	23.8
	1-3 years	104	38.2
	4-6 years	55	20.2
	> 6years	48	17.8
Clinic Location	Nairobi	222	82
	Mombasa	50	18
Clinic Size	Small (1-5) staff	162	59.5
	Medium (6–15 staff)	84	30.8
	Large (16+ staff)	26	9.7
EMR Adoption	No Adoption	62	22.9
	Partial Adoption	103	37.8
	Full Adoption	107	39.3

In addition to the socio-demographic information presented above, the researcher was interested in establishing the type of functionalities that are supported by EMR in the different clinics in Nairobi and Mombasa. Figure 4.1 below illustrates these findings. From the results, patient registration (95.7%), billing/invoicing (88.6%), and clinical history/notes (84.8%) are the most commonly used EMR functionalities among private dental clinics. This means that the majority of clinics that have adopted EMRs are primarily using them for basic and essential operational tasks, particularly those related to patient intake, record keeping, and financial transactions. Similarly, a high proportion of clinics reported using EMRs for treatment planning (81.0%), indicating that EMR systems are also being utilized in supporting clinical decision-making and patient management processes.

However, comparatively lower usage was observed for data reporting and analysis (72.4%) and appointment scheduling (69.5%). This suggests that while many clinics have adopted EMRs, fewer are utilizing them for advanced or supportive functions, such as analytics and workflow optimization. In addition, the finding that 2.9% of respondents reported not using any EMR system indicates that a small proportion of clinics remain fully non-digital, relying on alternative (likely manual) systems. These findings support the operational classification of EMR adoption because clinics demonstrated varying degrees of implementation across core EMR functions.

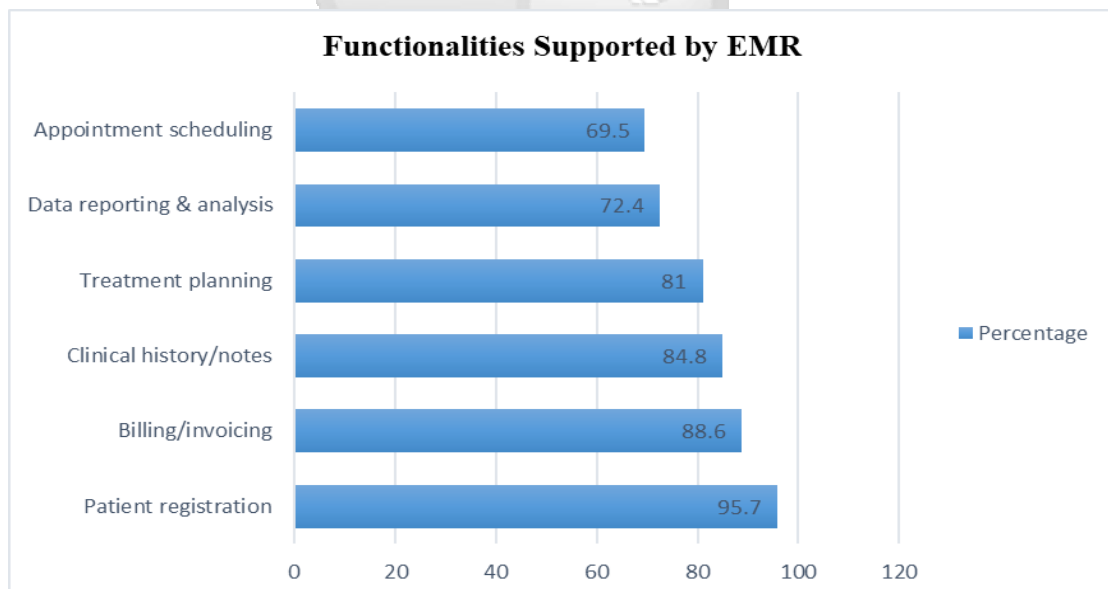


Figure 4.1 EMR Functionalities Supported

4.3 Data Analysis

4.3.1 Effect of Clinic size, Location, and Healthcare Worker Demographics on EMR Adoption

This section presents the analysis of the first objective, which was to analyze the relationship between selected clinic characteristics and healthcare worker demographics and the level of EMR adoption among private dental clinics in Nairobi and Mombasa Counties. Specifically, the analysis examines whether factors such as clinic size, clinic ownership, location, and respondents' socio-demographic characteristics are associated with the level of EMR adoption (partial or full). To achieve this, cross-tabulation and the Chi-square test of independence were employed to determine whether statistically significant relationships exist between the independent variables and EMR adoption.

The Chi-square (χ^2) test is a non-parametric statistical method used to assess whether there is a significant association between two categorical variables. Developed by Karl Pearson (1900), it compares observed frequencies in a contingency table with those expected if the variables were independent. It is especially useful for cross-tabulated survey data, such as Likert-scale responses across demographic groups. The statistical significance derived from these tests (e.g., p-values < 0.05) supports or rejects hypotheses of independence. This is critical in understanding whether targeted interventions should be customized for specific subgroups.

Table 4.3 below summarizes the results of Chi-square tests assessing associations between selected demographic variables and EMR adoption. The significance threshold was set at $p < 0.05$.

Table 4.3 Chi-Square Tests

Demographic	Chi² Statistic	Degrees of Freedom	p-value	Significant (p < 0.05)
Gender	0.096	2	0.953	No
Age Group	4.407	4	0.354	No
Years in Healthcare	7.992	4	0.092	No
Clinic Location	34.107	2	0.000	Yes
Clinic Size	44.402	6	0.000	Yes

Clinic Ownership	22.337	6	0.001	Yes
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The study examined the relationship between selected demographic and clinic characteristics and the level of EMR adoption using the Chi-square test of independence. The findings indicate that gender was not significantly associated with EMR adoption ($\chi^2 (2) = 0.096$, $p = 0.953$), suggesting that EMR adoption levels did not differ significantly between male and female respondents. Similarly, age group was not significantly related to EMR adoption ($\chi^2 (4) = 4.407$, $p = 0.354$), indicating that respondents across different age categories exhibited similar levels of EMR adoption. Years in healthcare also showed no statistically significant relationship with EMR adoption ($\chi^2 (4) = 7.992$, $p = 0.092$), implying that differences in work experience did not significantly influence adoption levels.

However, clinic location was found to have a statistically significant relationship with EMR adoption ($\chi^2 (2) = 34.107$, $p < 0.001$). This suggests that EMR adoption levels varied significantly across different clinic locations, possibly due to differences in infrastructure, technological access, institutional support, or resource availability. Similarly, clinic size was significantly associated with EMR adoption ($\chi^2 (6) = 44.402$, $p < 0.001$), indicating that small, medium, and large clinics differed significantly in their levels of EMR adoption. This finding suggests that larger clinics may possess greater financial, technical, and human resource capacity to support EMR implementation compared to smaller clinics.

The results further revealed that clinic ownership had a statistically significant relationship with EMR adoption ($\chi^2 (6) = 22.337$, $p = 0.001$). This indicates that adoption levels differed significantly across different ownership structures such as sole proprietorships, partnerships, and corporate-owned clinics. The variation may reflect differences in management structures, investment capacity, strategic priorities, and organizational readiness among the ownership categories.

Clinic-related characteristics, particularly clinic location, clinic size, and clinic ownership, exhibited statistically significant associations with EMR adoption, suggesting that adoption is structurally conditioned by institutional capacity rather than individual-level demographics. The absence of significance for gender, age group, and years in healthcare further indicates that EMR adoption in the study context is not

primarily driven by personal attributes of healthcare workers, but by organizational and contextual enablers such as resource availability, infrastructure, and management structure.

4.3.2 Effect of Individual, Organizational, and policy/environmental factors affecting EMR adoption in the target clinics

The second objective of the study was to determine the effect of Individual, Organizational, and policy/environmental factors affecting EMR adoption in the target clinics in Nairobi and Mombasa. The descriptive statistics for these are described below.

4.3.2.1 Overall Descriptive Statistics

Descriptive statistics were computed for the composite variables and the dependent variable. The results showed that the mean score for EMR system characteristics was 4.279 (SD = 0.676), indicating that respondents generally perceived EMR systems positively. Organizational readiness had a mean score of 4.113 (SD = 0.830), suggesting relatively high levels of readiness among clinics. The policy environment variable recorded a mean of 2.791 (SD = 0.935), indicating moderate perceptions regarding policy support and external funding. The average coded adoption score for EMR adoption was 1.849 (SD = 0.766), suggesting that most clinics were at low to moderate levels of EMR adoption.

Table 4.4 Overall Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Individual & System Factors	210	2	5	4.278571	.6761392
Organizational Factors	210	1	5	4.113492	.8303474
Policy & Environmental factors	272	1	5	2.79136	.9346195
EMR Adoption	272	1	3	1.849265	.7655398
Valid N (listwise)	272				

Furthermore, descriptive statistics for the individual items in the individual/system factors, organizational factors, and policy/environmental factors were computed to determine how the respondents answered each of the individual statements in the selected factors. The results are presented in the subsequent sections below:

4.3.2.2 Individual Factors Influencing EMR Use

The results established that respondents generally reported high levels of agreement with statements related to individual factors influencing EMR use, as reflected by mean scores above 4.0 for most statements. A significant proportion of respondents agreed or strongly agreed that they were familiar with using EMR systems, with 46 (22%) agreeing and 122 (58%) respondents strongly agreeing, reflected in a high mean score (Mean = 4.27, SD = 1.05). Similarly, the majority indicated that the EMR system is easy to learn, with 62 (30%) agreeing and 111(53%) strongly agreeing (Mean = 4.27, SD = 0.98), and easy to master, with 54 (26%) agreeing and 108 (51%) strongly agreeing (Mean = 4.20, SD = 0.99).

The system was also widely perceived as user-friendly, with 63 (30%) agreeing and 115 (55%) strongly agreeing (Mean = 4.32, SD = 0.93), and reliable in its performance, with 72% agreeing and 107 strongly agreeing (Mean = 4.30, SD = 0.91). In addition, 55 (26%) agreed and 111 (55%) strongly agreed that the system speed is sufficient for daily tasks (Mean = 4.26, SD = 0.93). On information quality, 47 (22%) agreed, and 120 (57%) strongly agreed that the EMR provides accurate and reliable information for clinical decisions (Mean = 4.27, SD = 1.02), while 51(24%) agreed and 124 (59%) strongly agreed that it provides comprehensive and relevant patient data (Mean = 4.36, SD = 0.92). Similarly, 49 (23%) agreed and 127 (60%) strongly agreed that the information is sufficient for clinical documentation needs (Mean = 4.34, SD = 1.01).

However, comparatively lower levels of agreement were observed regarding technical support, where 53 (25%) agreed and 87 (41.4%) strongly agreed, while a notable proportion expressed neutral or lower agreement (Mean = 3.87, SD = 1.32). Similarly, for vendor support, 55 (26%) agreed and 91(43%) strongly agreed, with some variation in responses (Mean = 3.99, SD = 1.11). Finally, on system usage, 46 (22%) agreed and 122 (58%) strongly agreed that they use EMR as part of their daily tasks (Mean = 4.21, SD = 1.14). However, responses were more varied for the statement “I cannot complete my tasks without the EMR system,” where only 37 (18%) agreed and 88 (42%) strongly

agreed, while a substantial proportion expressed disagreement (Mean = 3.58, SD = 1.32).

Overall, the findings show that a majority of respondents expressed agreement with statements relating to EMR usability, reliability, and usefulness, while perceptions of support and dependency on the system were comparatively less consistent. The results are illustrated in Table 4.5 below

Table 4.5 Individual Factors influencing EMR use

Statement	1	2	3	4	5	Mean	Std Dev
I am familiar with using EMR systems.	5	14	23	46	122	4.27	1.05
The EMR system is easy to learn.	7	4	26	62	111	4.27	0.98
It is easy to master the functions of the EMR system.	4	9	35	54	108	4.20	0.99
The EMR system is user-friendly.	5	5	22	63	115	4.32	0.93
The EMR system is reliable in its performance.	5	4	22	72	107	4.30	0.91
The speed of the EMR system is sufficient for my daily tasks.	1	11	32	55	111	4.26	0.93
The EMR provides accurate and reliable information for clinical decisions.	5	10	28	47	120	4.27	1.02
The EMR provides comprehensive and relevant patient data.	4	5	26	51	124	4.36	0.92
The information is sufficient for my clinical documentation needs.	6	9	19	49	127	4.34	1.01
When there is a technical issue, the support team resolves it promptly.	12	21	37	53	87	3.87	1.32
The EMR vendor provides reliable and effective support.	6	18	40	55	91	3.99	1.11
I use the EMR as part of my daily tasks.	13	5	26	46	120	4.21	1.14

I cannot complete my tasks without the EMR system.	36	19	30	37	88	3.58	1.32
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4.3.2.2 Organizational Factors and EMR Use

The findings on organizational factors indicate generally high levels of agreement among respondents, with mean scores ranging from 3.77 to 4.22. Overall, the results suggest that most private dental clinics have supportive organizational environments for EMR use, although variation exists across specific dimensions, particularly training.

A majority of respondents agreed that clinic leadership supports EMR adoption, with 66 (42.3%) agreeing and 107 (34.0%) strongly agreeing (Mean = 4.22, SD = 1.02). This indicates strong perceived leadership commitment to EMR implementation. Similarly, 51 (32.7%) agreed and 112 (42.3%) strongly agreed that the clinic provides adequate resources for EMR use (Mean = 4.17, SD = 1.11), reflecting generally positive perceptions of resource availability.

On system integration, 46 (29.5%) agreed, and 117 (40.4%) strongly agreed that the EMR system is well integrated into clinical workflow (Mean = 4.22, SD = 1.08). This suggests that most clinics have effectively embedded EMR systems into daily operations. Regarding technical support, 49 (31.4%) agreed and 109 (35.0%) strongly agreed that the clinic provides regular technical support (Mean = 4.11, SD = 1.16), indicating that ongoing system support is relatively well established.

In relation to innovation, 45 (28.8%) agreed and 115 (39.1%) strongly agreed that the clinic encourages innovation in digital health (Mean = 4.19, SD = 1.10), reflecting a generally positive organizational culture toward digital transformation.

However, relatively lower levels of agreement were observed for continuous training on EMR use. In this case, 43 (27.6%) agreed and 86 (20.5%) strongly agreed, while a notable proportion selected neutral or lower response categories (Mean = 3.77, SD = 1.27). This indicates that although training exists in some clinics, it is not as consistently implemented compared to other organizational support mechanisms.

Overall, the findings suggest that organizational support structures for EMR adoption are largely present in private dental clinics, particularly in leadership support, resource provision, workflow integration, and technical support. However, continuous training

remains a weaker area, indicating a potential gap in sustaining effective EMR utilization. The results are in Table 4.6 below

Table 4.6 Organizational Factors and EMR Use

Statement	1	2	3	4	5	Mean	Std Dev
Clinic leadership supports EMR adoption.	6	12	19	66	107	4.22	1.02
The clinic provides adequate resources for EMR use.	10	9	28	51	112	4.17	1.11
The EMR is well integrated into our workflow.	8	8	31	46	117	4.22	1.08
The clinic provides regular technical support.	12	9	31	49	109	4.11	1.16
The clinic offers continuous training on EMR use.	12	29	40	43	86	3.77	1.27
The clinic encourages innovation in digital health.	8	10	32	45	115	4.19	1.10

4.3.2.3 Policy/Environmental Factors and EMR Use

The findings for policy and environmental factors indicate comparatively lower levels of agreement among respondents, suggesting that external support structures for EMR adoption are less developed compared to organizational factors. Overall, perceptions of government and policy-level support were mixed, with notable variations across the different dimensions assessed.

A substantial proportion of respondents indicated that there are limited government incentives for EMR adoption, with 91 (58.3%) strongly disagreeing and 44 (28.2%) disagreeing, while only 17 (10.9%) agreed and 18 (11.5%) strongly agreed (Mean = 2.18, SD = 1.30). This suggests that most private dental clinics do not perceive meaningful financial or policy-based incentives from government to support EMR uptake.

Regarding regulatory challenges, responses were more distributed. A total of 57 (36.5%) strongly disagreed and 35 (22.4%) disagreed that regulatory barriers significantly hinder EMR implementation, while 50 (32.1%) were neutral, and 33

(21.2%) strongly agreed or agreed to the presence of such challenges (Mean = 2.77, SD = 1.42). This indicates mixed perceptions, suggesting that regulatory issues may affect clinics differently depending on their context.

For national policy support, responses were moderately positive. A total of 33 (21.2%) strongly disagreed and 31 (19.9%) disagreed that national policy supports EMR use in private clinics, while 61 (39.1%) remained neutral. In contrast, 39 (25.0%) agreed and 46 (29.5%) strongly agreed that supportive national policies exist (Mean = 3.16, SD = 1.35). This reflects a divided perception, with a significant proportion of respondents uncertain about the strength and visibility of national policy frameworks.

Similarly, external funding influence on EMR adoption showed a mixed pattern. A total of 45 (28.8%) strongly disagreed and 29 (18.6%) disagreed that external funding plays a role, while 50 (32.1%) were neutral. On the other hand, 38 (24.4%) agreed and 48 (30.8%) strongly agreed that external funding influences EMR adoption (Mean = 3.07, SD = 1.45). This indicates that while funding mechanisms exist, their reach and visibility may not be uniformly experienced across clinics.

Overall, the findings suggest that policy and environmental support for EMR adoption in private dental clinics is perceived as relatively weak compared to organizational-level support. In particular, government incentives and regulatory clarity appear to be lacking or inconsistently experienced, while perceptions of national policy and external funding remain divided among respondents. The results are in Table 4.7 below

Table 4.7 Policy/Environmental Factors

Statement	1 %	2 %	3 %	4 %	5 %	Mean	Std Dev
There are government incentives for EMR adoption.	91	44	50	17	18	2.18	1.30
The clinic faces regulatory challenges in implementing EMRs.	57	35	50	35	33	2.77	1.42
National policy supports EMR use in private clinics.	33	31	61	39	46	3.16	1.35
External funding influences EMR adoption.	45	29	50	38	48	3.07	1.45

4.3.2.4 Inferential Analysis

1. Correlation Analysis

Pearson's correlation analysis was conducted to examine the relationships among individual and system factors, organizational factors, policy and environmental factors, and EMR adoption. The results are presented in Table 4.8 below.

The findings indicated a strong positive and statistically significant correlation between individual and system factors and organizational factors ($r = 0.730$, $p < 0.01$), suggesting that higher levels of favorable individual and system-related perceptions are associated with more supportive organizational conditions within the sampled clinics. With respect to EMR adoption, individual and system factors exhibited a weak but statistically significant positive correlation ($r = 0.251$, $p < 0.01$), while organizational factors demonstrated a moderate positive and statistically significant relationship ($r = 0.385$, $p < 0.01$). These results indicate that higher levels of positive individual/system perceptions and organizational support are associated with higher levels of EMR adoption.

In contrast, policy and environmental factors showed a weak, statistically insignificant relationship with EMR adoption ($r = -0.054$, $p = 0.439$), suggesting no observable linear association in the study sample. These findings reflected associative relationships rather than causal effects, as correlation analysis does not establish causality, and therefore, no inference can be made that changes in individual, organizational, or environmental factors directly lead to changes in EMR adoption. The observed relationships merely indicate the magnitude and direction of the variables within the sample.

Table 4.8 Correlation Analysis

		Individual & System Factors	Organization al Factors	Policy & Environmenta l factors	EMR Adoption
System- RelatedFacto rs	Pearson	1	.730**	.107	.251**
	Correlation				
	Sig. (2-tailed)		.000	.123	.000
	N	210	210	210	210

Organizational Factors	Pearson Correlation	.730**	1	.093	.385**
	Sig. (2-tailed)	.000		.179	.000
	N	210	210	210	210
Policy/Environmental factors	Pearson Correlation	.107	.093	1	-.054
	Sig. (2-tailed)	.123	.179		.439
	N	272	272	272	272
EMR Adoption	Pearson Correlation	.251**	.385**	-.054	1
	Sig. (2-tailed)	.000	.000	.439	
	N	272	272	272	272

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

The strong positive correlation between Individual/System Factors and Organizational Factors ($r = 0.730$, $p < 0.01$) indicates substantial conceptual proximity between these constructs, suggesting that respondents who perceive EMR systems positively are also more likely to report supportive organizational environments. While this raises a potential concern for multicollinearity, it does not automatically imply construct redundancy, as both variables remained theoretically distinct under the adoption framework.

However, the magnitude of this correlation suggested a possible overlap in perceptual measurement, where organizational readiness may partially shape individual perceptions of system usability and vice versa. This reinforced the need for multicollinearity testing to ensure statistical independence in regression estimation. This was done using the VIF and tolerance test. The results are in table 4.9 below

Table 4.9 Test of Multicollinearity

Variable	VIF	Tolerance
Individual & System factors	2.149	0.465

Organizational factors	2.143	0.467
Policy & Environmental Factors	1.012	0.988

Table 4.9 shows the VIF values ranging from 1.012 to 2.149, confirming the absence of multicollinearity. The VIF values indicate that multicollinearity is not severe enough to bias coefficient estimates or inflate standard errors. Although the correlation matrix suggested moderate overlap between individual/system and organizational constructs, the VIF results confirm that this overlap does not reach levels that would compromise the stability or interpretability of the regression coefficients. Therefore, each predictor retains sufficient unique explanatory contribution within the model.

2. Regression Analysis

Regression analysis was conducted to examine the influence of the independent variables on EMR adoption among clinics. The analysis aimed to determine the extent to which demographic characteristics, EMR individual & system characteristics, organizational readiness, and policy/ environment factors predict the level of EMR adoption. Both linear regression and ordered logistic regression techniques were applied in the study.

The variation in sample size across regression models is due to differences in missing data patterns across variables included in each model. Linear regression models employed listwise deletion of incomplete cases, resulting in an analytical sample of 210 observations for models involving composite indices. In contrast, the ordered logistic regression models utilized a larger number of observations ($n = 272$) due to the inclusion of categorical variables and fewer missing data constraints. This reflects variable-specific missingness rather than inconsistency in data handling procedures.

4.2.3.5 Linear Regression Analysis of Demographic Variables and EMR Adoption

A linear regression analysis was conducted to examine whether demographic and workplace characteristics significantly influenced EMR adoption. The independent variables included gender, age group, years of experience, clinic location, and tenure, while EMR adoption was treated as the dependent variable.

The regression model was statistically significant ($F(5,266) = 5.71, p < 0.001$), indicating that the demographic variables jointly contributed to explaining variations in EMR adoption. However, the coefficient of determination ($R^2 = 0.0969$) showed that

only 9.69% of the variation in EMR adoption was explained by the demographic variables. This suggests that demographic factors alone had relatively weak explanatory power regarding EMR adoption. The low R^2 value observed suggests that EMR adoption is influenced by a broader set of factors not fully captured in the model. This suggests that while individual constructs explain part of the variation, other determinants may play a critical but unobserved role.

At the individual variable level, clinic location emerged as the only statistically significant predictor of EMR adoption ($\beta = -0.607$, $p < 0.001$). The negative coefficient suggests that clinics located in certain areas were less likely to report higher levels of EMR adoption. This finding may reflect disparities in infrastructure, financial resources, technological access, or management support across clinics in Mombasa and Nairobi.

Gender had a positive but statistically insignificant effect on EMR adoption ($\beta = 0.019$, $p = 0.839$), indicating that male and female respondents did not differ significantly in their likelihood of adopting EMRs. Age group also had an insignificant effect ($\beta = -0.036$, $p = 0.656$), suggesting that age differences among healthcare workers did not substantially influence adoption levels.

Similarly, years of experience ($\beta = 0.067$, $p = 0.447$) and tenure within the clinic ($\beta = -0.052$, $p = 0.397$) were statistically insignificant. These findings imply that work experience and duration of employment did not significantly determine the level of EMR adoption in the clinics studied. The results suggest that demographic characteristics play a limited role in influencing EMR adoption, with clinic location being the only important demographic determinant identified in the analysis. The results are in Table 4.10 below

Table 4.10 Linear Regression: Demographic Variables and EMR Adoption

EMR Adoption	Coef.	Std. Err.	P>t
Gender	.01933	.09507	0.839
Age Group	-.03634	.08145	0.656
Experience	.06726	.08838	0.447
Clinic Location	-.60684	.11653	0.000
Tenure	-.05189	.06120	0.397

_cons	2.3912	.18995	0.000
Model Summary			
R-squared	0.0969		
F(5, 266)	5.71		
		0.001	
Prob > F			
Observations	210		

4.2.3.6 Regression: EMR Individual & System Characteristics and EMR Adoption

A regression analysis was conducted to examine the effect of EMR system characteristics on EMR adoption while controlling for demographic variables. The model included gender, age group, experience, clinic location, tenure, and the composite EMR system variable.

The overall model was not statistically significant ($F(6,203) = 1.65$, $p = 0.1352$), indicating that the included variables jointly did not provide a strong explanation of EMR adoption. The coefficient of determination ($R^2 = 0.0465$) showed that the variables explained only 4.65% of the variation in EMR adoption, reflecting weak explanatory power. The relatively low R^2 values in the regression model indicates that EMR adoption is a multifactorial phenomenon influenced by additional latent or unmeasured variables not captured in the current model specification. This suggests that while individual and system constructs explain part of the variation, other determinants may play a critical role.

Despite the weak overall model fit, EMR system characteristics had a positive and statistically significant effect on EMR adoption ($\beta = 0.133$, $p = 0.011$). This finding indicates that improvements in EMR system usability, reliability, speed, accuracy, and information sufficiency increase the likelihood of EMR adoption. In practical terms, clinics are more likely to adopt EMR systems when the systems are perceived as user-friendly, efficient, and reliable.

All demographic variables remained statistically insignificant within this model, suggesting that system-related characteristics were more influential than demographic attributes in determining EMR adoption.

Table 4.11 Regression Analysis: EMR Individual & System Characteristics and EMR Adoption

EMR Adoption	Coef.	Std. Err.	P>t
Gender	-.02780	.07284	0.703
Age Group	-.02446	.06331	0.700
Experience	-.04413	.06838	0.519
Clinic Location	-.06930	.11226	0.538
Tenure	.00237	.05103	0.963
Indiv& System	.13267	.05156	0.011
_cons	1.1409	.28098	0.000

Model Summary

R-squared 0.0465
F(6, 203) 1.65

Prob > F 0.1352

Prob > F

Observations 210

4.2.3.7 Regression Analysis of Organizational Readiness and EMR Adoption

A subsequent regression model incorporated organizational readiness alongside EMR system characteristics and demographic variables. The purpose was to determine whether organizational factors improved the prediction of EMR adoption. The model was statistically significant ($F(7,202) = 5.61, p < 0.001$), indicating that the predictors jointly influenced EMR adoption. The R^2 value of 0.1629 showed that approximately 16.29% of the variation in EMR adoption was explained by the variables included in the model, representing an improvement over the previous regression model.

Organizational readiness had a positive and statistically significant effect on EMR adoption ($\beta = 0.271, p < 0.001$). This finding suggests that clinics with strong leadership support, adequate technical infrastructure, continuous staff training, sufficient resources, and supportive workflows were significantly more likely to achieve higher levels of EMR adoption.

Table 4.12 Regression Analysis: Organizational Readiness and EMR Adoption

EMR Adoption	Coef.	Std. Err.	P>t
Gender	-.05845	.06866	0.396
Age Group	-.00650	.05958	0.913
Experience	-.03624	.06425	0.573
Clinic Location	-.08766	.10551	0.407
Tenure	-.00320	.04794	0.947
Indiv & System	-.07573	.06239	0.226
Org Readiness	.27067	.05108	0.000
_cons	.92204	.26714	0.000

Model Summary

R-squared 0.1629

F(7, 202) 5.61

Prob > F

Observations 210

4.2.3.8 Multiple Regression Analysis Including Policy Environment

The final multiple regression model incorporated policy/environmental factors alongside EMR system characteristics, organizational readiness, and demographic variables.

The model was statistically significant ($F(8,201) = 5.31, p < 0.001$), indicating that the predictors jointly explained variations in EMR adoption. The R^2 value of 0.1745 indicates that the model explained 17.45% of the variation in EMR adoption, representing the strongest explanatory model among the linear regression analyses conducted.

Organizational readiness remained the strongest and only statistically significant predictor of EMR adoption ($\beta = 0.278, p < 0.001$). This confirms that organizational readiness is the strongest predictor identified influencing EMR adoption in clinics.

The policy environment variable had a negative but statistically insignificant effect ($\beta = -0.062, p = 0.094$). Although the coefficient suggests that the respondents perceived policy support as weak, the effect was not statistically strong enough to draw firm

conclusions. EMR system characteristics also remained statistically insignificant ($\beta = -0.079$, $p = 0.203$), further reinforcing the dominant role of organizational readiness over technical system qualities in explaining EMR adoption.

Table 4.13 Multiple Regression Analysis Including Policy Environment

EMR Adoption	Coef.	Std. Err.	P>t
Gender	-.0683429	.0686099	0.320
Age Group	-.0034944	.0593242	0.953
Experience	-.0408414	.0640224	0.524
Clinic Location	-.0796977	.1051463	0.449
Tenure	-.0169602	.0484260	0.727
Indiv & System	-.0794358	.0621513	0.203
Org Readiness	.2780137	.0510402	0.000
Policy/Environmental	-.0622836	.0370354	0.094
_cons	1.115809	.2898299	0.000
Model Summary			
R-squared	0.1745		
F(8, 201)	5.31		
	0.0000		
Prob > F			
Observations	210		

4.2.3.9 Ordered Logistic Regression

An ordered logistic regression analysis was conducted to examine the influence of EMR system characteristics, organizational readiness, policy environment, and demographic variables on the level of EMR adoption in clinics. Ordered logistic regression was considered appropriate because the dependent variable, EMR adoption, was ordinal in nature and categorized into three ordered levels representing no adoption, partial adoption, and full adoption.

The first ordered logistic regression model included EMR system characteristics, organizational readiness, policy environment, gender, age group, professional role,

experience, clinic location, and tenure as predictor variables. The overall model was statistically significant (LR $\chi^2(9) = 41.28$, $p < 0.001$), indicating that the independent variables jointly contributed significantly to explaining variations in EMR adoption levels. The pseudo R^2 value of 0.1418 suggests that approximately 14.18% of the variation in EMR adoption was explained by the variables included in the model. Although pseudo R^2 values are generally lower than R^2 values in ordinary least squares regression, the value indicates a reasonable explanatory power for an ordered logistic regression model.

The relatively low R^2 values indicate that EMR adoption is a multifactorial phenomenon influenced by other variables not captured in the current model specification. This suggests that while individual, organizational, and policy-related constructs explain part of the variation, other determinants not included in the model may play a critical but unobserved role.

The results showed that organizational readiness had a positive and statistically significant effect on EMR adoption ($\beta = 1.411$, $p < 0.001$). This implies that an increase in organizational readiness significantly increases the likelihood of higher levels of EMR adoption. Specifically, clinics characterized by strong leadership support, adequate resources, workflow integration, continuous training, technical support, and innovation culture were more likely to move from lower levels of EMR adoption to higher levels such as partial or full adoption. The large positive coefficient further indicates that organizational readiness was the strongest predictor of EMR adoption among all the variables included in the model.

EMR system characteristics had a negative but statistically insignificant effect on EMR adoption ($\beta = -0.399$, $p = 0.191$). This finding suggests that although factors such as system reliability, ease of use, speed, accuracy, and information sufficiency are important operational features, they did not significantly determine whether clinics achieved higher levels of EMR adoption. This may imply that the existence of favorable technical system features alone is insufficient to drive adoption without adequate organizational support structures.

Similarly, the policy/environment had a negative and statistically insignificant effect on EMR adoption ($\beta = -0.275$, $p = 0.119$). This indicates that government incentives,

regulatory frameworks, policy support, and external funding mechanisms did not significantly influence the likelihood of clinics attaining higher levels of EMR adoption. The insignificance of the policy/environmental factor may suggest limited implementation or effectiveness of existing policy support structures within the study context.

Among the demographic variables, gender ($\beta = -0.356$, $p = 0.286$), age group ($\beta = -0.034$, $p = 0.904$), professional role ($\beta = -0.066$, $p = 0.714$), experience ($\beta = -0.189$, $p = 0.535$), clinic location ($\beta = -0.422$, $p = 0.415$), and tenure ($\beta = -0.095$, $p = 0.679$) were all statistically insignificant. These findings indicate that personal and workplace demographic characteristics did not significantly determine the likelihood of higher EMR adoption levels once organizational and system-related factors were considered.

Organizational readiness consistently emerged as the most significant predictor of EMR adoption across all model specifications, indicating that structural and managerial capacity within clinics exerts a stronger influence on adoption outcomes than either individual perceptions or external policy conditions. This finding suggests that EMR adoption is less a function of technological acceptance alone and more a reflection of institutional preparedness, including leadership commitment, resource allocation, workflow integration, and internal capacity-building mechanisms.

Clinics with stronger organizational capacity and readiness are significantly more likely to achieve advanced levels of EMR implementation compared to clinics with weaker organizational structures.

The consistent insignificance of policy and environmental factors across both linear and ordered logistic models suggests that external institutional frameworks have limited direct influence on EMR adoption within the study context. This may indicate either weak enforcement of existing digital health policies, limited visibility of government incentives at facility level, or a gap between policy formulation and implementation. It may also reflect that clinics prioritize internal readiness over external incentives when making adoption decisions, especially in resource-constrained private healthcare environments.

The overall insignificance of demographic variables across models suggests that EMR adoption is not primarily determined by individual human capital characteristics such

as age, gender, or professional experience. Instead, adoption appears to be structurally embedded within organizational systems, implying that even highly skilled or experienced personnel are constrained or enabled by the institutional environment in which they operate.

Table 4.14 Ordered Logistic Regression

EMR Adoption	Coef.	Std. Err.	P>t
Gender	-.3558172	.3337685	0.286
Age Group	-.0336313	.2779511	0.904
Experience	-.1888777	.3041428	0.535
Clinic Location	-.4224179	.5183083	0.415
Tenure	-.0950254	.04794	0.947
Professional Role	-.0658606	.1794192	0.714
Indiv & System	-.3994587	.3058007	0.191
Org Readiness	1.411118	.2903889	0.000
Policy/Environmental	-.2746586	.1764102	0.119
Number of obs =	272		
LR chi2(9) =	41.28		
Prob > chi2 =	0.0000		
Log likelihood =	-124.88408	Pseudo R2 =	0.1418

A second ordered logistic regression analysis was conducted using only demographic variables, namely gender, age group, experience, clinic location, and tenure, to assess their independent influence on EMR adoption. The model was statistically significant overall (LR $\chi^2(5) = 27.09$, $p < 0.001$), indicating that the demographic variables jointly contributed to explaining differences in EMR adoption. However, the pseudo R^2 value of 0.0465 indicates that the explanatory power of the model was very low, with demographic factors accounting for only 4.65% of the variation in EMR adoption levels.

The findings showed that clinic location had a negative and statistically significant effect on EMR adoption ($\beta = -1.597$, $p < 0.001$). This suggests that clinics located in certain geographical areas were significantly less likely to attain higher levels of EMR adoption. The strong negative coefficient may reflect disparities in infrastructure

availability, technological support, internet connectivity, financial capacity, or institutional support across clinic locations.

On the other hand, gender ($\beta = 0.057$, $p = 0.817$), age group ($\beta = -0.096$, $p = 0.649$), experience ($\beta = 0.164$, $p = 0.464$), and tenure ($\beta = -0.123$, $p = 0.440$) were not statistically significant predictors of EMR adoption. This indicates that differences in personal demographic characteristics among healthcare workers did not significantly influence the likelihood of achieving higher EMR adoption levels.

Overall, the second ordered logistic regression model suggests that demographic characteristics have limited explanatory influence on EMR adoption, with clinic location emerging as the only important demographic factor affecting adoption levels among clinics.

Table 4.15 Ordered Logistic Regression

EMR Adoption	Coef.	Std. Err.	P>t
Gender	.0565407	.2442942	0.817
Age Group	-.0955698	.2097494	0.649
Experience	.1641337	.2241548	0.464
Clinic Location	-1.596936	.3212362	0.000
Tenure	-.1231256	.1593601	0.440

Number of obs = 272

LR chi2(9) = 27.09

Prob > chi2 = 0.0001

Log likelihood = -277.98122

Pseudo R2 = 0.0465

4.3.3 A Comparison of EMR Adoption and Implementation Experiences Between Nairobi and Mombasa Private Dental Clinics

The third objective of the study was to provide a comparison of EMR Adoption and implementation Experiences between Nairobi and Mombasa private dental clinics. Comparisons were made based on perceived Benefits of EMR Use, challenges in adoption and differences in Experiences between Nairobi and Mombasa. These were analyzed qualitatively under the three themes as shown below:

4.3.3.1 Distribution of EMR Adoption Status by County

The study assessed the level of Electronic Medical Record (EMR) adoption among private dental clinics in Nairobi and Mombasa Counties. As shown in Table 4.15, a total of 272 responses were analyzed, comprising 222 respondents from Nairobi and 50 respondents from Mombasa.

Findings from Nairobi indicated relatively higher levels of EMR adoption compared to Mombasa. Among respondents from Nairobi, 94 (42.3%) reported full EMR adoption, while 93 (41.9%) indicated partial adoption. Only 35 respondents (15.8%) reported having no EMR system in their clinics.

In contrast, Mombasa demonstrated lower levels of EMR adoption. More than half of the respondents in Mombasa, 27 (54.0%), reported no EMR adoption. Partial EMR adoption was reported by 10 respondents (20.0%), while only 13 respondents (26.0%) indicated full EMR adoption.

Overall, the findings suggest that private dental clinics in Nairobi exhibited substantially higher levels of EMR adoption compared to clinics in Mombasa. The observed variation may reflect differences in infrastructural capacity, organizational readiness, technological exposure, financial investment, and access to digital health support systems between the two counties.

Table 4.16 Distribution of EMR Adoption Status in Private Dental Clinics by County

EMR Adoption Status	Nairobi n (%)	Mombasa n (%)	Total n (%)
No EMR Adoption	35 (15.8%)	27 (54.0%)	62 (22.8%)
Partial EMR Adoption	93 (41.9%)	10 (20.0%)	103 (37.9%)
Full EMR Adoption	94 (42.3%)	13 (26.0%)	107 (39.3%)
Total	222 (100.0%)	50 (100.0%)	272 (100.0%)

4.3.3.2 Perceived Benefits of EMR Use

Across both Nairobi and Mombasa, respondents consistently described EMR systems as improving efficiency, documentation speed, and patient care. In Nairobi, many users emphasized the operational advantages of EMRs, particularly in streamlining workflows and reducing manual workload. For instance, one respondent noted that *“EMR has improved record keeping and accessibility of patient information,”* while another stated that it *“makes my work easy as a receptionist.”* These sentiments reflect a strong appreciation of EMR systems as tools that enhance daily clinical operations and administrative processes.

Similarly, Nairobi respondents frequently highlighted efficiency gains and improved service delivery, with one participant observing that EMR use *“makes work easier and efficient”* and another describing it as *“a lifesaver & should be adopted by all healthcare providers.”* The perception of EMR as an essential component of modern clinical practice was also evident in statements such as *“EMR is an important tool in the modern dental practice”* and *“EMR is the future of practice.”* These expressions indicate a high level of acceptance and normalization of digital systems within Nairobi-based clinics.

In Mombasa, although fewer respondents had extensive hands-on experience, those who had used EMRs reported similar benefits. One participant explained that *“EMR has been efficient and easy to use, making documentation easier to find and refer to,”* while another noted that *“going paperless and having all data in just a click makes life easier at the clinic.”* Even among those anticipating adoption, EMR was viewed positively as a system that would improve record-keeping and efficiency. A respondent who had not fully implemented EMR stated that *“record keeping would be more seamless,”* indicating expectations of improved organizational performance.

Overall, the perceived benefits across both regions converge around improved efficiency, faster documentation, better accessibility of records, enhanced data security, and improved patient care. However, Nairobi respondents tend to articulate these benefits from lived experience, whereas Mombasa respondents often express them as anticipated or partially experienced outcomes.

The observed inter-county differences further suggest respondents perceived that EMR adoption is spatially stratified, reflecting broader inequalities in digital infrastructure, investment capacity, and institutional maturity. Nairobi's higher adoption levels likely reflect its concentration of better-resourced facilities and stronger digital ecosystems, whereas Mombasa's mixed adoption patterns indicate uneven diffusion of health digitalization technologies across less centralized or resource-limited clinical environments. However, because infrastructure and digital ecosystem maturity were not directly measured, these findings should be interpreted cautiously.

4.3.3.2 Challenges of EMR Adoption

Despite the generally positive perception, respondents from both Nairobi and Mombasa identified several challenges that hinder effective EMR adoption. The most frequently cited challenges relate to infrastructure limitations, particularly internet connectivity and power supply. A Nairobi respondent stated that *"internet/power outages"* significantly affect system use, while another emphasized that *"internet failure greatly affects this."* These disruptions were consistently reported as major barriers to continuous and reliable EMR utilization.

Technical issues also emerged as a critical challenge. Respondents reported *"technical glitches," "system downtime,"* and instances where *"data is sometimes lost"* occurs. One participant noted that *"technical breakdowns"* interfere with operations, while another highlighted that *"when a patient revisits, it's much easier to get their information,"* but only when the system is functioning properly, implying vulnerability during system failures. These concerns point to reliability issues that can undermine trust in EMR systems.

Cost-related challenges were more prominently emphasized in Mombasa, where respondents frequently mentioned financial constraints as a barrier to adoption. One respondent observed that *"EMR are sometimes costly,"* while another noted *"high maintenance cost... including Internet costs and infrastructure."* Similarly, a participant indicated that *"cost efficiency is very important for all clinics to adapt to EMR in Kenya,"* suggesting that affordability remains a key determinant of adoption in resource-constrained settings.

Training and capacity gaps were also widely reported in both regions. Nairobi respondents expressed concerns such as *“lack of training,”* and one noted that *“we are not well trained and haven’t consistently been active to utilize the other aspects.”* Another respondent emphasized that *“regular training is missing,”* highlighting the need for continuous capacity building. In Mombasa, training challenges were often linked to limited exposure and adoption, with one respondent stating *“lack of training of the assistant”* as a barrier. These findings suggest that insufficient training not only limits effective use but also contributes to the underutilization of system features.

Staff resistance and organizational culture further influenced adoption. In Nairobi, some respondents pointed out that *“staff resistance”* and reliance on traditional methods hinder full utilization of EMR systems. One participant explained that *“the Drs trust paper and are so used to the system,”* while another noted that *“most EMR systems are built... not with the dentist in mind,”* contributing to reluctance in adoption. Similarly, in Mombasa, resistance was reflected in statements such as *“staff resistance”* and *“the leadership doesn’t support it and doesn’t wish to change from what is written.”* These narratives indicate that human and institutional factors play a significant role in shaping adoption outcomes.

4.3.3.3 Differences in Experience Between Nairobi and Mombasa

A key distinction between the two regions was in the level of exposure and integration of EMR systems. Nairobi respondents generally demonstrated deeper experience with EMR systems, often using them as core components of clinical workflows. This was reflected in statements such as *“we depend on EMR for invoicing and billing,”* and *“smooth workflow from one employee to another even after your shift has ended.”* Such comments indicated that EMR systems are embedded in daily operations, making clinics highly dependent on their functionality.

In contrast, Mombasa respondents exhibited more varied experiences, with some clinics fully adopting EMR while others have not implemented it at all. Several respondents indicated limited or no usage, with statements such as *“we don’t have a system yet, we use only Excel sheets to summarize our patients,”* and *“we are hoping to install one as the clinic grows.”* Others expressed conditional adoption, suggesting that EMR would be more suitable in larger or better-resourced settings: *“for this clinic... I don’t think*

an EMR would contribute positively... since it's small.” This reflected a more cautious or gradual approach to adoption in Mombasa.

Another notable difference was the presence of offline or hybrid systems in Mombasa. Some respondents reported using EMR systems that do not require internet connectivity, with one stating, *“Our EMR works offline, so we do not need internet.”* This contrasts with Nairobi, where cloud-based or internet-dependent systems appear more common, making clinics more vulnerable to connectivity disruptions but also more integrated into digital ecosystems.

Despite the challenges, overall attitudes toward EMR systems remained largely positive in both regions. Many respondents expressed strong support for continued or increased adoption. For example, one Nairobi respondent stated, *“EMR is a lifesaver & should be adopted by all healthcare providers,”* while another emphasized that *“EMR improves staff coordination and reduces errors, thereby improving workflow.”* These statements reflect a belief in the transformative potential of EMR systems.

In Mombasa, positive perceptions were also evident, though often accompanied by conditionality or future-oriented perspectives. One respondent noted that *“EMR is good and easy,”* while another indicated that *“it would be nice to have an EMR for the clinic.”* However, concerns about cost, infrastructure, and readiness contrasted these positive reviews, suggesting that adoption is influenced not only by perceived usefulness but also by contextual constraints.

4.4 Summary of Findings

The findings of the study indicate that Electronic Medical Records (EMR) adoption among private dental clinics in Nairobi and Mombasa is shaped by a combination of individual, organizational, and environmental factors, with organizational factors emerging as the most influential. The findings for the first objective indicate that socio-demographic and clinic characteristics have a limited influence on EMR adoption among private dental clinics in Nairobi and Mombasa. The study established that most of the workforce is relatively young, predominantly female, and moderately experienced, with the majority of clinics being small or medium-sized sole proprietorships.

EMR adoption was almost evenly split between partial and full adoption, suggesting gradual digital transformation across the sector. However, Chi-square analysis revealed that among all the variables examined, only age group had a statistically significant relationship with EMR adoption, while gender, years of experience, clinic size, clinic ownership, and location showed no significant association. This implies that demographic and structural characteristics of clinics do not independently determine EMR adoption, and that adoption is likely influenced by other underlying factors beyond basic socio-demographic attributes.

For the second objective, the findings show that individual, organizational, and policy/environmental factors collectively influence EMR adoption, although their effects differ in magnitude and significance. At the individual level, respondents expressed strong agreement that EMR systems are user-friendly, reliable, easy to learn, and useful for clinical decision-making, indicating positive perceptions that support adoption. Similarly, organizational factors such as leadership support, availability of resources, workflow integration, and technical support were highly rated, although continuous training emerged as a relatively weaker area. In contrast, policy and environmental factors were generally perceived as weak, with respondents reporting limited government incentives, moderate policy support, and mixed views on regulatory challenges and external funding. Inferential analysis further showed that organizational factors had a significant positive effect on EMR adoption and were the only statistically significant predictor in the regression model, while individual/system and policy/environmental factors did not show significant independent effects. This highlights the central role of internal organizational capacity in driving EMR adoption compared to individual perceptions or external policy conditions.

On the final objective, the qualitative comparison of EMR adoption and implementation experiences between Nairobi and Mombasa reveals both similarities and contextual differences. In both regions, respondents consistently reported benefits such as improved efficiency, faster documentation, better record accessibility, enhanced patient care, and reduced workload. However, Nairobi clinics demonstrated deeper integration of EMR systems into daily operations, with many respondents describing EMR as essential to workflow, billing, and coordination of services. In contrast, Mombasa clinics showed more varied experiences, with some fully adopting EMR systems while

others relied on manual processes or were in the early stages of adoption. Common challenges across both regions included internet and power outages, technical system failures, inadequate training, staff resistance, and high costs, though cost and infrastructure constraints were more prominently emphasized in Mombasa. Overall, while attitudes toward EMR systems were largely positive in both regions, Nairobi reflects more mature and experience-driven adoption, whereas Mombasa reflects a more cautious, resource-constrained, and uneven adoption landscape shaped by organizational readiness and infrastructural limitations.



CHAPTER FIVE

DISCUSSIONS, CONCLUSIONS, AND RECOMMENDATIONS

5.1 Introduction

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

5.2 Summary of the Study

The main purpose of the study was to investigate the factors influencing EMR adoption among private dental clinics in Nairobi and Mombasa Counties, Kenya. Guided by the Diffusion of Innovations (DOI) theory and the Technology Acceptance Model (TAM), the study examined how individual, organizational, and policy-level factors shape the decision to adopt and integrate EMRs in routine dental practice. A quantitative analytical cross-sectional quantitative design was employed, and data was collected using a structured online questionnaire and analyzed using descriptive statistics, chi-square distribution tests, and inferential analysis using chi-square tests, correlation analysis, and ordered logistic regression analysis to determine the association and predictive influence of individual and system-related, organizational, and policy/environmental factors on varying levels of EMR adoption among private dental clinics.

From the findings of the study, EMR adoption among private dental clinics in Nairobi and Mombasa is influenced by a combination of clinic-related, organizational, individual/system, and policy-level factors, with organizational readiness playing the most central role in shaping adoption outcomes. The Chi-square analysis revealed statistically significant associations between EMR adoption and clinic location, clinic size, and clinic ownership, while socio-demographic variables such as gender, age group, and years in healthcare did not show significant associations. This finding suggests that structural and organizational characteristics of clinics, including operational scale, ownership structure, resource capacity, and geographical context, are more important in influencing EMR adoption than the personal demographic characteristics of healthcare workers. Clinics located in Nairobi demonstrated higher levels of EMR adoption than clinics in Mombasa. Although these regional differences may reflect differences in contextual conditions, the present study did not directly measure these factors.

The Pearson correlation analysis revealed that individual & system factors and organizational factors have positive and statistically significant relationships with EMR adoption. This indicates that improvements in user-related perceptions such as usability, reliability, ease of learning, and perceived usefulness, as well as organizational aspects like leadership support, resource availability, workflow

integration, and technical support, are associated with higher levels of EMR adoption. Among the independent variables, organizational factors exhibited a stronger positive relationship with EMR adoption compared to individual & system factors, suggesting that organizational support plays a more influential role in shaping adoption outcomes. In contrast, policy and environmental factors showed a weak and statistically insignificant relationship with EMR adoption, implying that external regulatory and environmental conditions have limited direct influence on adoption decisions within the sampled clinics.

The regression analyses further revealed that organizational readiness was the only consistent and statistically significant predictor of EMR adoption across the regression models. This highlights the critical role of leadership support, workflow integration, technical infrastructure, staff training, resource availability, and internal coordination in influencing EMR adoption decisions. Although individual/system factors initially demonstrated a positive and statistically significant effect on EMR adoption, their influence became statistically insignificant after organizational readiness was introduced into the regression models. Similarly, policy/environmental factors did not show statistically significant independent effects on EMR adoption. Overall, the regression results underscore that organizational readiness is the primary driver of EMR adoption in private dental clinics, while individual/system and policy-related factors play a comparatively limited role in predicting adoption outcomes.

The ordered logistic regression analysis further reinforced these findings by demonstrating that organizational readiness significantly increased the likelihood of clinics achieving higher levels of EMR adoption, including progression from no adoption to partial and full adoption. The findings further showed that demographic variables had limited explanatory power regarding EMR adoption, although clinic location emerged as a significant determinant in the demographic-only ordered logistic regression model, suggesting the existence of regional disparities in infrastructure, technological access, and institutional support between clinics.

Qualitative insights complemented these quantitative findings by providing deeper contextual understanding of the factors influencing EMR adoption. Respondents consistently highlighted leadership support as a critical enabler, noting that clinics where management actively championed EMR implementation experienced smoother

transitions and higher levels of system utilization. Leadership commitment was described as essential in ensuring that adequate resources are allocated, expectations are clearly communicated, and EMR use is prioritized within daily operations. Staff training also emerged as an important facilitator, with respondents indicating that continuous training improved user confidence and reduced resistance among staff. Over time, as users became more familiar with the system, adoption became more seamless and integrated into routine clinical workflows.

Several barriers were identified across clinics in the study. High costs associated with purchasing, implementing, and maintaining EMR systems were frequently cited as major constraints, particularly for smaller clinics and clinics operating in resource-constrained settings. Technical challenges such as unreliable internet connectivity, power interruptions, and occasional system downtime were also reported to hinder consistent use, often disrupting workflow and forcing clinics to revert temporarily to manual record-keeping systems. Resistance to change among some staff members was another recurring theme, commonly linked to fear of increased workload, preference for traditional paper-based systems, and limited familiarity with digital technologies. Additionally, inadequate technical support, inconsistent training, and limited infrastructure were identified as challenges affecting the effective integration and sustained utilization of EMR systems within daily clinical operations.

Overall, the qualitative findings reinforce the quantitative results by showing that while EMR adoption is influenced by multiple factors, organizational readiness, leadership involvement, internal capacity-building efforts, and institutional support structures are the most critical drivers of successful implementation. Clinics that invest in training, technical infrastructure, workflow integration, and supportive organizational cultures are better positioned to overcome technical, financial, and behavioral barriers, thereby enhancing the effective adoption and utilization of EMR systems.

5.3 Discussion of Results

5.3.1 Clinic Size, Location, and Healthcare Worker Demographics on EMR Adoption

The first objective of the study aimed to examine the influence of clinic characteristics and healthcare worker demographics on EMR adoption. Chi-square analysis was used

to examine this relationship. The findings revealed that clinic location, clinic size, and clinic ownership had statistically significant associations with EMR adoption, while demographic variables such as gender, age group, and years in healthcare did not show significant relationships with EMR adoption. This indicates that EMR adoption is influenced more by institutional and structural characteristics of clinics than by personal demographic characteristics of healthcare workers.

The significant relationship between clinic location and EMR adoption suggests that geographical context influences the adoption of EMR systems. Clinics located in different regions may experience variations in infrastructure availability, internet connectivity, technical support, and access to digital health resources, which in turn affect adoption levels. This finding is consistent with studies such as Raturkar et al. (2015) and Mugo and Otieno (2021), which found that healthcare facilities located in areas with stronger ICT infrastructure and greater exposure to digital health initiatives tend to exhibit higher levels of EMR adoption.

Similarly, the significant association between clinic size and EMR adoption indicates that larger clinics are more likely to adopt EMR systems compared to smaller clinics. Larger facilities may possess greater financial resources, technical capacity, and human resources necessary to support EMR implementation. This finding aligns with Boonstra and Broekhuis (2010), who found that larger healthcare facilities are better positioned to adopt health information systems due to economies of scale and better organizational capacity.

The findings also revealed that clinic ownership significantly influences EMR adoption. Differences in ownership structure may reflect variations in management style, investment priorities, organizational culture, and decision-making processes. Corporate-owned or partnership clinics may have stronger financial and administrative capacity to support EMR adoption compared to sole proprietorship clinics. Similar findings were reported by Chauhan et al. (2018), who observed that organizational structure and ownership influence technological readiness and adoption decisions in healthcare institutions.

However, the absence of statistically significant relationships between EMR adoption and demographic variables such as gender, age group, and years in healthcare suggests

that personal characteristics of healthcare workers do not independently determine EMR adoption. This finding contrasts with studies such as Venkatesh et al. (2003), which emphasize the importance of user characteristics in technology acceptance. The current findings imply that organizational and clinic-level conditions may outweigh individual demographic differences in influencing EMR adoption among private dental clinics in Nairobi and Mombasa.

5.3.2 Individual, Organizational, and Policy Factors and EMR Adoption

The correlation analysis revealed that both individual/system factors and organizational factors were positively and significantly associated with EMR adoption, while policy and environmental factors exhibited a weak and statistically insignificant relationship. Organizational factors demonstrated a stronger association with EMR adoption than individual/system factors. However, the strong correlation observed between individual/system factors and organizational factors ($r = 0.730$, $p < 0.001$) suggests substantial overlap between these constructs. Although multicollinearity diagnostics indicated acceptable VIF values, the high correlation implies that the independent contribution of each construct should be interpreted with caution because some of the explanatory variance may be shared.

The regression analyses showed that organizational readiness remained statistically significant after controlling for demographic, individual/system, and policy/environmental factors. This finding suggests that perceptions of leadership support, resource availability, workflow integration, technical support, leadership support, and staff training were more strongly associated with higher EMR adoption levels than the other factors included in the models. However, given the cross-sectional nature of the study, these findings should not be interpreted as evidence that organizational readiness causes EMR adoption. Rather, they indicate that clinics reporting stronger organizational readiness also tended to report higher levels of EMR adoption.

These findings are broadly consistent with studies by Boonstra and Versluis (2014), Kimani et al. (2022), and Cresswell and Sheikh (2013), which identify organizational conditions as important correlates of successful health information system implementation. Nevertheless, the current study measured respondents' perceptions of organizational readiness rather than objective measures of leadership behaviour,

organizational investment, or implementation practices. Consequently, conclusions regarding the actual effectiveness of leadership or organizational actions should be made cautiously.

Although individual/system factors received highly positive ratings at the descriptive level and demonstrated a significant bivariate relationship with EMR adoption, they did not remain statistically significant in the multivariate models. One possible explanation is that the effects of perceived usability, reliability, information quality, and ease of use may partially overlap with organizational readiness, making it difficult to completely disentangle their independent influences. Therefore, the finding that organizational readiness remained significant should not be interpreted as evidence that individual/system factors are unimportant. Instead, it suggests that organizational and individual dimensions may operate jointly in shaping EMR adoption outcomes.

Similarly, policy and environmental factors did not emerge as significant predictors of EMR adoption. Respondents generally reported weak government incentives and mixed perceptions regarding policy support and external funding. However, the absence of statistical significance should not necessarily be interpreted as evidence that policy factors are irrelevant. The finding may reflect limited variation in respondents' perceptions, measurement constraints, or the possibility that policy influences operate indirectly through organizational processes rather than directly affecting adoption decisions at the clinic level. Similar observations have been reported by Mahomed et al. (2019), who found that national e-health policies alone are insufficient to guarantee adoption unless accompanied by institutional implementation capacity.

Overall, the findings suggest that organizational readiness exhibits the strongest statistical association with EMR adoption among the factors examined. However, the results should be interpreted as evidence of association rather than causation, and consideration should be given to the substantial overlap observed between organizational and individual/system factors when drawing conclusions about their relative importance.

5.3.3 Comparison of EMR Adoption Between Nairobi and Mombasa

The comparison of EMR adoption between Nairobi and Mombasa revealed notable differences in adoption experiences and implementation patterns between the two

counties. Qualitative findings showed that Nairobi clinics generally demonstrated more advanced integration of EMR systems into routine operations, while Mombasa clinics exhibited more varied and uneven adoption experiences.

The stronger integration of EMR systems in Nairobi may be attributed to better ICT infrastructure, stronger digital ecosystems, improved access to vendors and technical support, and greater exposure to digital health initiatives. Respondents from Nairobi frequently described EMR systems as essential components of workflow management, billing, coordination, and patient record management. These findings align with Mugo and Otieno (2021), who reported that healthcare facilities in Nairobi exhibit higher levels of digital health adoption due to stronger infrastructure and institutional support.

In contrast, Mombasa clinics reported greater challenges related to infrastructure limitations, financial constraints, internet connectivity, and technical support. Some clinics had not fully implemented EMR systems and continued to rely partly on manual systems. These findings are consistent with Hassan et al. (2022), who found that regional disparities in infrastructure and institutional support significantly affect digital health adoption across counties in Kenya.

Both counties reported common challenges such as system downtime, internet and power interruptions, insufficient training, staff resistance, and high implementation costs. However, cost and infrastructural barriers appeared more pronounced in Mombasa. These findings suggest that while perceptions toward EMR systems remain generally positive across both regions, differences in contextual and institutional conditions significantly shape adoption experiences.

The findings therefore demonstrate that EMR adoption is influenced not only by internal organizational readiness but also by broader regional and infrastructural environments. Clinics operating within stronger digital ecosystems are better positioned to implement and sustain EMR systems effectively.

5.4 Conclusions

5.4.1 Clinic Size, Location, and Healthcare Worker Demographics on EMR Adoption

The study concludes that clinic-related structural characteristics play a significant role in influencing EMR adoption among private dental clinics. Specifically, clinic location,

clinic size, and clinic ownership were found to have statistically significant associations with EMR adoption, while healthcare worker demographic characteristics such as gender, age group, and years in healthcare were not significantly associated with adoption levels.

The findings suggest that institutional and structural conditions within clinics are more important determinants of EMR adoption than individual demographic attributes of healthcare workers. Clinics with stronger resource capacity, supportive ownership structures, and favorable infrastructural environments are more likely to achieve higher levels of EMR adoption. Therefore, EMR adoption in private dental clinics is shaped more by organizational and contextual factors than by personal demographic characteristics.

5.4.2 Individual, Organizational, and Policy Factors and EMR Adoption

The study concludes that organizational readiness is the strongest predictor identified in this study. Organizational factors consistently emerged as the strongest and only statistically significant predictor of EMR adoption across the regression models. This indicates that leadership support, technical infrastructure, staff training, workflow integration, innovation culture, and resource availability are critical drivers of successful EMR implementation.

Although individual/system factors demonstrated positive perceptions and significant correlations with EMR adoption, they did not independently predict adoption once organizational factors were considered. Similarly, policy and environmental factors did not significantly influence EMR adoption despite moderate perceptions regarding policy support and external funding. These findings suggest that external policy frameworks and favorable user perceptions alone are insufficient to drive EMR adoption without strong internal organizational capacity.

The study therefore concludes that successful EMR adoption depends primarily on organizational preparedness and institutional support systems within clinics.

5.4.3 Comparison of EMR Adoption Between Nairobi and Mombasa

The study concludes that notable differences exist in EMR adoption and implementation experiences between private dental clinics in Nairobi and Mombasa. The findings showed that Nairobi clinics generally reported higher levels of EMR

adoption and greater integration of EMR systems into routine clinical and administrative operations. In contrast, Mombasa clinics exhibited more varied adoption patterns, with a larger proportion of respondents reporting partial adoption or continued reliance on manual systems.

Qualitative findings further revealed differences in implementation experiences across the two counties. Respondents from Nairobi more frequently described EMR systems as integral to daily workflows, billing processes, and patient record management, whereas respondents from Mombasa more often discussed challenges associated with adoption and the continued use of alternative record-keeping approaches. Despite these differences, respondents from both counties generally perceived EMR systems positively and acknowledged their potential benefits for improving efficiency, record accessibility, and patient care.

While the study identified significant regional differences in EMR adoption and implementation experiences, it did not directly measure factors such as ICT infrastructure, availability of technical support, financial capacity, or digital health ecosystem maturity. Consequently, the study cannot conclusively attribute the observed differences to these factors. Future research should investigate these contextual variables directly to better understand the mechanisms underlying regional variation in EMR adoption.

The study therefore concludes that EMR adoption patterns vary across counties and that contextual factors may play an important role in shaping adoption experiences. However, additional evidence is required to establish which specific regional conditions contribute to these differences.

5.5 Recommendations

5.5.1 Recommendations for Practice

Organizational readiness emerged as the strongest factor associated with EMR adoption. As such, private dental clinics should prioritize organizational preparation before investing in new EMR technologies. Private dental clinic owners should conduct organizational readiness assessments before selecting or implementing EMR systems. These assessments should evaluate leadership commitment, staff readiness, workflow

compatibility, resource availability, and technical support requirements to ensure successful implementation.

Clinic managers should establish structured EMR implementation committees comprising clinical, administrative, and technical personnel to coordinate adoption activities. These teams should oversee user training, monitor system utilization, address implementation challenges, and facilitate communication between staff and system vendors. Given that continuous training received comparatively lower ratings than other organizational factors, clinics should implement regular refresher training programmes rather than relying solely on initial training during system installation.

The findings also suggest the need for differentiated implementation approaches based on clinic size. Small clinics and sole proprietorships should adopt phased implementation strategies beginning with core functionalities such as patient registration, billing, and clinical documentation before expanding to more advanced functions. Larger clinics, which often possess greater organizational capacity, should focus on optimizing workflow integration, data analytics, and advanced system utilization to maximize the benefits of EMR adoption.

Furthermore, clinics should develop formal technical support mechanisms, including designated EMR champions or super-users within the facility who can provide first-line assistance to staff and promote consistent system utilization. Strengthening internal support structures may enhance organizational readiness and improve long-term EMR sustainability.

5.5.2 Recommendations for Kenya Dental Association

The Kenya Dental Association (KDA) should develop Continuing Professional Development (CPD) programmes focusing on EMR implementation, digital record management, and change management for private dental practitioners. In addition, the Association should facilitate peer-learning forums where clinics with successful EMR implementation can share practical experiences and lessons with clinics at earlier stages of digital transformation.

5.5.3 Recommendations for EMR Vendors

EMR vendors should tailor their products to the operational needs of private dental clinics by providing structured onboarding, post-implementation technical support,

periodic refresher training, and responsive maintenance services. Vendors should also design scalable solutions that accommodate the varying financial and operational capacities of small, medium, and large clinics.

5.5.4 Recommendations for Policy

Because policy and environmental factors were not statistically significant predictors of EMR adoption in this study, policy recommendations should focus on creating enabling conditions rather than assuming that policy interventions alone will increase adoption. The Ministry of Health should continue strengthening the national digital health agenda by developing implementation guidance tailored to private outpatient facilities, including dental clinics. The Kenya Medical Practitioners and Dentists Council (KMPDC) should encourage digital record management through professional guidance, dissemination of best practices, and incorporation of EMR preparedness into quality improvement initiatives for private dental facilities. County Departments of Health should collaborate with professional associations to provide technical support, awareness programmes, and implementation guidance for private dental clinics transitioning to EMR systems. Such tools would assist facilities in identifying weaknesses in training, workflow integration, leadership support, and resource allocation before implementation.

Professional associations and regulatory agencies should also facilitate knowledge-sharing platforms where clinics with successful EMR implementation experiences can share lessons, challenges, and practical solutions with facilities at earlier stages of adoption. This approach may be particularly beneficial for smaller clinics with limited implementation experience.

Finally, future policy interventions should be informed by additional research examining the specific contextual factors underlying regional differences in EMR adoption. Since this study did not directly measure infrastructure quality, financial capacity, or technical support availability, further evidence is needed before recommending targeted infrastructure or funding interventions.

5.6 Limitations of the Study

Several limitations should be considered when interpreting the findings of this study. First, the study employed a cross-sectional research design, which captured

respondents' perceptions and EMR adoption status at a single point in time. Consequently, the study identified associations among variables but could not establish causal relationships. For example, while organizational readiness was significantly associated with EMR adoption, it cannot be concluded that organizational readiness causes higher EMR adoption levels. It is equally possible that clinics with more advanced EMR systems subsequently develop stronger organizational support structures. A longitudinal design would have provided stronger evidence regarding the direction and evolution of these relationships over time.

Secondly, the study relied heavily on self-reported data obtained through questionnaires. As a result, the findings reflect respondents' perceptions rather than objective measures of organizational readiness, leadership behaviour, technical capacity, or EMR utilization. Respondents may have overestimated or underestimated the extent of organizational support, system effectiveness, or adoption levels due to recall bias, social desirability bias, or subjective interpretation of survey items. Although anonymity and confidentiality were emphasized during data collection to reduce response bias, the possibility of perception-based measurement error cannot be entirely ruled out.

Further, the study identified a relatively strong correlation between individual/system factors and organizational factors. Although multicollinearity diagnostics indicated acceptable statistical thresholds, the overlap between these constructs may have reduced the ability to fully isolate their independent effects on EMR adoption. Consequently, the finding that organizational readiness emerged as the only significant predictor should be interpreted with caution, as some of its explanatory influence may overlap with individual- and system-level factors.

Additionally, the study was restricted to private dental clinics located in Nairobi and Mombasa Counties. While these counties represent important urban healthcare settings in Kenya, the findings may not be directly generalizable to rural clinics, peri-urban facilities, public healthcare institutions, or larger hospitals. Organizational structures, resource availability, patient volumes, and technological environments may differ substantially across these contexts. Therefore, the findings should be interpreted primarily as evidence relating to urban private dental practice rather than the broader Kenyan healthcare sector.

Finally, although qualitative responses provided useful contextual insights, the study relied primarily on brief open-ended questionnaire responses rather than on in-depth qualitative methods such as interviews, focus group discussions, or case studies. This limited the ability to explore complex organizational dynamics, leadership processes, and contextual factors that may influence EMR adoption. A mixed-methods approach incorporating richer qualitative data could have provided a more comprehensive understanding of the mechanisms underlying the quantitative findings.

5.7 Suggestions for Further Studies

Future studies should employ longitudinal research designs to examine how EMR adoption evolves over time and to establish clearer temporal relationships between organizational readiness and adoption outcomes. Such studies would help determine whether organizational readiness precedes adoption or develops as a consequence of successful implementation.

Given the substantial overlap observed between individual/system factors and organizational factors, future research should further investigate the interaction between these constructs. Studies could examine whether organizational readiness mediates or moderates the relationship between user perceptions and EMR adoption, thereby providing a more nuanced understanding of the adoption process.

Future studies should also expand beyond urban private dental clinics to include public hospitals, private hospitals, rural health facilities, and peri-urban clinics. Such comparative studies would enhance the generalizability of findings and provide a broader understanding of EMR adoption across different healthcare contexts within Kenya.

In addition, future research should directly measure contextual factors that were not objectively assessed in the present study, including ICT infrastructure quality, internet reliability, technical support availability, financial capacity, vendor support, and organizational investment in digital health systems. This would help explain regional variations in adoption and provide stronger evidence regarding the determinants of EMR implementation.

Finally, future studies should adopt mixed-methods approaches incorporating interviews, focus group discussions, and case studies to explore how organizational

culture, leadership practices, staff attitudes, and implementation experiences shape EMR adoption. Such approaches would provide richer contextual insights and complement quantitative findings on EMR adoption determinants.



REFERENCES

- Abdekhoda, M. (2025). Applying electronic medical records. figshare. <https://doi.org/10.6084/m9.figshare.28302257>
- Abebe, Dr. M. A., Urgie, B. M., Lema, G. D., Yimam, M. A., Abosetugn, A. E., Dejene, T. M., Kebede, A. A., Gebreegziabher, Z. A., Feleke, A. K., Abebe, D. A., Amin, H. M., Mingude, A. B., & Sherif, Z. A. (2024). Factors influencing health professionals' attitudes towards electronic medical record implementation in Ethiopian hospitals: Insights from a cross-sectional study (2023) (preprint). JMIR Publications Inc. <https://doi.org/10.2196/preprints.63135>
- Abiy, R., Gashu, K. D., Asemaw, T., Tilahun, B., & Endehabtu, B. F. (2018). A comparison of electronic records to paper records in Antiretroviral Therapy Clinic in Ethiopia: What is affecting the quality of the data? *Online Journal of Public Health Informatics*, 10(2). <https://doi.org/10.5210/OJPHI.V10I2.8309>
- Adetoyi, O. E., & Raji, O. A. (2020). Electronic health record design for inclusion in sub-Saharan Africa medical record informatics. *Scientific African*, 7, e00304. <https://doi.org/10.1016/j.sciaf.2020.e00304>
- Ahmed, A., Karim, M. A. D. B., Maruf, R. I., & Nakashima, N. (2022, January 1). An Affordable and Standard Digital Healthcare management as a Service (HaaS) for Small Clinics in... Unknown. https://www.researchgate.net/publication/362365553_An_Affordable_and_Standard_Digital_Healthcare_management_as_a_Service_HaaS_for_Small_Clinics_in_Developing_Countries
- Akwaowo, C. D., Sabi, H. M., Ekpenyong, N., Isiguzo, C. M., Andem, N. F., Maduka, O., Dan, E., Umoh, E., Ekin, V., & Uzoka, F.-M. (2022). *Frontiers in Digital Health*, 4. <https://doi.org/10.3389/fdgth.2022.1017231>
- Alanazi, B., Butler-Henderson, K., & Alanazi, M. R. (2020). Factors influencing healthcare professionals' perception towards EHR/EMR systems in gulf cooperation council countries: A systematic review. *Oman Medical Journal*, 35(6), e192–e192. <https://doi.org/10.5001/omj.2020.85>
- An audit of oral diseases at a Nairobi centre, 2000–2004. (n.d.). *International Dental Journal*, 57(6), 439–444. <https://doi.org/10.1111/j.1875-595X.2007.tb00147.x>

- Anshari, M. (2019, June 22). Redefining electronic health records (EHR) and electronic medical records (EMR) to promote patient empowerment. Al-Jami'ah Research Centre.
https://www.researchgate.net/publication/337443049_Redefining_Electronic_Health_Records_EHR_and_Electronic_Medical_Records_EMR_to_Promote_Patient_Empowerment
- Aqleh, M. M., AL-Hashimi, M. S., Hamdan, A., & Razzaque, A. (2019). ACCEPTANCE AND USABILITY OF MEDICAL INFORMATICS AMONG PHYSICIANS IN BAHRAIN. Proceedings of the 11th International Conference on E-Health 2019, 51–58.
https://doi.org/10.33965/eh2019_201910l007
- Barnes, J., O'Hanlon, B., Feeley, F., Kimberly, M., Nelson, G., & Caytie, D. (2010). Private health sector assessment in Kenya. The World Bank.
<https://doi.org/10.1596/978-0-8213-8359-9>
- Boonstra, A., & Broekhuis, M. (2010). Barriers to the acceptance of electronic medical records by physicians from systematic review to taxonomy and interventions. BMC Health Services Research, 10, 231.
<https://doi.org/10.1186/1472-6963-10-231>
- Carmona, M. E. D. P., De Paz Carmona, H., & Carmona Calero, E. M. (2023). Digital transformation and education. A technical point of view. MDPI AG.
<https://doi.org/10.20944/preprints202303.0043.v1>
- Castillo, V. H., Martínez-García, A. I., & Pulido, J. (2010). A knowledge-based taxonomy of critical factors for adopting electronic health record systems by physicians: A systematic literature review. BMC Medical Informatics and Decision Making, 10(1), 1–17. <https://doi.org/10.1186/1472-6947-10-60>
- Chauhan, Z., Samarah, M., Unertl, K., & Jones, M. (2018). Adoption of electronic dental records: Examining the influence of practice characteristics on adoption in one state. Applied Clinical Informatics, 09(03), 635–645.
<https://doi.org/10.1055/s-0038-1667331>
- Chebole, G. C. (2015, January 1). Factors influencing adoption of electronic medical record systems in public health facilities in Kenya: A case of Nakuru county.
<https://erepository.uonbi.ac.ke/handle/11295/90435>

- Chen, R.-F., & Hsiao, J.-L. (2021). Health professionals' perspectives on electronic medical record infusion and individual performance: Model development and questionnaire survey study - PMC. *JMIR Medical Informatics*, 9(11).
<https://doi.org/10.2196/32180>
- Chen, Y., Xie, W., Gunter, C. A., Liebovitz, D., Mehrotra, S., Zhang, H., & Malin, B. (2015). Inferring clinical workflow efficiency via electronic medical record utilization - PMC. *AMIA Annual Symposium Proceedings*, 2015.
- Chepkwony, M. (2015). Factors influencing the adoption of electronic medical records technology in public health institutions in kenya: A case of hospitals in nairobi county.
- Cox, C. (2020, March 1). The sustainable development goals and aging: Implications for social work. Springer Nature.
https://www.researchgate.net/publication/338085486_The_Sustainable_Development_Goals_and_Aging_Implications_for_Social_Work
- Danso, K. O., Asagba, P. O., Yarhere, I., & Ghana Journal Of Nursing And Midwifery - Gjnmid. (2024, November 7). Implementing and adopting EHR systems in developing countries. Unknown.
https://www.researchgate.net/publication/385620254_Implementing_and_Adopting_EHR_Systems_in_Developing_Countries
- Digital Health Act (2023). The Digital Health Act, 2023. Kenya Law.
https://kenyalaw.org/kl/fileadmin/pdfdownloads/Acts/2023/TheDigitalHealthAct_2023.pdf
- Dimba, E. A. O., Gichana, J., Limo, A. K., Wakoli, K. A., Chindia, M. L., & Awange, D. O. (2007). An audit of oral diseases at a Nairobi centre, 2000–2004. *International Dental Journal*, 57(6), 439–444. <https://doi.org/10.1111/j.1875-595x.2007.tb00147.x>
- Dubale, A. T., Mengestie, N. D., Tilahun, B., & Walle, A. D. (2023). User satisfaction of using electronic medical record system and its associated factors among healthcare professionals in Ethiopia: A cross-sectional study. *BioMed Research International*, 2023(1). <https://doi.org/10.1155/2023/4148211>
- Enahoro , Q. E., Ogugua, J. O., Anyanwu, E. C., Akomolafe, O., Ifeoma Pamela Odilibe, & Andrew Ifesinachi Daraojimba. (2023). The impact of electronic health records on healthcare delivery and patient outcomes: A review. *World*

Journal of Advanced Research and Reviews, 21(2), 451–460.

<https://doi.org/10.30574/wjarr.2024.21.2.0478>

Farajollahi, M., Ghazisaeedi, M., Kalhori, S. R. N., & Hassanian-Moghaddam, H. (2024). Barriers and facilitators for the implementation of electronic dental record systems: Perspectives from a developing country. *International Journal of Medical Informatics*, 190, 105622. <https://doi.org/10.1016/j.ijmedinf.2024.105622>

Fatmasari, A., & Nadjib, M. (2024, October). Hospital readiness to implement electronic medical records: A systematic literature review. UI Scholars Hub; Jurnal ARSI : Administrasi Rumah Sakit Indonesia.

Gatiti, P., Ndirangu, E., Mwangi, J., Mwanzu, A., & Ramadhani, T. (2021). Enhancing healthcare quality in hospitals through electronic health records: A systematic review. *Journal of Health Informatics in Developing Countries*, 15(2).

Gopidasan, B., Amanullah, S., & Adebawale, A. (2022). Electronic Medical Records – A Review of Cost-Effectiveness, Efficiency, Quality of Care, and Usability. *Journal of Psychiatry Spectrum*, 1(2).

Greenhalgh, T., Wherton, J., Papoutsis, C., Lynch, J., Hughes, G., A’Court, C., Hinder, S., Fahy, N., Procter, R., & Shaw, S. (2017). Beyond Adoption: A new framework for theorizing and evaluating nonadoption, abandonment, and challenges to the scale-up, spread, and sustainability of health and care technologies. *Journal of Medical Internet Research*, 19(11), e367. <https://doi.org/10.2196/jmir.8775>

Gueye, M., Gueye, M. N., Mbaye, M., Abdoulaye, M., Diouf, A., Wade, M., Diakhate, A., Aidibe, I., & Moreau, J. (2021). Crossing the Line to Electronic Medical Records in subsaharian Africa: An obstetric and neonatal information system with perinatal indicators dashboard. *Journal of Health Science Research*, 14–20. <https://doi.org/10.18311/jhsr/2017/15932>

Hamdan, N. H., Mustapha, N. D., & Seman, S. A. (2024). GEOGRAPHICAL LOCATION AS A MODERATOR IN THE RELATIONSHIP BETWEEN ICT ADOPTION AND MICRO-ENTREPRENEURS’ PERFORMANCE IN MALAYSIA. *International Journal of Entrepreneurship and Management Practices*, 7(26), 379–393. <https://doi.org/10.35631/ijemp.726030>

- Hapsari, R. N. W., & Mamun, A. A. (2024). Oral health: Essential for overall well-being and quality of life. *Health Dynamics*, 1(11), 393–394.
<https://doi.org/10.33846/hd11101>
- Ho, S.-B., Chew, E.-Y., & Tan, C.-H. (2024, June 13). Streamlining dental clinic management for effective digitisation productivity and usability. Multimedia University.
https://www.researchgate.net/publication/381452632_Streamlining_Dental_Clinic_Management_for_Effective_Digitisation_Productivity_and_Usability
- Holden, R. J., & Karsh, B.-T. (2010). The Technology Acceptance Model: Its past and its future in health care. *Journal of Biomedical Informatics*, 43(1), 159–172. <https://doi.org/10.1016/j.jbi.2009.07.002>
- Igbinosa, Lawrence O., Evbuomwan, R., A. Okoromu, M., & S. Osarenkhoe, U. (2023). Oral health: A doorway to general well-being. In *Dentistry*. IntechOpen. <https://doi.org/10.5772/intechopen.109747>
- Investment Promotion Authority. (2025). Digital superhighway & creative economy. Investments. <https://www.investmentpromotion.go.ke/digital-superhighway-creative-economy?>
- Janssen, A., Donnelly, C., Elder, E., Pathmanathan, N., & Shaw, T. (2021). Electronic medical record implementation in tertiary care: Factors influencing adoption of an electronic medical record in a cancer centre. *BMC Health Services Research*, 21(1), 1–9. <https://doi.org/10.1186/s12913-020-06015-6>
- Jawhari, B., Ludwick, D., Keenan, L., Zakus, D., & Hayward, R. (2016). Benefits and challenges of EMR implementations in low resource settings: A state-of-the-art review. *BMC Medical Informatics and Decision Making*, 16(1), 1–12.
<https://doi.org/10.1186/s12911-016-0354-8>
- Jones-Esan, L., Somasiri, N., & Lorne, K. (2024, October 1). Enhancing Healthcare Delivery Through Digital Health Interventions: A Systematic Review on Telemedicine... Unknown.
https://www.researchgate.net/publication/384611219_Enhancing_Healthcare_Delivery_Through_Digital_Health_Interventions_A_Systematic_Review_on_Telemedicine_and_Mobile_Health_Applications_in_Low_and_Middle-Income_Countries_LMICs

- Kang'a, S., Muthee, V. M., Liku, N., Too, D., & Puttkammer, N. (2016). People, process and technology: Strategies for assuring sustainable implementation of emrs at public-sector health facilities in Kenya - PMC. AMIA Annual Symposium Proceedings, 2016.
- Kang'a, S., Puttkammer, N., Wanyee, S., Kimanga, D., Madrano, J., Muthee, V., Odawo, P., Sharma, A., Oluoch, T., Robinson, K., Kwach, J., & Lober, W. B. (2017). A national standards-based assessment on functionality of electronic medical records systems used in Kenyan public-Sector health facilities. *International Journal of Medical Informatics*, 97, 68–75.
<https://doi.org/https://doi.org/10.1016/j.ijmedinf.2016.09.013>
- Kariuki, N. N., & Richard, L. (2024). Factors influencing the adoption and implementation of the EMR among health care providers at Homabay County Teaching and Referral Hospital. *East African Journal of Health and Science*, 7(2), 40–48. <https://doi.org/10.37284/eajhs.7.2.2410>
- Kasaye, M. D., Mengestie, N. D., Beyene, S., Kebede, N., Ngusie, H. S., & Kalayou, M. H. (2023). Acceptance of electronic medical records and associated factor among physicians working in University of Gondar comprehensive specialized hospital: A cross-sectional study. *DIGITAL HEALTH*, 9.
<https://doi.org/10.1177/20552076231213445>
- Kaur, G., Mehta, A., Sahani, A., & Malik, S. (2021). Knowledge and practices of recording and maintaining patients 'dental records among private dental practitioners of Delhi, India. *Brazilian Journal of Oral Sciences*, 20, e214995–e214995. <https://doi.org/10.20396/bjos.v20i00.8664995>
- Kawaguchi, H., Koike, S., & Ohe, K. (2019). Facility and regional factors associated with the new adoption of electronic medical records in Japan: Nationwide longitudinal observational study. *JMIR Medical Informatics*, 7(2), e14026.
<https://doi.org/10.2196/14026>
- Kenya Ministry of Health. (2023, October). Major digital healthcare advancements unveiled at health conference. Ministry of Health.
<https://www.health.go.ke/major-digital-healthcare-advancements-unveiled-health-conference>
- Khanday, S. A., Vali, K. M., Junaid, Md., & Ahmad, M. (2024). Understanding Positivism: A Qualitative Exploration of its principles and relevance today.

- Advances in Image and Video Processing, 12(6), 531–543.
<https://doi.org/10.14738/aivp.126.17986>
- Khondowe, W. K., & Mpundu, M. (2024, August 17). Exploring challenges and opportunities encountered by private health facilities in Lusaka urban, Zambia: A... Unknown.
https://www.researchgate.net/publication/384343150_Exploring_challenges_and_opportunities_encountered_by_private_health_facilities_in_Lusaka_urban_Zambia_A_case_study_of_selected_private_health_facilities_in_Lusaka_Urb
[an_Zambia](https://www.researchgate.net/publication/384343150_Exploring_challenges_and_opportunities_encountered_by_private_health_facilities_in_Lusaka_urban_Zambia_A_case_study_of_selected_private_health_facilities_in_Lusaka_Urb)
- Kimathi, L. (2017). Challenges of the devolved health sector in kenya: Teething problems or systemic contradictions? *Africa Development*, 42(1), 55–77.
- Klar, R. (2004). Selected impressions on the beginning of the electronic medical record and patient information. *Methods of Information in Medicine*, 43(05), 537–542. <https://doi.org/10.1055/s-0038-1633913>
- KMPDC. (n.d.). KMPDC. Retrieved January 25, 2025, from
<https://kmpdc.go.ke/Registers/H-Facilities.php#>
- Kruse, C. S., Kothman, K., Anerobi, K., & Abanaka, L. (2016). Adoption factors of the electronic health record: A systematic review - PMC. *JMIR Medical Informatics*, 4(2). <https://doi.org/10.2196/medinform.5525>
- Kuffour, E. A. (2022). Barriers of utilizing an electronic health system in Sub-Saharan Africa. *Asian Journal of Education and Social Studies*, 39–49.
<https://doi.org/10.9734/ajess/2022/v32i130761>
- Kumar, P., Paton, C., & Kirigia, D. G. (2016). I've got 99 problems but a phone ain't one: Electronic and mobile health in low and middle income countries. *Archives of Disease in Childhood*, 101(10), 974–979. <https://doi.org/10.1136/ARCHDISCHILD-2015-308556>
- Kuo, K.-M., Liu, C.-F., & Ma, C.-C. (2013). An investigation of the effect of nurses' technology readiness on the acceptance of mobile electronic medical record systems. *BMC Medical Informatics and Decision Making*, 13(1), 1–14.
<https://doi.org/10.1186/1472-6947-13-88>
- Larsen, E., Doupe, M., & Chateau, D. (2018). Implications of electronic health record downtime: An analysis of patient safety event reports. *Journal of the American*

- Medical Informatics Association, 25(2), 187–191.
<https://doi.org/10.1093/JAMIA/OCX057>
- Lau, F., Partridge, C., Randhawa, G., & Bowen, M. (2013). Applying the clinical adoption framework to evaluate the impact of an ambulatory electronic medical record. *Studies in Health Technology and Informatics*, 183, 15–20.
- Lau, F., & Price, M. (2017, February 27). Chapter 3 clinical adoption framework. NCBI Bookshelf.
<https://www.ncbi.nlm.nih.gov/books/NBK481588/?report=printable>
- Lederman, R., Brainin, E., & Ben-Assuli, O. (2024). The electronic medical record—a new look at the challenges and opportunities. *Future Internet*, 16(3).
<https://doi.org/10.3390/fi16030074>
- Levin, K. A. (2006). Study design III: Cross-sectional studies. *Evidence-Based Dentistry*, 7(1), 24–25. <https://doi.org/10.1038/sj.ebd.6400375>
- Li, C., Zhou, G., He, K., Qi, T., Zhang, W., Tian, F., Zheng, Q., & J, H. (2019). Implementation of national health informatization in China: Survey about the status quo - PubMed. *JMIR Medical Informatics*, 7(1).
<https://doi.org/10.2196/12238>
- Listiowati, E., Pratama, D. D., Pramayanti, Y., & Wulandari, R. D. (2025). Understanding user acceptance of electronic medical records: A mixed method study. MPPKI (Media Publikasi Promosi Kesehatan Indonesia), 8(9). <https://doi.org/10.56338/mppki.v8i9.7581>
- Maarsingh, H., Oyler, K., Tuhaise, G., Kiwanuka, J., Ssali, P., & Maarsingh, E. J. (2022). Implementing electronic health records on a medical service trip improves the patient care process. *Frontiers in Health Services*, 2, 960427.
<https://doi.org/10.3389/frhs.2022.960427>
- Majid, I. A., Alikutty, F. K., Qadah, H. Z., Kofiyh, K. A., Alsaadi, R. A. D., Alsubhi, R. M., & Irfan, A. N. (2023). Influence of practice characteristics on the adoption of electronic dental records in Jeddah, Saudi Arabia. *Healthcare Informatics Research*, 29(3), 239–245.
<https://doi.org/10.4258/hir.2023.29.3.239>
- Malhotra, N., & Lassiter, M. (2014, March 28). The coming age of electronic medical records: From paper to electronic. Clute Institute.

- <https://www.researchgate.net/publication/298341897> The Coming Age Of Electronic Medical Records From Paper To Electronic
- Masana, N., & Muriithi, G. (2017, September 5). Technology-Organization-Environmental factors affecting the adoption of an integrated cloud-based EMR... Unknown.
- <https://www.researchgate.net/publication/388698376> Technology-Organization-Environmental Factors Affecting the Adoption of an Integrated Cloud-Based EMR System in the Free State Province?enrichId=rgreq-cbd371c7a0feaaac83ac2bf2eb0f536e-XXX&enrichSource=Y292ZXJQYWdlOzM4ODY5ODM3NjtBUzoxMTQzMtI4MTMwNzkxMDQ0MkAxNzM4NzM5Mjg4OTMw&el=1_x_2&_esc=p
ublicationCoverPdf
- Mbego, S. (2023, October 18). Kenya launches medical records unification system. CIO Africa. <https://cioafrica.co/kenya-launches-medical-records-unification-system/?>
- Meeks, D. W., Smith, M. W., Taylor, L., Sittig, D. F., Scott, J. M., & Singh, H. (2014). An analysis of electronic health record-related patient safety concerns. *Journal of the American Medical Informatics Association*, 21(6), 1053–1059. <https://doi.org/10.1136/AMIAJNL-2013-002578>
- Memon, A., Memon, M. S., & Memon, D. M. (2024). From paper to pixels: EMR as the solution to prescription errors in Pakistan. *Journal of Pakistan Medical Association*. <https://doi.org/10.47391/jpma.20677>
- Mijin, N., Jang, H., Choi, B., & Khongorzul, G. (2017). Attitude toward the use of electronic medical record systems: Exploring moderating effects of self-image. *Information Development*, 35(1), 67–79. <https://doi.org/10.1177/0266666917729730>
- Ministry of Health, Kenya. (2016). Kenya National eHealth Policy 2016-2030. Ministry of Health, Kenya. https://extranet.who.int/countryplanningcycles/sites/default/files/public_file_rep/KEN_Kenya_National-eHealth-Policy_2016-2030.pdf
- Ministry of Investments, Trade & Industry . (n.d.). Digital superhighway & creative economy. Investments. Retrieved January 31, 2025, from

<https://www.investmentpromotion.go.ke/digital-superhighway-creative-economy?>

- Montagu, D., Raman, A. V., & Sarker, M. (2022). Harnessing the contribution of the private health care sector toward public health goals. In *Making Health Systems Work in Low and Middle Income Countries* (pp. 421–434). Cambridge University Press. <https://doi.org/10.1017/9781009211086.028>
- Moturi, A. K., Suiyanka, L., Mumo, E., Snow, R. W., Okiro, E. A., & Macharia, P. M. (2022). Geographic accessibility to public and private health facilities in Kenya in 2021: An updated geocoded inventory and spatial analysis. *Frontiers in Public Health*, 10. <https://doi.org/10.3389/fpubh.2022.1002975>
- Moukoubi Lipenguet, G., Ngoungou, E. B., Roberts, T., Kouna Ndouongo, P., & Kombila, U. D. (2022). Evaluation of the intention to use the electronic medical record (EMR) by health professionals in healthcare facilities of Libreville and Owendo in Gabon. *JAMIA Open*, 5(4), ooac096. <https://doi.org/10.1093/jamiaopen/ooac096>
- Muema, J. K. (2014). Adoption of integrated healthcare information system in Nairobi County: Kenyatta National Hospital versus Mater Hospital. *International Journal of Science and Engineering Applications*. <https://doi.org/10.7753/IJCATR0311.1007>
- Muinga, N., Magare, S., Monda, J., & Paton, C. (2018, December 3). Survey of Electronic Health Record (EHR) Systems in Kenyan Public Hospitals: A mixed-methods survey (Preprint). Unknown. https://www.researchgate.net/publication/329436456_Survey_of_Electronic_Health_Record_EHR_Systems_in_Kenyan_Public_Hospitals_A_mixed-methods_survey_Preprint
- Musabi, A., & Kipkebut, A. (2024). Healthcare Services Interoperability in Kenya: Challenges and Opportunities. *E-Health Telecommunication Systems and Networks*, 13, 1–11. <https://doi.org/10.4236/etsn.2024.131001>
- Naamati-Schneider, L. (2024). Strategic changes and challenges of private dental clinics and practitioners in Israel: Adapting to a competitive environment. *Israel Journal of Health Policy Research*, 13(1). <https://doi.org/10.1186/s13584-024-00645-5>

- Ngugi, P. N., Were, M. C., & Babic, A. (2021). Users' perception on factors contributing to electronic medical records systems use: A focus group discussion study in healthcare facilities setting in Kenya. *BMC Medical Informatics and Decision Making*, 21(1), 1–14.
<https://doi.org/10.1186/s12911-021-01737-x>
- Nguyen, L., Bellucci, E., & Nguyen, L. T. (2014). Electronic health records implementation: An evaluation of information system impact and contingency factors. *International Journal of Medical Informatics*, 83(11), 779–796.
<https://doi.org/10.1016/j.ijmedinf.2014.06.011>
- Ngwashi, C., Asnong, C., Oliveira, V., & Holthof, B. (2023). Evaluating the impact of a digital hospital information management system on the operational and financial performance of health facilities in Kenya - ORA - Oxford University Research Archive. *International Journal of Health Sciences and Research*, 13(3).
- Nichols, A. L., & Edlund, J. (2023). Choosing a Research Design (chapter 5) - The Cambridge Handbook of Research Methods and Statistics for the Social and Behavioral Sciences. Cambridge Core.
<https://www.cambridge.org/core/books/abs/cambridge-handbook-of-research-methods-and-statistics-for-the-social-and-behavioral-sciences/choosing-a-research-design/092CFBBA1220D1393386973ABE65942A>
- Njoroge, C. (2014). Factors influencing adoption of electronic health record systems in small private health facilities: a Case of Ruiru district, Kiambu county, Kenya.
- Njoroge, M., Zurovac, D., Ogara, E. A. A., Chuma, J., & Kirigia, D. (2017). Assessing the feasibility of eHealth and mHealth: A systematic review and analysis of initiatives implemented in Kenya. *BMC Research Notes*, 10(1), 1–11. <https://doi.org/10.1186/s13104-017-2416-0>
- Odekunle, F. F., Odekunle, R. O., & Shankar, S. (2017). Why sub-Saharan Africa lags in electronic health record adoption and possible strategies to increase its adoption in this region. *International Journal of Health Sciences*, 11(4), 59–64.
- O'Donnell, A., Kaner, E., Shaw, C., & Haighton, C. (2018). Primary care physicians' attitudes to the adoption of electronic medical records: A systematic review and evidence synthesis using the clinical adoption framework. *BMC Medical*

- Informatics and Decision Making, 18(1). <https://doi.org/10.1186/s12911-018-0703-x>
- Okumu, B. A., Catherine, L. M., Kruger, E., & Marc, T. (2019, November 11). Demographics of Kenyan dentists under the predevolved system of government; a dental workforce study. African Journals Online. https://www.researchgate.net/publication/351002797_Demographics_of_Kenyan_dentists_under_the_predevolved_system_of_government_a_dental_workforce_study
- Okumu, B. A., Tennant, M., Kruger, E., Kemoli, A. M., Roberts, F. A., & Seminario, A. L. (2022). Geospatial analysis of dental access and workforce distribution in Kenya. *Annals of Global Health*, 88(1), 104. <https://doi.org/10.5334/aogh.3903>
- Omair, A. (2015). Selecting the appropriate study design for your research: Descriptive study designs. *Journal of Health Specialties*, 3(3), 153–156. <https://doi.org/10.4103/1658-600X.159892>
- Ouheda, S., Murray, P., Alam, K., & Alotaibi, Y. (2024). Assessing the impact of innovation processes on electronic systems technology adoption. *Emerging Science Journal*, 8(5). <https://doi.org/10.28991/esj-2024-08-05-02>
- Owino, R. (2021). Towards universal health coverage. *Kabarak Journal of Research & Innovation*, 11(3), 283–298. <https://doi.org/10.58216/kjri.v11i3.78>
- Owolabi, K. A., D., N. E., & Ajao, A. N. (2020, July 7). Factors influencing the adoption of clinical informatics tools among medical doctors in South Africa. Sarada Ranganathan Endowment for Library Science. https://www.researchgate.net/publication/346545634_Factors_Influencing_the_Adoption_of_Clinical_Informatics_Tools_among_Medical_Doctors_in_South_Africa
- Oyoo, E., & Wagah, G. (2024, November 24). The assessment of health financing factors influencing the realization of universal health care in Kenya;... *International Journal of Scientific and Research Publications (IJSRP)*. https://www.researchgate.net/publication/387286893_The_Assessment_of_Health_Financing_Factors_Influencing_the_Realization_Of_Universal_Health_Care_in_Kenya

are In Kenya A Case Of Kisumu County Hospital And Jaramogi Oging
a Odinga Teaching And Referral Hospital In K

- Price, W. N. (2017). Risk and resilience in health data infrastructure. Social Science Research Network. <https://doi.org/10.2139/SSRN.2928997>
- Progress on implementing and using electronic health record systems. (2023). In OECD Health Working Papers. Organisation for Economic Co-Operation and Development (OECD). <https://doi.org/10.1787/4f4ce846-en>
- Riaz, F. (2021, August). Farhan Riaz, Saima Sabir, Umer Abdullah, Muhammad Shairaz Sadiq, Ejaz Husain Sahu, Muhammad Salman Chishty (S. Sabir, U. Abdullah, M. S. Sadiq, E. H. Sahu, & M. S. Chishty, Eds.). Pakistan Journal of Medical & Health Sciences. <https://pjmhsonline.com/published-issues/2021/august/82070>
- Ruotsalainen, I., Valtanen, M., Kärämä, R., Umer, A., Parikka, S., Lundqvist, A., & Lindström, J. (2024). Influencing factors in digital health intervention uptake: The interplay of education, lifestyle, and digital literacy. In Communications in Computer and Information Science (pp. 322–332). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-59091-7_21
- Science Journal of Public Health. (2023). Implementation of Kenya Electronic Medical Records (KenyaEMR): Costs and efficiencies. Science Journal of Public Health, 11(5). <https://doi.org/10.11648/j.sjph.20231105.11>
- Servant, A., Martín-Martín, D., & Romero, I. (2024). Digital transformation of oral health care: Measuring the digitalization of dental clinics. Social Indicators Research. <https://doi.org/10.1007/s11205-024-03366-z>
- Setia, M. S. (2016). Methodology series module 3: Cross-sectional studies. *Indian Journal of Dermatology*, 61(3), 261–264. <https://doi.org/10.4103/0019-5154.182410>
- Shah, S. M., Nyanasegram, T., Cruz, E. D., Lazi, K., Singh, K., Anwar, Z. A., Ramdhan, A. R., & Sinal, M. S. bin. (2024). NAVIGATING THE DIGITAL HEALTH RECORD: CHALLENGES IN THE ADOPTION AND IMPLEMENTATION OF ELECTRONIC MEDICAL RECORDS IN SOUTHEAST ASIA COUNTRIES - A NARRATIVE REVIEW. Authorea, Inc. <https://doi.org/10.22541/au.171907108.87483259/v1>

- Shelke, P. M., & Bagade, J. V. (2022). Electronic health records. In *Disruptive Developments in Biomedical Applications* (pp. 259–274). CRC Press.
<https://doi.org/10.1201/9781003272694-21>
- Sidek, Y. H., & Martins, J. T. (2017). Perceived critical success factors of electronic health record system implementation in a dental clinic context: An organisational management perspective. *International Journal of Medical Informatics*, 107, 88–100. <https://doi.org/10.1016/j.ijmedinf.2017.08.007>
- Singh, A., Jadhav, S., & Roopashree, M. (2020). Factors to overcoming barriers affecting electronic medical record usage by physicians. *Indian Journal of Community Medicine*, 45(2), 168. https://doi.org/10.4103/ijcm.ijcm_478_19
- Srivastava, Dr. S., & Mittal, Dr. S. (2024). *SAMPLING IN NURSING RESEARCH. In Futuristic Trends in Pharmacy & Nursing Volume 3 Book 13* (pp. 29–36). Iterative International Publisher, Selfypage Developers Pvt Ltd.
<https://doi.org/10.58532/v3bgpn13p1ch5>
- Sun, J., Garcia, A., & Wang, Y. (2018, January 1). Ambulatory EMR adoption in the USA: A longitudinal study. Unknown.
https://www.researchgate.net/publication/323381421_Ambulatory_EMR_Adoption_in_the_USA_A_Longitudinal_Study
- Sykes, L., & Bookhan, V. (2023, February 1). Embracing new technology, with caution. Unknown.
https://www.researchgate.net/publication/369948485_Embracing_new_technology_with_caution
- Tamadur, S., Akyürek, Ç. E., Al-Shdayfat, N. M., & Alsaqqa, H. H. (2024). Assessment of factors influencing healthcare provider's acceptance of electronic health record in Jordanian hospitals. *Journal of Health Management*. <https://doi.org/10.1177/09720634241278863>
- Tandon, A. (2020). Practical affordance: EMR use within outpatient consulting on women's health. In *IFIP Advances in Information and Communication Technology* (pp. 180–193). Springer International Publishing.
https://doi.org/10.1007/978-3-030-64697-4_14
- Tchaiwe, Z. (2021). Organizational levels' involvement in electronic health system adoption in Nairobi: A case study of Radiant Group of Hospitals. <https://suplus.strathmore.edu/items/6761a68a-7e59-4c5d-9970-87509e84f51d>

- Thit, W. M., Myint Thu, S. W. Y., Kaewkungwal, J., Soonthornworasiri, N., Theera-Ampornpant, N., Kijsanayotin, B., Lawpoolsri, S., Naing, S., & Pan-ngum, W. (2020). User acceptance of electronic medical record system: Implementation at Marie Stopes International, Myanmar. *Healthcare Informatics Research*, 26(3), 185–192. <https://doi.org/10.4258/hir.2020.26.3.185>
- Thu, S. W. Y. M., Kijsanayotin, B., Kaewkungwal, J., Soonthornworasiri, N., & Pan-
Ngum, W. (2017). Satisfaction with paper-based dental records and perception of electronic dental records among dental professionals in Myanmar. *Healthcare Informatics Research*, 23(4), 304–313. <https://doi.org/10.4258/hir.2017.23.4.304>
- Tilahun, B., & Fritz, F. (2015). Modeling antecedents of electronic medical record system implementation success in low-resource setting hospitals. *BMC Medical Informatics and Decision Making*, 15(1), 1–9. <https://doi.org/10.1186/s12911-015-0192-0>
- Trudel, M.-C., Marsan, J., Paré, G., Raymond, L., Ortiz de Guinea, A., Maillet, É., & Micheneau, T. (2017). Ceiling effect in EMR system assimilation: A multiple case study in primary care family practices. *BMC Medical Informatics and Decision Making*, 17(1). <https://doi.org/10.1186/s12911-017-0445->
- Tsagaankhuu, S., Amgalan, E., Damba, T., & Zhang, X. (2021). Estimating the impacts of hospitals' organisational and geographical characteristics on the adoption of health information technology in mongolian hospitals. *Journal of Healthcare Engineering*, 2021, 1–7. <https://doi.org/10.1155/2021/8836625>
- van Mens, H. J. T., Duijm, R. D., Nienhuis, R., de Keizer, N. F., & Cornet, R. (2020). Towards an adoption framework for patient access to electronic health records: Systematic literature mapping study. *JMIR Medical Informatics*, 8(3), e15150. <https://doi.org/10.2196/15150>
- Vijayanthi, I. P., & Vidhukumar, K. P. (2020, January 3). Research designs- an Overview. Branch of Indian Psychiatric Society (Kerala). https://www.researchgate.net/publication/338383815_Research_designs-_an_Overview
- Vimalachandran, P., Wang, H., Zhang, Y., & Zhuo, G. (2016). The Australian PCEHR system: Ensuring privacy and security through an improved access

- control mechanism. *ICST Transactions on Scalable Information Systems*, 3(8), 151633. <https://doi.org/10.4108/eai.9-8-2016.151633>
- Walji, M. F. (2023). Informatics approaches to improve the quality of dental care. *Orthodontics & Craniofacial Research*, 26(S1), 98–101. <https://doi.org/10.1111/ocr.12655>
- Wang, X., & Cheng, Z. (2020). Cross-sectional studies: What are they good for? *Chest*, 158(1), S65–S71. <https://doi.org/10.1016/j.chest.2020.03.012>
- Waronja, J. N., & Mogote, Dr. C. (2024). Evaluating the impact of electronic medical records on patient management and service integration in Mombasa County, Kenya. *International Journal of Scientific and Research Publications*. <https://www.ijsrp.org/research-paper-0324.php?rp=P14713330>
- WHO. (2022). The global status report on oral health 2022. <https://www.who.int/team/noncommunicable-diseases/global-status-report-on-oral-health-2022/>
- Wiedenbeck, S., McCain, K. W., & Morton, M. E. (2008). Use and acceptance of an electronic health record: Factors affecting physician attitudes. *Proceedings of the American Society for Information Science and Technology*, 44(1), 1–16.
- Willie, M. M. (2024). Population and target population in research methodology. *Golden Ratio of Social Science and Education*, 4(1), 75–79. <https://doi.org/10.52970/grsse.v4i1.405>
- Woldemariam, M. T., & Jimma, W. (2023). Adoption of electronic health record systems to enhance the quality of healthcare in low-income countries: A systematic review. *BMJ Health & Care Informatics*, 30(1), e100704. <https://doi.org/10.1136/bmjhci-2022-100704>
- Wolverton, C. C., & Lanier, P. A. (2019). Utilizing the technology-organization-environment framework to examine the adoption decision in a healthcare context. In *Advances in IT Standards and Standardization Research* (pp. 401–423). IGI Global. <https://doi.org/10.4018/978-1-5225-7214-5.ch018>
- World Health Organization. (2016, January 1). Global diffusion of eHealth: Making universal health coverage achievable: Report of the third global survey on eHealth. <https://iris.who.int/handle/10665/252529>

- Yamane, Y. (1967). Y.mane, Y. (1967). Mathematical formulae for sample size determination. - References. Scientific Research Publishing.
<https://www.scirp.org/reference/referencespapers?referenceid=2995457>
- Yi, M. (2018). Major issues in adoption of electronic health records. Journal of Digital Information Management, 16(4), 180.
<https://doi.org/10.6025/jdim/2018/16/4/180-191>
- Yoo, S., Lim, K., Jung, S. Y., Lee, K., Lee, D., Kim, S., Lee, H.-Y., & Hwang, H. (2022). Examining the adoption and implementation of behavioral electronic health records by healthcare professionals based on the clinical adoption framework. BMC Medical Informatics and Decision Making, 22(1), 210.
<https://doi.org/10.1186/s12911-022-01959-7>
- Zaheer, S., & Sayed, S. A. (2013, July 8). Evaluation of EMR implementation in a private hospital from user's perspective. 2nd Annual Global Healthcare Conference (GHC 2013). https://doi.org/10.5176/2251-3833_ghc13.28



APPENDICES

Appendix I: Letter of Introduction & Consent form

Title of Study: Factors Influencing the Adoption of Electronic Medical Records (EMRs) in Private Dental Clinics in Kenyan Cities

Dear Participant,

You are invited to participate in a research study conducted by Dr. Khadija Aliyan, an MBA student specializing in Healthcare Management. This study is part of my academic requirement and aims to explore the factors influencing the adoption of Electronic Medical Records (EMRs) in private dental clinics within urban centers in Kenya.

The purpose of this study is to understand the challenges and opportunities associated with EMR adoption and how factors at the individual, organizational, and policy levels affect the decision-making process. Insights from this research will contribute to the development of strategies to improve the adoption and utilization of EMRs in private dental clinics, ultimately enhancing service delivery and patient outcomes.

Participation Details:

- Participation in this study is voluntary.
- You will be required to complete a questionnaire that will take approximately 30 minutes of your time.
- The questionnaire includes questions about your perceptions, experiences, and opinions regarding EMR adoption and use in your clinic.

Confidentiality:

- All information you provide will be kept strictly confidential.
- Your responses will be anonymized, and no personal identifiers, such as your name or your clinic's name, will be linked to the data.
- Data will be securely stored on password-protected servers and the information you provide will be used primarily for academic research as part of a Master's thesis at Strathmore University. In addition to fulfilling academic requirements, the findings will be shared with relevant health

authorities, professional associations, and stakeholders to help improve electronic medical record (EMR) adoption in private dental clinics and strengthen digital health policies in Kenya.

Risks and Benefits:

- There are no known risks associated with participating in this study.
- When you contribute to this research, you will help provide valuable insights that may improve the adoption and effectiveness of EMRs in private dental clinics, ultimately benefiting the healthcare sector.

If you agree to participate, please confirm your consent by signing this form (if administered physically) or selecting the consent checkbox before proceeding to the online questionnaire.

Thank you for your time and valuable input. If you have any questions or concerns regarding this study, please feel free to contact me at kkaliyan@gmail.com or 0716765760.

You can also reach out to SU-ISERC in case of ethical concerns on ethicsreview@strathmore.edu or +254730734418.

Sincerely,

Dr. Khadija Aliyan

MBA Student, Healthcare Management
Strathmore University.

Consent Statement:

I have read and understood the information provided above. I voluntarily agree to participate in this research, with the understanding that I can withdraw at any time and that my responses will remain confidential.

☐ I confirm and consent to the questionnaire.

☐ I decline to consent the questionnaire.

Appendix II: Questionnaire

Research Title: Factors Influencing the Adoption of EMRs in Private Dental Clinics in Kenyan Cities

Instructions for Respondents:

Complete all sections of the questionnaire.

Your responses will remain confidential and will be used for academic research purposes only.

Section 1: Demographic and Clinic Information

1. **Age:**
 - ☐ 20-30 years
 - ☐ 31-40 years
 - ☐ 41-50 years
 - ☐ Above 50 years
2. **Gender:**
 - ☐ Male
 - ☐ Female
 - ☐ Prefer not to say
3. **Professional Role:**
 - ☐ Dentist
 - ☐ Dental Assistant
 - ☐ Community Oral Health Officer
 - ☐ Administrative Staff
 - ☐ Other (please specify): _____
4. **Years of Experience in the Healthcare Sector:**
 - ☐ Less than 5 years
 - ☐ 5–10 years
 - ☐ More than 10 years
5. **How long have you worked in this clinic?**
 - ☐ Less than 1 year
 - ☐ 1–3 years
 - ☐ 4–6 years
 - ☐ More than 6 years
6. **Clinic Location**
 - ☐ Nairobi
 - ☐ Mombasa
7. **Clinic Ownership Type:**
 - ☐ Sole Proprietorship
 - ☐ Partnership
 - ☐ Corporate-Owned

8. **Clinic Size (Number of Staff):**
- ☐ Small (1–5 staff)
 - ☐ Medium (6–15 staff)
 - ☐ Large (16+ staff)
9. **What best describes the level of EMR adoption in your clinic?**
- ☐ No EMR implemented
 - ☐ Partial EMR implementation (limited functions only)
 - ☐ Full EMR implementation (used across most clinical operations)
10. **If EMR is used, what functionalities are active? (Select all that apply)**
- ☐ Patient registration
 - ☐ Clinical history/notes
 - ☐ Billing/invoicing
 - ☐ Treatment planning
 - ☐ Data reporting
 - ☐ Other (please specify): _____

If you selected “No EMR implemented,” please proceed to Section 4.

Section 2: Individual and System Factors

For clinics with EMR systems only.

Please indicate your level of agreement with each statement:

(1 = Strongly Disagree, 5 = Strongly Agree)

Statement	1	2	3	4	5
11. I am familiar with using EMR systems.	☐	☐	☐	☐	☐
12. The EMR system is easy to learn.	☐	☐	☐	☐	☐
13. It is easy to master the functions of the EMR system.	☐	☐	☐	☐	☐
14. The EMR system is user-friendly.	☐	☐	☐	☐	☐
15. The EMR system is reliable in its performance.	☐	☐	☐	☐	☐
16. The speed of the EMR system is sufficient for my daily tasks.	☐	☐	☐	☐	☐
17. The EMR provides accurate and reliable information for clinical decisions.	☐	☐	☐	☐	☐
18. The EMR provides comprehensive and relevant patient data.	☐	☐	☐	☐	☐
19. The information is sufficient for my clinical documentation needs.	☐	☐	☐	☐	☐

Statement	1	2	3	4	5
20. When there is a technical issue, the support team resolves it promptly.	☐	☐	☐	☐	☐
21. The EMR vendor provides reliable and effective support.	☐	☐	☐	☐	☐
22. I use the EMR as part of my daily tasks.	☐	☐	☐	☐	☐
23. I cannot complete my tasks without the EMR system.	☐	☐	☐	☐	☐

Section 3: Organizational Factors

Please indicate your agreement:

Statement	1	2	3	4	5
24. Clinic leadership supports EMR adoption.	☐	☐	☐	☐	☐
25. The clinic provides adequate resources for EMR use.	☐	☐	☐	☐	☐
26. The EMR is well integrated into our workflow.	☐	☐	☐	☐	☐
27. The clinic provides regular technical support.	☐	☐	☐	☐	☐
28. The clinic offers continuous training on EMR use.	☐	☐	☐	☐	☐
29. The clinic encourages innovation in digital health.	☐	☐	☐	☐	☐

Section 4: Policy and Environmental Factors

Statement	1	2	3	4	5
30. There are government incentives for EMR adoption.	☐	☐	☐	☐	☐
31. The clinic faces regulatory challenges implementing EMRs.	☐	☐	☐	☐	☐
32. National policy supports EMR use in private clinics.	☐	☐	☐	☐	☐
33. External funding influences EMR adoption.	☐	☐	☐	☐	☐

Section 5: Perceived Outcomes

33. **Benefits experienced from EMR use** (*Select all that apply*)

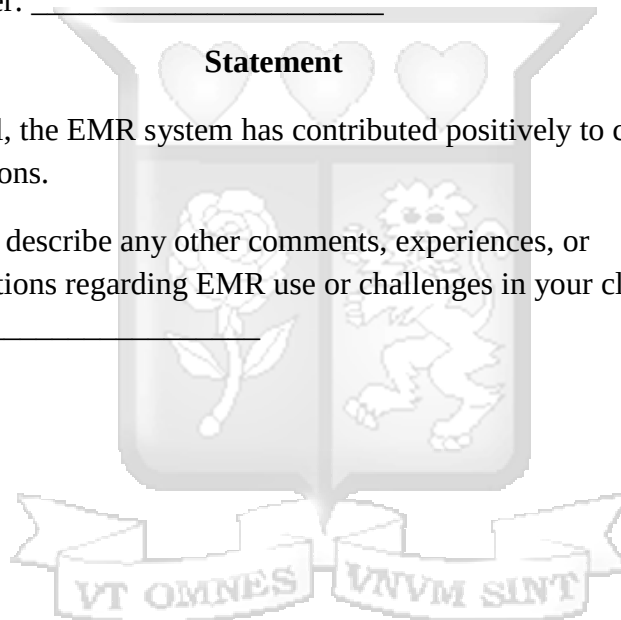
☐ Improved patient care

- ☐ Faster documentation
- ☐ Enhanced data security
- ☐ Reduced workload
- ☐ Increased efficiency
- ☐ Better decision-making
- ☐ Other: _____

34. Challenges encountered *(Select all that apply)*

- ☐ High maintenance costs
- ☐ Staff resistance
- ☐ Internet/power outages
- ☐ Technical glitches
- ☐ Lack of training
- ☐ Data security concerns
- ☐ Other: _____

Statement	1	2	3	4	5
35. Overall, the EMR system has contributed positively to clinic operations.	☐	☐	☐	☐	☐
36. Please describe any other comments, experiences, or suggestions regarding EMR use or challenges in your clinic. _____					



Appendix III: SU IREC Ethical Approval Letter



16th October 2025

Dr Aliyan Khadija,
khadija.aliyan@strathmore.edu

Dear Dr Aliyan,

RE: Factors Influencing Adoption of Electronic Medical Records Amongst Private Dental Clinics in Nairobi and Mombasa Counties, Kenya

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-masters** research proposal. Your application reference number is **SU-ISERC3023/25**. The approval period is from **16th October 2025 to 15th October 2026**.

This approval is subject to compliance with the following requirements:

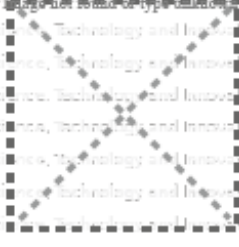
- i. Only approved documents including (informed consents, study instruments, and MTA) will be used
- ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
- iii. Death and life-threatening problems and serious adverse events or unexpected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

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

Yours sincerely,

Mr Ambrose Rachier,
Chairperson; SU-ISERC

Appendix IV: NACOSTI Ethical Approval Letter

 REPUBLIC OF KENYA RefNo: 371467	 NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY & INNOVATION Date of Issue: 12/November/2025
RESEARCH LICENSE	
	
This is to Certify that Dr. Khadija Khalid Aliyan of Strathmore University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Mombasa, Nairobi on the topic: FACTORS INFLUENCING ADOPTION OF ELECTRONIC MEDICAL RECORDS AMONGST PRIVATE DENTAL CLINICS IN NAIROBI AND MOMBASA COUNTIES, KENYA. for the period ending : 12/November/2026.	
License No: NACOSTI/P/25/4182014	
371467 Applicant Identification Number	Ag. Director General NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY & INNOVATION
Verification QR Code 	
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See overleaf for conditions	

Appendix V: Similarity Report



Page 2 of 123 - Integrity Overview

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