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Journal of Health Informatics in Africa

Editorial to JHIA Vol. 13 (2026) Issue 1

Nicky Mostert

Editor-in-Chief, *Journal of Health Informatics in Africa*

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Welcome to this landmark issue of the *Journal of Health Informatics in Africa*. With fifteen carefully selected papers, this is our largest issue to date—a testament to the growing momentum and maturity of health informatics research across the continent. The breadth and depth of scholarship represented here reflect the diverse challenges and innovative solutions emerging from African healthcare systems as they navigate the complexities of digital transformation.

The papers in this issue span a remarkable spectrum of topics, from artificial intelligence and machine learning applications to user-centred design, implementation science, and digital health governance. Collectively, they demonstrate that African researchers are not merely adopting global health informatics frameworks but are actively shaping them to address the continent's unique realities, resource constraints, and opportunities.

SYNOPSES OF PAPERS IN THIS ISSUE

Maake et al. (636) present "A Digital Counter-Gambling Intervention for Online Gambling Students Using Interactive Mobile Application Messaging." This study developed and preliminarily evaluated the ICGIM system, an intervention targeting online gambling disorder among university students in Kenya. Grounded in User-Centered Design and behavioural psychology, the intervention incorporated daily motivational messages, sponsor calls, chat support, and financial tracking features. Preliminary findings suggested reduced self-reported gambling frequency and positive perceptions of the intervention's supportive features, highlighting the potential of tailored digital interventions to address gambling-related behavioural health challenges among young Africans.

Turra, Gilbert, and Kondo (627) contribute "Improving Tuberculosis Detection with Deep Learning in X-Ray Imaging," developing a VGG19-based convolutional neural network for TB detection in Tanzania. Achieving 96% accuracy, the model suggests the feasibility of AI-driven diagnostic tools in resource-constrained settings. The study's emphasis on low-cost hardware compatibility and offline operability makes it particularly relevant for deployment in peripheral health facilities across sub-Saharan Africa.

Dyers, van Greunen, and Hahomed (585) propose *"A User Experience Model for Health Data Visualization for Managerial Decision Support."* Using a Design Science Research approach, the study addresses the need to better align routine health information system (RHIS) data visualisation with the diverse decision-making contexts, cognitive needs, and user characteristics of health managers. The resulting UX Model for RHIS DataViz incorporates purposeful data storytelling, cognitive load, data quality, interaction, user attributes, and contextual factors. The model provides a practical and theoretically informed framework to guide the design and assessment of RHIS data visualisation tools intended to support managerial decision-making in public health systems.

Munyao et al. (584) present a systematic review of "The Use of Machine Learning and Internet of Things Technologies in Maternal Healthcare." Their analysis of 50 studies reveals significant gaps in integrated

IoT-ML frameworks, particularly the limited consideration of tinyML for on-device, real-time analytics and the reliance on smartphones as intermediaries for data transmission. The review identifies the need for intelligent monitoring systems capable of capturing both maternal and fetal vital signs and supporting the early prediction of pregnancy complications, while providing recommendations and a roadmap for future research in this area.

Djamba et al. (669) propose *"A Context-Aware Information Systems Architecture for Sustainable E-Health Implementation in the Democratic Republic of Congo."* Addressing the infrastructural, organisational, and institutional challenges affecting e-health implementation in fragile and resource-constrained healthcare environments, the study integrates technology adoption determinants with information-systems architectural principles. The proposed layered and modular architecture emphasises interoperability, offline capability, scalability, security, and resilience, providing a structured roadmap for sustainable digital health implementation in the DRC and similar resource-constrained settings.

Nicholas and Kantaris (652) examine *"Influence of Demographic Characteristics on Health Workers' Acceptance of Biometric-Controlled Health Informatics Systems."* Their quantitative study of health workers in Ugandan public hospitals, grounded in the Technology Acceptance Model, finds that gender and education level significantly predict acceptance, whereas age and professional experience do not. The findings highlight the importance of considering demographic differences when implementing biometric-controlled health informatics systems and suggest that implementation strategies may need to incorporate differentiated communication, training, and user-support approaches.

Ssegujja, Msanjila, and Shao (526) explore *"Patient Perspectives on mHealth for Maternal and Pre-maternal Health Services in Resource-Constrained Settings."* Using a user-centred design approach involving 60 mothers in Uganda, the study identifies key requirements for improving maternal e-service delivery, including multimedia content, multilingual capabilities, offline access, telemedicine consultations, and emergency support. The proposed framework seeks to address limitations in existing predominantly SMS-based interventions by supporting more comprehensive maternal e-services across pregnancy, childbirth, and the postnatal period.

Okalebo and Wausi (621) present a systematic review of *"Absorptive Capacity Theory and its Application to mHealth Technologies for Adverse Drug Reaction Reporting in Uganda."* Their analysis of 25 studies shows that absorptive capacity operates across individual, team, and organisational levels, providing a multi-level theoretical lens for understanding mHealth utilisation in pharmacovigilance. The review identifies organisational, leadership, cultural, and team-level determinants that shape knowledge absorption and digital health adoption, thereby contributing to the theoretical understanding of mHealth utilisation and providing a conceptual basis for strengthening pharmacovigilance in public healthcare environments.

Rahman and Sharmin (615) contribute *"Rapid Retinopathy Detection using Ablation-Guided Deep Learning."* Systematically comparing twelve combinations of deep learning feature extractors (VGG16, ResNet152V2, and Xception) with classical machine-learning classifiers, the study identifies the Xception–Random Forest hybrid as the best-performing model, achieving 91.1% testing accuracy. The ablation experiment demonstrates the potential of hybrid DL–ML pipelines to improve classification performance while reducing computational demands, supporting their potential use in cost-effective and scalable diabetic retinopathy screening in resource-constrained healthcare settings.

Irongo, Adebesin, and Foster (563) conduct a systematic literature review on *"Compliance with Interoperability Standards in Implementing Digital Health in Low- and Middle-Income Countries."* Guided by the Technology-Organisation-Environment (TOE) framework, they identify barriers to compliance with interoperability standards across three domains: technological (inadequate IT infrastructure, limited standardisation and fragmentation, contextual adaptation challenges, and performance, maintenance and usability issues), organisational (inadequate leadership and governance, limited capacity, and resistance to change), and environmental (inadequate legal and regulatory frameworks, insufficient compliance monitoring, data security and privacy challenges, and financial constraints). The findings provide a foundation for targeted, multi-level interventions to strengthen interoperability compliance and support sustainable digital health implementation in LMICs.

Ofoe et al. (592) examine "Enhancing Diabetes Mellitus Diagnosis and Management in Ghana through Supervised Learning." Using clinical data from 3,407 patient records, the study compares Gaussian Naive Bayes, Random Forest, and XGBoost algorithms for diabetes prediction. XGBoost achieved the highest accuracy (99.5%) on the held-out test set, identifying it as a promising candidate for integration into a machine learning-based clinical decision support system in Ghana, particularly in settings where specialist services are limited. However, the model requires external and prospective validation before clinical deployment.

Mishio, Adong, and Adjei (617) investigate factors influencing user acceptance of electronic health record systems in low-resource settings in Ghana. Using a cross-sectional study of 373 healthcare workers at Tamale Teaching Hospital, the study found a high level of acceptance (97%) of the Lightwave Health Information Management System (LHIMS), alongside a significant improvement in positive attitudes following its implementation. Multivariable logistic regression identified 20 or more years of computer use (OR = 6.307) and being a medical doctor (OR = 7.443) as factors significantly associated with user acceptance. Despite the high acceptance, users reported persistent implementation challenges, including complex system interfaces, power interruptions, inadequate equipment, and poor internet connectivity.

Chumba, Waema, and Ochieng (647) explore *"Relational Mechanism in Community-Based Health Information System Governance."* Using a mixed-methods approach across two Kenyan counties, the study identifies eleven practices associated with the CBHIS governance relational mechanism, including stakeholder engagement, data review meetings, dialogue days, and community health chalkboards. The research finds a positive and statistically significant relationship between the relational governance mechanism and community health outcomes, with the mechanism explaining 39.6% of the variance in community health outcomes ($R^2 = 0.396$). The findings offer practical insights into strengthening CBHIS governance and community health system performance.

Sibanda and Ndlovu (700) present a "Deployment-Oriented Evaluation of an Explainable Tabular Transformer for Tuberculosis Outcome Prediction." Using synthetic healthcare data, the study develops a framework integrating transformer architecture, SHAP-based explainability, calibration assessment, and subgroup consistency screening. The model achieved 82.1% accuracy and an AUC-ROC of 0.872, demonstrating methodological feasibility for resource-constrained settings while emphasizing that external validation and prospective clinical evaluation are required before clinical deployment.

Djamba et al. (706) propose a *Strategic Implementation Framework for Sustainable E-Health Deployment in Fragile Healthcare Systems: Evidence from the Democratic Republic of Congo*. Building on empirical evidence from an e-health adoption model and context-aware design principles, the study develops a five-phase implementation framework encompassing planning and stakeholder engagement, system design and development, pilot implementation and capacity building, phased scale-up and national integration, and continuous monitoring, evaluation, and sustainability. The framework seeks to bridge the gap between e-health adoption research and practical, sustainable deployment, providing structured guidance for policymakers, healthcare institutions, and system designers in resource-constrained and fragile healthcare settings.

ACKNOWLEDGEMENTS

The publication of this substantial issue would not have been possible without the dedication and scholarly rigour of our authors. We extend our sincere gratitude to each researcher who has entrusted their work to the *Journal of Health Informatics in Africa*. Your contributions—whether from the laboratory, the clinic, the community, or the policy space—advance our collective understanding and push the boundaries of what is possible in African health informatics. We are particularly encouraged by the diversity of countries represented in this issue, reflecting the pan-African nature of our journal's mission.

We also wish to acknowledge and thank our reviewers, whose expert evaluations ensure the quality and integrity of the work we publish. Peer review is the cornerstone of academic excellence, and our reviewers volunteer their time and expertise generously. Without their critical engagement, methodological scrutiny, and constructive feedback, the papers in this issue—and indeed the journal itself—would not achieve the standards we collectively uphold. Reviewers are the unsung heroes of scholarly publishing, and we are deeply grateful for their contributions.

INVITATION TO REVIEW

As the *Journal of Health Informatics in Africa* continues to grow, the demand for high-quality, timely reviews increases correspondingly. We are always seeking to expand our pool of reviewers, particularly researchers with expertise in health informatics, health information systems, digital health, implementation science, medical informatics, computer science, public health, and related disciplines. If you are willing to contribute to the scholarly community by serving as a reviewer, we invite you to contact the editorial team. We particularly welcome reviewers who can offer expertise in the methodological, technical, or contextual dimensions of health informatics research in Africa. Please contact us from your institutional e-mail account, and include your areas of expertise and ORCID identifier if available. We especially encourage early-career researchers to consider this opportunity to engage with the peer-review process.

FOREWORD

As we reflect on the contributions in this issue, we are struck by the thematic coherence that emerges despite the diversity of topics. Several papers address the application of artificial intelligence and machine learning to pressing health challenges—diabetes, tuberculosis, diabetic retinopathy—demonstrating the growing sophistication of African data science research. Others explore the critical human dimensions of digital health, including user acceptance, patient perspectives, and organisational readiness, reminding us that technology alone does not transform health systems. Governance and interoperability emerge as central concerns, with multiple papers identifying the need for robust frameworks, standards, and accountability mechanisms to ensure that digital health investments deliver sustainable value.

Perhaps most encouraging is the increasing attention to implementation science—the systematic translation of evidence into practice. Several papers in this issue move beyond demonstrating technical feasibility to address the "how" of sustainable deployment: how to align systems with workflows, how to build capacity, how to engage stakeholders, how to monitor and evaluate. This reflects a maturation of the field, as health informatics researchers recognise that innovation is only meaningful when it leads to improved health outcomes.

We hope readers will find inspiration, insight, and practical guidance in these pages. As always, we welcome your feedback, submissions, and engagement with the journal. Together, we are building the evidence base for health informatics in Africa and contributing to the digital transformation of healthcare across the continent.

Prof. Nicky Mostert
August 2026

Journal of Health Informatics in Africa

Compliance with Interoperability Standards in Implementing Digital Health in Low and Middle-Income Countries

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Background and Purpose: Low- and Middle-income Countries (LMICs) bear over 70% of global mortality and morbidity, compounded by systemic healthcare challenges. In response, many LMICs have adopted Digital Health (DH) to transform patient management and overall care. However, the transformative potential of DH is constrained by poor interoperability among diverse systems, which undermines effective data sharing and informed decision-making. This study explores the factors that hinder compliance with interoperability standards in DH implementations in LMICs.
Methods: A Systematic Literature Review (SLR) was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, with peer-reviewed articles retrieved from PubMed, Scopus, and ScienceDirect. The search, covering the literature from January 1, 2015, to January 30, 2025, was refined using relevant keywords. Out of 865 screened articles, 38 underwent full-text assessment, and 22 met the quality criteria for analysis.
Results: The analysis, structured using the Technology-Organisation-Environment (TOE) framework, identified key barriers. Technological challenges include inadequate Information Technology (IT) infrastructure, limited standardization, fragmented systems, and adaptation difficulties. Organizational barriers involve weak leadership, poor governance, limited technical capacity, and resistance to change. Environmental obstacles include outdated regulations, weak compliance monitoring, data security concerns, and financial constraints.
Conclusions: These findings underscore the need for a coordinated, multi-level approach to enhance interoperability compliance in DH, thereby improving healthcare outcomes in LMICs. Targeted interventions are essential to drive sustainable DH implementation in LMICs.

Keywords: Compliance, Digital Health, Interoperability standards, Low- and Middle-income Countries, LMICs.

1 Introduction

Low- and Middle-income Countries (LMICs) account for over 70% of global mortality and morbidity rates [1-3]. These high disease burdens are further stressed by systemic healthcare challenges, including a shortage of skilled personnel, weak governance, and inadequate information systems infrastructure [4-6]. In response, several LMICs have implemented health sector reforms to enhance healthcare service delivery [7-9]. A significant aspect of these reforms involves using digital health (DH) interventions to improve healthcare delivery, leveraging the increasing network connectivity and mobile phone usage.

DH is defined as the development and application of digital technologies and data to enhance health outcomes [10-12]. According to the World Health Organization (WHO), DH encompasses various domains, including Electronic Health (eHealth), Mobile Health (mHealth), the Internet of Things (IoT), and Artificial Intelligence (AI). Furthermore, Al Meslamani [13], Kabore et al. [14] and Ramnath [15] note that DH encompasses many technologies, including big data, robotics, machine learning, remote monitoring, genomics, smart wearables, blockchain, telehealth, and telemedicine. The rise of DH holds significant promise for transforming healthcare delivery in LMICs by facilitating more efficient patient management, remote care, chronic disease management, operational efficiency, care coordination, and robust data management and analytics [16-18].

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Despite their transformative potential, DH solutions implemented in LMICs are often not interoperable, thereby hampering effective data exchange and limiting the capacity to enhance healthcare delivery [19-21]. Interoperability in DH, as defined by Kawamoto et al. [22], Kobusinge [20], Kramer and Moesel [23], and Torab-Miandoab et al. [24], refers to the capability of DH to share and utilize data to advance healthcare objectives. An interoperable DH solution is crucial for facilitating the seamless and secure exchange of data, which enhances informed decision-making and improves healthcare delivery, underpinned by established interoperability standards [22, 25].

Interoperability standards are the most critical drivers of DH interoperability, ensuring seamless exchange and use of data across fragmented and varying vendors' DH solutions [26-29]. These standards consist of technical specifications that define common protocols, data formats, guidelines, and languages for interoperability [26, 29, 30]. Notably, standards such as Fast Healthcare Interoperability Resources (FHIR), Health Level Seven (HL7), and Aggregate Data Exchange (ADX) have been adopted across several LMICs to enhance healthcare delivery [25, 31, 32].

Compliance with interoperability standards is essential for the successful implementation of DH solutions that could transform healthcare delivery [27, 33-35]. However, LMICs often face inadequate compliance with interoperability standards due to various technological, organizational, and environmental factors [27, 33-35]. Despite frameworks provided by the International Telecommunication Union (ITU) and the WHO advocating for the use of interoperability standards, many LMICs struggle with adherence [36, 37]. Additionally, Bincoletto [38], Jonnagaddala et al. [39], Nsaghurwe et al. [21], and Pine [40] highlight the scarcity of literature addressing the factors hindering compliance with interoperability standards in DH implementation within LMICs.

This study reported in this paper conducted a systematic literature review (SLR) to provide an overview of current knowledge of factors that hinder compliance with interoperability standards in the implementation of DH in LMICs and to identify gaps in existing literature. It is anticipated that the findings from the SLR will offer valuable insights for policymakers, healthcare providers, technology developers, researchers, and other key stakeholders. These insights can guide the development of targeted interventions to enhance the effectiveness of DH and transform healthcare outcomes in LMICs. The paper is structured as follows: Section 2 outlines the research methodology, Section 3 presents the results, and Section 4 discusses the implications of the findings, with the conclusions in Section 5.

2 Materials and methods

This study was based on the PRISMA guidelines by Page et al. [41]. The primary research question addressed in this paper was: "What are the factors that hinder compliance with interoperability standards in implementing digital health in low and middle-income countries?" Peer-reviewed research papers were retrieved from three electronic databases (i) PubMed, (ii) Scopus and (iii) ScienceDirect. The selection of these databases was based on their prior utilization in similar studies, including those by Alunyu et al. [42], Higman et al. [43], and Palojoki et al. [44], as well as their comprehensive coverage of DH and interoperability standards in LMICs.

The study's primary objective, to synthesise and document factors that hinder compliance with interoperability standards in implementing digital health in low and middle-income countries, guided the identification of keywords. The primary keywords were "digital health", "interoperability standards", "compliance", "low- and middle-income countries", and "factors hindering". Synonyms and related terms for each keyword were generated to ensure a comprehensive search.

For "digital health", associated terms included "health information systems", "eHealth", and "health information technology". For "interoperability standards", the related term was "interoperability". For "compliance", the associated terms were "adherence" and "conformity". For "low- and middle-income countries", synonyms included "developing countries", "LMICs", and "resource-constrained countries". Finally, for "factors hindering", the related terms were "barriers" and "challenges". These terms were combined using Boolean operators, "OR" to include synonyms and "AND" to connect different keywords. The resulting search phrase was: ("digital health" OR "health information systems" OR "eHealth" OR "health information technology") AND ("interoperability standards") AND ("compliance" OR "adherence" OR "Conformity") AND ("low- and middle-income countries" OR "developing countries" OR "LMICs" OR "resource-constrained countries") AND ("barriers" OR "challenges" OR "factors hindering").

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The search phrase was tested and refined in PubMed, Scopus, and ScienceDirect to fine-tune search terms, maximise the retrieval of relevant studies, and minimise irrelevant results.

2.1 Inclusion and exclusion criteria

The inclusion and exclusion criteria were meticulously defined to ensure a comprehensive and the retrieval of relevant literature, capturing diverse studies that shed light on factors hindering compliance with interoperability standards in DH implementation within LMICs, as illustrated in Table 1:

Table 1. Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
Peer-Reviewed Articles: Only peer-reviewed publications, including original research, case studies, and reviews, were considered to ensure quality, reliability, and diverse perspectives.	Topic Relevance: Studies that did not discuss interoperability standards in DH were excluded, ensuring that the SLR addresses the core issues pertinent to DH implementation.
LMIC Focus: Studies focused on LMICs, as classified by the World Bank, recognizing their unique DH implementation challenges would differ from high-income countries.	Geographic Scope: Studies not focused on LMICs were excluded to maintain the study's relevance to LMIC-specific challenges and contexts.
Interoperability Barriers: Included studies specifically addressed barriers, challenges, or obstacles to compliance with interoperability standards in DH implementation.	Language: Articles not published in English were excluded to maintain access and consistency in the analysis.
Digital Health Scope: Research covered various DH domains, including eHealth, electronic health records (EHRs), health information exchanges (HIEs), telehealth, and mHealth, ensuring a comprehensive view of interoperability challenges.	Publication Date: Articles published before 2015 were excluded to ensure the review reflects the most recent developments and trends in DH interoperability.
Language & Publication Date: Only English-language articles published between January 1, 2015, and January 30, 2025, were included to ensure relevance while capturing recent developments.	

2.2 Screening process and quality assessment

PubMed, Scopus, and ScienceDirect databases were filtered to retrieve only papers published between January 1, 2015, and January 30, 2025, ensuring relevance while capturing recent developments. The database search retrieved a total of 1,007 records, including PubMed (651), Scopus(204), and ScienceDirect (152). All identified studies were imported into EndNote 20.6 for meticulous reference management. Following an initial screening, 142 duplicate sources across the three databases were deleted. Thereafter, the remaining 865 sources were screened to ensure that they met the inclusion criteria. Titles and abstracts were assessed against predefined inclusion criteria, leading to the exclusion of 646 records; three were non-English, six were editorials, 623 were review articles, and 14 were published before 2015. This resulted in 219 articles that underwent full-text assessment for eligibility. Upon detailed examination, 181 articles were excluded due to inadequate and out-of-context discussions on compliance with interoperability standards. Thereafter, the remaining 38 papers were assessed for quality using the following quality assessment (QA) questions:

1. Does the paper adequately discuss technological, organizational, or environmental factors that hinder compliance with interoperability standards in digital health implementation?
2. Does the paper explore the different dimensions or components of these hindering factors within the Technology-Organization-Environment (TOE) framework?
3. Does the paper analyse how these hindering factors impact the successful implementation and scaling of interoperable digital health solutions in LMICs?

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For QA1, papers that only mentioned factors hindering compliance with interoperability standards were awarded a score of 0, those that provided a limited explanation were awarded 0.5, while those that provided an adequate discussion were awarded 1. For QA2, papers that did not categorize factors under the TOE framework were awarded a score of 0, those that partially mapped factors to at least one TOE dimension were awarded 0.5, and those that comprehensively categorized factors under all three TOE dimensions were awarded 1. For QA3, papers that did not discuss the impact of non-compliance were awarded a score of 0, those that provided at least one impact were awarded 0.5, while those that discussed two or more impacts were awarded 1. Thus, a paper could have a maximum score of 3. Only sources that obtained at least 1.5 were considered for inclusion in the SLR. Following the QA process, a total of 22 papers were included in the final analysis. Figure 1 illustrates the source selection process.

We analyzed these 22 papers using descriptive statistics to examine paper distributions by year of publication and document type. Qualitative content analysis was used to extract concepts and map the identified factors to the TOE framework. The results of this analysis are presented in Section 3.

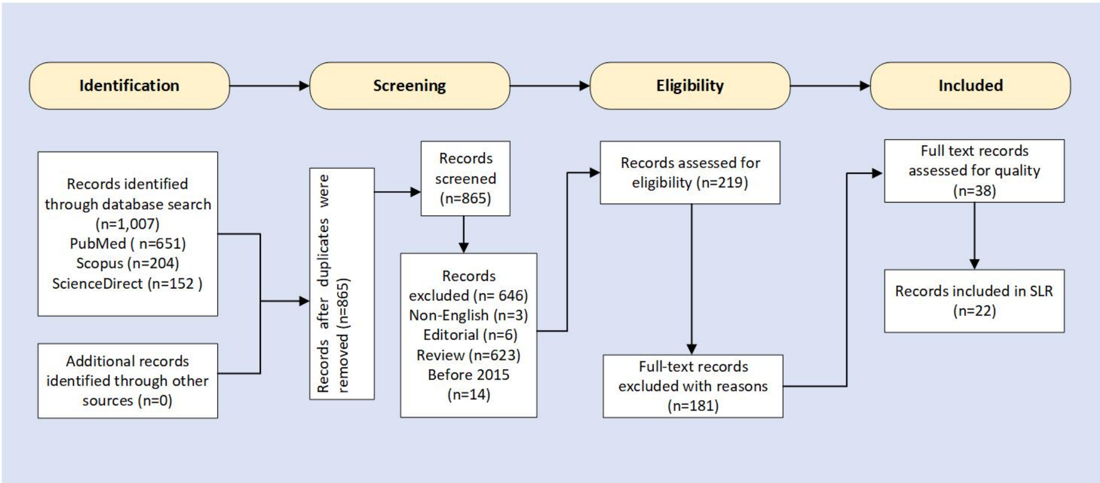

Figure 1. SLR screening process

2.3 Ethical Considerations

This SLR involved the analysis of existing literature and did not require ethical approval as it did not involve primary data collection or interaction with human subjects. However, ethical considerations were taken into account by ensuring proper citation and acknowledgement of all sources used in the review as prescribed by Taquette and Borges [45].

3 Results

This section presents the findings derived from the analysis of the 22 studies included in the SLR.

3.1 Basic quantitative analysis results

The descriptive statistical analysis of 22 papers included in the SLR by publication year revealed that a single paper was published in 2015 and 2018, respectively (see Figure 2). The number of publications increased to two in 2020 and 2022, respectively, followed by a notable rise to five in 2021. In 2023, the number of publications reached four, before peaking at six in 2024. The analysis further shows one publication in 2025. This is because the sources included in the SLR were retrieved on January 30, 2025.

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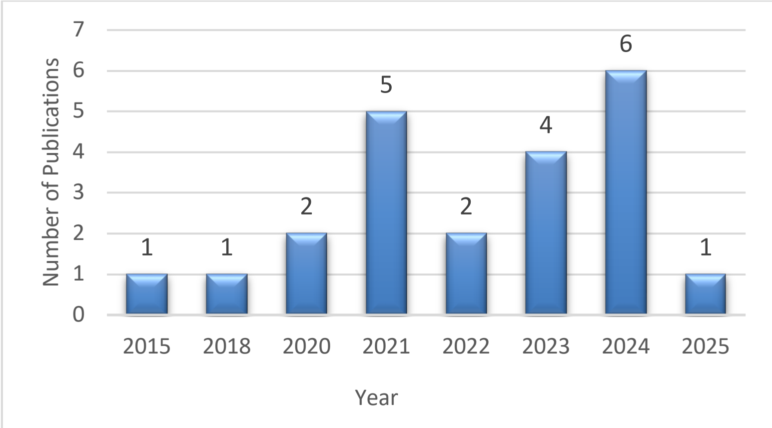

Figure 2. Number of publications per year

The analysis by document type revealed that the majority of the papers (19) were journal articles, while the remaining three were conference proceedings. The analysis by source databases showed that 13 (59.1%) of the papers were retrieved from PubMed, six (27.1%) from Scopus and three (13.6%) from ScienceDirect.

3.2 Basic qualitative analysis results

The qualitative analysis of the 22 selected studies followed a structured approach to identify barriers to compliance with interoperability standards in DH implementation across LMICs. Data were systematically extracted and organized in Excel, with key study characteristics including publication details, study setting, findings, and reported challenges recorded in separate columns. Through initial coding, descriptive labels were assigned to frequently mentioned challenges, capturing patterns across multiple studies. These codes were then reviewed and grouped into broader themes, reflecting common obstacles such as technical constraints, organisational limitations, and regulatory gaps. To ensure a structured interpretation, the TOE framework was adopted as an analytical model for categorizing these themes into interdependent domains.

The TOE framework, developed by DePietro [46], explains how organizations adopt and implement technological innovations based on three key contexts: technological, organizational, and environmental. This framework was selected for its capacity to provide a comprehensive analysis of the multifaceted factors that impact interoperability in DH implementations [46]. It offers a structured approach to identifying and understanding barriers across these three dimensions [46].

1. Technological Context – Encompasses internal and external technologies relevant to the organisation, including system capabilities, infrastructure, and interoperability standards.
2. Organisational Context – Includes internal factors such as structure, resource availability, management processes, and organisational capacity to support technology adoption.
3. Environmental Context – Covers external influences such as regulatory frameworks, policy fragmentation, market conditions, and socio-economic factors that impact technology implementation.

The application of the TOE framework has been established in various studies examining factors that influence technology adoption in similar contexts. For instance, Al Hadwer et al. [47] conducted a systematic review that emphasized organizational factors impacting cloud-based technology adoption, underscoring the framework's utility in understanding readiness and capability. Similarly, Anthony Jnr [48] investigated telehealth adoption during public health emergencies, utilizing the TOE framework to explore the determinants that influence implementation. Assaye et al. [49] assessed readiness for big health data analytics in Ethiopian health sectors through the TOE analytical lens, while Ngongo et al. [50] examined the determinants of mHealth adoption in Kenyan hospitals, revealing the interplay among technological, organizational, and environmental factors.

This study applied the TOE framework to systematically analyse the barriers to interoperability in DH implementation in LMICs. These barriers are categorized into technological (e.g., legacy systems, lack of standardization, and infrastructure limitations), organizational (e.g., governance weaknesses, resource constraints, and limited technical capacity), and environmental (e.g., regulatory gaps, fragmented policies,

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and market dynamics) factors. By structuring these challenges within the TOE framework, this study provides a deeper understanding of interoperability constraints and informs strategic interventions to enhance compliance in LMICs. Based on the synthesis of the sources included in the SLR and guided by the TOE framework, successful compliance with interoperability standards requires a balance between technological capabilities, organisational capacity, and external environmental factors (see Figure 3).

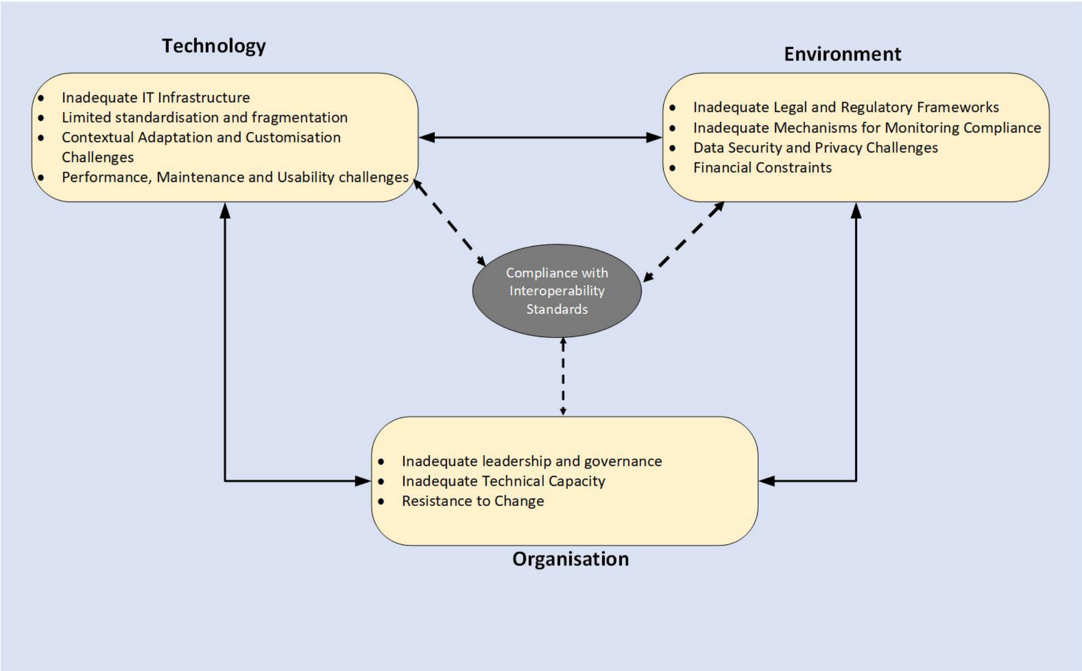

Figure 3. A conceptual framework of the factors that hinder compliance with interoperability standards using the TOE framework

3.2.1 Technology Factors

- Inadequate IT infrastructure: One of the technological factors that was found to hinder compliance with interoperability standards was inadequate IT infrastructure in LMICs. Inadequate IT infrastructure entails deficiencies in the foundational technological systems required for seamless data exchange and compliance with interoperability standards in DH. This factor was identified from seven sources included in the SLR [39, 51-56]. Studies reported that many LMICs have to contend with insufficient hardware, outdated software, unreliable network connectivity, and unstable electricity, which collectively hinder compliance with interoperability standards [39, 51-56]. It was further noted by Bagyendera et al. [51] that inadequate internet connectivity, limited server capacity, and a lack of data analysis tools in several health facilities across LMICs significantly impede data collection, storage, and sharing. Additionally, Jonnagaddala et al. [39] emphasised that such infrastructural weaknesses limit the ability to adopt and sustain interoperable systems, thereby hindering effective compliance with interoperability standards in LMICs.
- Limited standardization and fragmentation: Limited standardization and fragmentation were additional technological factors found to hinder compliance with interoperability standards. Standardization ensures uniform technical protocols for compatibility and interoperability, while fragmentation arises from a lack of coordination, leading to isolated and incompatible systems. These closely interlinked factors were highlighted by three sources included in the SLR [39, 51, 52]. LMICs were reported to have a limited availability of universally adopted standardised data formats leading to inconsistent data structures across DH, complicating the consolidation and exchange of data across platforms [39, 51, 52]. Furthermore, Bille et al. [52] emphasized that LMICs are characterised by variations in medical terminologies that amplify challenges with complying with interoperability standards, resulting in inconsistencies in the recording of diagnoses, treatments, and procedures. These discrepancies increase

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the risk of misinterpretation, data mismatches, and disruptions in care coordination, which ultimately impact treatment outcomes.

Additionally, Bagyendera et al. [51] and Bille et al. [52] noted that LMICs have a high prevalence of fragmented, independently deployed DH solutions, which create isolated data silos, further hindering seamless information exchange and compliance with interoperability standards. Bagyendera et al. [51] and Bille et al. [52] attribute the high prevalence of fragmented DH in LMICs to limited centralised governance, inconsistent funding sources, and the adoption of donor-driven vertical programs that prioritise specific health interventions over integrated system development.

- Contextual adaptation and customisation challenges: Contextual adaptation and customization challenges were also reported as key technological hindrances to compliance with interoperability standards in the implementation of digital health in LMICs across two sources in the SLR [57, 58]. The contextual adaptation and customization challenges relate to the limited ability to modify interoperability standards during DH implementation to fit the local context in LMICs. It was reported that interoperability standards, such as HL7 and FHIR, which are widely used in LMICs, have not been adequately adapted to local contexts, leading to misalignment with the specific interoperability requirements and challenges of these settings [57, 58]. It was also observed that DH solutions deployed in LMICs have frequently been designed for developed contexts, with limited consideration for local cultural and operational interoperability requirements, creating technical challenges in adaptation and compliance with standards [57, 58].
- Performance, maintenance, and usability issues: Several sources [54, 57, 59, 60] identified technological challenges, such as performance, maintenance, and usability issues, as significant barriers to compliance with interoperability standards in LMICs. Several DH solutions in LMICs face limited optimization in terms of performance, usability, and availability, creating obstacles to effective implementation and adherence to interoperability standards [57]. Examples include slow Electronic Medical Record (EMR) response times due to inadequate servers at health facilities, complex DH interfaces that hinder navigation, and unreliable internet connectivity, which disrupts access to cloud-based platforms in rural facilities [57]. Additionally, frequent technical malfunctions in DH solutions, often caused by poor system design and inadequate testing, disrupt seamless data exchange and undermine user trust, thereby reducing compliance with interoperability standards [59]. The lack of sufficient maintenance of IT infrastructure, including networks and hardware, exacerbates these challenges, contributing to unstable environments that further compromise interoperability [54]. Moreover, LMICs often rely on outdated DH solutions, making it difficult to comply with evolving interoperability standards due to the need for regular updates and rigorous testing [60]. The dominance of proprietary technologies developed by multiple vendors in many LMICs also restricts interoperability, as these vendors maintain market dominance, which leads to widespread non-compliance with established standards [60].

3.2.2 Organizational Factors

- Inadequate leadership and governance: From an organizational perspective, 11 sources [39, 51-55, 61-65] identified inadequate leadership experience and weak governance structures as significant impediments to compliance with interoperability standards in LMICs. Several public health and ICT sector leaders across LMICs were found to frequently demonstrate limited political will and commitment to enforce policies and guidelines that mandate compliance with interoperability standards [39]. Additionally, governance structures in LMICs are frequently reported to be insufficiently developed to support the formulation and enforcement of digital health interoperability standards [54, 64]. Furthermore, LMICs were found to generally have limited well-established leadership frameworks, governance mechanisms, and dedicated regulatory bodies to ensure adherence to organizational policies, procedures, and best practices necessary for interoperability compliance [54].

  In addition, it was reported that healthcare organizations in LMICs frequently struggle to align their internal processes and structures with the requirements necessary for compliance with interoperability standards [62, 63]. Specifically, LMICs were noted to exhibit inconsistent organizational practices, coupled with unclear roles and responsibilities concerning interoperability standards, leading to fragmented implementation processes and weakened compliance efforts [63]. Similarly, a survey by Kiwanuka et al. [61] reported that only 46% of respondents perceived DH governance at the facility level to be strong. This was attributed to the absence of formal guidelines and an overreliance on ad-hoc measures at facilities, which create inconsistencies and inefficiencies in

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data governance practices [61]. It was also emphasized that governance guidelines in LMICs are often inadequate, unclear, or undocumented, making it challenging to ensure the integrity and reliability of health data, an essential factor for compliance with interoperability standards [51]. Poorly defined governance structures and mechanisms in LMICs were reported to contribute to weak coordination, ineffective enforcement of leadership and governance regulations, and the inability to ensure compliance with interoperability standards [53].

Furthermore, the lack of adequately structured frameworks and guidelines to support the adoption and standardization of digital health interoperability in LMICs was reported [52, 63, 64]. Studies observed that governance frameworks in LMICs are often insufficient to facilitate the systematic adoption of interoperability standards, resulting in inconsistencies and incomplete compliance [63, 66]. Additionally, in several LMICs, interoperability governance guidelines were noted to exist primarily as informal mental models rather than structured documents, making compliance more challenging [51]. The absence of well-documented interoperability procedures was identified as a barrier to effective communication and coordination among key stakeholders in LMICs, including government agencies, healthcare institutions, technology providers, and policymakers [52, 64]. These gaps were reported to have slowed progress in the implementation of interoperable DH solutions and led to inconsistencies in the application of standards, ultimately weakening overall compliance efforts.

- Inadequate capacity: 14 sources [39, 51, 53-57, 59, 61-63, 66-68] identified inadequate capacity in LMICs, characterized by knowledge gaps, insufficient training, and a shortage of skilled personnel, as a substantial obstacle to compliance with DH interoperability standards. Many LMICs face a shortage of skilled personnel with the expertise needed to manage and implement interoperability standards [57]. A shortage of skilled personnel in LMICs is reported to hamper the development, monitoring, and compliance with DH interoperability standards [55]. Moreover, awareness of interoperability principles was found to be insufficient not only among healthcare professionals in LMICs but also at the institutional level [39]. Specifically, a limited understanding of Enterprise Architecture (EA) and interoperability standards among key stakeholders, including government bodies, healthcare organizations, and IT professionals across LMICs, was highlighted, impeding the effective implementation of interoperability initiatives [39]. LMICs were further reported to experience a shortage of staff responsible for managing DH and data at healthcare facilities, leading to operational disruptions and undermining efforts to maintain consistent interoperability [51, 56, 66, 67]. Several clinicians in LMICs frequently use shorthand or submit incomplete information, resulting in poor data quality and inaccurate entries that undermine the integrity of health records, which is crucial for effective interoperability [67].

  Another key dimension of inadequate capacity is the scarcity of structured and consistent training programs for healthcare workers, IT professionals, and policymakers involved in DH implementation [53, 61, 62, 66, 67]. A survey revealed that while 70% of healthcare workers had received training on various healthcare topics including patient privacy and confidentiality, fewer than half had been trained in DH and interoperability standards [62]. Moreover, LMICs were found to exhibit a limited availability of training and educational programs for healthcare providers, regulators, and other key stakeholders, especially regarding the importance of interoperability and adherence to DH standards [53]. It was further noted that LMICs have not integrated DH interoperability courses into existing health professional training curricula, creating an educational gap and hindering the development of essential knowledge and skills required to ensure compliance with interoperability standards [61, 66, 67]. LMICs were also observed to have a shortage of health professionals trained in key interoperability areas such as medical coding, with those trained often possessing outdated knowledge, further hindering the progress towards interoperability [61, 67].
- Resistance to change**:** Resistance to change in LMICs is significantly driven by insufficient involvement of both users and management in the decision-making and DH design processes [52, 61, 63, 65]. Inadequate stakeholder involvement in DH design in LMICs was observed to result in misalignment with operational requirements, workflow disruptions, resistance, and non-compliance with interoperability standards [61, 65]. A survey of healthcare stakeholders in an LMIC revealed that only 36% of participants felt engaged in DH planning, while 52% reported insufficient management participation, leading to misaligned systems and resistance to interoperability standards for data exchange and use [61]. Healthcare professionals in LMICs were also found to rely on traditional record-keeping methods, with frequent resistance to DH due to concerns about usability, workload, and workflow disruptions, hindering digital transformation and compliance with standards [52]. LMICs were further noted to lack sufficient national strategies to raise awareness about DH

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interoperability standards, leading to high resistance and inconsistent adherence across healthcare facilities [63].

3.2.3 Environmental Factors

- Inadequate legal and regulatory frameworks: Six sources [52, 63-65, 69, 70] detailed inadequate legal and regulatory frameworks as one of the factors hindering compliance with DH interoperability standards. Numerous legal and regulatory frameworks in LMICs are inadequately designed to meet the specific requirements for interoperability, particularly concerning data exchange, privacy, and the ethical use of health data, thereby impeding compliance with DH interoperability standards [53, 61]. Several LMICs were indicated as having outdated legal and regulatory guidelines that fail to address the complexities of DH systems, leading to inconsistencies in data sharing, weak enforcement of standards, and regulatory gaps, thereby hindering compliance with interoperability standards [61, 71]. The inadequacy of clear, enforceable operational, legal and regulatory frameworks for DH in LMICs leads to inconsistencies in data sharing, weak enforcement of standards, and regulatory gaps, thereby hindering compliance with interoperability standards [39, 53, 68, 71]. The absence of clear and enforceable operational, legal and regulatory frameworks for DH in LMICs leads to inconsistent implementation and adherence to DH interoperability standards, resulting in fragmented DH systems that impede effective data exchange and compromise patient care [34, 39, 53, 68, 70]. For example, the frequent absence of clear frameworks for patient control over personal health data in LMICs is indicated to pose a significant challenge to data sharing and collaboration across DH systems, hindering compliance with DH interoperability standards [53, 69].

  Additionally, a slow evolution of legal and legislative frameworks in LMICs was highlighted as a hindrance to aligning these frameworks with evolving standards, thereby hindering compliance [53]. LMICs were also noted to face challenges in developing standardised, scalable, and interoperable DH systems due to diverse cross-border legal and regulatory frameworks across these settings, leading to non-compliance with interoperability standards [34].
- Inadequate monitoring of compliance: From the studies analysed in the SLR, eight sources [55, 57, 61, 63, 64, 66, 68, 71] identified inadequate monitoring of compliance with interoperability standards as an additional barrier to achieving DH standards compliance in LMICs. Regulatory frameworks in LMICs were found to have insufficient mechanisms for monitoring compliance with interoperability standards, which directly contributes to low adoption and weak enforcement [61, 63, 64, 68]. LMICs were further reported to have weak institutional capacity characterized by insufficient staffing and limited structures dedicated to monitoring compliance with interoperability standards [55, 61, 63]. Specifically, a lack of an adequate framework for monitoring compliance with interoperability standards, specifying stakeholders, enforcement mechanisms, risk assessment procedures, and procedures for escalation in cases of non-compliance was noted in LMICs [55, 57, 63, 66]. Limited awareness among key stakeholders about monitoring compliance with interoperability standards was also found to hinder the prioritisation of these standards in DH planning, routine implementation, oversight, and inclusion in DH guidelines [61, 71]. It was further highlighted that several LMICs perceive monitoring compliance with interoperability standards as the responsibility of health development partners, who serve as the principal funding entities for many digital health initiatives in these contexts [57, 61].
- Data security and privacy challenges: Based on analysis of sources included in the SLR, six [34, 53, 61, 65, 70, 72] indicated that ensuring compliance with interoperability standards is severely challenged by pervasive data privacy and security issues. The legislation in LMICs was noted to be deficient in addressing data confidentiality, ethics, and privacy concerns, particularly related to the secure collection and transfer of personal data across DH systems, hindering compliance with standards [61]. A scarcity of regular data audits and secure data handling was highlighted in LMICs, raising the risk of unauthorized access to sensitive health data, thereby eroding trust across DH stakeholders and hindering adherence to interoperability standards [70]. At the health facility level, although several LMICs were found to have physical security measures like security personnel and locked server environments, there were concerns about the limited availability of measures to ensure data security and compliance with interoperability standards [61, 70]. Evidence further indicated that in LMIC health facilities, data privacy and security measures are typically adopted directly from governing bodies such as Ministries of Health, but rarely adapted to local contexts or integrated with interoperability compliance measures [61].

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- Financial Constraints: Eight studies [39, 51, 52, 54, 59, 61, 63, 65] reported that financial constraints significantly hinder compliance with interoperability standards in the implementation of DH in LMICs. It was highlighted that LMICs have constrained healthcare budgets, making it difficult to invest in and sustain interoperable DH systems, thereby reducing overall compliance with interoperability standards [54, 59, 63]. A survey conducted among healthcare stakeholders found that only 38% of respondents believed that health facilities and the Ministry of Health had adequate financial capacity to support DH interoperability initiatives, such as infrastructure, hindering compliance [61]. Beyond initial investments, LMICs were reported to face significant operational costs to sustain the technical support needed to address ongoing DH interoperability challenges, ultimately deterring health facilities from maintaining these systems and hindering compliance [51].

  The overall shortage of financial resources for DH in LMICs was cited as undermining regulatory oversight, as Ministries of Health struggled to secure adequate funding for continuous monitoring and enforcement of interoperability standards [52]. Additionally, the shortage of financial resources in LMICs was noted to hamper workforce capacity development, limiting the ability to effectively manage and evolve digital health systems in line with interoperability requirements [39]. Furthermore, LMICs were reported to frequently rely on donor funding, which undermines the long-term sustainability of DH initiatives, leading to fragmented services and difficulties in maintaining compliance with interoperability standards over time [65].

4 Discussion

This systematic review aimed to identify the factors that hinder compliance with interoperability standards in the implementation of DH in LMICs. Using the TOE framework [73] as a theoretical lens, the findings reveal a complex interplay of barriers across the technology, organizational and environmental dimensions. These challenges are not isolated but rather interrelated, suggesting that sustainable progress towards compliance with DH interoperability standards in LMICs requires integrated interventions that address each dimension simultaneously.

4.1 Technological Barriers

One of the most prominent findings from SLR is the pervasive inadequacy of IT infrastructure in several LMIC settings. Inadequate hardware, outdated software, unreliable network connectivity, and unstable power supplies significantly impede seamless data exchange, which is required for interoperability and compliance with standards [39, 51-56]. These infrastructural weaknesses not only limit the initial adoption of interoperable systems but also compromise their long-term sustainability. These findings echo previous research that underscores the critical need for robust and scalable IT systems to support digital transformation in LMICs [74-77].

Limited standardization and system fragmentation emerged as additional technological barriers. The lack of sufficient universally adopted data formats and consistent medical terminologies leads to isolated data silos, complicating efforts to consolidate and exchange information across DH platforms and compliance with standards [39, 51, 52]. The prevalence of independently deployed solutions further exacerbates this problem, making compliance with interoperability standards more challenging and increasing the risk of data mismatches and misinterpretation of clinical information. These issues have been highlighted in earlier studies that call for harmonized standards to improve health data quality and care coordination [28, 42, 78, 79].

Contextual adaptation and customization challenges also play a significant role. While interoperability standards such as HL7 and FHIR are widely used, they often are not sufficiently tailored to meet the unique cultural and operational needs of LMICs [56, 58]. This misalignment between global standards and local requirements creates technical difficulties that hinder both adoption and ongoing compliance. Additionally, performance, maintenance, and usability issues, exacerbated by poor system design and insufficient testing, undermine user trust and disrupt the consistent implementation of interoperable systems [54, 57, 59, 60]. Together, these technological challenges call for context-sensitive approaches that ensure both technical robustness and local relevance.

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4.2 Organizational Barriers

At the organization level, the SLR highlights inadequate leadership and weak governance structures as major impediments to compliance with interoperability standards. A significant number of studies [39, 51-55, 61-65] reported that limited political will and fragmented internal processes contribute to the absence of enforceable digital health policies and guidelines. For example, survey data revealed that only 46% of respondents perceived digital health governance at the facility level to be strong [61]. This lack of adequate structured governance results in inconsistent adherence to interoperability standards, thereby slowing down the implementation of integrated DH systems.

Inadequate capacity further compounds these organizational issues. A shortage of skilled personnel, limited training opportunities, and insufficient knowledge about interoperability principles have been reported across multiple studies [39, 51, 53-57, 59-61, 63, 66-68]. This deficit not only hinders the development and monitoring of interoperable systems but also contributes to resistance to change. Stakeholder resistance, often driven by inadequate involvement in the decision-making processes and misaligned system designs, disrupts workflows and deters the adoption of digital solutions [52, 61, 63, 65]. These findings suggest that improving capacity through targeted training programs and enhanced stakeholder engagement is essential for overcoming organizational barriers.

4.3 Environmental Barriers

The external environment presents its own set of challenges. Inadequate legal and regulatory frameworks in many LMICs create significant uncertainty around data exchange, privacy, and ethical use of health data [52, 63-65, 70]. Outdated or insufficient regulatory guidelines contribute to inconsistent enforcement of interoperability standards, leading to fragmented DH systems, which could compromise patient care [39, 53, 68, 71]. The slow evolution of these legal frameworks, combined with challenges in standardizing cross-border regulations, further impedes the development of scalable and interoperable systems.

Closely linked to regulatory challenges is inadequate monitoring of compliance. Eight studies [55, 57, 61, 63, 64, 66, 68, 71] underscored that the lack of robust mechanisms for continuous oversight reduces accountability and allows non-compliant practices to persist. Moreover, pervasive data security and privacy concerns undermine stakeholder confidence in DH systems. Inadequate measures for secure data handling and insufficient adaptations of security protocols to local contexts pose significant risks for data breaches and unauthoriezd data sharing [34, 52, 61, 65, 70].

Financial constraints further complicate the environmental landscape. Limited healthcare budgets and reliance on donor funding restrict the necessary investments in infrastructure, human capital, and regulatory oversight [39, 51, 52, 54, 59, 61, 63, 65]. The cumulative effect of these financial limitations is a cyclical challenge that hinders the long-term sustainability of DH initiatives and compliance with evolving interoperability standards.

5 Conclusions

This SLR revealed that achieving compliance with interoperability standards in LMICs is a multifaceted challenge encompassing technological, organizational, and environmental domains. Overcoming these barriers requires a coordinated, multi-level approach that not only improves IT infrastructure and standardization but also strengthens governance, builds technical capacity, and modernizes regulatory frameworks. Such a holistic strategy is vital for creating resilient, sustainable DH systems that can improve patient care and health outcomes in resource-constrained settings.

The findings of this SLR have important implications for policymakers, healthcare providers, and technology developers working in LMICs:

1. Addressing Infrastructural Deficits: Strategic investments are critical to creating a robust technological foundation for interoperable DH systems.
2. Enhancing Organizational Governance and Building Technical Capacity: Comprehensive training programs and improved stakeholder engagement are essential for overcoming internal resistance and ensuring effective implementation.
3. Updating Legal Frameworks and Establishing Robust Monitoring Mechanisms: Alongside securing sustainable financing, these steps are necessary to create an enabling external environment.

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The literature identifies several key gaps, including inadequate IT infrastructure, fragmented governance, and a lack of scalable solutions for challenges such as power outages, unreliable internet, and technical expertise shortages. Furthermore, there is insufficient exploration of effective governance frameworks and compliance monitoring mechanisms. To address these gaps, future research should focus on evaluating the impact of capacity-building initiatives, public-private partnerships, and context-specific adaptations of interoperability standards. Additionally, future studies should investigate the development of scalable governance models and robust monitoring systems to ensure systematic compliance enforcement in LMICs, which will support the creation of sustainable and resilient DH ecosystems.

This review has limitations, in particular, the reliance on peer-reviewed literature, and the exclusion of non-English studies may have introduced publication bias and limited the generalisability of the findings. The use of quality assessment questions that were specifically aligned with the TOE framework could also have constrained the number of studies that met the QA criteria. Future reviews could benefit from broader inclusion criteria and the integration of grey literature to capture a wider spectrum of experiences and contexts.

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Statement on conflicts of interest

None

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Rapid Retinopathy Detection using Ablation-Guided Deep Learning

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Background and Purpose: The Prevalent cause of vision loss is diabetic retinopathy (DR) worldwide, impacting millions of people, and is projected to increase dramatically in countries in Asia and Africa. Early and prompt detection is crucial for reducing the likelihood of complications; However, manual detection is labour-intensive, resource-intensive, and have chance of human error. Deep learning (DL) and machine learning (ML) have improved automatic DR detection.; however, published literature also exists on ablation studies that compare combinations of DL feature extractors and traditional classifiers. The current study intends to systematically compare different DL models: VGG16, ResNet152V2 and Xception, combined with classical classifiers: Decision Tree (DT), k-Nearest Neighbours (k-NN), Artificial Neural Networks (ANN), and Random Forest (RF) to see which produces the most optimal model for DR detection. The study systematically compares different combinations to explore the potential use of hybrid DL-ML pipelines for improving DR classification performance and reducing computational costs, ultimately contributing to the development of an automated DR screening pipeline.
Methods: Using a dataset from EyePACS, 88.29GB in size, which included 35,126 labelled fundus images and 53,576 unlabelled fundus images. The images were sized for specific models (224×224 pixels for VGG16/ResNet152V2; 290×290 for Xception) and converted to greyscale. Three pretrained DL models (VGG16, ResNet152V2, Xception) were used for the feature extraction part of the process, and four different ML classifiers (RF, DT, K-NN, ANN). In total, there were twelve different combinations of models to extract features and classifiers to classify them. Using the available GPU power for the accelerator, the model was trained, validated, and tested in Google Colab. Confusion matrix-derived accuracy, recall, precision, and F1-score data were used to gauge the models' performance. The training and validation process involved optimising the hyperparameters and epochs (up to 30 epochs). An early stopping criterion was also added to all models to reduce the scope of overfitting.
Results: The hybrid Xception-RF model had the highest testing accuracy at 91.1% and the fully connected CNN models reached a maximum of 79.0%. VGG16-RF achieved a comparable accuracy (90.3%). Fully connected models achieved reasonably consistent accuracy, but hybrid models achieved improved accuracy over fully connected. Performance analysis suggests that class imbalance was an underlying advantage of the hybrid classification, particularly in the mild DR classes. It also suggests the advantages of transfer learning and RF-based classification in large-scale and imbalanced datasets.
Conclusions: In this study, it was shown that combining DL feature extractors with classical ML classifiers (Decision tree classifiers) could enhance the accuracy of DR detection. The best combination of the Xception-RF model was able to classify DR on a large, imbalanced dataset with advanced metrics. Using transfer learning with only a few epochs was sufficient and cost-effective. It is evident that adopting hybrid DL-ML pipelines can be highly effective for DR screening, especially in low-resourced healthcare systems, which allows for scalable practices. All in all, the next procedural study should make use of balanced datasets with wider population demographics and enhance further classification performance through different DL architectures.

Keywords: Diabetic Retinopathy, Deep Learning, Ablation Study, Convolutional Neural Networks, Transfer Learning, Random Forest

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1 Introduction

Diabetes is a chronic illness that can initiate several complications, including damage to the nervous system, kidneys, eyes, feet, skin, and ears, as well as impairing memory and reasoning [1]. Complications associated with diabetes can be classified as acute and chronic complications. Recurring complications comprise microvascular disease and macrovascular disease. In conclusion, diabetes is a leading cause of sickness and death worldwide [2]. Recognising diabetes at an early stage and optimally managing diabetes allows the diabetic person to live longer and have better health [3]. It is estimated that one out of ten adults worldwide have diabetes (10.5%), with good expectation of this increasing to 12.2% by 2045 [4]. More than 54% of adult diabetics globally live in the continents Asia and Africa (21% and 33% respectively) [5]. This is a problem given the limitations in the diagnosis and management. It has been reported that nearly half (44.7%) of adult diabetics are undiagnosed and therefore, unaware of their affliction, and the risk of other problems associated [4]. There is evidence that the condition known as diabetic retinopathy may cause damage to the blood vessels in the retina [6]. Early detection and treatment of this retinopathy can prevent blindness and vision impairment [7]. The literature contains a number of techniques for analysing retinal pictures, such as DL and ML techniques, which aid in the diagnosis and treatment of diabetic retinopathy [3].[4]. Two subsets of artificial intelligence methods, machine learning (ML) and deep learning (DL), learn from data and have a variety of applications, such as object classification, detection, and segmentation. [10]. To categorise the degree of diabetic retinopathy, for instance, machine learning may utilise optical coherence tomography angiography (OCTA) pictures to extract features [6]. In another example, deep learning may use fundus images, in order to identify microaneurysms, haemorrhages and exudates and to measure the level of diabetic retinopathy as a continuum [7]. This means that these techniques potentially increase the accuracy, overall efficiency and reliability of the screening for diabetic retinopathy, whilst lessening the human effort and observation involved [8][9].

Initially, the diagnosis of diabetic retinopathy relied entirely on trained clinicians manually analysing retinal images, which was labour-intensive, time-consuming, and prone to subjective variability. Advances in digital imaging enabled automated analysis of fundus images, reducing clinical workload and improving consistency. However, early machine learning methods still required manual feature engineering. The emergence of deep learning, particularly convolutional neural networks, eliminated the need for handcrafted features and significantly improved diagnostic accuracy. As a result, hybrid approaches combining deep feature extraction with classical classifiers have become a promising direction for automated medical image analysis.

Comparing ML and DL for cervical cancer classification [24]: This study compared the ResNet-50 model with XGB, Support Vector Machine (SVM), and Random Forest (RF) models in order to identify four common disorders using cervicography images. According to this study, ResNet-50 outperforms classical classifiers in terms of accuracy, sensitivity, specificity, and F1 score. According to the research, in order to improve the model's interpretability, robustness, and reliability, it needs be verified on bigger, more varied datasets, such as clinical data and CT scans.

DL image classification data augmentation [25]: This paper presents data augmentation-based image style transfer for deep learning models in image classification. Using a dataset of ten animal categories, style transfer produced new images. The authors claim that the data augmentation produced greater accuracy for all four deep learning models (InceptionV3, ResNet50, VGG16, AlexNet) when analysed on the enlarged dataset. They advocated for expanding the use of data augmentation to other datasets and domains, considering further testing of style transfer methods, and examining how data augmentations influence different deep learning architectures. A review of DL and ML dermatoglyphics fingerprint pattern classification literature [26]: This review paper covers 50 DL/ML fingerprint pattern classification papers. The review paper covers skills based on DL using CNN, ML based on SVM, and optimisation methods. The review paper addressed research problems in fingerprint pattern classification, as well as potential future research directions, including handling noisy, unbalanced, and low-resolution patterns, as well as complex patterns.

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Machine Learning Fashion Image Classification Review [27]: To classify 60,000 Zalando Research images of various fashion categories into 10 different image classifications, this study examines four different deep learning methods (AlexNet, GoogleNet, VGG16, and ResNet50) and four different machine learning models (ANN, KNN, SVM, and RF). The study shows that the GoogleNet classifier has the most accuracy at 93.75% and ResNet50 is second at 92.5% and VGG16 at 91.25% and then AlexNet 90% accuracy. With an average accuracy CS (goal) of 88.71%, the study also demonstrates that Artificial Neural Networks (ANN) outperform machine learning (ML) continuous accuracies in terms of average accuracy. The leaning made some changes also to consider like the DenseNet and the InceptionV3 DL models, some changes to data rotating and flipping and also consider SIFT and SURF for the feature extraction models.

CNN/ML Similarity Image Classification [28]: This study compared the features and image classification methods in ML and CNN. The paper used 1000 Caltech101 images. CNNs had better accuracy and time performance than typical ML algorithms; the paper indicates that SIFT features with SVM scored 83%. The paper stated that it would use the CIFAR-10 and ImageNet datasets, LBP and HOG features, and tune the parameters of the ML and CNN algorithms.

Embedded Computer Vision [31]: Vora and Shrestha's research paper targeted diabetic retinopathy detection using embedded computer vision. The potential accuracy of the trained model in identifying diabetic retinopathy was close to 76%.

There were no other studies doing ablation model studies to determine diabetic retinopathy from retinal fundus images. There was no research on that topic, and with the estimated accuracy of between 60-80%, that is extremely likely to help an ophthalmologist with AI research. The following were the aims:

- To carry out ablation experiments with a series of DL models and finally a series of classifiers.
- To find the most accurate diabetic retinopathy detection using the combination and cooperation of the DL model with a classifier.

The paper is broken down into five sections. Section II provides a description of the methodology. Section III contains the experimental outcomes. Section IV presents a review of the study's findings and potential directions for future research. Section V contains a closing statement.

2 Methodology

2.1 Machine learning concepts

Particularly when utilising convolutional neural networks (CNNs), deep learning (DL) approaches outperform traditional machine learning techniques for feature extraction and picture classification.There are two primary parts to a CNN: a feature extractor, made up of convolutional and pooling layers, and a classifier made up of any machine learning (ML) method; for instance, in the process of developing a CNN for image classification, in order to calculate the actual classification, the CNN pulls "features" from each input image, such as edges and shapes. When elaborating on the classifier, the fully connected layer can be replaced with other classifiers, like SVM, RF, or DT, to improve overall classification performance.[11][17]

For instance, when constructing a CNN for image classification, the CNN's use of "features" such as edges and forms determines the actual categorisation for each input image. For example, while VGG16 contains only 16 layers for image classification, ResNet152V2 utilises identity mappings to facilitate learning. In contrast, Xception relies on depth-wise separable convolutions rather than regular convolutions for improved interpretation of the input image.[12][13][14][15][16].

Combining DL approaches with ANN, RF, DT, and k-Nearest Neighbours (k-NN) classifiers can further increase classification accuracy. ANN is very flexible, but can be computationally expensive. RF creates a robust ensemble of decision trees, DTs are simple and intuitive, and k-NN is an easy and powerful technique for classification applications.[18][19][20][21].

2.2 Deep learning's application to retinopathy

A growing number of ophthalmologists are using deep learning to detect and assess diabetic retinopathy (DR), a condition associated with diabetes that can result in vision loss. Lesions such as microaneurysms

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and bleeding damage the retina's blood vessels in DR. The detection procedure makes use of retinal imaging, such as optical coherence tomography (OCT) and fundus images, and optical coherence tomography angiography (OCTA). Deep learning algorithms can automatically assess image quality, detect lesions, and classify DR using established grading criteria [7]. Figure 1 illustrates the various stages of retinopathy.

Ophthalmologists use retinal images from cameras (fundus camera) to determine the disease pathology. The four phases of proliferative diabetic retinopathy (PDR) and non-proliferative retinopathy are mild, moderate, and severe. Blindness or sight loss could result from blood vessel damage as the illness develops. [23].

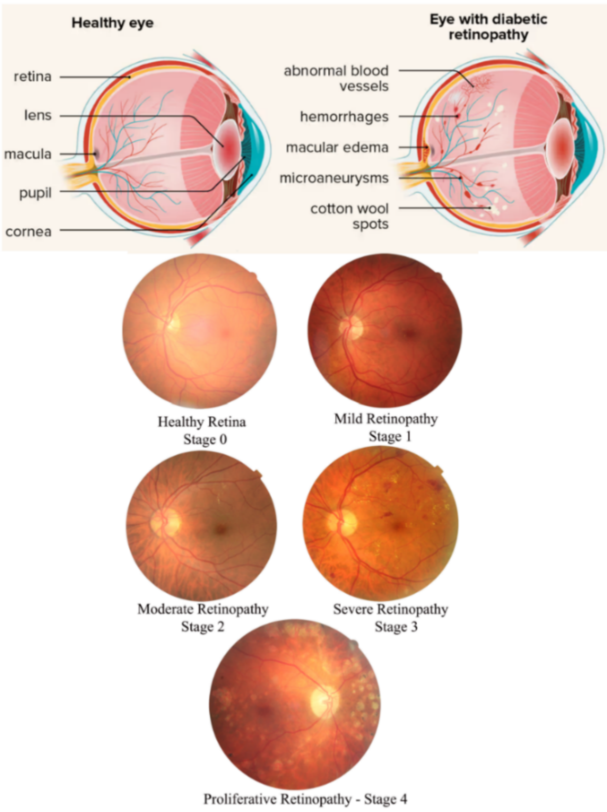

Figure 1. Diabetic Retinopathy Stages

2.3 Experimentation

This proposed ablation experiment will investigate image processing, feature extraction, classification, and performance measurement using four classifiers (ANN, RF, DT, and k-NN) and three deep learning models (VGG16, ResNet152V2, and Xception). Deep learning is ideal for extracting such complex features from large image datasets based on its ability to recognise patterns, scalability, and limited preprocessing requirements. Data from images was collected from EyePACS and stored on Kaggle. Processing was then conducted on Google Drive and Google Colab. Python was selected as the programming language due to its ease of use and extensive library.

Image classification is a supervised learning problem that assigns class labels to images into known categories. VGG16, ResNetV2, and Xception were applied as feature extractors, employing transfer learning to improve efficiency and machine learning classifiers ensure accurate categorisation.

The experiment produced a total of twelve model scenarios by combining features from a DL model with traditional classifiers and was applied to training, validation, and testing on new images. Performance of the models was measured using a confusion matrix.

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Google Colab is the cloud-based Jupyter Notebook environment used in the experiment. Processing was performed in the cloud using Google Cloud's large-scale image categorisation with its own GPUs (Tensor Processing Units). According to estimates, it contained 40 GB of GPU memory, 83 GB of RAM, and a premium GPU subscription to allow for plenty of capability.

2.4 Datasets and model evaluation metrics

EyePACs allowed us to utilise their Kaggle public image dataset, which comprised 88.29 GB of data. This dataset consisted of 15 zip files with 53,576 unlabelled images for testing and 35,126 labelled images for training. We divided the 35,126 photos into two training and validation folders, using 10,500 for validation and 24,626 for training. The image files were organised in order of retinopathy severity, where 0 was no retinopathy and 4 was the most severe retinopathy.

The study used a 3-step process. The first step was to convert all photographs to greyscale and resize them. The Xception model was used with a 290 x 290-pixel resolution, while VGG16 and ResNetV2 each used a 224 x 224-pixel resolution. Each model was uploaded to two separate folders. The second step involved training the models on the processed images, and the third step involved validating the remaining processed images.

The fact that both files included five subfolders classified by retinopathy indicates that the data was not fully balanced. However, this is the reality of the real world, where disease databases are more representative, as they generally have more samples that are considered disease-free.

We implemented a confusion matrix to show model performance, which compared actual class labels against predicted class labels (TABLE I). While simultaneously showcasing our model's accuracy, precision, recall, and other metrics, the confusion matrix enabled us to pinpoint the model's benefits and drawbacks.

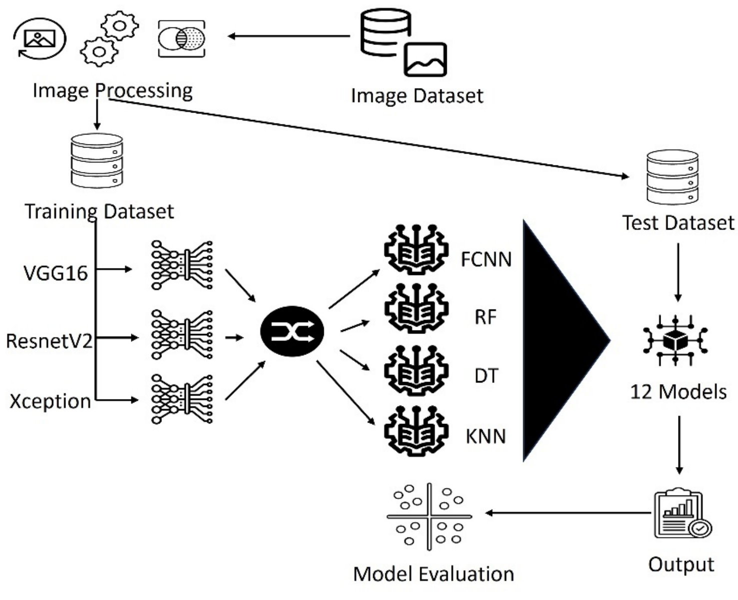

Figure 2. Methodology of the Ablation Experiment

Data augmentation and class balancing:

No explicit synthetic data augmentation (such as rotation, flipping, or colour jittering) was applied in this study. The models were trained on the original dataset distribution to preserve the real-world imbalance in diabetic retinopathy prevalence. Similarly, no oversampling or undersampling strategies were used for class balancing. Instead, robustness to class imbalance was implicitly handled by the Random Forest ensemble classifier, which demonstrated superior performance on minority classes compared to fully connected CNN models.

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Table 1. Confusion matrix metrics.

Metric	Formula	Significance
Accuracy	(TP + TN)/ (TP + TN + FP + FN)	The frequency with which a model or entity makes accurate predictions is a straightforward indicator of accuracy; however, if either the data points are imbalanced or there are more than two classes, the accuracy metric can be misleading.
Precision	TP/(TP+FP)	Precision is a statistic that shows how accurate a model or entity is; it determines the percentage of true positives among all anticipated positives. For spam or fraud detection, for example, precision is a helpful measure to have when you want to limit false positives at all costs.
Recall	TP/(TP+FN)	Recall is a metric that indicates how accurately an entity or model predicts; that is, it determines the ratio of actual positives to all anticipated positives. Recall is useful when you do not want to produce false negatives (e.g., medical diagnoses or loyal customers).
F1	2* (Precision * Recall) / (Precision + Recall)	Since the F1 score is the harmonic mean of precision and recall, it assigns equal weights to false positives and false negatives. The F1 score is a number between 0 and 1 that represents the model's matching prediction performance, where 0 indicates a complete failure and 1 indicates a perfect match. The F1 score benefits from unbalanced data and is highly exposed at the accuracy and coverage points.

2.5 Image Processing Challenges and Solutions

During this study, JPEG images of varying sizes were scaled down and converted to greyscale (pixel range: 0-255). A standard CPU took 25 hours to process 35,126 images. The images were saved as NumPy arrays on a cloud drive, resulting in four arrays for the 224x224 and 290x290 pixel train and test datasets.

The project's next stage was to create three deep learning models to extract information from the images. Although normalisation is a normal practice, it was not applied during this study due to hardware constraints in Google Colab, which has 83 GB of RAM and 40 GB of GPU RAM. TensorFlow was set to utilise 70% of the GPU RAM, but at times it exceeded this limit, causing issues with the system.

The final stage of this analysis involved incorporating image features into machine learning classifiers, including a Random Forest classifier optimised with a grid search. The Random Forest classifier was optimised using grid search over key hyperparameters, including number of estimators (100 to 1000), maximum tree depth (None, 10, 20, 50), minimum samples per split (2, 5, 10), and maximum feature selection strategy (sqrt, log2). The final configuration selected the parameter set yielding the highest validation accuracy.

2.6 Mathematical representation of the experiment

Problem Setup and Approach

Let X be the set of images of the human eye retina, and let

$$Y = \{0,1,2,3,4\}$$

be the set of labels corresponding to the five categories of diabetic retinopathy. Our objective is to discover a function.

$$f: X \to Y$$

that can accurately classify any image $x \in X$ into its correct label $y \in Y$.

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Approach

Various deep-learning methods and machine-learning classifiers as building blocks were employed for the function f.
Each deep learning method D is a function that holds an image $x \in X$ and yields a feature vector:

$$D(x) \in \mathbb{R}^n$$

where n is the feature space's dimension.
Each machine learning classifier C is a function that holds a feature vector $v \in \mathbb{R}^n$ and outputs a label:

$$C(v) \in Y$$

Function Definition

The function is defined for any combination of a machine learning classifier C and a deep learning technique D:

$$f_{D,C}: X \to Y$$

by

$$f_{D,C}(x) = C(D(x))$$

Training and Evaluation

We trained each function's logs and tested them on a database of images and corresponding labels, measuring their performance using a variety of metrics, including Accuracy, precision, recall, and F1-score.

Some hyperparameters were also changed (Table II) and tested with varying numbers of epochs to derive the optimal condition for performance for each function $f_{D,C}$. Hyperparameters that influence the behaviour of learning algorithms include the number of hidden layers, batch size, and learning rate. Conversely, epochs specify the number of times the full training dataset is used to train the learning algorithm.

Table 2. Hyperparameters were used in the experiment.

Algorithm	Hyperparameter	Value used
VGG16	i. input_shape	(224, 224, 3)
	ii. include_top	FALSE
	iii. weights	imagenet
	iv. pooling	None
	v. classes	1000
Resnet152V2	i. input_shape	(224, 224, 3)
	ii. include_top	FALSE
	iii. weights	imagenet
	iv. pooling	None
	v. classes	1000
Xception	i. input_shape	(290, 290, 3)
	ii. include_top	FALSE
	iii. weights	imagenet
	iv. pooling	None
	v. classes	1000
Random Forest	i. n_estimators	1000
	ii. max_depth	None
	iii. criterion	Gini
	iv. min_samples_leaf	1
	v. min_samples_split	2
	vi. bootstrap	TRUE

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	vii.	max_features	Sqrt
	viii.	n_jobs	-1
	ix.	N_splits	10
Decision Tree	i.	Criterion	Gini
	ii.	splitter	best
	iii.	max_depth	None
	iv.	min_samples_split	2
	v.	min_samples_leaf	1
	vi.	max_features	None
KNN	i.	n_neighbours	5
	ii.	weights	uniform
	iii.	algorithm	auto
	iv.	leaf_size	30
	v.	p	2
	vi.	metric	minkowski

The mathematical representation of the experiment can be explained below.
Given:

$$X, Y, \{D_1, D_2, D_3, D_4, D_5\}, \{C_1, C_2, C_3, C_4, C_5\}$$

For each:

$$D_i \in \{D_1, D_2, D_3, D_4, D_5\},\ C_j \in \{C_1, C_2, C_3, C_4, C_5\}$$

Define:

$$f_{D_i,C_j}(x) = C_j(D_i(x))$$

Train and Test:
Train and test f_{D_i,C_j} on a dataset of $(x, y) \in X \times Y$.
Measure:
Evaluate the performance of f_{D_i,C_j} using some metric M.
Optimize:
Tune hyperparameters and epochs of f_{D_i,C_j} to maximize M.
Report:
Identify and report the best function f_{D_i,C_j} and its corresponding performance.

To represent the whole experiment in one formula, Let ε represent the overall experiment, $\mathcal{M}$ represent the set of DL models, $\mathcal{C}$ represent the set of ML classifiers, $\mathcal{H}$ represent the set of hyperparameters, $\phi_{\mathcal{M}}$ represent the feature extraction function for model $\mathcal{M}, \gamma_{\mathcal{C}}$ represent the classification function for the classifier $\mathcal{C}$, Δ_{train} and Δ_{test} represent the training and testing datasets, $\boldsymbol{\eta}$ represents the hyperparameter vector, and Π represents the performance metric.

$$\varepsilon = \sum_{\mathcal{M}\in\mathcal{M}} \sum_{\mathcal{C}\in\mathcal{C}} \sum_{\boldsymbol{\eta}\in\mathcal{H}} \Pi\left(\gamma_{\mathcal{C}}\left(\sum_{x_i\in\Delta_{\text{test}}} \phi_{\mathcal{M}}(x_i, \boldsymbol{\eta}) + \lambda \cdot \nabla_{\eta}\mathcal{L}_{\mathcal{M}}(\boldsymbol{\eta})\right), Y_{\text{test}}\right)$$

In this representation:
λ represents a regularisation parameter.
$\nabla_{\eta}\mathcal{L}_{\mathcal{M}}(\boldsymbol{\eta})$ is a representation of the gradient of a loss function $\mathcal{L}_{\mathcal{M}}$ in relation to the hyperparameters $\boldsymbol{\eta}$.

3 Results

There are twelve combinations based on three DL models and four classifiers. The sets of hyperparameter settings were held to optimal settings, and identical sets of parameters for model algorithms were used across all varieties. At the end of each epoch, a computation is performed to yield loss and accuracy values. It calculates the accuracy and loss to find out how well the model is working. The loss number shows how well the model predicts the correct outcome given the information at hand. Our goal is to minimise this

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number as much as possible. The accuracy is a measure of how well the model can categorise the photos within the pre and post-test training sets. There is a connection between the ability to increase training accuracy, decrease loss, and increase testing accuracy. As testing and training accuracy increase, loss reduces. If the model is trained for too long, it will begin to overfit to the training data, meaning it will perform at the upper end of model accuracy on the data it was trained on, but will perform worse with new data. To avoid overfitting and underfitting during the training phase, it is crucial to choose the right number of epochs. This experiment compared the model's accuracy throughout training and testing across a maximum of 30 epochs.

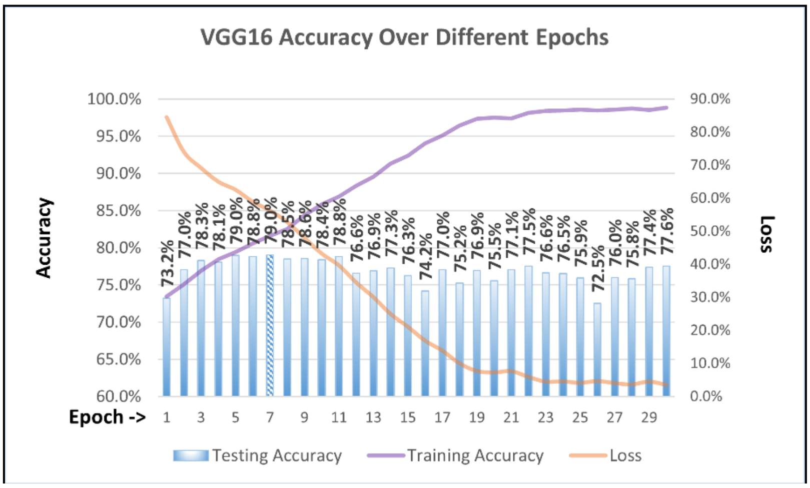

Figure 3. The fully connected VGG16 model's accuracy and loss during training and testing

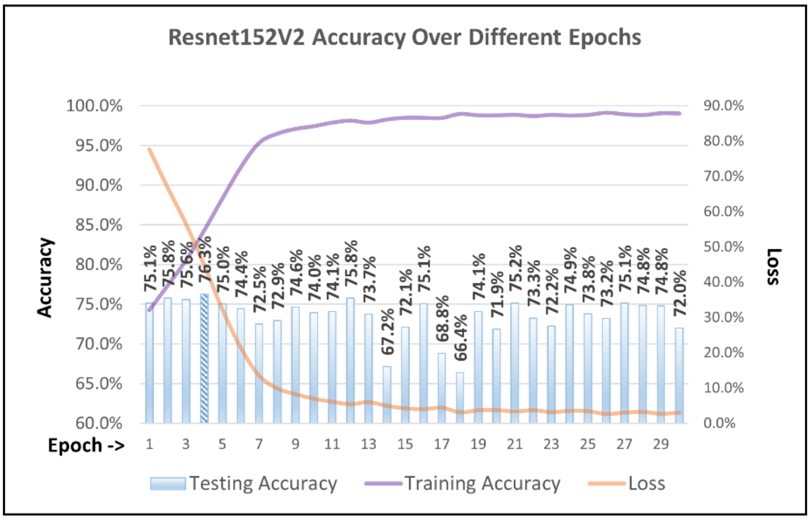

Figure 4. Accuracy and loss of a fully linked ResNet V2 model during training and testing

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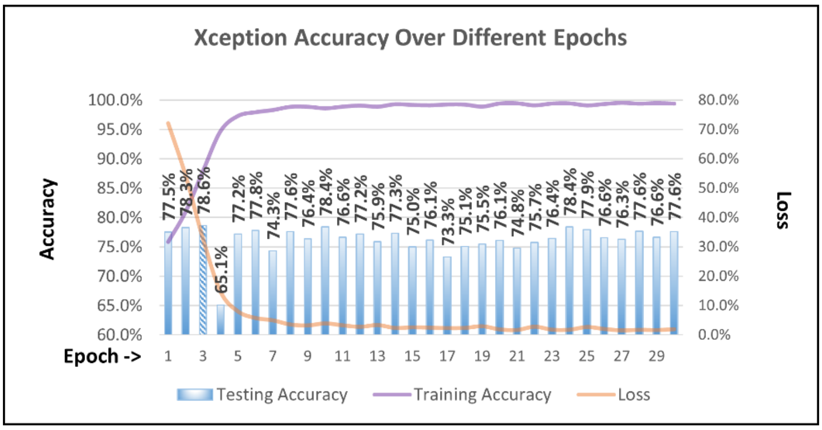

Figure 5. Xception model accuracy and degradation over various epochs

The performance of the fully connected VGG16 model is detailed in Figure 3. Training and testing adjustments were investigated over 30 epochs. The training accuracy peaked at 98.9% with a loss of 3.5% at epoch 30, indicating good convergence. Testing accuracy peaked earlier at approximately epochs 5 and 7 at about 79.0%, but gradually deteriorated thereafter. This indicates that testing accuracy was subject to overfitting effects at this point. The training accuracy at epoch 7 was still moderate at 81.6%, which suggests that some balance existed at this stage between the generalisation of the model and learning features with divergence occurring thereafter.

The ResNet152V2 model is demonstrated in Figure 4. The training accuracy peaked at a maximum of 99.1% with a minimum loss of 2.6% being achieved at epoch 26. The peak value for testing accuracy occurred much earlier, however, usually around epochs 4 with a reading of 76.3% with a concomitant training accuracy reading of 84.3%. This again indicates that while training was being improved upon the capability for generalisation of the model was being lost after early epochs of fitting, which is a classical symptom of overfitting. The Xception model also gave rise to interesting results shown in Figure 5. The peak training accuracy achieved was 99.5% with the lowest loss scored obtaining a figure of 1.5% at epoch 27. The peak value for testing accuracy on this occasion was recorded as 78.6% at epoch 3 followed by a plateau followed by some marginal deterioration thereafter. Again the striking difference in testing accuracy and the high training accuracy suggested that was an indication of the presence of overfitting when epochs increase beyond those at the earlier stages of training.

It is clear from examining all three CNN architectures detailed that the peak testing accuracies occurred within the first 5–7 epochs of training, followed by a drop off performance after further training epochs taken. This is indicative that for large data sets such as diabetic retinopathy classification, early stopping in this case after a few epochs is optimal in retaining values for generalisations and avoiding the appearance of overfitting. VGG16, ResNet152V2 and Xception architectures were applied in this study as feature extractors for downstream fully connected CNNs interfaced with Random Forest (RF), Decision Tree (DT) and K-Nearest Neighbour (KNN) machine learning algorithms. The combination yielded twelve hybrid combinations, which were compared by means of 10-fold cross-validation studies, which showed considerable variations in accuracy results. The comparative charts suggest that the testing accuracies on these series all follow earlier epoch appearance styles in accuracy climb, indicating that CNN feature extraction with classical machine learning algorithms could lend itself to attaining appreciable amounts improvement values in visual patterns factoring as few training iterations as possible.

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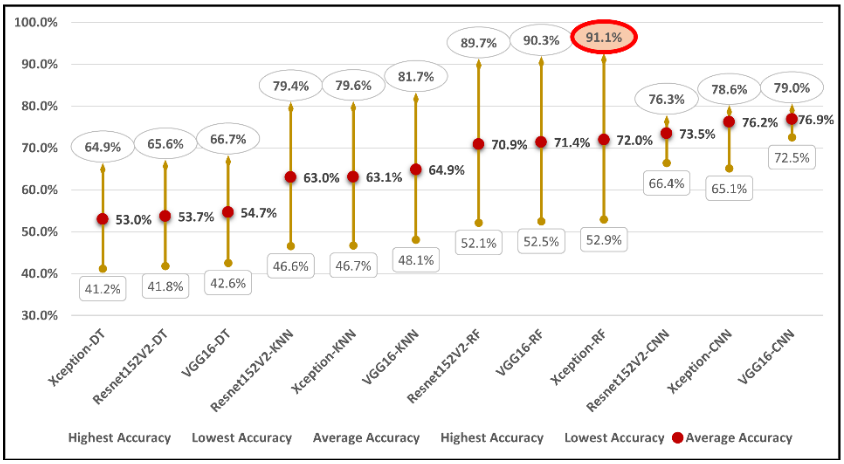

Figure 6. Testing the accuracy of twelve models

The combination of deep learning based feature extractor routines with traditional machine learning classifiers as illustrated in Figure 6 provided substantial increases in testing performance. The CNN architectures yielded testing performance in the region of 76.3-79.0% on outcomes. The hybrid models provide significant improvements with some yielding performance of over 90% accuracy. Of the twelve models employed, the best performing testing accuracy was exhibited by the Xception-Random Forest (Xception-RF) combo achieving performance of 91.1%, which was considerably better than all other combinations. The success of this model is due to the combined capability of representation of depth of the Xception model inused with the stability of the ensemble learning Random Forest classifier, producing effective generalisation performance. This particular model gave an average accuracy of about 72% over the epochs employed, which illustrates the consistent performance over the totality of the training process. The VGG16-Random Forest (VGG16-RF) achieved performance accuracy in the second best testing performance category producing 90.3% with an average accuracy of 71.4%, which was somewhat similar to that of the Xception-RF configuration. The further affirmation of strength in performance of Random Forest is therefore foreshadowed by these results the implemented hybrid structures giving stability in performance being somewhat modified, but demonstrated poorer performance where testing accuracy did plateau in the region of 76-79% during the testing session. This would no doubt indicate an ability of the structures of CNN architectures to give decent capabilities of learning features, but rather of the improved existence of hybrid learning structures (in other words, a coupling of the deep features with classifier of the decision type, rather indicating), of facilitated learning structure capability with discrimination power increasing and generality for robustness, of the models in employed structure. It may therefore ultimately conclude that classes of hybrid deep structures using CNN based routines of feature extraction in used with either heavier classifiers of adaptation as RF varieties or distance based properties either such as KNN classifiers shall give better returns in matters of testing accuracy, than the pure CNN's in used. The overall observations of the stability of average accuracy of epochs in the relevant studies gives a tendency for better convergence and correctabilities of overfitting phenomenon strongly, especially in those models involving RF as the superior classifier in used technology.

3.1 Computational efficiency:

From an empirical standpoint, hybrid models required significantly less training time than fully connected CNNs, as only feature extraction was performed by deep networks, while classification was performed using lightweight machine learning classifiers. Fully connected CNNs required end-to-end backpropagation across all layers for each epoch, whereas hybrid models converged faster due to reduced parameter optimisation. This indicates that hybrid DL–ML pipelines are computationally more efficient and scalable for large datasets.

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3.2 Sensitivity analysis:

Qualitative analysis of prediction behaviour indicates that hybrid models, particularly Xception-RF, exhibit higher sensitivity to mild and moderate DR classes than fully connected CNNs. The hybrid classifiers exhibited improved discrimination between adjacent severity levels (e.g., mild vs. moderate), which are typically more difficult to separate. This suggests that Random Forest is more robust to class overlap and noisy features, thereby improving sensitivity in clinically critical borderline cases.

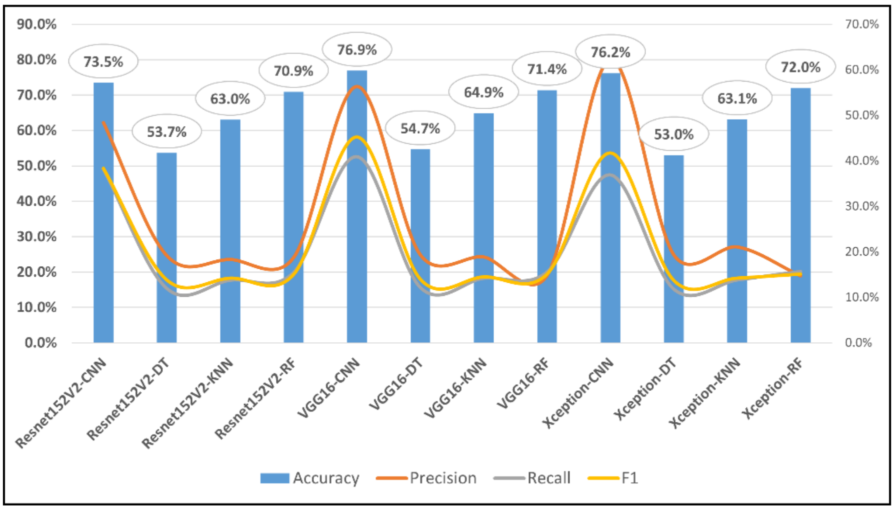

Figure 7. Twelve models' performance graph using confusion matrix measurements

Figure 7 displays the evaluation's findings in terms of metrics from the confusion matrix. The four models with the highest average accuracies were the fully connected Resnet152V2, VGG16, Xception, and hybrid model Xception-RF. Only fully linked models, however, outperformed the other three metrics—F1, Precision, and Recall—in a comparable manner. Although none of the models attained the highest testing accuracy, the fully connected Xception and VGG16 models outperformed the others. The model's performance suffered due to the discrepancy in class counts in categorical picture data.

3.3 Ablation summary of model combinations:

Across the twelve evaluated combinations, Random Forest consistently outperformed ANN, DT, and KNN when paired with deep feature extractors. The ranking of classifiers by overall performance was RF > ANN > KNN > DT. Among feature extractors, Xception produced the most discriminative representations, followed by VGG16 and ResNet152V2. The best overall configuration was Xception-RF (91.1%), while the weakest was Xception-DT (41.2%), demonstrating the dominant role of classifier choice in hybrid pipelines.

4 Discussion

There were only twelve combinations of classifiers (ANN, RF, DT, KNN) and deep learning algorithms (VGG16, Resnet152V2, and Xception) due to time and resource constraints. Experiments with numerous other completely connected CNNs were not possible for this study. This could be a possibility for future research. A fully connected DL model, VGG16, had the best prediction accuracy at the same time, at 79%; but during the first epoch of the experiment, Xception had the worst prediction accuracy at 65.1%. The total measurement range of variation for this type was 13.9%, so for Prediction (Ev) training and testing it can be considered reasonable if say, one model has 85% at Epoch 10 and 80% at Epoch 15, and other model is +/- 10% with the other model being +/- 5% on prediction testing. In terms of training and testing models for comparison of accuracy in classification, the Xception-Rf model (Xception-Based Deep Learning) produced an overall predicted accuracy of 91.1%. Xception-DT is the model in this group that is worse at

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classification compared to other classification models. The predictions with Xception-DT for the correct classification category were 41.2%, which varied more than those of other models, and this difference increased by 49.9% when most models predicted annual change measurements.

In the training of fully connected models, as indicated, the number of epochs is usually 30. However, the performance of a modified classification model using feature training stopped improving after the 7th epoch. The performance levels for testing anonymous data began to decline, as observed in all cases, and performance dropped over time. In this work [32], which uses deep learning to diagnose diabetic retinopathy, I mention that the worst performance for a model, as indicated by the prediction change (Ev) values, was around the 15th training epoch for all models. For the performance test of a model, it is possible to have different hyperparameters set to different values for features and classifiers. This represents a significant area for future research. The poor performance results regarding the classification of this type of data are also due to the class imbalance of the images reported within the dataset itself. In the future, tests like this may be conducted using more representative data. Other important information was also missing from the images (e.g., patient demographics). The impacts of age and other eye conditions, for instance, can alter the retina and are not considered here, but they can be considered significant considerations in the future.

Random Forest outperforms other classifiers primarily due to its ensemble nature, which reduces variance and improves robustness to noisy and high-dimensional feature spaces. Deep learning feature extractors generate complex and redundant representations, which are effectively handled by Random Forest through random subspace sampling and majority voting. In contrast, ANN and KNN are more sensitive to noise and class imbalance, while Decision Trees tend to overfit high-dimensional data.

4.1 Statistical interpretation:

Although formal statistical significance testing (e.g., paired t-tests) was not performed due to computational constraints and the absence of multiple independent training runs, the observed performance gaps between top-performing models (e.g., Xception-RF vs. fully connected CNNs) were sufficiently large (>10%) to suggest practical and meaningful performance differences.

4.2 Generalizability considerations:

While the EyePACS dataset provides a large and diverse sample, the generalisability of the proposed models to other clinical datasets (e.g., Messidor, APTOS, DDR) remains an important consideration. Differences in camera type, illumination, patient demographics, and grading standards may affect model performance. However, since the proposed framework relies on transfer learning and generic feature representations, the hybrid DL–ML approach is expected to generalise reasonably well with minimal fine-tuning.

Recent state-of-the-art DR detection systems using end-to-end deep learning architectures report accuracies in the range of 80–88% on public datasets such as EyePACS and Messidor. The proposed Xception-RF hybrid model achieves a competitive accuracy of 91.1% while requiring fewer training epochs and reduced computational cost. This highlights the effectiveness of hybrid architectures as a lightweight alternative to fully end-to-end deep learning systems.

5 Conclusion

This work greatly benefited from the use of deep learning for feature extraction and conventional classifier techniques for picture classification; the combination of Random Forest and Xception was able to determine the stage of retinopathy with a success rate of more than 91%. All performance-measuring criteria were impacted by the small number of cases in the moderate retinopathy group, which is frequently ignored as having no retinopathy. The best classifier was Random Forest, however optimised RF might produce even better outcomes. When it came to detecting diabetic retinopathy in retina fundus images, using a fully connected CNN model with a large number of training epochs did not significantly improve the results.

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Seven epochs were enough to train the fully connected models on this kind of image when employing the transfer learning technique. RF was the top classifier, and VGG16 was the best feature extractor. Xception-RF was the best model we could create.

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Journal of Health Informatics in Africa

Systematic review of the Absorptive Capacity Theory and its' application to mHealth Technologies for Adverse Drug Reaction reporting in Uganda

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Background and Purpose- Mobile health (mHealth) technologies are increasingly important for improving healthcare delivery and patient safety. In Uganda, expanding digital infrastructure offers opportunities to use mobile devices for communication, data collection, and patient management. However, utilization of mHealth technologies for reporting Adverse Drug Reactions (ADRs) remains low, limiting the effectiveness of pharmacovigilance systems. While prior studies have examined mHealth applications in maternal and child health, infectious disease management, and health education, little research has systematically explored their underutilization in ADR reporting. This systematic review sought to examine how Absorptive Capacity (ACAP) has been defined, conceptualized, and operationalized in Information Systems (IS) research, identifies its levels of analysis and key determinants, and assesses its relevance as a theoretical lens for understanding enablers of mHealth utilization for ADR reporting in Uganda.

Methods - Peer-reviewed English-language studies published between 2010 and 2025 that examined ACAP in IS, information technology, mHealth innovations, or ADR reporting were reviewed. Searches were conducted in PubMed, Scopus, Web of Science, IEEE Xplore, and Google Scholar, following Joanna Briggs Institute (JBI) systematic review guidelines. Screening and duplicate removal were documented using a PRISMA flow diagram. Of 134 records identified, 25 studies met the inclusion criteria.

Results - The review found that ACAP is a dynamic, multi-level capability comprising structural elements such as knowledge systems and infrastructure, and behavioral elements including learning and collaboration. These capacities operate at individual, team, and organizational levels .

Conclusions - Understanding mHealth utilization for ADR reporting in Uganda requires integrating individual, team, and organizational absorptive capacities. This multi-level approach provides deeper insight into how mHealth technologies can strengthen pharmacovigilance in public healthcare environments.

Keywords : Absorptive Capacity, mHealth technologies, Utilization, Adverse Drug Reactions, Pharmacovigilance, Healthcare

1 Introduction

The advent of mobile health (mHealth) technologies presents a transformative opportunity for improving healthcare service delivery and patient safety worldwide [1]. mHealth, which encompasses the use of mobile devices and applications to support medical and public health practices, has gained traction due to its potential to enhance communication, data collection, and patient management [2][3]. Recent advancements in mobile devices, sensors, and connectivity have further expanded the scope of mHealth, positioning it as a cost-effective platform for addressing persistent gaps in health service delivery, especially in underserved and remote communities [4]. Innovations such as mobile applications, wearable devices, telemedicine platforms, and digital health records have enabled more efficient data collection, remote monitoring, and patient engagement, thereby improving access to essential health services [5]. These technologies have been applied across diverse areas including chronic disease management, maternal and child health, mental health, and disability services, while also empowering patients through improved health literacy and patient-centred care models [6] [7]. At the same time, mHealth forms a critical component of the broader digital transformation of healthcare, which leverages digital technologies to improve clinical practices, service efficiency, and health outcomes [8]. The integration of digital tools into healthcare systems supports better management of large volumes of health data, enhances quality control, and reduces service delivery costs [9]. This transformation also creates new opportunities for healthcare practitioners

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by reshaping training, workflows, and decision-making processes, reinforcing the role of mHealth as a key enabler of modern, responsive, and data-driven healthcare systems [10] [11].

Over the past decade, Uganda has seen a significant increase in the integration of digital technologies into healthcare delivery, driven by the country's expanding Internet access [12]. The Ministry of Health (MoH), through the Digital Health Strategy (2020–2024) and the Health Sector Development Plan (HSDP III), has prioritized the use of mHealth technologies for disease surveillance, health information dissemination, and reporting of health events, including Adverse Drug Reactions [13]. These policy frameworks provide an enabling environment for digital health innovation; however, their effective implementation depends heavily on the institutional absorptive capacity of healthcare facilities and frontline health workers [14]. According to [15], mobile phones, due to their widespread availability and portability, have become an effective tool for disseminating targeted health information. For instance, short messaging service (SMS) capabilities are utilized for various purposes, including disease surveillance and patient notifications, such as reminders for medical appointments and medication adherence, thereby enhancing public health outcomes [16]. As emphasized by [15], the integration of mHealth technologies into healthcare systems offers significant potential for enhancing the efficiency and effectiveness of healthcare service delivery. While mHealth technologies present immense opportunities for improving healthcare delivery in Uganda, their utilization remains relatively low [17]. Research indicates that although a substantial number of healthcare workers are aware of mHealth technologies, many have yet to use them, particularly for tasks such as disease diagnosis and reporting Adverse Drug Reactions. Empirical evidence by [18] on mHealth access and utilization indicates that, among 87 participating healthcare professionals, the majority possessed knowledge of mHealth technologies. However, only 38% had ever used such technologies, 55% had never used them, and 7% were uncertain about their prior usage. This underutilization underscores a persistent gap between awareness and practical application of mHealth solutions for ADR reporting. The low utilization of mHealth technologies in reporting ADRs presents a critical challenge, particularly in low-resource settings where such innovations hold substantial potential to improve healthcare outcomes [17]. As such, further research is needed to examine the low utilization of mHealth technologies in reporting ADRs [19].

Numerous studies have identified a range of barriers to mHealth utilization at both individual and organizational levels to include aspects such as financial, social, legal, and ethical [20]. Other factors include limited awareness of mHealth benefits, low digital literacy, lack of interoperability, data security concerns, and insufficient empirical evidence supporting cost-effectiveness. However, despite these well-documented obstacles, there remains limited research examining the underutilization of mHealth technologies in reporting ADRs through the theoretical lens of Absorptive Capacity [21]. Existing studies have tended to focus on areas of family planning and reproductive health, maternal and child health, infectious disease management, health education and promotion, and nutrition and dietary support [22]. Reporting ADRs is critical for improving pharmacovigilance, ensuring patient safety, and enhancing healthcare outcomes [23]. As such, this systematic review aims to address this gap by exploring how Absorptive Capacity Theory can be applied as a theoretical lens to understand the enablers of mHealth utilization for reporting Adverse Drug Reactions in public healthcare settings. By using ACAP to identify the underlying barriers and enablers of utilization of mHealth technologies in reporting ADRs, the study generates insights that could inform strategies for improving the uptake and effective use of mHealth innovations, particularly in reporting ADRs in resource-constrained healthcare environments. Our review sought to address the following research questions:

- RQ1: How has Absorptive Capacity been defined, conceptualized, and operationalized in peer-reviewed Information Systems literature?
- RQ2: What are the levels of analysis of Absorptive Capacity?
- RQ3: What factors have been identified as key determinants influencing Absorptive Capacity?
- RQ4: How can Absorptive Capacity be used to explain the enablers of mHealth utilization for reporting Adverse Drug Reactions in public healthcare settings in Uganda?

We address these questions through a scoping review of peer-reviewed articles, conference papers, and institutional reports published between 2010 and 2025. This approach allows us to synthesize how Absorptive Capacity has been defined and conceptualized, while identifying recurring themes and gaps. The review also highlights the different levels of analysis at which Absorptive Capacity has been applied and examines the determinants that shape its development. In doing so, the study advances theoretical understanding of Absorptive Capacity within Information Systems research and offers practical insights for strengthening mHealth utilization and pharmacovigilance in resource-constrained healthcare settings.

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2 Materials and Methods

This systematic literature review was conducted in accordance with the Joanna Briggs Institute (JBI) methodology for scoping reviews, ensuring a systematic and rigorous approach to identifying, selecting, and synthesizing relevant literature. It was reported by the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) framework. Validity was ensured through a predefined protocol, explicit inclusion criteria, multi-database searching, and theory-guided synthesis of findings, ensuring accurate representation of the literature. Reliability was enhanced by documenting and standardizing the review procedures, enabling replication of the search, screening, and synthesis process.

2.1 Inclusion criteria

The review focused exclusively on peer-reviewed journal articles to ensure the use of credible and academically rigorous sources. Only studies published in English were considered, to allow for accurate comprehension and analysis. Articles included in the review specifically focused on Absorptive Capacity in Information Systems, Information Technology, mHealth innovations, and ADR reactions. A key inclusion criterion was that the studies must explicitly apply, discuss, or integrate the Theory of Absorptive Capacity, whether as a theoretical framework, analytical lens, or conceptual construct. To enhance contextual relevance, the review included studies conducted in developing countries or within public healthcare settings, reflecting environments like Uganda. Additionally, the review was limited to literature published between 2010 and 2025 to capture contemporary developments in both mHealth and Absorptive Capacity Theory.

2.2 Exclusion criteria

Studies were excluded if they did not discuss or reference the Theory of Absorptive Capacity, even if they were related to mHealth, as such studies would not inform the conceptual framing of the current research. Research conducted exclusively in private healthcare settings was also excluded, as the organizational dynamics and resource environments differ significantly from public systems like Uganda's. Other excluded works included conference abstracts, editorials, commentaries, and dissertations, as these do not meet the empirical and peer-reviewed standard of evidence required for this review. Lastly, studies focusing solely on mobile applications outside the healthcare domain were also excluded to maintain a clear focus on mHealth innovations.

2.3 Search Strategy

To identify relevant literature for this systematic review, a comprehensive and structured search strategy was employed across multiple academic databases. A purposive and criterion-based sampling approach was used, whereby only studies that met the inclusion criteria were retained for synthesis. The primary aim of the search was to locate peer-reviewed journal articles that examine how Absorptive Capacity has been conceptualized and applied within the context of mHealth innovations in healthcare settings. The search was conducted using a combination of keywords and boolean operators to capture a wide range of relevant studies. Core search terms included: "Absorptive Capacity" AND "mHealth", "mHealth technologies" AND "healthcare", "innovation adoption" AND "Absorptive Capacity", and "knowledge absorption" AND "digital health" AND “Adverse Drug Reactions”. These terms were adapted to suit the syntax requirements of each database and were combined using boolean operators like AND, OR, and NOT to refine the results.

The databases searched included PubMed, Scopus, Web of Science, IEEE Xplore, and Google Scholar. PubMed captures biomedical and public health literature, IEEE Xplore covers technological and engineering perspectives, while Scopus, Web of Science, and Google Scholar provide broad, multidisciplinary indexing to ensure inclusivity and minimize publication bias. Filters were applied to limit the results to articles published in English, between 2010 and 2025, and in peer-reviewed journals. Manual searches of the reference lists of relevant articles were also conducted to identify additional studies that may not have appeared in the initial database results, a process known as backward citation tracking. To manage and screen the identified articles, reference management software, Zotero, was used to remove duplicates and organize sources. Titles and abstracts were screened based on the inclusion and exclusion criteria, followed by a full-text review of selected articles to

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determine their eligibility for final inclusion. This systematic search strategy ensured a rigorous and transparent process for gathering literature that could meaningfully inform the conceptualization of Absorptive Capacity in mHealth research, particularly in contexts similar to the Ugandan healthcare system.

2.4 Study Selection

The study selection process of study followed a structured and transparent approach in line with the JBI methodology for scoping reviews. After conducting comprehensive searches across selected databases, all identified records were imported into the Zotero reference management tool to facilitate the removal of duplicate entries. The selection process was carried out in two main stages: title and abstract screening, followed by full-text review. In the first stage, the titles and abstracts of all retrieved articles were screened against the predefined inclusion and exclusion criteria. At this stage, studies that did not meet the criteria, such as those not focused on mHealth, not mentioning Absorptive Capacity, or conducted in non-healthcare settings, were excluded. Articles that appeared potentially relevant were then subjected to full-text review in the second stage. During this phase, the full texts were reviewed to confirm eligibility. The reasons for exclusion at the full-text stage were recorded for transparency and accountability. The entire selection process was documented using a PRISMA flow diagram (Figure 1), which outlines the number of records identified, screened, excluded, and ultimately included in the final synthesis. This rigorous selection process ensured that only studies meeting the methodological and conceptual criteria of the review were included, thereby enhancing the credibility and reliability of the findings.

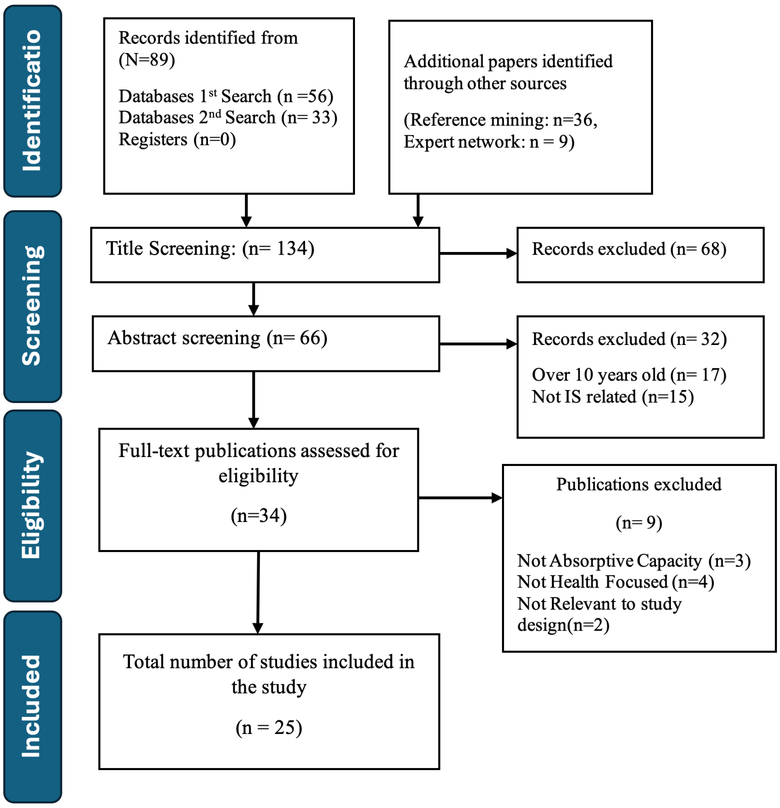

Figure 1. Search results and study selection and inclusion process

Figure 1 shows that a total of 89 records were retrieved from electronic databases, comprising 56 from the first search and 33 from a second round of database searches. Additionally, supplementary records were identified through reference mining (36 records) and consultations with an expert network (9 records), resulting in a broader pool of potentially relevant studies. After compiling all sources, a total of 134 unique records underwent title screening. At this stage, 68 records were excluded for reasons such as irrelevance to the research topic or lack of

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alignment with the inclusion criteria. The remaining 66 records were subjected to abstract screening, during which 32 additional articles were excluded, 17 for being more than ten years old, thus not meeting the currency criteria, and 15 for lacking relevance to information systems (IS), a core element of the review focus. This left 34 full-text articles, which were assessed comprehensively for eligibility based on the established inclusion and exclusion criteria. From this pool, 9 articles were excluded at the full-text review stage. The reasons for exclusion included: lack of focus on Absorptive Capacity (n=3), studies that were not health-focused (n=4), and studies with designs that did not align with the scope of the review (n=2). Ultimately, 25 studies met all the criteria and were included in the final synthesis of the scoping review. These studies collectively provided valuable insights into how absorptive capacity has been conceptualized and operationalized in the context of mHealth innovations in healthcare, laying the foundation for conceptualizing the current study on the utilization of mobile health technologies for reporting adverse drug reactions by Ugandan healthcare professionals.

2.5 Data extraction

During the data extraction phase of the review, a structured template was developed to capture key information from each included study. The data extracted covered a wide range of themes aimed at supporting a comprehensive understanding of how ACAP has been conceptualized and applied within the context of mHealth innovations. To begin with, basic study characteristics were collected, including the name of the author(s), publication year, journal or source of publication, the country or geographical focus, and details about the organization(s) involved in the study. Additionally, the study design or methodology employed in each article was noted to provide insights into the research approaches commonly used in ACAP and mHealth literature. Particular attention was paid to how each study defined Absorptive Capacity, including its origin and theoretical development, to trace how the concept has evolved. Where applicable, any modifications or extensions of the original ACAP theory were documented. This included information on the dimensions of Absorptive Capacity referenced in the studies, such as acquisition, assimilation, transformation, and exploitation of knowledge, as well as the levels of analysis (individual, group, organizational, team, or environmental level) at which ACAP was explored. Furthermore, data were extracted on the determinants of Absorptive Capacity, such as prior related knowledge, Research and Development (R&D), or external collaborations.

The applications of Absorptive Capacity within each study were also recorded, focusing on the types of indicators, measurement approaches, instruments, or scales used to assess ACAP. Studies were examined for their focus on various forms of innovation, whether technological (mobile platforms), procedural (health reporting processes), or strategic (policy implementation), and how such innovations were introduced or integrated into existing systems. Details on the adoption process, including the conditions under which innovations were accepted and put into practical use, were extracted as well. Further emphasis was placed on studies that explored the application of ACAP in Health Information Systems (Health IS), with a particular focus on mHealth technologies. Specific attention was given to the role and effectiveness of mHealth technologies in Uganda to establish contextual relevance. The review also captured insights related to the reporting of ADRs using mHealth platforms, an area central to the present study. Finally, the review documented how the selected studies demonstrated the relevance of Absorptive Capacity to the utilization of mHealth technologies in healthcare. This included examining how knowledge acquisition, assimilation, transformation, and exploitation influenced the uptake and consistent use of mHealth technologies, particularly in low-resource public healthcare settings such as those in Uganda. Through this approach, the extracted data provided a strong foundation for conceptualizing ACAP in the context of mHealth technologies for ADR reporting.

2.6 Data analysis and presentation

Data were analyzed and presented in accordance with the research questions guiding this scoping review. The analysis involved a systematic examination of the selected literature to extract relevant information pertaining to each of the four guiding questions. First, the data were analyzed to identify how the concept of ACAP has been defined and conceptualized within the Information Systems literature. Particular attention was paid to how scholars have framed the dimensions of ACAP, and how these have evolved over time. Second, the analysis explored the levels of analysis at which Absorptive Capacity has been applied. Studies were categorized based on whether they examined ACAP at the individual, group, organizational, team, or inter-organizational level, and patterns across these levels were identified and synthesized. Third, the review identified the key determinants of

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Absorptive Capacity. These included internal organizational factors such as prior related knowledge, Research and Development, Individual Absorptive Capacity, and external factors like environmental dynamism and institutional support. The analysis sought to highlight how these determinants contribute to or hinder an entity's absorptive capabilities. Finally, the data were analyzed to determine how Absorptive Capacity Theory can be used as a theoretical lens to understand the enablers of mHealth technologies utilization, specifically in the context of reporting ADRs in public healthcare settings. The analysis highlighted how ACAP has been applied to interpret knowledge processes, innovation adoption, and system readiness in low-resource environments, such as Uganda. The findings are presented thematically under each of the four research questions, providing a structured synthesis of the existing literature and laying the groundwork for future empirical inquiry.

3 Results

3.1 Definitions, Conceptualizations, and Operationalizations of Absorptive Capacity in Information Systems Literature

Results show that all 25 (100%) papers reviewed acknowledge the foundational work of [24] , illustrated in Figure 2, who originally defined ACAP as a firm's capacity to identify valuable external knowledge, integrate it, and apply it for commercial gain. 18(72%) of the studies conceptualize ACAP as a multidimensional organizational capability encompassing the processes of knowledge acquisition, assimilation, transformation, and exploitation. For instance, [25] define ACAP as comprising these four interrelated routines, emphasizing its dynamic and developmental nature. These studies generally depict ACAP as an evolving capacity that enables organizations to manage external knowledge effectively, facilitating innovation and competitive advantage over time. The emphasis is on how organizations build routines and structures that support continuous learning and knowledge flow internally. Across the literature, Absorptive Capacity has been conceptualized both as a potential capacity and a realized capacity. [26] [27] highlight that Potential ACAP refers to an organization's ability to acquire and assimilate external knowledge, and Realized ACAP focuses on transforming and exploiting this knowledge to drive innovation and improve performance. These dimensions capture the sequential processes involved in converting external knowledge into actionable outcomes [28]. Specifically, acquisition refers to identifying and obtaining relevant external knowledge, assimilation involves interpreting and understanding this knowledge, transformation focuses on combining it with existing internal knowledge, and exploitation represents the application of transformed knowledge to achieve organizational goals [26] [29]. This conceptualization added granularity to the understanding of ACAP and provided a structured basis for its application across diverse contexts [30] [31].

About 5 (20%) of the reviewed papers focus on ACAP as a facilitator of organizational learning and change, highlighting its role in preparing firms for technology adoption and adaptation. These studies typically associate higher levels of ACAP with increased organizational readiness to implement new technologies by enabling better internal knowledge sharing, internalization, and application. Importantly, many of these works underscore the critical role of top management in fostering ACAP through strategic leadership, resource support, and creating a knowledge-sharing environment, which enhances the organization's capacity to utilize external knowledge assets.

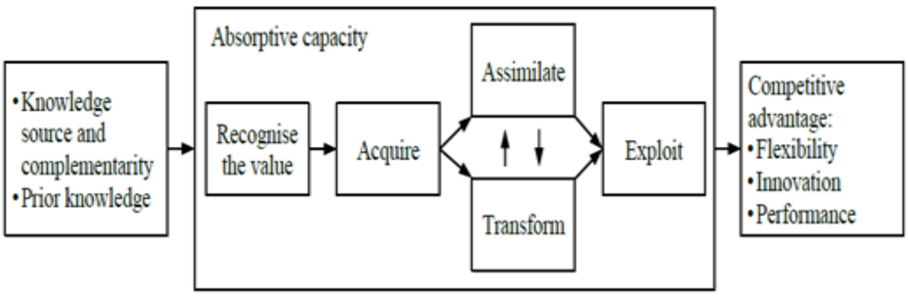

Figure 2. Absorptive capacity components: Source: Cohen and Levinthal (1990)

A smaller subset, around 2(8%), conceptualizes ACAP within the framework of a firm's dynamic capabilities and strategic resilience. This perspective views ACAP less as a set of processes but as a strategic resource that underpins a firm's ability to adapt to external pressures such as regulatory changes, market shifts, or technological

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disruptions. These studies argue that ACAP, as part of an organization's broader strategic capability, contributes to sustained innovation, organizational agility, and long-term competitive advantage by enabling ongoing adaptation and learning in complex environments. They viewed ACAP as a mechanism by which organizations develop innovation capabilities and sustain competitive advantage, especially in complex and dynamic environments such as healthcare.

Literature consistently conceptualizes ACAP as a comprehensive, adaptable organizational resource that encompasses multiple routines and processes for knowledge management. While most definitions emphasize its dynamic and developmental aspects (72%), a significant portion highlight its role in organizational learning (20%) and strategic resilience (8%). These varying perspectives collectively reinforce the idea that ACAP is central to effective technology adoption, innovation, and maintaining competitive advantage in rapidly changing environments. These findings indicate that while the majority of studies frame ACAP as an organizational-level construct, there is growing recognition of the influence of social, behavioral, and institutional factors in shaping how ACAP is developed and operationalized.

Table 1. Conceptualization of Absorptive Capacity

Perspective	Share of Studies	Key Conceptual Focus	Representative Scholars/Studies	Core Characteristics	Implications for Practice and Theory
Multidimensional Organizational Capability	18 studies (72%)	ACAP as a set of interrelated processes: acquisition, assimilation, transformation, and exploitation of knowledge	[25] [26] [32]	Views ACAP as a dynamic, developmental, and routinized process enabling continuous learning and innovation.	Enhances understanding of ACAP as a process-based capability that fosters innovation and sustained competitive advantage through effective external knowledge utilization.
Facilitator of Organizational Learning and Technology Adoption	5 studies (20%)	ACAP as an enabler of learning, knowledge sharing, and technological adaptation	[33] [34] [35] [36] [37]	Focuses on internal learning, knowledge integration, and managerial support. Highlights the role of top management, leadership, and culture in enhancing absorptive potential.	Shows ACAP as a learning-oriented capability that improves readiness for technology implementation, especially in evolving environments.
Dynamic Capability / Strategic Resilience Perspective	2 studies (8%)	ACAP as part of a firm's broader dynamic capabilities and strategic resource base	[38] [39]	Conceptualizes ACAP as a strategic resource that underpins adaptability to external shocks, regulatory changes, and technological disruptions.	Positions ACAP within strategic management theory, linking it to organizational agility, resilience, and long-term innovation capacity.

Source: *Authors' synthesis from reviewed literature (2010–2025*)

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3.2 Operationalization of Absorptive Capacity

Out of the papers reviewed, a clear majority, 17 (68%), focus primarily on the definition and conceptualization of absorptive capacity, emphasizing its role as a dynamic organizational capability for learning and knowledge use. In contrast, only 8 (32%) of the studies proceed to operationalize absorptive capacity through measurable dimensions and indicators explicitly. This pattern indicates that while the concept of absorptive capacity is well established theoretically, empirical operationalization remains comparatively limited and uneven across the literature.

Among the studies that operationalize absorptive capacity, all 8 (100%) converge on the four-dimensional structure of acquisition, assimilation, transformation, and exploitation, suggesting strong consensus on these core dimensions. Specifically, acquisition is operationalized in 7 (88%) of the studies using indicators such as environmental scanning, R&D investment, external partnerships, and prior related knowledge, highlighting its role as a boundary-spanning capability. Assimilation is operationalized in 7 (88%) of the studies through indicators related to knowledge sharing, cross-functional communication, training, and documentation, reflecting its grounding in organizational learning routines.

Table 2. Operationalization of Absorptive Capacity

Dimension	Defining Characteristics	Indicators	Representative Studies
Acquisition	Ability to identify and acquire external knowledge	Environmental scanning; R&D investment; external partnerships; prior knowledge	[30] [40] [41] [42]
Assimilation	Ability to interpret and internalize knowledge	Knowledge sharing; cross-functional communication; training; documentation	[30] [40] [41] [42]
Transformation	Ability to combine new and existing knowledge	Reconfiguration of routines; integration of ideas; experimentation	[30] [40] [41] [42]
Exploitation	Ability to apply knowledge for value creation	New products/services; process improvements; performance gains	[30] [40] [41] [42]

Source: *Authors' synthesis from reviewed literature (2010–2025*

The transformation dimension appears in 6 (75%) of the operationalized studies, with indicators focusing on the reconfiguration of routines, integration of ideas, and experimentation, underscoring its role in recombining new and existing knowledge. Similarly, exploitation is operationalized in 6 (75%) of the studies, primarily through indicators of new products or services, process improvements, and performance gains, thereby linking absorptive capacity to tangible organizational outcomes. Overall, these findings show that although fewer studies move beyond conceptual discussion, those that do demonstrate strong alignment in how absorptive capacity is operationalized, reinforcing its applicability for empirical analysis of technology adoption and innovation outcomes.

3.3 Levels of Analysis of Absorptive Capacity

The concept of ACAP has been analyzed at different levels of analysis within the literature. Based on the reviewed papers, the levels of analysis primarily include individual,11(44%), group 4(16%), organizational, 21(85%), and team-level, 4(16%). Each level provides a unique perspective on how ACAP functions within organizations and influences technology adoption, innovation, and competitive advantage. Below is a detailed discussion of these levels.

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Table 3. Level of analysis of ACAP

Level of Analysis	Unit of Analysis	Indicators / Measures of ACAP	Key Conceptual Focus	Representative Studies	Implications for Research and Practice
Individual Level	Individual employees or managers within the Organization	•Knowledge acquisition and learning ability • Expertise and prior related knowledge • Cognitive ability and motivation • Individual leadership and empowerment	ACAP as a function of individual skills and learning processes that underpin organizational absorptive routines	[28] [35] [43]	Building individual learning and skill development enhances organizational ACAP. Leadership commitment fosters conducive knowledge-sharing environments.
Group Level	Workgroups or functional units within the organization	• Knowledge sharing within & across groups • Communication & collaboration routines • Problem-solving & joint decision-making practices	ACAP as a social process where group interactions facilitate assimilation & transformation of knowledge	[31] [44] [27]	Strengthening intra- and inter-group communication improves knowledge diffusion and innovation outcomes.
Organizational Level	Organization as a whole	• Knowledge acquisition, assimilation, transformation, and exploitation routines • R&D intensity and innovation systems • Organizational learning culture and structure	ACAP as a dynamic organizational capability that evolves through structured systems and processes	[30] [32] [26] [35] [45] [36]	Enhancing structural systems, R&D capacity, and organizational learning improves innovation and strategic adaptation.
Team Level	Teams at the Meso Level- Outside the Organization	• Team learning and interaction frequency • Improvisation and harmonization processes • Shared cognition and collective problem-solving • Knowledge identification and transfer	ACAP as a meso-level construct that captures the collective ability of teams to absorb and apply knowledge in dynamic contexts	[46] [47]	Recognizing team-level absorptive capacity helps bridge micro–macro gaps and promotes innovation through adaptive team learning and collaboration.

Source: *Authors' synthesis from reviewed literature (2010–2025*)

Studies that had the individual in the organization as a unit of analysis represented 11(44%) of the reviewed data set. The studies emphasize the role of individual managers and employees in developing and utilizing ACAP. At this micro level, ACAP is associated with individual staff members' human capital, expertise, and knowledge management practices. The capacity for knowledge acquisition and transformation begins with individual learning

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processes. For example, [28] [35] [43] posit that individual routines and skills are foundational to organizational routines, underscoring the importance of individual capabilities in knowledge assimilation. [43] highlight the role of individual leadership and empowerment, suggesting that top management's beliefs and participation influence the organizational environment and thus impact ACAP's development. This implies that at the individual level, developing skills, fostering individual learning, and encouraging participation are essential for building overall organizational ACAP.

While less explicitly detailed in the reviewed studies, 4(16%) of the studies relate to the role of groups within organizations. The emphasis at the group level is on how knowledge is shared, assimilated, and exploited across units within the organization. This includes routines, communication channels, and collaborative practices. The notion that organizational routines for knowledge sharing and integration are built upon group interactions. The role of organizational socialization, problem-solving groups, and cross-functional groups in facilitating the transformation and exploitation phases of ACAP [31] [44] [27] . This implies that effective internal communication, collaboration, and shared routines between groups are vital for enhancing ACAP at this intermediate level.

Most prominently discussed in the literature, 21(85%) of the reviewed studies, notably, [30] and [32], ACAP is conceptualized as an organizational capability comprising routines and processes for knowledge acquisition, assimilation, transformation, and exploitation. For example, [26] define ACAP as a set of organizational routines and processes that enable firms to manage knowledge effectively. The papers, by adopting an organizational definition, emphasize that ACAP is a dynamic capability that evolves through organizational routines, systems, and structures that facilitate learning and innovation, and hence the organizational level unit of analysis. Key dimensions of ACAP at this level include knowledge acquisition-which refers to the organization's routines for sensing external knowledge, assimilation- which refers to the internal processes for understanding and interpreting external knowledge, transformation- which is considered as the ability to reconfigure or recombine internal knowledge for new applications, and exploitation- which entails institutionalizing and applying knowledge to generate value and competitive advantage. Study results from this unit of analysis illustrate that organizations with high ACAP can better recognize, internalize, and utilize external knowledge for strategic benefits, including technology adoption like mHealth innovations [35] [45] [36]

The team-level analysis of ACAP, as articulated by [46] [47] emphasizes understanding how knowledge absorption processes function within the meso-level context of teams, rather than at the macro-organizational or micro-individual levels. [46] propose a novel conceptualization of absorptive capacity specifically at the team level, introducing four new dimensions that capture the unique dynamics of knowledge processing within teams. These dimensions include identification, which refers to a team's ability to recognize individuals' specialized knowledge areas and promote internal knowledge sharing; harmonization, which involves coordinating diverse perspectives to integrate individual knowledge into a shared understanding; improvisation, defined as the capacity to generate creative solutions under time or resource constraints; and consummation, the ability to articulate and communicate newly acquired knowledge effectively. Together, these dimensions form a comprehensive and multidimensional model that reflects the active and dynamic nature of team-level absorptive capacity [47]. Unlike firms, which benefit from stability, established routines, and organizational memory, teams are often temporary, diverse, and operate in fluid environments, lacking structured memory systems. As such, their knowledge absorption processes are more complex and less reliant on embedded routines. The team's effectiveness in recognizing, assimilating, and applying external knowledge, therefore, depends on these newly proposed capabilities, which are essential for navigating the challenges of diversity, limited resources, and high contextual variability.

The reconceptualization of Absorptive Capacity by [46] introduces a multi-level framework that distinguishes between macro-level latent processes and meso-level active processes. At the macro level, which reflects the traditional understanding of Absorptive Capacity, the organization engages in four key activities: recognizing the value of external knowledge, acquiring that knowledge, assimilating and transforming it internally, and finally exploiting it to improve organizational performance. These activities occur over time, resulting in a progression from the organizational knowledge stock at time T_1 to an enhanced knowledge stock at time T_2.

A critical innovation in this framework is the introduction of the meso-level active context. This level represents the actual behavioral and operational mechanisms through which knowledge is put into use within the organization. The interaction between these two levels is facilitated through explicit linkages. A macro-to-meso link occurs when newly recognized knowledge is transferred into the meso-level for active engagement. Conversely, the meso-to-macro link feeds the outcomes of meso-level experimentation, such as prototypes of products or processes, back into the macro-level exploitation phase. These bi-directional links emphasize the

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dynamic and iterative nature of knowledge absorption, where both levels contribute to organizational learning and innovation.

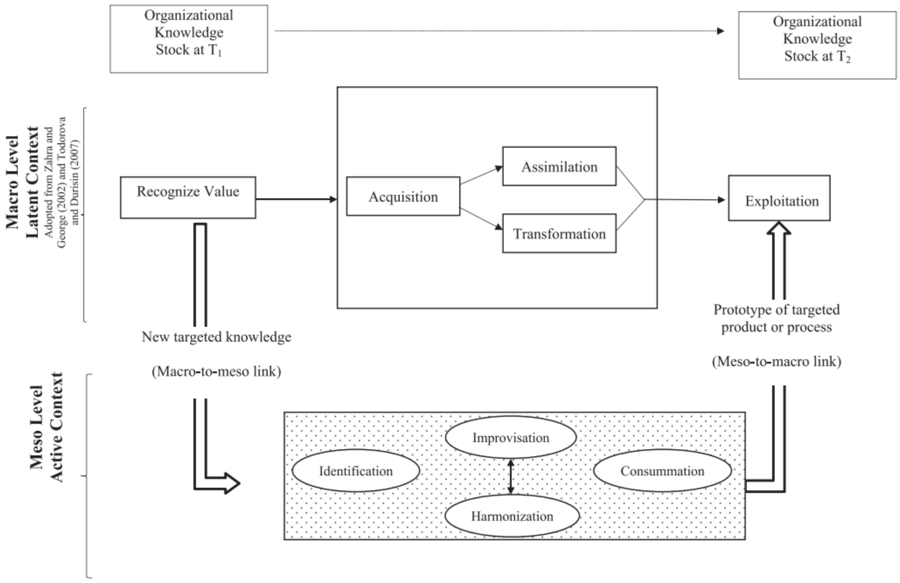

Figure 3. Reconceptualizing Absorptive Capacity, Yildiz, Murtic, and Zander (2024).

In this case, [46] model expands the traditional view of ACAP by embedding an active meso-level layer that captures the practical enactment of knowledge. This conceptualization highlights that knowledge absorption is not only a cognitive or structural process but also a behavioral and contextual one, deeply rooted in the day-to-day practices of organizational actors. It thereby provides a more comprehensive understanding of how organizations learn and innovate over time.

(a) Comparison and contrast between Team-level and other group-levels

Compared to traditional group-level conceptual frameworks of ACAP , which emphasize structured routines, formal communication channels, and collective knowledge assimilation across functional units, the team-level framework advanced by [46] offers a more dynamic, behaviourally grounded perspective. Whereas group-level models view ACAP as emerging from stable organizational routines that facilitate coordination and knowledge sharing, the team-level conceptualization focuses on the active enactment of knowledge processes within smaller, adaptive units operating outside the organization. This contrasts with earlier models that largely treat knowledge absorption as a linear, process-driven activity. The team-level approach thus complements rather than replaces group-level unit of analysis by revealing how absorptive capacity manifests as an emergent, practice-based capability within collaborative teams, bridging the gap between individual cognition and organizational learning.

Table 4. Comparison of Group vs Team-Level Conceptualizations of ACAP

Dimension	Group-Level ACAP	Team-Level ACAP
Unit of Analysis	Workgroups or functional units within organizations	Teams as independent, adaptive learning systems outside the Organization
Core Focus	Knowledge sharing, coordination, and assimilation through established organizational routines	Dynamic enactment of knowledge processes through improvisation and collaboration
Key Processes	Acquisition, assimilation, transformation, exploitation	Identification, harmonization, improvisation, consummation

Nature of Processes	Structured, routine-based, and largely top-down	Emergent, behaviorally enacted, and context-dependent
Underlying Mechanisms	Organizational socialization, communication channels, and cross-functional collaboration	Team creativity, adaptability, and shared cognition
Knowledge Flow	Vertical and formalized; directed through organizational structures	Horizontal and fluid; iterative between team members and organizational layers
Contribution to ACAP Theory	Explains how organizations coordinate and institutionalize knowledge	Explains how teams activate and operationalize knowledge absorption under dynamic conditions

Source: *Authors' synthesis from reviewed literature (2010–2025*)

3.4 Determinants Influencing Absorptive Capacity

A central determinant of absorptive capacity, identified in 19 out of 25 studies (76%), is the organization's, individual's, or team's ability to recognize, acquire, and gather relevant external knowledge. [48] [32] [28] consistently highlight prior related knowledge as essential for identifying valuable external information. Recognition of knowledge involves the processes and mechanisms through which organizations scan the environment, establish sensing routines, and allocate resources for knowledge search. Empirical studies demonstrate that knowledge acquisition is supported by R&D investments, patent portfolios, and established routines for external engagement, all of which enhance an organization's capacity to detect and access external knowledge flows.

Seventeen studies (68%) emphasize knowledge assimilation as a key process in absorptive capacity, involving how organizations interpret, understand, and internalize the knowledge they acquire. Assimilation entails developing shared understanding, building internal communication channels, and creating learning routines that foster collective sense-making. This determinant is particularly influenced by team dynamics such as trust, collaboration, and the formation of shared mental models. These studies show that effective assimilation relies on an organization's cognitive structures and internal social capital, which enable the conversion of new information into accessible and actionable knowledge.

Fifteen of the reviewed papers (60%) discuss knowledge transformation or conversion as another critical determinant. This involves the ability to combine newly acquired knowledge with existing knowledge to generate new insights, refine processes, or create novel practices. Transformation typically occurs through internal routines that support learning integration and adaptation. The literature links this capability to organizational flexibility, integrative mechanisms, and the presence of dynamic routines that allow for the recombination of knowledge. Transformation is especially vital in adapting external knowledge to fit internal operations and in facilitating innovation.

Almost half of the reviewed studies,12(48%) address knowledge exploitation, which refers to the organization's ability to apply absorbed knowledge to practical ends such as product innovation, service improvement, or process optimization. Exploitation represents the realization of absorptive capacity, where knowledge is put to use to achieve performance outcomes. Supporting findings suggest that exploitation is associated with innovation output, R&D effectiveness, and creative problem-solving. Organizations with robust mechanisms for knowledge application are better positioned to turn ideas into tangible outcomes and sustain competitive advantage.

Group-level capabilities were highlighted in 13 studies (52%), underscoring the micro-foundations of absorptive capacity within group settings. These capabilities include skills such as identification of internal knowledge, improvisation under uncertainty, integration of diverse viewpoints, and consummation the clear articulation of new knowledge. These competencies are particularly important in R&D and project-based teams where knowledge processes are decentralized and less routinized. The literature suggests that teams with strong internal coordination, cognitive diversity, and a learning-oriented culture significantly enhance absorptive capacity at the organizational level.

Leadership and organizational culture were identified as important determinants in 11 studies (44%). Leadership influences absorptive capacity by shaping strategic vision, fostering openness to external ideas, and facilitating resource allocation. Transformational leadership styles, in particular, promote a culture of learning,

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risk-taking, and collaboration factors that are conducive to effective knowledge absorption. Cultural attributes such as trust, openness, and innovation orientation also determine how knowledge is shared and integrated across organizational boundaries. Cross-cultural studies further indicate that cultural compatibility affects the ease with which external knowledge is assimilated and exploited.

The most commonly cited determinant, mentioned in 20 studies (80%), is the availability of organizational resources and routines. This includes knowledge management systems, institutionalized processes, learning infrastructures, and organizational slack. These elements form the structural backbone that supports the absorptive capacity process, facilitating both the acquisition and transformation of knowledge. The presence of well-established routines and supportive infrastructures ensures that knowledge flows are captured, processed, and disseminated effectively throughout the organization.

Nine studies (36%) address the role of resource constraints and the need for improvisation in sustaining absorptive capacity. In settings with limited access to financial, technological, or human resources, such as many public healthcare systems, organizations must rely on creativity, flexibility, and spontaneous problem-solving to absorb and apply knowledge. Improvisation allows teams to adapt quickly to changing conditions and make efficient use of available resources. This determinant is particularly relevant in volatile environments, where traditional routines may not suffice and agility becomes essential for knowledge absorption.

Twelve papers (48%) highlight external networks and relationships as significant enablers of absorptive capacity. Alliances, partnerships, and collaborations with external entities such as universities, research institutions, suppliers, and customers serve as vital sources of new knowledge. Strength, diversity, and trust within these networks determine the quantity and quality of knowledge flows. Robust external linkages not only enhance knowledge acquisition but also facilitate assimilation by offering platforms for dialogue, shared learning, and co-creation.

Finally, 11studies (44%) point to contextual and contingency factors as influencing the effectiveness of the other determinants. Variables such as team size, task complexity, industry dynamics, technological uncertainty, and environmental turbulence affect how absorptive capacity is developed and operationalized. These studies argue that the relative importance of each determinant may vary depending on the organizational setting, making absorptive capacity a context-sensitive construct. This insight supports the need for adaptive and tailored approaches to building absorptive capacity across different sectors and organizational forms.

The high prevalence of resources and routines (80%) highlights their central role in enabling absorptive capacity, while recent studies increasingly emphasize team-related determinants such as identification and improvisation, signaling a shift toward a more granular, team-level understanding of knowledge processes. Although leadership and cultural factors are addressed slightly less frequently, they remain crucial in shaping the organizational environment that supports absorptive activities.

Relatedly, [48] notes that Absorptive capacity is shaped by a combination of internal and external factors. They explained that internal factors encompass elements such as the organization's existing knowledge base, the individual absorptive capacity of employees, their educational levels, and the diversity of their professional backgrounds. Additional contributors include the roles played by gatekeepers, the effectiveness of cross-functional communication, the prevailing organizational culture, the size of the company, and its level of organizational inertia [28].

Furthermore, investment in research and development and human resource management significantly influences absorptive capacity [27]. On the external front, [42] note that the knowledge environment surrounding the organization and its position within broader knowledge networks play a pivotal role. An organization must possess a high level of ACAP to effectively integrate and apply external knowledge, particularly in contexts such as technology transfer, where diffusion channels, organizational interactions, and R&D resources are vital for success [49]. The implications of an organization's prior knowledge base, the individual absorptive capacity of employees, and investment in R&D on overall ACAP and competitiveness are profound [28]. A well-developed knowledge base enhances a firm's ability to recognize, assimilate, and exploit new information, fostering continuous innovation and adaptability in dynamic markets [27].

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Table 5. Determinants of Absorptive Capacity

Determinant	Number of Papers	Percentage (%)	Description Summary
Knowledge Acquisition	19	76%	Recognizing and gathering relevant external knowledge.
Knowledge Assimilation	17	68%	Interpreting and understanding acquired knowledge.
Knowledge Transformation /Conversion	15	60%	Converting knowledge into usable formats and routines.
Knowledge Exploitation / Application	12	48%	Applying knowledge to innovate and improve.
Group-Level Capabilities	13	52%	Skills like identification, improvisation, integration at team level.
Leadership and Culture	11	44%	Leadership style and organizational culture influence absorptive capacity.
Resources and Routines	20	80%	Availability of routines and knowledge resources.
Resource Constraints and Improvisation	9	36%	Handling resource limitations via improvisation.
External Relationships and Networks	12	48%	External linkages providing critical outside knowledge.
Contextual and Contingency Variables	11	44%	Influences from environment, size, and technology complexity.

Source: *Authors' synthesis from reviewed literature (2010–2025)*

Employees with high individual ACAP, supported by diverse educational and professional backgrounds, contribute to the effective internalization and application of external knowledge, thereby improving organizational learning [50]. Additionally, sustained investment in R&D not only strengthens technological capabilities but also enhances knowledge-sharing mechanisms, leading to superior innovation performance and competitive advantage [26].

Firms that strategically cultivate these elements position themselves as industry leaders, capable of responding swiftly to emerging opportunities and challenges, thus securing long-term sustainability and market dominance [51].

3.5 Application of Absorptive Capacity Theory in Explaining mHealth Utilization for Adverse Drug Reaction Reporting

The reporting of Adverse Drug Reactions is a critical component of pharmacovigilance that ensures drug safety and efficacy [52]. Globally, the state of ADR reporting is varied, with well-established systems in developed countries but significant gaps in developing regions [53]. To address these issues, there have been efforts to develop regional pharmacovigilance centers and integrate ADR reporting into existing healthcare frameworks, although progress is slow and uneven across the continent [54] [55]. In Uganda, the process of reporting Adverse Drug Reactions begins with the reporter, who may be a healthcare professional such as a doctor, nurse, pharmacist, or other health worker, identifying and documenting a suspected ADR using the National Drug Authority (NDA)-ADR reporting form. The reporter has three submission options, first, the report is submitted to the Regional Pharmacovigilance Centre, usually located in the pharmacy section of the regional referral hospital. These centres serve as the first point of technical verification and support, ensuring that reports are complete before forwarding them to the NDA. Secondly, the report may be collected by NDA Regional Officers, who either pick reports

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directly from health facilities or receive notifications from facility-based pharmacovigilance focal persons. This ensures coverage in districts and facilities that lack regional centres. Lastly, the report goes directly to the NDA Head Office in Kampala, where it is received, acknowledged, and reviewed by pharmacovigilance experts. The head office provides feedback to the reporter and integrates the information into the national ADR database for further causality assessment and regulatory action. Additionally, reporters can submit ADRs directly through digital platforms such as WhatsApp, the NDA online portal, the Med Safety mobile app, or email, enhancing real-time data transmission. These multiple pathways and feedback loops between reporters, regional centres, NDA regional officers, and the NDA Head Office reflect a decentralized yet coordinated pharmacovigilance system, ensuring efficient ADR detection, validation, and response across Uganda's healthcare network.

Relating Uganda's Adverse Drug Reaction reporting process to the three levels of analysis of Absorptive Capacity, individual, organizational, and team, demonstrates how knowledge identification, assimilation, transformation, and exploitation occur across different actors and structures in the national pharmacovigilance system. At the individual level, absorptive capacity manifests through the healthcare professionals (reporters) who identify and document ADRs. Their ability to recognize potential drug reactions depends on individual knowledge, prior experience, and professional judgment. This stage aligns with ACAP's knowledge acquisition and assimilation dimensions, where the healthcare worker must interpret clinical symptoms, determine causality, and utilize available digital tools such as the Med Safety mobile app or online reporting portal. Enhancing individual ACAP through continuous professional training, digital literacy, and pharmacovigilance awareness ensures that frontline reporters can effectively detect and communicate ADRs using mobile technologies.

At the organizational level, absorptive capacity is represented by the NDA, which institutionalizes systems for collecting, validating, and analyzing ADR reports nationally. NDA's organizational ACAP involves the transformation of individual and team knowledge into national pharmacovigilance intelligence through databases such as VigiBase and policy feedback mechanisms. It encompasses processes like knowledge transformation and exploitation, where lessons from ADR data inform regulatory decisions, safety alerts, and health system learning.

At the team level, absorptive capacity emerges through collaboration within and between healthcare facility teams, such as regional hospitals and district health offices. These teams collectively verify, harmonize, and transmit ADR reports to ensure data accuracy and completeness. This collaborative process reflects [46] meso-level ACAP, emphasizing identification, harmonization, improvisation, and consummation. For instance, team members identify key knowledge sources (ADR reporting technologies), harmonize interpretations through peer review, improvise when digital systems or internet access fail, and consummate the process by submitting validated reports to NDA. Team-level absorptive capacity is therefore critical in enabling adaptive learning and ensuring consistent knowledge flow between health facilities and regional centres.

We therefore Shall develop and adopt a multi-level analytical theoretical approach that integrates the individual, organizational and team levels as key lenses to understand and explain the utilization of mHealth for ADR. This is driven by the observations that the Ugandan pharmacovigilance system relies on cross-functional collaboration between individuals, facility teams, and organizational structures, operating in resource-limited and dynamic environments.

4 Discussion

The results of this systematic review provide a comprehensive understanding of how Absorptive Capacity has evolved conceptually and empirically within the Information Systems (IS) literature and how this framework can be applied to understand the enablers of mobile technology utilization for Adverse Drug Reaction reporting in Uganda's public healthcare system. Across the reviewed studies, the findings reveal that ACAP has transitioned from a narrowly defined organizational process to a multilevel, dynamic capability encompassing individual, team, and organizational dimensions. This reconceptualization not only broadens theoretical understanding but also has direct implications for how health systems, particularly in low-resource settings, adopt and utilize digital innovations such as mHealth technologies.

The review confirms that ACAP remains grounded in the foundational work of [24], who introduced it as a firm's ability to identify, assimilate, and exploit external knowledge for innovation and performance improvement. However, subsequent research, including studies by [25] [56], has expanded ACAP into a multidimensional construct comprising four interrelated processes: acquisition, assimilation, transformation, and exploitation. This dynamic perspective, adopted by 72% of reviewed studies, frames ACAP as an evolving

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organizational capability rather than a static asset. It highlights the continuous nature of learning and adaptation required to integrate external knowledge into internal practices. The findings also reveal a distinction between Potential ACAP (the ability to acquire and assimilate knowledge) and Realized ACAP (the ability to transform and apply knowledge). This differentiation is particularly relevant in public healthcare contexts like Uganda, where the gap between potential and realized ACAP can determine the success of technology-enabled pharmacovigilance systems.

A smaller but growing body of research (20%) positions ACAP as a facilitator of organizational learning and technological adaptation, emphasizing leadership, organizational culture, and resource allocation as enablers of knowledge utilization. This orientation aligns closely with healthcare environments, where the introduction of mHealth technologies for ADR reporting requires behavioral and cultural change alongside technical adoption. Finally, a subset of studies (8%) views ACAP through the lens of dynamic capabilities and strategic resilience, framing it as an adaptive mechanism that allows organizations to withstand environmental turbulence, regulatory change, and technological disruption. This is particularly salient for Uganda's public healthcare system, which operates under resource constraints and shifting health priorities. Here, ACAP enables organizations to respond adaptively by leveraging both internal and external knowledge for sustainable innovation.

The review identifies four levels of ACAP analysis, individual, group, organizational, and team each offering distinct but interconnected insights into how knowledge absorption occurs. The individual level (44%) highlights the importance of personal learning, professional expertise, and cognitive ability in identifying and interpreting new knowledge. In the context of Uganda's ADR reporting, this corresponds to the healthcare workers (doctors, nurses, and pharmacists) who recognize and document suspected drug reactions. Their ability to utilize mHealth tools such as the Med Safety app depends on their digital literacy, motivation, and previous exposure to pharmacovigilance training. Strengthening individual-level ACAP through continuous capacity building and digital awareness is therefore fundamental for effective ADR surveillance.

The group level (16%) represents collective learning within departments or functional units, focusing on internal communication, collaboration, and shared routines. While this level enhances intra-organizational coordination, the results indicate that its role remains under-theorized and less developed in the ACAP literature. Most studies treat groups as intermediaries between individuals and the organization, emphasizing formalized processes rather than adaptive behavior. In contrast, the organizational level (85%) is the most established domain, viewing ACAP as a structured set of routines that allow organizations to scan environments, absorb knowledge, and institutionalize innovations. Within Uganda's pharmacovigilance system, the National Drug Authority (NDA) exemplifies organizational-level ACAP through its established procedures for collecting, validating, and analyzing ADR reports. These processes translate individual and team-level knowledge into institutional intelligence that informs policy decisions, regulatory actions, and system-wide learning.

However, a notable development in recent scholarly work is the recognition of the team level (16%), as advanced by [46]. This framework introduces a meso-level perspective, conceptualizing teams as adaptive, learning-oriented entities that bridge micro-level individual actions and macro-level organizational structures. Unlike traditional group-level approaches that emphasize stability and formal routines, [46] highlight behavioral, interactive, and improvisational dynamics that enable teams to absorb and apply knowledge in fluid, real-time contexts. The four new dimensions proposed identification, harmonization, improvisation, and consummation, capture the lived realities of teams operating in complex and uncertain environments, such as Uganda's regional pharmacovigilance centres. These teams often function under time constraints, resource limitations, and infrastructural challenges, making adaptability and improvisation central to their absorptive processes. The [46] framework, therefore, fills a theoretical gap by explaining how collective learning and innovation occur through interaction and contextual adaptation rather than solely through predefined routines.

The results identify a range of determinants that shape ACAP across levels, with organizational resources and routines (80%) emerging as the most frequently cited factor. These include formalized knowledge management systems, institutional processes, and learning infrastructures that enable consistent knowledge flow. In Uganda, the NDA's national ADR reporting system and digital reporting platforms represent such institutional mechanisms that support knowledge acquisition and exploitation. Knowledge acquisition (76%), assimilation (68%), and transformation (60%) remain core functional determinants that directly influence innovation outcomes. These processes depend heavily on prior knowledge bases, R&D investments, and cross-functional collaboration, all areas that can be strengthened through deliberate policy and capacity interventions in Uganda's healthcare sector.

The review also emphasizes team-level capabilities (52%) such as identification, improvisation, and integration of diverse perspectives as crucial micro-foundations of ACAP. These findings reinforce the importance of [46]

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behavioral model, which positions teams as active agents of knowledge absorption rather than passive implementers of organizational strategies. In resource-constrained settings, where improvisation and creativity are necessary for problem-solving, team-level absorptive capacity determines how effectively mobile technologies are adopted and used for ADR reporting. Additional determinants such as leadership and culture (44%), external networks (48%), and contextual factors (44%) highlight that absorptive capacity is deeply embedded in both social and institutional contexts. Transformational leadership and an innovation-oriented culture foster trust and openness to external ideas, which are prerequisites for successful knowledge assimilation. External partnerships with international regulatory bodies and academic institutions further enrich the knowledge base and enhance collective learning. Applying the absorptive capacity framework to Uganda's ADR reporting process in future studies shall illustrate how knowledge absorption and utilization occur across individual, team, and organizational levels.

5 Conclusion

This systematic review set out to explore how Absorptive Capacity has been defined, conceptualized, and applied within the Information Systems literature, to identify its levels of analysis, key determinants, and potential application as a theoretical lens for understanding the enablers of mobile technology utilization in Adverse Drug Reaction reporting within Uganda's public healthcare system. The findings offer several important conclusions that contribute both to theory and to practice.

First, the review confirms that Absorptive Capacity has evolved into a multidimensional and dynamic construct that extends beyond its original economic interpretation by [24]. Literature overwhelmingly supports the view of ACAP as a process-oriented capability comprising interlinked stages of acquisition, assimilation, transformation, and exploitation of knowledge, which together enable continuous learning, innovation, and adaptability. This dynamic and developmental nature of ACAP allows organizations and systems, such as Uganda's pharmacovigilance infrastructure, to remain responsive to technological change and external knowledge flows. The distinction between Potential and Realized ACAP adds theoretical clarity by illustrating how organizations progress from recognizing valuable knowledge to applying it in ways that generate measurable performance outcomes.

Second, the results show that ACAP operates at multiple, interdependent levels: individual, team, and organizational, each contributing uniquely to the knowledge absorption process. At the individual level, ACAP manifests through healthcare workers' cognitive ability, expertise, and motivation to recognize and report ADRs using mobile tools. At the team level, it is reflected in the collaborative dynamics among health facility teams, regional pharmacovigilance centres, and district health officers, who collectively verify, harmonize, and transmit ADR data. At the organizational level, it is expressed through the institutional structures and learning systems of the National Drug Authority, which transform and exploit aggregated knowledge for regulatory and public health decision-making. These multilevel interactions underscore that ACAP is not confined to organizational structures alone but emerges from the continuous interplay between people, teams, and institutions, a perspective that traditional single-level models fail to capture.

Third, the review identifies several determinants that shape the development and strength of absorptive capacity. The most influential are organizational resources and routines, which provide the structural foundation for knowledge management, alongside leadership, culture, and external partnerships, which create an enabling environment for learning. Equally important are team-level capabilities such as improvisation, harmonization, and collective problem-solving, especially in settings characterized by uncertainty and resource limitations. These determinants affirm that ACAP is both a structural and behavioral construct, dependent on how well knowledge systems are supported institutionally and enacted socially within and across organizations. The findings also demonstrate that absorptive capacity is context-sensitive, shaped by environmental turbulence, resource constraints, and institutional maturity, all of which are prominent features of Uganda's healthcare environment.

Fourth, the study establishes that Absorptive Capacity offers a robust theoretical lens for analyzing and strengthening digital health adoption and innovation. It bridges the gap between technological readiness and behavioral adaptability by emphasizing learning as a continuous, iterative process. In conclusion, Absorptive Capacity serves as both a diagnostic and prescriptive framework for enhancing digital innovation in healthcare.

Future research should examine how individual, team, and organizational absorptive capacities interact to shape sustained mHealth utilization for ADR reporting in the public healthcare system, with particular emphasis on the

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meso-level dynamics of team learning and coordination. Investigating these multi-level interactions will provide deeper insights into how layered knowledge processes support effective pharmacovigilance in resource-constrained settings.

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Patient Perspectives on mHealth for Maternal and Pre-maternal Health Services in Resource-Constrained Settings

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Background and Purpose: With the rapid evolution of computing trends and the growing use of technology in the healthcare sector, maternal healthcare delivery and accessibility require a transformative shift. However, studies indicate that the integration of technology into maternal service delivery remains slow. This is largely due to the absence of comprehensive frameworks that support diverse access to maternal electronic services (e-services), as existing scholarly work has mainly focused on maternal information provision. While such information provision has been valuable in enabling pregnant and new mothers to access appropriate educational content from accredited healthcare workers, it is predominantly delivered through text-based SMS, reflecting limited use of multimedia and mobile capabilities. Therefore, the purpose of this study was to investigate the requirements for developing an improved and comprehensive framework for maternal e-service delivery from patients' perspectives.
Methods: This study has been conducted following the user-centred design (UCD) approach where both pregnant and new mothers were engaged in the requirement-gathering process by responding to a questionnaire tool to understand what should be considered while developing an improved framework to comprehensively support the delivery of maternal e-services in this era where technology is seen as a source of solutions to various aspects. The requirements centred on four themes: 1) demographic information of the participants, 2) awareness of maternal e-services, 3) assessment of the utilization of maternal e-services relative to maternal health challenges, and 4) security and privacy of data in technologically supported applications.
Results: As a result, this paper reveals a set of requirements identified as potential for developing a mobile health framework to improve access to maternal healthcare through the digitized delivery of maternal services, based on patient (pregnant and new mothers) perspectives.
Conclusion: This paper contributes to scholarly knowledge by identifying key requirements for developing a framework to enhance maternal healthcare access through technological solutions, particularly in settings where technology itself is a limited resource. These requirements serve as a foundation for creating interventions that have the potential to transform maternal service delivery and improve healthcare outcomes.

Keywords: Maternal E-Services, Maternal Healthcare, Health Informatics, Mobile Health.

1 Introduction

Mobile health (mHealth) regards the application of information technology that pertains to the utilization of mobile devices such as smartphones, tablets, wearables, and wireless technology to strengthen and enhance different spheres of healthcare and medicine [1–5]. The core objective of mHealth is to harness the capabilities of these devices to offer more accessible, streamlined, and tailored health services [6] The healthcare industry has embraced the potential of mHealth through numerous innovative developments that have aided various aspects of health management [7–9]. Medical innovations in the realm of mobile health are integral across various domains, spanning computer-aided disease diagnosis and automated patient care in critical settings, including Intensive Care Units, and computer-based systems for managing patient information [10,11]. These extend to patient-centric healthcare approaches, facilitating in-store transactions

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for medical products such as medications and cosmetics in pharmacies and clinics, supporting well-informed clinical decision-making, telemedicine, and more care [12, 13]. Notable examples of medical innovations include HealthTap, Augmented Infant Resuscitator (AIR), WebMD, Pocket Pharmacist, and Teladoc [14–16]. These have steadily transformed health systems around the world [17, 18].

The success of mHealth is facilitated by the growing adoption of mobile devices due to their resilient features [19]. These include seamless connectivity, low cost of ownership (affordability), support for data persistence and offline capabilities, portability of devices to enable mobility of users, and high-performing location-awareness features typically using Global Positioning Systems [20,21]. This provides cohesive support for the introduction and development of mHealth applications [22]. In Uganda, the number of smartphones recorded has experienced a consistent increase in each quarter, starting from 4.57 million in the initial quarter of 2018 and subsequently surpassing 10 million by the initial quarter of 2022 [23]. Further studies showed that at the beginning of 2023, Uganda had approximately 11.77 million individuals using the Internet, with an Internet penetration rate of 24.6% [23,24].

In the context of maternal health, it is regrettably observed that the adoption of technological innovations remains significantly delayed, particularly in resource-constrained environments, including developing nations such as Uganda [25]. This delay is worsened by the absence of interventions to improve access maternal healthcare services [26]. Consequently, maternal healthcare challenges in developing countries become even more complex, increasing the risks associated with inadequate care [27–29] .In this situation, several crucial problems become apparent as discussed below.

Pregnant women and new mothers often find themselves facing distressing and potentially dangerous situations due to limited access to critical health information. This extends to essential aspects of maternal care, such as proper prenatal care, recognition of warning signs during pregnancy and receiving guidance on postnatal care [30]. Unfortunately, this information gap can result in far-reaching consequences, including delayed or inappropriate responses to maternal health issues. When expectant mothers and new parents are unable to access the necessary knowledge and resources, they are vulnerable to potentially life-threatening complications that might otherwise be preventable or manageable with timely intervention. As such, addressing this disparity in health information access appears imperative to ensure the well-being of both mothers and their newborns, highlighting the need for better maternal health education and support systems.

The absence of mHealth platforms, which facilitate telemedicine consultations and appointment management, could pose significant barriers for pregnant women seeking timely healthcare services. These obstacles have detrimental consequences as delayed care may intensify maternal complications [31]. In the absence of technological solutions, pregnant individuals may struggle to schedule and promptly access the healthcare they need. Delayed care further compounded the challenges already faced during pregnancy, potentially compromising the health and well-being of both the mother and unborn child. To mitigate these barriers and ensure prompt provision of maternal healthcare, it is crucial to promote the adoption of mHealth platforms and telemedicine services, thereby enhancing accessibility and responsiveness in maternal care delivery [32–35].

The absence of mobile health (mHealth) frameworks is particularly concerning during emergencies across the three critical stages of maternal life pregnancy, childbirth, and the postnatal period. Emergencies such as severe bleeding, high blood pressure, prolonged labour, pregnancy and postpartum complications (especially among mothers who deliver via caesarean section) often demand immediate medical intervention. However, many mothers lack timely access to healthcare support during these life-threatening situations, leading to preventable complications and increased maternal morbidity and mortality. MHealth interventions play a vital role in enabling rapid communication with healthcare providers when urgent assistance is required. Without these technologies, there is a significant risk of hindering the timely summoning of emergency support, potentially resulting in adverse outcomes for both the mother and the unborn child [36]. In moments of crisis, every second counts and the ability to swiftly connect with healthcare professionals can make a crucial difference in ensuring the safety and well-being of expectant mothers. Therefore, the integration of mHealth solutions into maternal care is not only essential for convenience but also for the preservation of life, underlining the critical need to bridge this gap in emergency support for pregnant women.

The utilization of mobile health (mHealth) technologies plays a pivotal role in tracking and monitoring critical maternal health data, such as pregnancy trimesters, weeks of amenorrhea, foetal growth indicators, and maternal vital signs. Monitoring these parameters is essential for aligning maternal education, preparing

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for delivery, and detecting potential complications early. Without these tools, healthcare providers may face challenges in recognizing warning signs, increasing the risk of maternal mortality [37,38]. Continuous collection and analysis of maternal data through mHealth solutions allow healthcare professionals to identify deviations from normal health patterns promptly, enabling timely interventions and appropriate medical measures. Therefore, integrating mHealth for comprehensive data tracking is not merely a convenience but a vital component in improving maternal healthcare outcomes and reducing maternal mortality.

In light of this situation, the integration of technology is crucial to facilitate convenient and immediate delivery and support for services necessitated by mothers during the different stages of maternal health, that is, prenatal, delivery, and postpartum stages [39] Therefore, the involvement of technology in maternal health is required to deliver and support core maternal e-services [40]. The perpetuated goal is to mitigate the crucial problems discussed above ensure safe deliveries and achieve satisfactory postpartum outcomes to preserve the lives of both mothers and newborn infants [41,42].

Studies have consistently emphasized the growing integration of mobile health (mHealth) innovations in maternal healthcare, emphasising significant advancements, particularly in the realm of maternal e-services. Many studies have explored the potential of mHealth to deliver maternal education through mobile messages, typically disseminated by healthcare providers to expectant mothers, covering a wide array of critical topics. Notably, most existing frameworks primarily rely on text-based messages for this purpose, with only a few rare attempts to explore voice interactions. While these initiatives have their merits, the current frameworks are limited by their heavy reliance on text and voice communication for maternal health education. This accentuates the pressing need for an improved framework that broadens the scope of maternal e-services, harnesses multimedia capabilities for content delivery and takes a more holistic approach to address the multifaceted needs of maternal care [51]. With emphasis on this situation, this paper discusses the requirements and determinants for developing an improved framework to comprehensively support access to maternal e-services in low-resource settings using Uganda as the case study.

2 Materials and Methods

To attain the set objectives, the study formulated a research question (RQ) that was fundamental in guiding the deliverability of the projected results. The question stated as follows;

RQ1: What are the requirements to be considered in developing a mobile health-driven framework to enhance maternal e-services delivery in Uganda?

To answer the research question (RQ1), researchers adopted the user-centred design approach where mothers were involved in the study. The study prioritized the active involvement of mothers as the primary stakeholders in the determination of the requirements necessary for designing a mobile health framework to enhance the delivery and support of maternal electronic services. The study targeted mothers aged 15 to 50 years, as this age range includes the majority of women who are pregnant or have recently given birth. By focusing on this age group, the study aimed to capture the experiences and needs of most of the population utilising maternal e-services

Participants were recruited from Mbarara Regional Referral Hospital (MRRH), commonly known as Mbarara Hospital, located in Mbarara in the Western Region of Uganda. MRRH is the referral hospital for the region, serving the districts of Mbarara, Bushenyi, Ntungamo, Kiruhura, Ibanda, and Isingiro. The hospital was chosen for this study due to its extensive capacity to accommodate pregnant and new mothers from various parts of southwestern Uganda, offering both private and public healthcare services. This made it an ideal location to gather a diverse group of participants and ensure balanced data collection for the study. Participants were purposively selected based on specific criteria to ensure their direct involvement in maternal health matters and their willingness to provide relevant insights and information regarding maternal e-services. This sampling method was chosen because it allows for the intentional selection of individuals who possess specific characteristics or experiences pertinent to the research objectives, thus ensuring a more focused and relevant data collection process. Therefore, researchers sampled 60 mothers although a larger sample could have been determined using Yamane's formula, 60 participants were chosen for in-depth engagement. The corresponding estimated margin of error was 5%, which is acknowledged as a limitation of the study.

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Participant views and insights were collected using a questionnaire tool, a structured set of questions designed to gather information efficiently. This approach was chosen for its ability to standardize responses, ensure participant anonymity, and provide accessibility through various distribution methods. The questionnaire was administered in person by trained research assistants, who provided clear instructions and explanations to all participants. Utilizing questionnaires, the study aimed to efficiently gather insights from mothers about their experiences with maternal e-services, facilitating comprehensive analysis and informed decision-making. The questionnaire was structured into four sections, denoted as Sections A, B, C, and D.

Section A: Demographics captured non-identifiable information from mothers, including age (15–50 years), language proficiency, education level, area of residence, and mobile device ownership.

Section B: Awareness of Maternal E-Services explored mothers' knowledge and use of digital maternal health services, access methods, service types, language preferences, cost considerations, and offline accessibility.

Section C: Current Assessment of Maternal E-Services evaluated perceptions of four key areas: maternal education, emergency support, telemedicine consultations, and medication and investigation management, focusing on effectiveness, accessibility, and reliability.

Section D: Privacy and Security of Data gathered views on data protection, existing security measures, and concerns about insecure platforms, and preferred features to ensure confidentiality and safety in maternal e-service delivery.

Following the completion of data collection, respondents' responses were entered into SPSS, a widely used data analysis tool. This process began with coding the data to prepare it for analysis. Since all data variables were categorical, with some being nominal and others ordinal values, each response was assigned a numerical code for easier interpretation and manipulation. For instance, Likert scale values indicating the level of agreement were coded using numeric values (e.g., Strongly Agree as 5, Agree as 4, Neutral as 3, Disagree as 2, and Strongly Disagree as 1). Subsequently, descriptive analysis was conducted to gain insights into the distribution of responses. This involved generating cross tables, frequency tables, and histogram graphs to examine relationships and patterns within the data. Cross tables were particularly useful in exploring associations between two categorical variables, providing valuable insights into the respondents' perceptions and behaviors. Frequency tables provided a summary of the distribution of responses for each variable, while histogram graphs visually depicted the frequency distribution of responses. SPSS was selected for its extensive features, which enabled comprehensive statistical data analysis, facilitating the exploration and interpretation of the collected data.

The validity and reliability of the data were ensured through several measures implemented by the researcher. Firstly, to enhance validity, careful attention was paid to the design of the questionnaire, ensuring that it accurately captured the relevant constructs and variables of interest related to maternal e-services. Questions were selected based on literature, study objectives, and relevance to maternal experiences and validated by experts. While some researchers' judgments were unavoidable, efforts were made to minimize bias by using clear, neutral, and participant-centred wording, providing consistent instructions, and standardizing administration. This ensured the responses genuinely reflected participants' experiences. This explains why the questionnaire tool was a composition of various sections, each with a unique purpose. Furthermore, efforts were made to minimize biases during data collection by providing clear instructions to participants and maintaining consistency in administration procedures. To ensure reliability, inter-rater reliability tests were conducted for any subjective assessments or coding processes involved in the data analysis, ensuring consistency in interpretation among different researchers. Moreover, test-retest reliability checks were performed by administering the questionnaire to a subset of participants on two separate occasions and assessing the consistency of their responses over time. SPSS served as the tool for data analysis, while STATA was occasionally used to cross-check and confirm the consistency of results between the two platforms. This measure supported confidence in the reliability of the study's findings and analytical procedures. Overall, these rigorous validation and reliability procedures helped to strengthen the credibility and trustworthiness of the data collected for the study. The figure below summarizes the process under which the study was executed.

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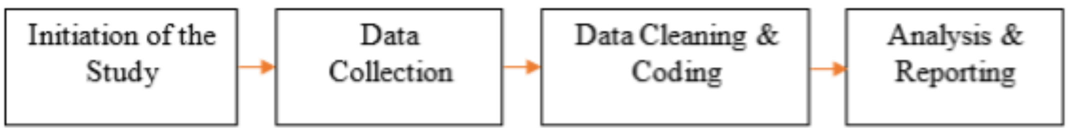

Figure 1. Organization of the study activities

The research was ethically cleared by the Vice Chancellor of the University of Dodoma on behalf of the University Research Ethics Committee, the Government, and the Tanzania Commission of Science and Technology (COSTECH) on 27th October 2023 under Ref. No. MA.84/261/02/'A'/60/124. The study was also approved at the data collection centre, Mbarara Regional Referral Hospital, on 12th February 2024. Furthermore, before engaging in the study, participants provided implicit consent by willingly responding to the data collection questionnaire, signifying their voluntary participation. The consent statement was stated at the beginning of the data collection tool as “By responding to this questionnaire, you have consented to be part of the study.” Participants also retained the right to withdraw their involvement at any time. To protect participant privacy and confidentiality, collected data was anonymized. These ethical measures ensured the commitment to upholding the highest standards of research integrity and participant well-being.

3 Results

In this study, requirements are defined as the essential conditions or capabilities that a mobile health-driven framework must fulfill to effectively enhance maternal e-services delivery in Uganda. These are meant to ensure that the framework meets the needs of both healthcare providers and expectant mothers. On the other hand, determinants are regarded as the factors that influence the successful implementation and adoption of the framework. These may encompass socio-cultural attitudes, economic conditions, healthcare infrastructure, technological literacy, and policy environment that affect how the framework is utilized and its overall impact on maternal health outcomes. Understanding both requirements and determinants is crucial for developing a robust, user-centered, and contextually appropriate mobile health solution.

3.1 Age Variations and Support to Multimedia Content Delivery

Understanding the age groups and differences among mothers is a key factor in designing an inclusive e-service framework, as it provides insight into how mothers of different ages respond to various aspects such as the use of multimedia in delivering maternal education. As presented in Table 1, 78.3% (48.3% and 30%) agreed on the multimedia capability to improve access to maternal education. Upon diving into various age groups, it becomes clear that a large percentage agreed upon this at each variation. For instance, among mothers aged 26 – 35 years, 45.9% agreed, whereas 35.1% strongly confirmed the need for multimedia in this regard.

In general, multimedia, including videos and infographics, serves as a versatile tool in e-service frameworks, appealing to mothers of all age groups. Its dynamic nature offers an engaging platform for accessing information, accommodating diverse learning styles and preferences. Whether through interactive modules or educational videos, multimedia facilitates comprehension of complex concepts and enhances information retention. Its visual appeal not only enriches user experience but also encourages active engagement. By integrating multimedia elements into e-service frameworks, designers can create inclusive environments that cater to mothers' varied needs and preferences across different age groups. Therefore, with support for multimedia from mothers of different age groups, the Framework should be developed, placing multimedia as a key requirement to enhance access to maternal education.

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Table 1. Correlation between age and support for multimedia content delivery

Age Groups	Mothers' Support to Multimedia Capabilities					
	Strongly Disagree	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**	**Total**
15 – 25 years	0	1	4	4	3	9
	0%	11.1%	44.4%	44.4%	33.3%	100%
26 – 35 years	3	1	3	17	13	37
	8.1%	2.7%	8.1%	45.9%	35.1%	100%
36 – 45 years	0	0	4	8	1	13
	0%	0%	30.8%	61.5%	7.7%	100%
46 and above	0	0	0	0	1	1
	0%	0%	0%	0%	100%	100%
Total	3	2	11	29	18	60
	5%	3.3%	13.3%	48.3%	30%	100%

3.2 Proficiency in languages and support for Multilingual E-service access

Understanding the language proficiency of participants was crucial for designing a comprehensive framework, aiming to assess mothers' satisfaction with the language used in rendering maternal e-services on digital platforms. Table 2 shows that 50 (83.3%) mothers expressed proficiency in English. However, regarding satisfaction, only 46.7% (15% and 31.7%) confirmed being satisfied with the language used on digital platforms for maternal e-services, indicating a significant gap in meeting mothers' language preferences. Presenting information in mothers' preferred languages ensures comprehension of critical healthcare instructions and educational content, empowering informed decision-making and fostering user engagement. This promotes inclusivity by eliminating language barriers for all mothers seeking access to healthcare information and support through e-services. Consequently, the framework's design can prioritize English as the primary medium for delivering maternal e-services, while acknowledging the potential for multilingual innovations to cater to the diverse language preferences of mothers.

Table 2. Language Proficiency and Correlation with Satisfaction

Language	Measure of Satisfaction in Language						
	Extremely Dissatisfied	**Dissatisfied**	**Neutral**	**Very Satisfied**	**Satisfied**	**N/A**	**Total**
English	2	1	14	9	16	8	50
	4%	2%	28%	18%	32%	16%	100%
Runyankole	0	0	4	0	3	0	7
	0%	0%	57.1%	0%	42.9%	0%	100%
Luganda	0	1	0	0	1	0	2
	0%	50%	0%	0%	50%	0%	100%
Other	0	0	1	0	0	0	1
	0%	0%	100%	0%	0%	0%	100%
Total	2	2	19	9	19	8	60
	3.3%	3.3%	31.7%	15%	31.7%	15%	100%

3.3 Area of Residence and Data Persistence Features

Examining participants' areas of residence (rural vs. urban) was important for designing a maternal e-service framework that caters to diverse locations, aiming to understand the relationship between residence and internet affordability. Table 3 indicates that 88.3% (53) of respondents lived in urban areas compared to rural residents. However, the affordability of the internet remains a challenge, with 66.3% (15% as not affordable at all, 15% as slightly affordable, and 33.3% as moderately affordable) not positively indicating the ability to afford internet connectivity while accessing e-services, regardless of residence. With this in mind, 88.3% of respondents agreed that enabling offline features in mobile apps for maternal service

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delivery can reduce reliance on internet connectivity, thus enhancing accessibility and usability. This observation denoted the importance of incorporating features that enable low resource utilization, such as downloadable educational resources and data persistence, to facilitate offline access to information. By including such features, the framework can ensure accessibility and usability across diverse settings, including areas with limited internet and power infrastructure.

Table 3. Residence areas against Internet affordability

Residence	Not at all affordable	Slightly affordable	Moderately affordable	Very Affordable	Extremely Affordable	Total
Urban areas	8	8	17	17	3	53
	15.1%	15.1%	32.1%	32.1%	5.7%	100%
Rural areas	1	1	3	2	0	7
	14.3%	14.3%	42.9%	28.6%	0%	100%
Total	9	9	20	19	3	60
	15%	15%	33.3%	31.7%	5%	100%

3.4 Possession of Mobile Devices and Adoption of the Framework

Given that mothers are the primary beneficiaries of the maternal e-service framework, it was essential for the study to examine their access to mobile devices like smartphones or tablets. This investigation provides insight into the prevalence of mobile devices within the community, indicating the potential viability of the mobile application for maternal e-services. As presented in Table 4, the study revealed that 96.7% of participants, possessed smartphones, while a minority (3.4%), comprising two mothers, had access to smartphones through sharing or family members. This observation exposes the significance of designing a mobile health framework for maternal e-services given the widespread presence of mobile devices among the participants.

Table 4. Possession of Mobile Phone Results

Access to Mobile Devices	Frequency	Percent (%)
Own a smartphone	58	96.7
Borrow or share a smartphone	1	1.7
Use a family member's phone	1	1.7
Total	60	100.0

3.5 Utilization of Maternal E-Services and Stage of Services Access

Building upon the understanding of mothers' awareness of maternal e-services, the study further investigated utilization through a simple "Yes/No" question. This aimed at understanding the stage of maternal health at which the services were accessed, as well as the type/nature of the services, to inform on the gap between service coverage and maternal stage consideration. As presented in Table 5, only 41.7% (25) confirmed having accessed maternal e-services, compared to the 58.3% (35) who had never accessed these services. Delving into stages, although 60% expressed not accessing maternal health services across all three stages, only 28% reported accessing them during prenatal care, indicating a gap in the labor and delivery stage and newborn care stage. Reflecting on these findings, the framework should consider the provision of maternal e-services to mothers across the three core stages of maternal health to support the diverse needs of mothers, especially pregnant and new mothers.

Table 5. Utilization of Maternal E-Services against Stage of Utilization

	Maternal Stage access the services				
Measure of Utilization	**Prenatal**	**Delivery /Birth**	**Postnatal**	**None of these**	**Total**
Yes	15	1	1	8	25
	60%	4%	4%	32%	100%

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No	2	2	3	28	35
	5.7%	5.7%	8.6%	80%	100%
Total	17.0	3	4	36	60
	28.3%	5%	6.7%	60%	100%

3.6 Location-Supported Access

With mobile devices equipped with real-time location capabilities, the development of mobile applications for delivering e-services should leverage this feature to enhance service access. Location-based functionalities offer significant benefits, particularly in rural areas. For example, e-service applications could utilize location data to identify nearby healthcare facilities, recommend relevant specialists, or facilitate connections with local support groups such as Village Health Teams. By incorporating such features, the framework goes beyond mere information dissemination, providing mothers with actionable resources tailored to their geographical location. As depicted in Table 6, a significant majority of 58.3% (35 participants) agreed, while 33% (20 participants) strongly agreed that facilitating access to services tailored to the user's current location could provide a more efficient way to access nearby services, ultimately saving time and reducing expenses. In alignment with this, the framework should be developed with the provision of location-customized services.

Table 6. Support for Location-Based Access to Maternal E-Services

Response	Frequency	Percent (%)
Strongly Disagree	2	3.3
Disagree	0	0
Neutral	3	5.0
Agree	35	58.3
Strongly Agree	20	33.3
Total	60	100.0

3.7 Maternal Health Education/Information Provision

The rapid expansion of the internet and mobile technology has transformed the landscape of information dissemination, presenting a tool for narrowing the knowledge gap in maternal healthcare. The maternal e-services framework has the potential to capitalize on this advancement by providing a comprehensive array of educational resources in intuitive digital formats. This is paramount as digital content transcends geographical constraints, ensuring accessibility for mothers residing in remote areas. The framework is viewed to facilitate seamless updates and broadcasting of the latest evidence-based information. By offering diverse formats such as text articles, captivating videos, informative infographics, and downloadable audio for offline access, the framework will cater to varied learning preferences, empowering mothers with the requisite knowledge for informed decision-making. The majority of participants, comprising 58.3%, accessed maternal education in text form, indicating a predominant preference for textual information over multimedia. This contrasts with the findings presented in Table 1, where a larger portion of participants agreed on the importance of multimedia for maternal education. As a result, the framework should be developed with an emphasis on the significance of multimedia content to enhance the accessibility of maternal health information, ensuring alignment with user preferences and needs.

3.8 Emergency Response and Support Services

The widespread availability of smartphones with GPS capabilities, coupled with the emergence of real-time API integrations, signifies a transformative shift in emergency response for maternal health. In dire situations where a mother faces complications, the emergency features of applications could be activated. Leveraging the smartphone's GPS functionality and secure API connections, the application can transmit the mother's precise location to emergency medical services. This real-time location data holds the potential to significantly reduce response time by promptly dispatching the nearest transport services, such as an

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ambulance, through another secure API integration. This could provide the mother with access to virtual support resources or deliver targeted educational materials on managing emergencies until assistance arrives. This seamless integration of mobile technology, location-based services, and emergency response systems equips mothers with immediate assistance and essential knowledge during critical junctures, instilling a sense of security throughout their pregnancy journey. The aim of this was to understand the rate at which emergencies occur in maternal life (pregnancy, childbirth, and the postnatal period) and also the response time to these situations. Recognizing the inevitability of emergencies, a substantial majority of participants, 60%, confirmed encountering emergencies during maternal life, including pregnancy, childbirth, or the postpartum period. Despite this high number, only 8.3% reported accessing emergency support immediately or within an hour. With 71.7% of mothers experiencing delayed access to support due to the lack of quick and reliable ways to connect to healthcare centres during critical moments, there is an urgent need for an improved framework. The framework should prioritize integrating rapid response mechanisms, such as transport support services, to enhance timely assistance and support during emergencies in maternal life.

3.9 Telemedicine Consultations and Appointments

In today's digital world, advancements in technology are rapidly reshaping the landscape of healthcare delivery. Telemedicine consultations and appointment services are increasingly vital components of modern healthcare systems, particularly for geographically isolated communities or individuals facing mobility limitations. This trend is driven by the growing demand for remote healthcare services, fueled by factors such as convenience, accessibility, and the need for timely interventions. By eliminating the need for lengthy commutes, these services ensure timely access to essential healthcare, especially during critical periods like pregnancy. Utilizing appointment scheduling systems enables mothers to conveniently book appointments online and receive electronic reminders, overcoming geographical barriers and facilitating timely interventions. With this requirement in mind, the study aimed to investigate the state of queues and the presence of applications to manage the appointment process as one of the approaches to mitigate long queues. The study observed that the majority of participants, constituting 66.7%, encountered prolonged wait times in queues while seeking attention from healthcare professionals during their maternal journey. Additionally, 58.3% admitted the absence of platforms for handling appointments, whether web-based or mobile, to schedule appointments related to maternal healthcare, with an additional 13.3% (seven participants) expressing uncertainty about their usage. Although there may be existing tools supporting appointment booking in other healthcare domains [52], the comprehensive nature of the maternal health framework should also integrate such services to enhance accessibility and minimize delays in receiving maternal care.

Delving into the telemedicine aspect, the majority of participants, comprising 76.7%, endorsed the idea of engaging in remote consultations with healthcare professionals for maternal health issues, and 95% confirmed the convenience of these virtual meetings and consultations. In conjunction with appointment services, the framework can incorporate a dedicated component for integrating telemedicine consultations, recognizing the importance of remote consultations for maternal health support. This does not imply a replacement of physical facility visits but rather serves to assist and support the initiation and continuation of maternal care, especially in distance-constrained situations.

3.10 Treatments and Investigations Management Services

The proliferation of mobile health (mHealth) apps and secure online portals presents a significant opportunity for the maternal e-service framework to enhance medication adherence and treatment management. By integrating with e-prescription platforms, mothers can receive electronic medication prescriptions directly from healthcare providers. This process can be complemented by medication reminder apps to ensure timely dosing, significant portion, representing 86.6%, confirmed convenience in using a secure digital platform. This illustrates the critical role of data security measures in fostering user trust and promoting the adoption of mobile-based e-services.

Security being an important aspect in utilizing digital platforms, the majority of respondents, accounting for 55% highlighted that improved encryption methods are perceived as the most robust security mechanism in mobile health frameworks. This was followed by other mechanisms such as user education on privacy and data, with 41.7% endorsing this approach. In consideration of these preferences, the framework can contemplate the implementation of robust security measures, including but not limited to password protection and data encryption, to ensure the security of user data when accessing maternal services. These measures aim to address the security concerns and privacy needs of users.

4 Discussions

This study focuses on low-resource countries, characterized by limited technology adoption, with Uganda serving as a case study for developing nations. The integration of technology-based innovations in maternal health services remains minimal in these settings. Instead, traditional methods are predominantly used to support maternal health. A common practice is maternal education delivered through antenatal visits to health facilities. However, these traditional approaches come with significant challenges. The long distances between homes and health facilities, geographical barriers, and adverse climatic conditions can endanger the lives of pregnant women. Additionally, during the COVID-19 pandemic, physical meetings were restricted, further complicating access to these services. Health facilities often face long queues due to a shortage of healthcare workers, resulting in delayed care. Emergencies in maternal health are also inadequately addressed under these constraints. These limitations highlight the urgent need for improved technological interventions in maternal health services in low-resource countries. Numerous frameworks such as 1) The Mobile Alliance for Maternal Action (MAMA) framework [43,44], 2) the AI Pregnancy Companion Chatbot (PCC) Framework [45,46], 3) the AI Framework for Fetal Health Status Prediction [47], 4) The Mobile Health Communication Framework for Postnatal Care in Rural Kenya [22], [48], 5) The Mobile Health Messaging Service and Helpdesk Framework for South African Mothers (MomConnect) [49]. 6) KIA E-Health Framework Maternal and Child Health Services in Indonesia [50] have been studied to support access to maternal e-services to improve maternal healthcare delivery. However, these frameworks have predominantly focused on maternal education delivered through SMS and mobile messages as systematically reviewed and discussed by Ssegujja et al [51]. There has been little emphasis on other e-services that have the potential to enhance maternal healthcare delivery significantly.

Reflecting on these limitations, we have investigated the determinants and requirements necessary for designing a maternal e-services framework. Given the widespread use of mobile devices 96.7% of respondents reported having access to them the proposed framework should be mobile health-driven. This focus leverages the proliferation of mobile technology to address the identified needs. The framework will provide guidelines for developing mobile applications that translate these requirements into practical solutions, taking into account the relevant factors and determinants. Key determinants have been identified, each contributing to the selection of requirements for an effective maternal e-services framework. The table below illustrates the relationship between these factors and the corresponding requirements:

Table 7. Requirements for designing an mHealth framework to enhance the delivery and support of maternal e-services with supporting factors presented as determinants

Determinant	Supported Requirement	Code
Age variations	Multimedia content delivery for maternal education	R001
Language Proficiency	Integrating multilingual capabilities in maternal e-services delivery	R002
Area of Residence and Internet Affordability	Enabling data persistence for offline access even with no active internet content e.g., for maternal education information	R003
Possession of Mobile devices	Adoption of mobile application resulting from the framework implementation	R004
Utilization of maternal e-services and stage accessed	Ensuring service delivery to support mothers across all levels of maternal health typical prenatal, delivery/childbirth and postnatal.	R005
Geographic barriers	Offering access to services tailored to mother's location	R006
	Introducing telemedicine consultations for remote patient management	R007
Long Queues in health facilities seeking of maternal health support	Enabling appointment management services	R008
Occurrence of emergencies	Integrating emergency support services	R009

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Occurrence of medical challenges and forgetting medical prescriptions during maternal health	Integrating Treatments and Investigations Management services	R010
Need for security and convenience in using secure application	Integrating encryption protocols, secure logins, and robust access controls serve as vital safeguards for protecting sensitive maternal health information	R011

Proper attention to identified requirements and their determinants has the potential to significantly improve access to maternal e-services in low-resource settings. Considering factors such as age variations, language proficiency, geographic barriers, the occurrence of emergencies, possession of mobile devices, and the need for security and convenience in using secure applications, a comprehensive maternal e-services framework can be developed. This framework will facilitate the creation of user-friendly, multilingual mobile applications that function offline, provide real-time emergency support, and offer telemedicine consultations. Such a comprehensive approach ensures that maternal health services are more accessible, timely, and effective, ultimately leading to better health outcomes for mothers and their children. The integration of secure application protocols further enhances the reliability and trustworthiness of these e-services, encouraging widespread adoption and sustained usage.

Despite their complementary nature, certain requirements present contradictions that must be addressed for effective implementation. For instance, multimedia content delivery (R001) depends on internet connectivity, which may be costly or unreliable in low-resource settings. Therefore, offline access (R003) becomes essential to address this limitation by allowing pre-downloaded or cached low-bandwidth content, such as text summaries or compressed audio, to ensure continuous access to maternal education and support even without internet connectivity. Telemedicine also typically depends on real-time internet connectivity, which conflicts with the need for offline access in regions with poor or unstable networks. This can be resolved by incorporating asynchronous telemedicine options, such as text-based consultations or pre-recorded video guidance, which function offline or with intermittent connectivity, while still allowing real-time consultations when stable internet access is available.

5 Summary and Future Work

In conclusion, developing a mobile health-driven maternal e-services framework has the potential to greatly enhance maternal healthcare delivery, especially in low-resource settings. By addressing everyday challenges faced by pregnant and new mothers such as difficulty reaching healthcare facilities, long waiting times, limited support during complications, lack of guidance on maternal care, and interruptions in follow-up care while also ensuring data privacy and security, such a framework can use mobile technologies to provide timely, accessible, and user-centred maternal healthcare.

Future work should focus on the design, development, and practical implementation of this framework. This includes creating detailed technical guidelines that integrate the identified user requirements, Human Computer Interaction principles, and healthcare delivery standards to offer maternal e-services in a comprehensive, cohesive, and contemporary manner. Pilot studies across different regions should be conducted to evaluate the framework's effectiveness, usability, and scalability, ensuring that it accommodates diverse user needs and contextual challenges.

Additionally, continuous refinement of mobile applications within the framework is essential. This involves iterative testing with real users, collecting feedback to enhance usability, accessibility, and reliability, and adapting the system to incorporate emerging technologies and healthcare protocols. Ultimately, the aim is to create a robust, inclusive, and practical maternal e-services platform that supports mothers across pregnancy, childbirth, and the postnatal period, thereby contributing to improved maternal health outcomes at scale.

Statement on Conflicts of Interest

The authors declare no conflict of interest

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Influence of Demographic Characteristics on Health Workers' Acceptance of Biometric-Controlled Health Informatics Systems: Evidence from Selected Regional Referral Public Hospitals in Uganda

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The integration of biometric technology into health informatics promises improved security and efficiency in healthcare delivery, yet its success hinges on end-user acceptance, particularly in low-resource settings where health workers' attitudes and experiences may differ markedly from those in high-income contexts. While demographic factors such as age, gender, education, and professional experience are known to influence technology adoption more broadly, their specific impact on health workers' acceptance of Biometric Controlled Health Informatics (BCHI) in Ugandan public hospitals remains underexplored. The study therefore aimed to examine how these key demographic variables shape health workers' acceptance of BCHI, using the Technology Acceptance Model (TAM) as the guiding theoretical framework. A quantitative, cross-sectional design was employed, involving 244 clinical and non-clinical health workers from two regional referral hospitals in Uganda, with data collected through a structured, self-administered questionnaire that measured core TAM constructs including attitude, actual usage, perceived usefulness, perceived ease of use, and behavioral intention; the instrument demonstrated good reliability (Cronbach's α 0.885–0.920). Multiple linear regression analyses were then used to assess the unique predictive power of each demographic factor on the TAM constructs. The findings revealed that gender and education level were significant predictors of BCHI acceptance, whereas age and years of professional experience were not. Male health workers reported less favorable attitudes, lower perceived usefulness and ease of use, and reduced actual usage compared to their female counterparts, while Certificate/Diploma-qualified staff showed the highest acceptance across most constructs and Bachelor's degree holders consistently reported lower acceptance, especially for perceived ease of use. In conclusion, acceptance of BCHI among Ugandan health workers is not uniform but is distinctly patterned by gender and educational background, underscoring the need for differentiated implementation strategies, tailored communication and training for male staff and degree-holding cadres, and deliberate use of Certificate/Diploma-level staff as champions to support a more effective, context-sensitive rollout.

Keywords: Biometric technology, Technology acceptance, Health informatics, Demographic factors, Uganda.

1 Introduction

The integrity of medical records is fundamental to safe and effective healthcare delivery [1]. In Uganda, as in many healthcare systems around the world, protecting medical records from unauthorised access and tampering is a critical challenge with direct consequences for patient safety. Documented incidents, such as the case of newborn swapping at Mulago National Referral Hospital linked to the illicit alteration of medical documents, show the severe risks posed by weak identity verification and access control systems [2]. Such breaches facilitate medical fraud, compromise clinical decision-making, and erode public trust in healthcare institutions. Biometric controlled health informatics (BCHI) systems embed fingerprint, facial recognition or other biometric sensors into electronic health record platforms to streamline patient identification; secure data access, and improve service delivery. Medical records are crucial for maintaining

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a patient's health history, documenting treatments, tracking progress, and ensuring continuity of care [3]. To maintain patient confidentiality and privacy, access to these records is typically restricted to authorised healthcare providers [4]. Biometrics, which encompasses unique physical or behavioural characteristics, offers a method for individual identification [5]. These identifiers include physiological traits such as the face, fingerprint, iris, retina, hand geometry, and ear shape, as well as behavioural traits such as signature, gait, speech, and handwriting [5,6]. Thus, the integration of biometric systems into healthcare informatics represents a transformative frontier in healthcare delivery, promising to enhance security, streamline patient identification, and improve the accuracy of health records [7,8,9]. Biometric technologies, which authenticate individuals based on their unique physiological and behavioural characteristics such as fingerprints, iris patterns, or facial recognition, offer a robust alternative to traditional identification methods which are prone to error and fraud [10,5,11]. These systems can safeguard sensitive patient data, ensure better linkage of medical information to the correct individual, and control access to critical healthcare applications and physical areas, thereby forming a cornerstone of modern, secure health informatics infrastructure [12, 13,14].

However, the successful deployment and efficacy of any technological innovation in healthcare are fundamentally contingent upon its acceptance by the end-users, who are the health workers who interact with systems daily [15,16]. As noted by [17], technology acceptance is deeply influenced by the perceptions and attitudes of its users [17]. In hospitals, where workflow efficiency and data integrity is paramount, user resistance can significantly undermine the potential benefits of even the most advanced systems [18]. Demographic variables such as gender, ethnicity, education, and age play a significant role in shaping technology acceptance [19,20]. For instance, studies in other sectors indicate that younger individuals may exhibit higher familiarity and comfort with new technologies, while differences based on professional specialisation can affect perceived usefulness and ease of use [21]. Within healthcare, these demographic factors may intersect with unique professional norms, concerns about patient privacy, and the high-stakes clinical environment, creating a complex landscape for biometric adoption [22].

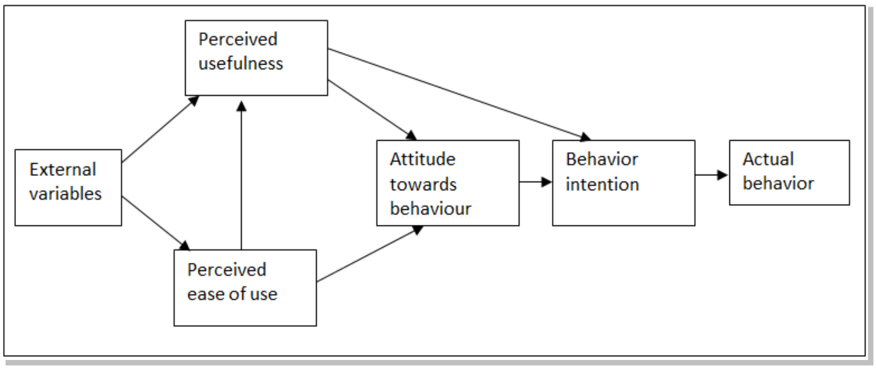

Fig. 1. Technology Acceptance Model (TAM), adopted for the study

This study is grounded in the Technology Acceptance Model (TAM), the predominant theoretical framework for investigating individual acceptance of information systems as show in Figure 1 above [23]. Originally adapted from the Theory of Reasoned Action [24], TAM posits that an individual's behavioural intention to use a technology is primarily determined by their perceived usefulness (the degree to which a person believes using the system will enhance their job performance) and perceived ease of use (the degree to which a person believes using the system will be free of effort) c. In the context of this research, these core TAM constructs – Perceived Usefulness, Perceived Ease of Use, and the resulting Behavioural Intention – operationalise the dependent variable: Acceptance of Biometric Controlled Health Informatics (BCHI). The model provides the essential mechanism to investigate this study's central question: how the independent variables, namely demographic characteristics of health workers in Ugandan public hospitals, influence these foundational perceptions and, consequently, their overall acceptance of the biometric system. By applying TAM, the study moves beyond merely documenting acceptance levels to explaining the psychological and contextual pathways through which individual differences shape technology adoption in a critical healthcare setting.

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In several African countries, biometric systems are being implemented to enhance various aspects of healthcare administration. For instance, in Kenya and Uganda, biometric technology is utilised to monitor healthcare worker attendance in rural settings, aiming to improve accountability and service delivery [25]. Concurrently, nations such as Ghana, Rwanda, and Zambia have adopted biometric systems for health insurance enrolment and identity verification. This application seeks to prevent fraudulent enrolment and streamline administrative processes, thereby increasing the efficiency of health insurance schemes [26]. Despite the clear importance of user demographics, research specifically examining their influence on acceptance of biometric systems among health workers in Uganda remains sparse. Most studies on biometrics in healthcare have focused on technical feasibility, accuracy, or broad surveys of patient attitudes, leaving a gap in understanding the healthcare professional's perspective [27].

Ugandan public hospitals have documented cases of medical record tampering [2]. Such breaches compromise patient safety, enable medical fraud, and erode institutional trust. Biometric authentication technology offers a potential solution through its unique ability to link digital identities to immutable physiological characteristics, making unauthorised access extremely difficult. The Ugandan Ministry of Health has recognised this potential, with Dr Tumwesigye endorsing fingerprint biometrics for tracking antiretroviral therapy patients as part of the national e-health strategy [28]. However, implementation success depends fundamentally on user acceptance. Research consistently identifies healthcare professional resistance as a critical barrier to biometric system adoption [29,30]. Concerns about privacy invasion, data security, and technological complexity drive this reluctance [31,32]. While studies have examined the technical feasibility of biometrics in healthcare and broad patient attitudes, there is a scarcity of research specifically investigating how the demographic profiles of healthcare professionals influence their acceptance of these systems [27]. The purpose of this study is to investigate the influence of demographic factors on the acceptance of Biometric-Controlled Health Informatics (BCHI) among health workers in Ugandan public hospitals. The study is grounded in the Technology Acceptance Model (TAM), which provides a framework for understanding how perceptions of usefulness and ease of use drive behavioural intention and actual use [23]. The primary research question guiding this inquiry is how do key demographic characteristics (age, gender, educational level, professional cadre, and years of experience) influence health workers' acceptance of biometric-controlled health informatics systems in Ugandan public hospitals?

2 Materials and methods

This research employed a quantitative, correlational study design to assess the influence of demographic factors on the acceptance of Biometric Controlled Health Informatics (BCHI). The design was embedded within a larger sequential explanatory mixed-methods framework, with this specific objective addressed by the initial quantitative phase [33]. The study protocol received full ethical approval from the Unicaf University Research Ethics Committee (UREC), the Uganda National Council for Science and Technology (UNCST), and the Uganda National REC. Prior to participation, all subjects provided written informed consent, having been fully informed of the study's purpose, their right to withdraw at any time without consequence, and the measures in place to ensure the confidentiality and anonymity of their data. The source population was defined as all clinical and non-clinical health workers employed at two public regional referral hospitals in Uganda: Gulu Regional Referral Hospital and Soroti Regional Referral Hospital. Eligibility criteria included being a formally employed health worker (clinical or non-clinical) at one of the two study sites during the data collection period. There were no exclusion criteria based on department or role, as the aim was to capture a holistic view of the hospital workforce. Participant selection aimed for a representative sample to allow for generalisation of findings related to demographic influences [34].

A systematic random sampling technique was applied to obtain a probability sample from the available staff lists (sampling frames) provided by the human resources departments of both hospitals [35]. This method ensured every eligible health worker had a known, equal chance of selection, minimising selection bias. The sample size was determined a priori using a precision-based formula for a finite population [36], with inputs of a 95.5% confidence level ($Z=2.005$), maximum variability ($p=0.5$), and a desired precision (e) of 0.02. This calculation yielded a target sample of 127 participants from Gulu RRH and 117 from Soroti RRH, for a total of $N=244$.

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The primary research instrument was a structured, self-administered questionnaire [37,38]. The questionnaire comprised several sections. Section A collected data on the independent demographic variables: age (continuous), gender (categorical), highest educational level (ordinal), years of professional experience in healthcare (ordinal), and professional cadre. Section D measured the dependent variable (BCHI acceptance) using a modified version of the established Technology Acceptance Model (TAM) questionnaire [23, 39]. This section contained multi-item scales measuring Perceived Usefulness (4 items), Perceived Ease of Use (3 items), and Behavioural Intention to Use (2 items). All items used a five-point Likert response format from 'Strongly Disagree' to 'Strongly Agree' [40]. Data collection was conducted on-site at the two hospitals. Questionnaires were distributed to selected participants and collected upon completion, ensuring a high response rate and data integrity.

All quantitative data were prepared and analysed using IBM SPSS Statistics (Version 29). The analysis plan for this objective was formulated as follows. First, descriptive statistics (frequencies, percentages, means, and standard deviations) were computed to describe the sample's demographic composition and summarise the scores on the acceptance scales. Second, inferential statistics were employed to test the relationships between demographics and acceptance. Independent samples t-tests and one-way Analysis of Variance (ANOVA) were used to compare mean acceptance scores across categorical demographic groups (e.g., gender and education categories). Correlation analysis (Pearson's or Spearman's) assessed the relationship between continuous/ordinal variables (age, experience) and acceptance scores. Finally, a standard multiple linear regression analysis was conducted as the primary model to evaluate the unique contribution of each demographic factor while controlling for the others, assessing overall model fit (R^2) and the significance of individual predictors (β coefficients) [41]. the quantitative analysis identified statistical relationships, the sequential design allowed for subsequent qualitative data to be used interpretively. [42, 43, 44].

3 Results

The study findings are structured to first establish the robustness of the measurement instruments and the distributional properties of the data. It then provides a demographic profile of the participant before regression analyses. The analyze examine the influence of key demographic factors namely age, gender, and education level on health workers' acceptance of Biometric Controlled Health Informatics (BCHI), as measured by the core constructs of the Technology Acceptance Model: which are Perceived Usefulness, Perceived Ease of Use, Attitude, Actual Usage, and Behavioral Intention.

Reliability refers to the consistency, stability, and repeatability of a measurement instrument or procedure [45] indicating that repeated administration of the same instrument should yield consistent results. In this study, the reliability of the five key constructs used to measure the influence of demographic factors on the acceptance of Biometric Controlled Health Informatics (BCHI) among health workers was rigorously assessed to ensure the validity of the quantitative findings.

Table 1. Cronbach Reliability Statistics Results

Construct	No. of Items	Cronbach's α
1. Perceived Usefulness	5	.920
2. Perceived Ease of Use	6	.885
3. Attitude	5	.893
4. Actual Usage	6	.891
5. Behavioral Intention	5	.919

This reliability analysis confirms that all five constructs measuring health workers' acceptance of Biometric Controlled Health Informatics (BCHI) systems in Ugandan public hospitals show strong to excellent internal consistency. The Cronbach's alpha coefficients, ranging from .885 to .920, all comfortably exceed the conventional threshold of .70 [46], indicating the scales are reliable for use in subsequent analyses.

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Perceived Usefulness (α = .920) and Behavioral Intention (α = .919) exhibit excellent reliability. These are core constructs in technology acceptance models and are central to the study's second research question, which investigates the relationship between personality traits and BCHI acceptance. Their high reliability ensures that measurements of health workers' perceptions about the utility of BCHI systems and their actual intention to use them are stable and consistent.

Perceived Ease of Use (α = .885), Attitude (α = .893), and Actual Usage (α = .891) all demonstrate good reliability. These scales are crucial for understanding the practical and psychological barriers to adoption highlighted in the problem statement, such as user reluctance, privacy concerns, and the challenges of integrating new technology into clinical workflows. The reliable measurement of Actual Usage is particularly important for exploring the influence of demographic factors like experience, as outlined in the third research question.

The results on the normality assessment indicate that all five variables meet the assumptions required for parametric statistical analysis. As presented in Table 1, the skewness values for the variables range from -0.215 to 0.112. According to established psychometric guidelines, skewness values between -0.5 and +0.5 are generally considered acceptable for assuming a normal distribution in social science research [47, 48]. This aligns with recent methodological research, which confirms that for most statistical models in the health sciences, the effect of skewness is negligible within this range [49]. In our data, Attitude shows minimal positive skewness (0.112), and Perceived Easiness exhibits slight negative skewness (-0.215). The skewness values for Actual Usage (-0.029) and Perceived Usefulness (0.009) approach perfect symmetry, while Behavioural Intention demonstrates acceptable negative skewness (-0.101). Regarding kurtosis, all variables display negative values ranging from -0.157 to -0.846. Field (2024) notes that kurtosis values within approximately ±1.0 are generally acceptable for most parametric analyses, a guideline supported by Hatem et al. (2022), who emphasise that such minor deviations from mesokurtosis (kurtosis = 0) do not significantly compromise the validity of standard tests like ANOVA or linear regression [50, 51]. The obtained values fall well within this acceptable range, indicating slightly flatter-than-normal distributions, which is a common and manageable pattern in applied research [52]. Furthermore, with an adequate sample size (N=244), the central limit theorem ensures the robustness of parametric inference even when mild deviations in distributional shape are present, reinforcing the suitability of these variables for subsequent analysis [49].

The normality of all five variables Attitude, Actual Usage, Perceived Usefulness, Perceived Ease of Use, and Behavioural Intention toward Biometric-Controlled Health Informatics was assessed to validate assumptions for parametric analysis. This statistical evidence was shown by the normality probability plots, in which the observed data points closely followed the diagonal reference line, confirming the absence of significant skew or outliers. With an adequate sample size (N = 244) and the assurances afforded by the Central Limit Theorem, the robustness of parametric inference is further supported. Consequently, these variables are deemed suitable for subsequent parametric regression analysis.

Table 2. Participant Demographics

Characteristic	Categories	Frequency (n)	Percentage (%)	Mean(SD)
District / Hospital	Gulu	127	52.0	
	Soroti	117	48.0	
Gender	Female	127	52.0	
	Male	117	48.0	
Age (Years)				**38.02 (9.239)**
Education Level	Basic	10	4.1	
	Certificate/Diploma	98	40.2	
	Bachelor's Degree	108	44.3	
	Master's Degree	23	9.4	
	PhD	5	2.0	
Years Employed	Less than 1 year	14	5.7	
	1-5 years	62	25.4	
	5-10 years	94	38.5	

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	10-15 years	40	16.4	
	15+ years	34	13.9	

The demographic characteristics of the 244 participating health workers from Gulu and Soroti Regional Referral Hospitals are presented in Table 1. The sample was nearly evenly split by hospital location, with 52.0% (n=127) from Gulu and 48.0% (n=117) from Soroti, and by gender, with 52.0% female and 48.0% male participants. The average age of respondents was 38.02 years (SD = 9.239). In terms of educational attainment, the majority held a post-secondary qualification: 40.2% possessed a certificate or diploma, 44.3% held a bachelor's degree, and 11.4% had completed postgraduate studies (master's or PhD). Only 4.1% reported a basic level of education as their highest. Regarding professional tenure, the sample were experienced, with most health workers (38.5%) having served for 5-10 years. A combined 68.8% had more than five years of service, while a smaller proportion (5.7%) had been employed for less than one year. This profile indicates a sample of mature, educated, and experienced health professionals, providing a solid foundation for examining how these demographic factors relate to the acceptance of biometric technology.

The regression analysis reveals which demographic factors significantly predict health workers' overall attitude toward Biometric Controlled Health Informatics (BCHI). Gender emerged as a significant predictor ($\beta = -.180$, $p = .005$), indicating that, compared to females, male health workers reported a significantly less favourable attitude toward the technology, holding other factors constant. Educational level also showed significant effects, with the bachelor's degree category serving as the reference. Health workers with a basic education level ($\beta = .138$, $p = .030$), a certificate/diploma ($\beta = .214$, $p = .002$), and a master's degree ($\beta = .169$, $p = .010$) all reported significantly more positive attitudes than those holding a bachelor's degree. Notably, attitudes among PhD holders did not differ significantly from Bachelor's degree holders. In contrast, age was not a statistically significant predictor of attitude in this model ($\beta = .044$, $p = .495$). Collectively, these results suggest that professional gender and specific educational backgrounds are key demographic dimensions influencing acceptance, while age, within this sample, does not appear to be a determining factor.

Table 3. Regression Analysis of Demographic Factors Predicting Actual Usage of BCHI

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.226	.053		23.090	.000
	Age	.001	.001	.045	.713	.477
	Gender	-.048	.022	-.133	-2.159	.032
	Basic level of education	.126	.056	.140	2.259	.025
	Certificate/Diploma level of education	.107	.024	.295	4.488	.000
	Masters level of education	.112	.039	.184	2.885	.004
	PhD level of education	.212	.077	.169	2.740	.007

a. Dependent Variable: **Actual Usage of BCHI**

The regression analysis of demographic predictors on the log-transformed Actual Usage of Biometric Controlled Health Informatics (BCHI) as shown in Table 3 above reveals a distinct pattern of significant influences. Mirroring the findings for attitude, gender remains a significant predictor ($\beta = -.133$, $p = .032$), with male health workers reporting significantly lower levels of actual usage compared to their female counterparts. Educational level demonstrates even more pronounced and widespread significance in predicting usage behavior. Using a bachelor's degree as the reference category, health workers at nearly every other educational level reported significantly higher log-transformed usage scores. This includes those with a basic education ($\beta = .140$, $p = .025$), a certificate/diploma ($\beta = .295$, $p < .001$), a master's degree ($\beta = .184$, $p = .004$), and notably, those with a PhD ($\beta = .169$, $p = .007$). The strong, positive coefficient for the Certificate/Diploma group suggests they are the most active users relative to bachelor's degree holders. Consistent with the attitude model, age was not a statistically significant

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predictor of actual usage (β = .045, p = .477). These results indicate that while gender and educational background are robust demographic determinants of both attitude and practical engagement with BCHI, educational attainment exhibits a particularly strong and consistent relationship with the level of actual system use.

Table 4. Regression Analysis of Demographic Factors Predicting Perceived Usefulness towards BCHI

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.221	.054		22.798	.000
	Age	.002	.001	.098	1.551	.122
	Gender	-.058	.022	-.163	-2.616	.009
	Basic level of education	.061	.056	.068	1.078	.282
	Certificate/Diploma level of education	.101	.024	.279	4.202	.000
	Masters level of education	.044	.039	.073	1.139	.256
	PhD level of education	-.132	.078	-.105	-1.686	.093

Coefficients[a]

a. Dependent Variable: **Perceived Usefulness of** BCHI

The regression analysis examining the demographic predictors of perceived usefulness as shown in Table 4 above reveals a more selective pattern of influence compared to attitude and actual usage. Gender again emerges as a significant predictor (β = -.163, p = .009), with male health workers perceiving the biometric system as significantly less useful than female workers when controlling for other variables. Regarding educational level, only one group showed a statistically significant difference from the bachelor's degree reference category. Health workers holding a certificate/diploma reported a significantly higher perception of the system's usefulness (β = .279, p < .001). In contrast, those with a basic education (β = .068, p = .282), a master's degree (β = .073, p = .256), and a PhD (β = -.105, p = .093) did not differ significantly from bachelor's holders in their perceived usefulness scores, though the negative coefficient for PhD holders approaches significance and suggests a trend toward lower perceived usefulness. Age remained a non-significant predictor in this model (β = .098, p = .122). These findings suggest that while gender influences perceptions across dimensions, the belief that the technology enhances job performance (perceived usefulness) is most strongly and uniquely associated with health workers who have mid-level vocational training (certificate/diploma), rather than those with higher academic degrees.

Table 5. Regression Analysis of Demographic Factors Predicting Perceived Easiness of BCHI

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.330	.047		28.543	.000
	Age	.000	.001	-.016	-.245	.806
	Gender	-.063	.019	-.204	-3.255	.001
	Basic level of education	.115	.049	.149	2.356	.019
	Certificate/Diploma level of education	.046	.021	.145	2.180	.030
	Masters level of education	.075	.034	.143	2.219	.027
	PhD level of education	.157	.068	.144	2.306	.022

Coefficients[a]

a. Dependent Variable: **Perceived Easiness of BCHI**

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The regression analysis for Perceived Ease of Use as shown in Table 5 above presents the most consistent and widespread demographic influence observed across all TAM constructs. Gender maintained a strong and significant negative relationship (β = -.204, p = .001), indicating that male health workers find the biometric system significantly less easy to use than their female colleagues. Notably, in contrast to other models, every educational level demonstrated a significant positive effect on perceived ease of use when compared to the Bachelor's degree reference group. Health workers with a Basic education (β = .149, p = .019), a Certificate/Diploma (β = .145, p = .030), a Master's degree (β = .143, p = .027), and a PhD (β = .144, p = .022) all reported finding the system easier to use than those holding a Bachelor's degree. The standardized coefficients (Beta) are remarkably similar across these groups, suggesting a uniform educational advantage over the reference category. As with all previous models, age was not a significant predictor (β = -.016, p = .806).

Table 6. Regression Analysis of Demographic Factors Predicting Behaviour intention towards BCHI

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.232	.057		21.648	.000
	Age	.001	.001	.061	.946	.345
	Gender	-.036	.024	-.098	-1.539	.125
	Basic level of education	.100	.060	.107	1.665	.097
	Certificate/Diploma level of education	.077	.026	.203	2.997	.003
	Masters level of education	.118	.042	.187	2.851	.005
	PhD level of education	.145	.083	.111	1.743	.083

Coefficients[a]

a. Dependent Variable: **Behaviour intention towards BCHI**

The regression analysis for behavioural intention as shown in Table 6 above reveals a pattern distinct from the other Technology Acceptance Model (TAM) constructs. Unlike the consistent findings for attitude, actual usage, perceived usefulness, and perceived ease of use, gender was not a statistically significant predictor of intention to use the biometric system in the future (β = -.098, p = .125). This suggests that while gender influences current attitudes, perceptions, and usage, it does not directly predict the future intention to adopt the technology when other demographic factors are controlled. For educational level, the findings show partial significance. Health workers with a Certificate/Diploma (β = .203, p = .003) and those with a Master's degree (β = .187, p = .005) reported significantly stronger behavioral intentions than those with a Bachelor's degree. The coefficients for those with a basic education (β = .107, p = .097) and a PhD (β = .111, p = .083) were positive and approached but did not reach conventional statistical significance. As with all other models, Age was not a significant predictor (β = .061, p = .345). These results indicate that future adoption intentions are most strongly shaped by specific mid-to-high levels of formal education (certificate/diploma and master's), while the influence of gender dissipates at this forward-looking stage of the acceptance process.

4 Discussion

The findings reveal that gender and educational attainment significantly predict BCHI acceptance among health workers, while age shows no effect. Notably, male participants reported less favorable attitudes, lower perceived usefulness and ease of use, and reduced actual usage compared to females—a pattern contrasting general technology adoption literature but rooted in healthcare-specific dynamics.

Male health workers voiced strong concerns about perceived surveillance and loss of autonomy, describing BCHI as "being watched" or "micromanaged," viewing it primarily as a tool to monitor presence rather than support clinical work. This ties into a threat to professional authority, where several male clinicians felt mandatory biometric checks contradicted their seniority and experience, framing the system

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as infantilizing. Adding to this, men often expressed skepticism about benefits, questioning how BCHI truly improved patient care and seeing it mainly as an administrative burden. These perceptions may explain the gender gap, aligning with biometric privacy research where men show higher skepticism , though the disparity vanishes when predicting future behavioral intention—indicating initial resistance doesn't derail long-term commitment.

Educational attainment emerged as the most nuanced predictor, defying a simple linear link to acceptance. Certificate/diploma holders—the core clinical and administrative workforce—demonstrated the highest levels across perceived usefulness, ease of use, and usage. Bachelor's degree holders (the largest group) lagged, especially in ease of use, where all others rated the system higher. This suggests vocational training better equips users for task-oriented tools like BCHI, while bachelor's-linked factors (e.g., workflows, expectations) create barriers. These results extend prior work on professional background in health IT, challenge biases favoring "highly educated" staff, and support non-significant age effects in professional contexts .

Integrating Alomari and Soh's UTAUT-HS model[53] for mIoT in Saudi hospitals reinforces these insights: Performance Expectancy and Social Influence drive intent, with Computer/English Self-Efficacy (CESE) as a strong predictor [53]. Their moderators highlight demographic variations, including Perceived Threat to Autonomy (PTA) for clinicians vs. non-clinicians and older users [53]. This synthesizes with Kitsiou et al. on demographics, Sultana and Akter [55] on psychological readiness, and James et al. [56] on biometric privacy/invasiveness.

Thus, BCHI implementation demands a holistic framework addressing this interplay. Strategies should tailor to demographics (e.g., clinicians, males, diploma holders), build self-efficacy, harness social influence, and design systems minimizing surveillance/autonomy threats—transparently balancing security, privacy, and invasiveness.

5 Conclusion

The research demonstrated that personality traits, demographics (such as age, education, and experience), and TAM factors (perceived usefulness and ease of use) together accounted for 52% of the variance in attitudes toward BCHI. Supporting qualitative evidence highlighted organizational factors like training in mitigating resistance.

These results connect directly to the study's aims and research questions, backed by robust empirical data (statistics, participant quotes, and models), underscoring BCHI's promise for improving accountability and efficiency in resource-constrained environments through complementary training and change management. A mixed-methods approach enhanced validity by combining quantitative results (e.g., surveys of 244 health workers indicating 57% familiarity with biometrics and SEM analyses accounting for 45-52% variance in acceptance and attitudes). This triangulation provided comprehensive insights into BCHI adoption challenges in Ugandan hospitals.

Practically, the study recommends focused strategies, including training for non-technical personnel (limited to 57% attendance-tracking familiarity) and solutions for technical glitches. Implementing these could propel BCHI adoption in Gulu and Soroti hospitals, strengthening data security, attendance accountability, and operational efficiency in line with Uganda's e-health agenda for reliable public health services.

Furthermore, policymakers in Uganda, including the Ministry of Health, Public Service Commission, district administrations, and ICT Authority, should draw on these insights to initiate staged BCHI pilots incorporating uniform standards, role-specific training, infrastructure improvements, and stringent privacy safeguards—advancing a user-centric digital health evolution.

Finally, future research should integrate advanced methodologies, widen geographic coverage, and probe additional variables to counter this study's shortcomings, notably its restriction to two regional referral hospitals, heavy reliance on qualitative methods, and limited depth in assessing personality effects, infrastructure issues, and enduring results.

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A Context-Aware Information Systems Architecture for Sustainable E-Health Implementation in the Democratic Republic of Congo

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Background and Purpose: The digital transformation of healthcare systems through e-health technologies has become a strategic priority for improving healthcare accessibility, efficiency, and quality, particularly in developing countries. However, successful implementation requires not only user adoption but also robust, interoperable, and secure information systems architectures adapted to local contexts. This study aims to propose a context-aware information systems architecture to support sustainable e-health implementation in the healthcare sector of the Democratic Republic of Congo (DRC), where infrastructural constraints and institutional challenges remain significant barriers
Methods: The study builds upon an empirically validated e-health adoption model derived from integrated Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) constructs. Key technological, organizational, and institutional requirements were identified and translated into architectural design specifications. A layered architecture approach was adopted, incorporating interoperability standards, data security mechanisms, privacy protection, and modular components to ensure compatibility with existing health information systems and adaptability to resource-constrained environments.
Results: The proposed architecture comprises five interrelated layers: infrastructure, application, data management, interoperability, and security governance. The framework addresses contextual challenges such as limited ICT infrastructure, intermittent connectivity, and varying levels of digital literacy among healthcare professionals. It supports essential digital health services, including electronic health records, telemedicine, health information exchange, and mobile health applications. The architecture demonstrates scalability, flexibility, and resilience, enabling phased implementation and long-term sustainability.
Conclusions: By aligning technological design with empirically identified adoption determinants and policy requirements, the proposed framework contributes to both digital health implementation practice and information systems architecture research in resource-constrained settings. The study provides practical guidance for policymakers, healthcare institutions, and system designers seeking to deploy sustainable e-health solutions in the DRC and similar developing healthcare systems.

Keywords: E-Health, Information Systems Architecture, Digital Health, Health Informatics, Interoperability, Developing Countries, Democratic Republic of Congo Introduction

1 Introduction

The digital transformation of healthcare systems has emerged as a global priority aimed at improving the accessibility, efficiency, and quality of healthcare services. Advances in information and communication technologies have enabled the development of various digital health solutions, including electronic health records, telemedicine platforms, mobile health applications, and health information exchange systems [1]. These technologies have the potential to enhance clinical decision-making, streamline health service delivery, and improve patient outcomes [2]. In recent years, governments and international organizations have increasingly recognized the strategic importance of digital health in strengthening healthcare systems and achieving universal health coverage [3]. E-health systems enable better management of medical

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information, facilitate communication between healthcare providers, and support data-driven healthcare policies. As a result, digital health has become a key component of healthcare modernization strategies worldwide [4].

Despite these opportunities, the implementation of e-health systems requires more than the simple deployment of digital technologies. Successful digital health initiatives depend on the existence of robust information systems architectures capable of supporting interoperability, data security, system scalability, and integration with existing healthcare infrastructures [5]. Although digital health technologies offer significant benefits, their implementation remains particularly challenging in developing countries. Many healthcare systems in low- and middle-income countries face structural constraints such as limited ICT infrastructure, unreliable internet connectivity, insufficient technical expertise, and inadequate financial resources [6]. These limitations often hinder the effective deployment and sustainability of digital health initiatives.

In addition to technological barriers, institutional and organizational challenges may also affect the adoption and implementation of e-health systems [7]. Healthcare institutions may lack the necessary governance structures, regulatory frameworks, and technical support mechanisms required to manage complex digital infrastructures. Furthermore, varying levels of digital literacy among healthcare professionals may limit the effective use of digital health technologies in clinical practice [8].

In fragile healthcare systems such as that of the Democratic Republic of Congo, these challenges are further amplified by broader socio-economic constraints and infrastructural limitations. system interoperability, data integration, security management, and long-term sustainability [9]. In many cases, digital health solutions are implemented as isolated systems that lack the ability to communicate effectively with other healthcare information systems.

In the Democratic Republic of Congo, the healthcare sector has witnessed increasing interest in the adoption of digital health technologies aimed at improving health information management and service delivery [10].However, the absence of a comprehensive and context-aware information systems architecture has limited the effective integration of digital health solutions across healthcare institutions [3].As a result, many digital health initiatives struggle to achieve long-term sustainability due to the absence of integrated and context-adapted information systems architectures [4].

While numerous digital health initiatives have been introduced in developing countries, many of these projects face difficulties related to existing digital health systems often operate independently, resulting in fragmented data management, limited interoperability, and challenges in ensuring data security and privacy [4]. These limitations highlight the need for a structured and context-sensitive information systems architecture capable of supporting sustainable e-health implementation in the Congolese healthcare environment.

The main objective of this study is to propose a context-aware information systems architecture that can support the sustainable implementation of e-health systems in the healthcare sector of the Democratic Republic of Congo.

This study contributes to both the digital health and information systems architecture literature in several ways.

First, the research proposes a context-aware architectural framework specifically designed for healthcare systems operating in resource-constrained environments. Unlike conventional information systems architectures developed for technologically advanced settings, the proposed framework considers the infrastructural and institutional realities of developing healthcare systems.

Second, the study integrates insights from an empirically validated e-health adoption model with information systems architecture design principles. By linking technology adoption determinants with system architecture requirements, the research provides a more holistic perspective on digital health implementation.

Third, the proposed architecture introduces a layered design framework that incorporates infrastructure, applications, data management, interoperability mechanisms, and security governance components. This structure facilitates the development of scalable and interoperable digital health systems capable of supporting various healthcare services, including electronic health records, telemedicine, and mobile health applications.

Finally, the study provides practical guidance for policymakers and system designers seeking to implement sustainable e-health solutions in the Democratic Republic of Congo and similar developing healthcare environments.

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2 Literature Review

2.1 Digital Health Architecture

Digital health architecture refers to the structured design of technological components, standards, and processes that support the development, deployment, and integration of digital health solutions [11]. It provides the foundation for implementing electronic health records, telemedicine platforms, mobile health applications, and health information exchange systems within healthcare environments [12].

Modern digital health architectures increasingly adopt layered and service-oriented approaches to ensure flexibility, scalability, and interoperability [13]. These architectures typically include infrastructure components, application services, data management systems, communication networks, and governance mechanisms. Cloud computing, mobile technologies, and distributed data platforms have further transformed digital health architecture by enabling remote access to healthcare services and facilitating data sharing across geographical boundaries [13].

However, the design of digital health architectures must account for contextual constraints, particularly in developing countries. Conventional architectures developed for technologically advanced environments may not be suitable for healthcare systems with limited infrastructure, intermittent connectivity, and constrained technical capacity [14]. As a result, researchers increasingly emphasize the need for context-aware architectures that adapt technological design to local conditions, resource availability, and institutional capabilities.

Furthermore, digital health architectures must address critical issues such as system reliability, data security, privacy protection, and long-term sustainability. Failure to incorporate these considerations may lead to fragmented systems, data silos, and ineffective healthcare service delivery.

2.2 Information Systems Architecture in Healthcare

Health Information Systems (HIS) architecture refers to the structural organization of information technologies used to collect, process, store, and exchange health-related data[61]. A well-designed HIS architecture enables healthcare institutions to manage clinical information efficiently, support decision-making processes, and coordinate healthcare services across different levels of the health system.

Traditional HIS architectures often consisted of isolated applications developed for specific functions, such as patient registration, laboratory management, or billing. While these systems improved operational efficiency within individual departments, they frequently lacked integration capabilities, resulting in fragmented information flows and duplicated data[57].

Contemporary HIS architecture emphasizes integrated platforms capable of supporting comprehensive healthcare information management. Enterprise architecture frameworks are increasingly applied to healthcare systems to align technological solutions with organizational goals and operational processes. Such approaches facilitate interoperability, standardization, and scalability while enabling the integration of legacy systems with new digital applications [15].

In developing healthcare environments, the absence of coordinated architectural frameworks often leads to the proliferation of independent digital solutions implemented by different stakeholders. This fragmentation reduces the effectiveness of health information systems and complicates efforts to establish national health information infrastructures. Therefore, the development of coherent and adaptable HIS architectures is essential for supporting sustainable digital health transformation [16].

2.3 Interoperability in Health Information Systems

Interoperability is widely recognized as a fundamental requirement for effective digital health implementation. It refers to the ability of different information systems, devices, and applications to exchange data and interpret shared information in a meaningful way. Interoperability enables seamless communication between healthcare providers, institutions, and information platforms, thereby supporting coordinated patient care and efficient health service delivery [17].

Interoperability can be categorized into several levels, including technical interoperability (data exchange), semantic interoperability (shared meaning of data), and organizational interoperability

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(alignment of policies and processes). Achieving these levels requires the adoption of standardized data formats, communication protocols, and governance frameworks.

Lack of interoperability remains one of the most significant barriers to digital health implementation worldwide. Fragmented systems prevent the effective sharing of patient information, hinder clinical decision-making, and limit the potential benefits of digital health technologies. In resource-constrained healthcare environments, interoperability challenges are often exacerbated by inconsistent standards, limited technical expertise, and insufficient coordination among stakeholders [18].

Interoperability is particularly critical for national health information exchange systems, which aim to integrate data from multiple sources, including hospitals, clinics, laboratories, and public health agencies. Without interoperable architectures, healthcare systems risk becoming collections of isolated digital tools rather than integrated platforms capable of supporting comprehensive healthcare management [19].

2.4 E-Health Implementation in Developing Countries

The implementation of e-health systems in developing countries presents unique challenges that extend beyond technological considerations. While digital health initiatives have the potential to improve healthcare accessibility and efficiency, their success depends on a complex interplay of infrastructural, organizational, financial, and socio-cultural factors [20].

Many developing countries face significant barriers, including limited ICT infrastructure, unreliable electricity supply, inadequate funding, and shortages of skilled personnel. These constraints often lead to the partial or unsuccessful implementation of digital health projects. Additionally, weak regulatory frameworks and governance structures may complicate issues related to data protection, privacy, and system accountability [4].

Another critical challenge is the sustainability of e-health initiatives. Projects implemented with external funding or pilot programs may fail to scale up or continue after initial support ends. Sustainable implementation requires long-term planning, local capacity building, and alignment with national health strategies [21].

Despite these challenges, developing countries also present opportunities for innovative digital health solutions tailored to local contexts. Mobile health technologies, for example, have shown significant potential in regions where mobile phone penetration exceeds access to traditional healthcare infrastructure. However, the effectiveness of such solutions depends on their integration into broader health information systems architectures [22].

In the case of the Democratic Republic of Congo, the healthcare system faces multiple structural constraints, including geographical barriers, limited infrastructure, and resource shortages. These conditions underscore the need for a context-aware architectural framework capable of supporting scalable, interoperable, and secure digital health systems adapted to local realities [4].

2.5 Research Gap

Although extensive research has been conducted on digital health technologies, health information systems, and interoperability, relatively few studies have focused on the development of context-aware information systems architectures tailored to fragile healthcare environments. Existing frameworks often assume the availability of stable infrastructure, advanced technical capacity, and strong institutional support conditions that may not exist in many developing countries.

Moreover, many digital health initiatives prioritize technology deployment without adequately addressing architectural integration and long-term sustainability. This gap highlights the need for comprehensive frameworks that align technological design with contextual constraints, adoption determinants, and policy requirements.

Therefore, this study seeks to address this gap by proposing a context-aware information systems architecture specifically designed to support sustainable e-health implementation in the Democratic Republic of Congo.

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3 Research Context: Healthcare System in the DRC

3.1 Overview of the Healthcare System in the DRC

The healthcare system of the Democratic Republic of Congo (DRC) is characterized by a multi-tiered structure designed to deliver services at primary, secondary, and tertiary levels. The system is organized around health zones, which serve as the fundamental administrative and operational units responsible for delivering primary healthcare services to defined populations [23]. Each health zone typically includes a network of health centers supported by a referral hospital that provides more specialized medical services [24].

Despite this structured organization, the healthcare system faces significant challenges related to resource constraints, workforce shortages, and uneven distribution of healthcare facilities. Rural and remote areas often experience limited access to qualified medical personnel and essential health services, contributing to disparities in healthcare delivery across the country. In addition, healthcare financing relies heavily on out-of-pocket payments, which can limit access to care for vulnerable populations [25].

Public, private, and faith-based organizations all play important roles in service provision, resulting in a heterogeneous healthcare landscape. While this pluralistic system expands service availability, it also creates coordination challenges and inconsistencies in service quality and data management practices [26].

3.2 Current State of Digital Health Infrastructure

Digital health infrastructure in the DRC remains at an early stage of development. Although several initiatives have been introduced to modernize health information management, the adoption of digital technologies across healthcare institutions is uneven and fragmented. Many facilities continue to rely on paper-based record systems, which limit the efficiency of data collection, storage, and retrieval [20].

Where digital systems exist, they are often implemented as standalone applications designed for specific functions, such as disease surveillance, patient registration, or reporting to national health authorities. These systems frequently lack interoperability, preventing seamless data exchange between healthcare institutions and administrative levels [27].

Access to reliable ICT infrastructure remains a major constraint. Internet connectivity is inconsistent, particularly in rural areas, and electricity supply is often unstable. Healthcare facilities may lack sufficient computing equipment, secure data storage solutions, and technical support personnel. Consequently, the functionality of digital health systems is frequently constrained by infrastructural limitations [3].

Mobile technologies have shown potential for expanding digital health services, given the relatively high penetration of mobile phones compared to fixed internet infrastructure. However, the integration of mobile health applications into broader health information systems remains limited.

3.3 Challenges for E-Health Implementation

The implementation of e-health systems in the DRC is hindered by a complex combination of technological, organizational, and institutional challenges [28].

From a technological perspective, limited ICT infrastructure, intermittent connectivity, and unreliable electricity supply significantly restrict the deployment and operation of digital health systems [1].These constraints affect system availability, data synchronization, and real-time communication capabilities [46].

Organizational challenges include insufficient technical capacity within healthcare institutions, limited training opportunities for healthcare professionals, and resistance to technological change [29]. Many healthcare workers may lack the digital skills necessary to effectively use advanced information systems, which can reduce adoption rates and system utilization [10] [30].

Institutional factors also play a critical role. The absence of comprehensive national standards for health information systems, interoperability frameworks, and data governance policies complicates the integration of digital solutions across the healthcare sector. In addition, funding limitations may impede the procurement of equipment, system maintenance, and long-term sustainability of digital health initiatives [4] [55].

Socio-cultural factors, such as trust in digital technologies and concerns about data privacy, may further influence the acceptance of e-health systems among both healthcare professionals and patients [10].

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Taken together, these challenges highlight the need for a context-aware information systems architecture specifically designed to address the realities of healthcare delivery in the DRC. Such an architecture must be robust, scalable, interoperable, and adaptable to environments with constrained resources while ensuring data security and system reliability.

4 Methodological Approach

4.1 Research Design

This study adopts a design science research approach to develop a context-aware information systems architecture for sustainable e-health implementation in the Democratic Republic of Congo. Design science is particularly appropriate for research aimed at creating and evaluating technological artifacts intended to solve real-world problems. In this context, the artifact consists of a conceptual architecture tailored to the needs and constraints of a resource-constrained healthcare environment [31].

The research combines empirical evidence derived from healthcare professionals with theoretical insights from digital health, information systems architecture, and technology adoption literature. Rather than focusing solely on user behavior or technical specifications, the study integrates both perspectives to ensure that the proposed architecture aligns with practical requirements and contextual realities.

The research process follows an iterative approach involving problem identification, requirement analysis, architectural design, and conceptual validation. This process ensures that the resulting framework addresses the key challenges identified in the healthcare system while remaining adaptable to evolving technological conditions.

4.2 Data Sources and System Requirements

The architectural design is informed by multiple data sources to ensure its relevance and applicability to the healthcare context of the Democratic Republic of Congo.

Secondary data sources include policy documents, national health strategies, reports from international organizations, and existing literature on digital health implementation in developing countries. These sources contributed to the identification of institutional, regulatory, and infrastructural requirements that must be considered in architectural design.

Based on these inputs, both functional and non-functional requirements were defined. Functional requirements include support for electronic health records, telemedicine services, health information exchange, and reporting systems. Non-functional requirements encompass system scalability, interoperability, reliability, security, privacy protection, and resilience to infrastructural disruptions such as power outages or connectivity failures.

4.3 Analytical Framework for Architecture Design

The architecture is developed using a layered analytical framework that integrates principles from enterprise architecture, health information systems design, and digital health implementation models. This framework ensures that the proposed system addresses technical, organizational, and governance dimensions simultaneously [32].

The analytical process begins with mapping the identified requirements to architectural components. Infrastructure constraints, such as limited connectivity and hardware availability, inform the design of the infrastructure layer. User needs and clinical workflows guide the application layer, while data management requirements shape the structure of the data layer [33].

Interoperability considerations are addressed through the incorporation of standardized communication protocols and data exchange mechanisms, enabling integration with existing health information systems and external platforms. Security and privacy requirements are embedded across all layers through governance mechanisms, access control policies, and data protection strategies.

The framework emphasizes modularity and scalability, allowing the architecture to evolve as technological capacity improves. It also prioritizes resilience, ensuring that core system functions remain operational even under constrained conditions.

By combining empirical evidence, theoretical principles, and contextual analysis, the methodological approach supports the development of a comprehensive architecture capable of facilitating sustainable e-health implementation in the Democratic Republic of Congo

5 Proposed E-Health Information Systems Architecture

5.1 Architectural Design Principles

This section presents the proposed e-health information systems architecture designed to support secure, interoperable, scalable, and context-appropriate digital health services in the Democratic Republic of Congo (DRC). The architecture addresses the technical challenges identified in earlier chapters and aligns with the functional and non-functional requirements of e-health systems in low-resource and fragile settings such as North Kivu. It adopts a layered and modular approach to ensure flexibility, maintainability, and sustainability.

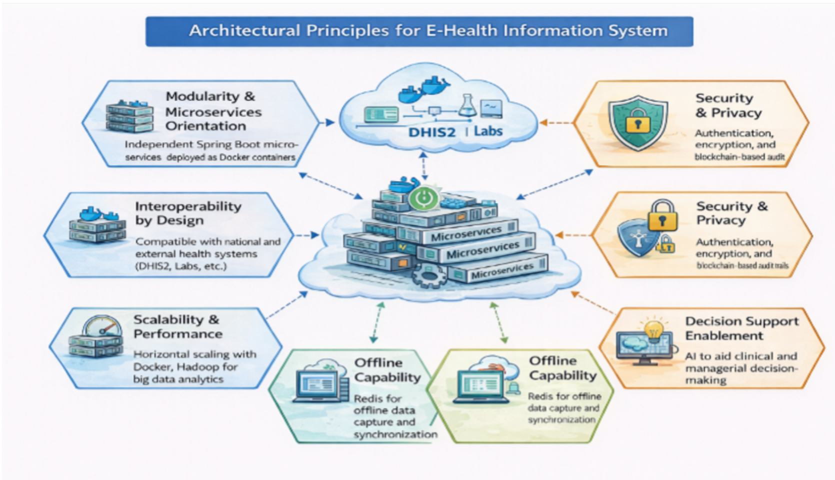

Fig. 1. Architectural Principles for E-Health System

The proposed e-health architecture is built upon several foundational principles designed to ensure flexibility, resilience, and effectiveness within the complex healthcare landscape. Central to this design is a Modularity and Microservices Orientation, which utilizes the Spring Boot framework to decouple functional components. This approach ensures that each service can be developed, deployed, and scaled independently, thereby preventing system-wide failures during updates [34].

Furthermore, the framework prioritizes Interoperability by Design to facilitate seamless communication with existing national and external health systems, such as DHIS2 and various laboratory platforms. By implementing standardized RESTful APIs and adhering to global health data standards, the architecture effectively eliminates data silos and enables a unified view of patient information [35]. To safeguard this information, Security and Privacy measures are integrated into every layer of the system. This defense-in-depth strategy employs advanced authentication, authorization, and encryption protocols, complemented by blockchain-based audit mechanisms that ensure the integrity and traceability of sensitive health records [36].

To meet the high-performance demands of modern medicine, the architecture emphasizes Scalability and Performance. Through the use of Docker containers for horizontal scaling and the integration of big data technologies like Hadoop, the system is capable of processing and analyzing vast quantities of healthcare data efficiently [37]. Additionally, the architecture includes a robust Offline Capability specifically designed for remote areas with unstable internet connectivity. By leveraging Redis and local storage for data capture and subsequent synchronization, the system ensures that healthcare delivery remains uninterrupted regardless of network status [38].

Finally, the system is enhanced through Decision Support Enablement, where artificial intelligence (AI) components are directly integrated into the workflow. These tools assist both clinicians and managers by providing data-driven insights, which significantly improve diagnostic accuracy and institutional resource management [39].

5.2 Logical Architecture

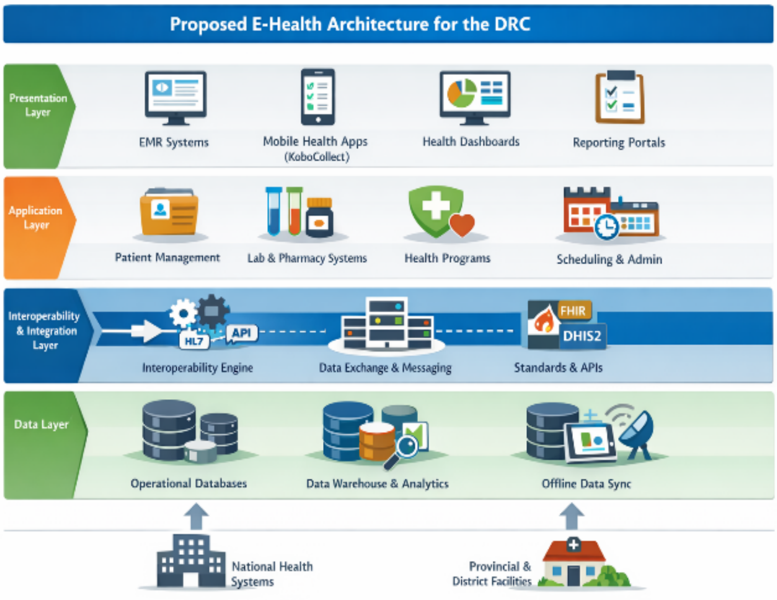

Fig. 2 Proposed E-Health Architecture for the DRC

The proposed e-health architecture for the Democratic Republic of Congo is conceived as a layered, modular, and interoperable information system designed to support healthcare service delivery, data management, and decision-making across different levels of the health system. The architecture aims to address the technical, organizational, and contextual challenges identified in the Congolese healthcare sector, particularly in provinces such as North Kivu, while remaining adaptable to future expansion and technological evolution.

At a high level, the architecture is organized into four main layers: the presentation layer, the application layer, the interoperability and integration layer, and the data layer. Each layer performs a specific function while interacting seamlessly with the others to ensure efficient data flow and system coordination.

The presentation layer represents the user interface through which healthcare professionals and administrators interact with e-health systems [40]. This layer includes web-based and mobile applications such as electronic medical records (EMR), health management dashboards, mobile data collection tools, and reporting interfaces. The design of this layer emphasizes usability, accessibility, and support for low-bandwidth environments, recognizing the diverse technological capabilities of health facilities in the DRC.

The application layer consists of core health information system components that support clinical, administrative, and public health functions. These include systems for patient registration, clinical documentation, laboratory and pharmacy management, appointment scheduling, and health program monitoring. Each application module operates independently while adhering to shared standards that enable integration across the architecture.

The interoperability and integration layer serves as the backbone of the proposed architecture. It enables communication and data exchange between disparate applications and systems through standardized interfaces, APIs, and messaging services. This layer ensures that information generated at facility level can be aggregated, shared, and reused at district, provincial, and national levels, thereby reducing data silos and improving coordination across the health system [41].

The data layer provides centralized and decentralized data storage, management, and analytics capabilities. It includes operational databases for transactional data, data warehouses for aggregated reporting, and analytics tools to support monitoring, evaluation, and decision-making. Mechanisms for data synchronization are incorporated to support offline data capture and delayed transmission in areas with limited connectivity [42].

Overall, the proposed e-health architecture is designed to be flexible, scalable, and context-aware, allowing gradual implementation and integration with existing health information systems in the DRC. By combining technical robustness with user-centered considerations, the architecture seeks to support effective e-health adoption while enhancing the quality, accessibility, and reliability of health information across the healthcare system.

5.3 Physical Architecture

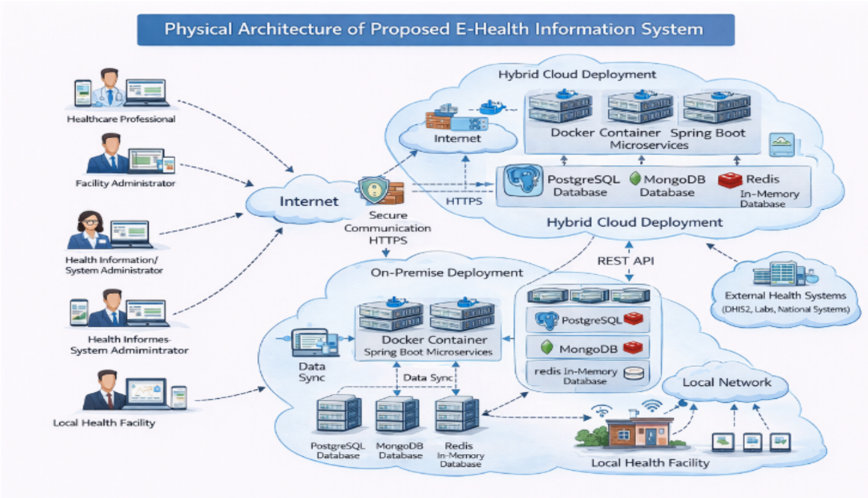

Fig. 3. Physical Architectural of Proposed E-Health Info. System

The physical architecture of the system defines the strategic deployment of components across infrastructure resources to ensure high availability and operational consistency. At the foundation of the Server Environment, all backend services are encapsulated within Docker containers. This containerization strategy enables a uniform deployment pipeline across development, testing, and production environments, effectively mitigating the "it works on my machine" syndrome and simplifying the management of complex dependencies [43].

To address the diverse geographical and technological landscape of the DRC, the system utilizes a Cloud and On-Premise Hybrid Deployment model [1]. This flexible approach allows the architecture to accommodate local health facilities that may have limited or intermittent internet connectivity by hosting critical services on-site, while simultaneously synchronizing with national-level data centers for centralized management and data aggregation [44]. The integrity of this distributed network is maintained through rigorous Network Security protocols. Secure communication across all nodes is mandated via HTTPS, while the infrastructure is further protected by advanced firewalls and strategic network segmentation to prevent lateral movement in the event of a security breach [45].

Finally, the architecture leverages Distributed Storage and Processing to manage the vast influx of medical information. By utilizing Hadoop clusters, the system provides a scalable environment for large-scale data storage and complex analytics. This distributed capability is essential for supporting population health analysis and long-term policy planning, allowing health authorities to derive actionable insights from regional and national data patterns [46].

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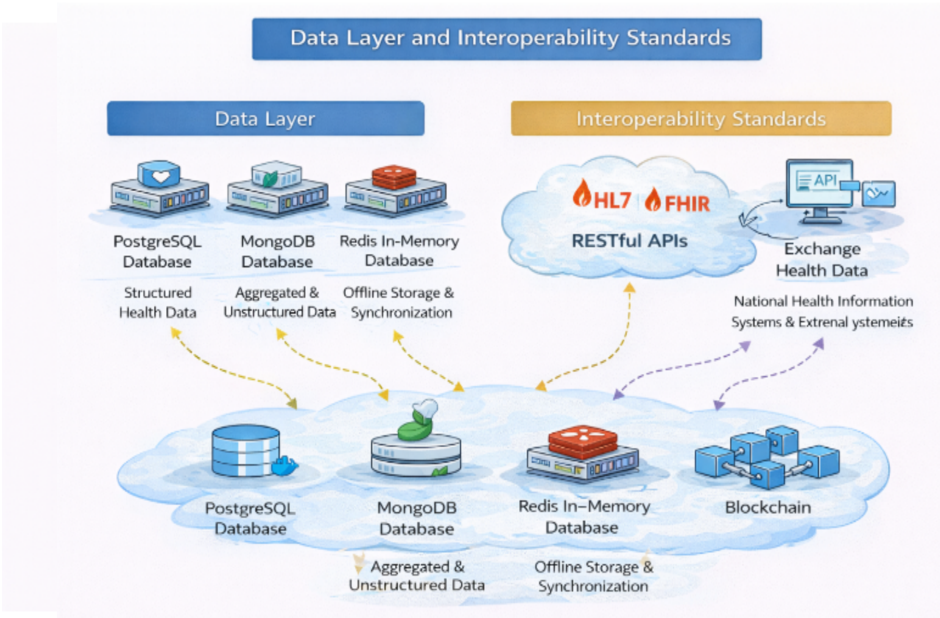
5.4 Application Layer Architecture

Fig. 4. Application Layer Architecture



The application layer of the proposed system is engineered using a microservices-based architecture built on the Spring Boot framework. This design begins with the Patient and Clinical Management Services, which function as the core of the clinical workflow. These services are responsible for managing patient registration, maintaining comprehensive electronic medical records, and facilitating the capture and retrieval of patient history. By isolating these functions, the system ensures that sensitive clinical data remains accessible and organized for frontline healthcare providers [47].

Complementing the clinical services are the Facility Management Services, which streamline the operational aspects of healthcare institutions. This module supports the management of appointments and integrates laboratory and pharmacy data to ensure a cohesive supply chain and service flow. Furthermore, these services automate facility-level reporting, which is essential for tracking institutional performance and resource utilization [48]. To add a layer of intelligence to these operations, Decision Support Services are integrated directly into the application layer. These AI-driven modules perform real-time analysis of clinical and operational data to generate proactive alerts, clinical recommendations, and predictive insights, thereby enhancing the precision of medical interventions [49].

The security and governance of the application are maintained through User and Access Management Services. This component is dedicated to managing user profiles, defining complex roles and permissions, and overseeing the authentication processes required to protect system integrity. This ensures that only authorized personnel can access specific tiers of sensitive health information [50]. Finally, the Interoperability Services act as the gateway for external communication. By utilizing standardized REST APIs and universal data formats, these services enable the seamless exchange of information with external health platforms and national databases, ensuring that the system remains an integrated part of the broader digital health ecosystem [51].

5.5 Data Layer and Interoperability Standards

Fig. 5. Data Layer and Interoperability Standards

The data layer of the proposed architecture is specifically engineered to manage heterogeneous health data while maintaining high levels of integrity, availability, and interoperability. To handle structured transactional information, such as detailed patient records, user accounts, and facility management data, the system utilizes a Relational Database (PostgreSQL). This choice ensures ACID compliance and strong data consistency, which are vital for maintaining accurate medical histories and administrative accuracy [52].

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To accommodate the diverse nature of medical documentation, a NoSQL Database (MongoDB) is integrated to store unstructured and semi-structured data, including clinical notes and aggregated health statistics. This provides the schema flexibility required to capture varied clinical inputs that do not fit into rigid tables [53]. Furthermore, to address the specific challenge of low-connectivity environments in the DRC, an In-Memory Database (Redis) is employed. This component supports an effective offline mode through advanced caching and high-speed data synchronization, ensuring that healthcare workers can remain productive even when the primary network is unavailable [54].For high-level insights, the architecture incorporates a Big Data Platform (Hadoop), which enables large-scale analytics, comprehensive reporting, and real-time population health monitoring. This analytical power is balanced by the integration of Blockchain Technology, which provides a decentralized and secure audit trail. The blockchain ensures data integrity verification and establishes critical trust mechanisms for sensitive health transactions, making the medical record immutable and verifiable [55]. Finally, the layer is unified by strict Interoperability Standards, supporting protocols such as HL7/FHIR and utilizing RESTful APIs. These standards facilitate seamless integration with both national and international health information systems, ensuring that the data layer is not an island but a connected node in the global health network [56].

5.6 Requirements Analysis for E-Health Systems

The success of an e-health information system largely depends on a clear understanding of its requirements. In the context of the Democratic Republic of Congo, and particularly in resource-constrained environments such as North Kivu, the requirements analysis must reflect both the operational needs of healthcare stakeholders and the technical constraints of the existing infrastructure. This section presents the functional and non-functional requirements that guide the design and implementation of the proposed e-health system architecture.

Functional Requirements.

Functional requirements define what the e-health system is expected to do in order to support healthcare delivery, management, and decision-making. The proposed system must enable patient information management, including patient registration, electronic medical records, consultation history, and continuity of care across health facilities. Healthcare professionals should be able to capture, update, retrieve, and share patient data securely and efficiently.

The system must also support clinical and administrative workflows, such as appointment scheduling, laboratory and pharmacy management, and reporting of health services. These functions should be implemented through modular applications that can operate independently while remaining interoperable through standardized interfaces.

Another key functional requirement is data collection and aggregation. The system should allow health workers to collect data using mobile and web-based tools, including offline data capture where internet connectivity is limited. Collected data must be synchronized automatically when connectivity is restored and aggregated at district, provincial, and national levels for monitoring and evaluation purposes.

Interoperability is a central functional requirement. The system must exchange data with existing health information systems using standardized protocols and RESTful APIs. Integration with national platforms such as DHIS2 is essential to ensure consistency in health reporting and policy alignment.

The architecture must also include decision-support capabilities. By integrating analytics and artificial intelligence components, the system should provide alerts, trends, and recommendations to assist healthcare providers and policymakers in clinical and strategic decision-making.

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Finally, the system must incorporate security and access control functions, including user authentication, authorization, audit logging, and consent management, to ensure that only authorized users can access sensitive health information.

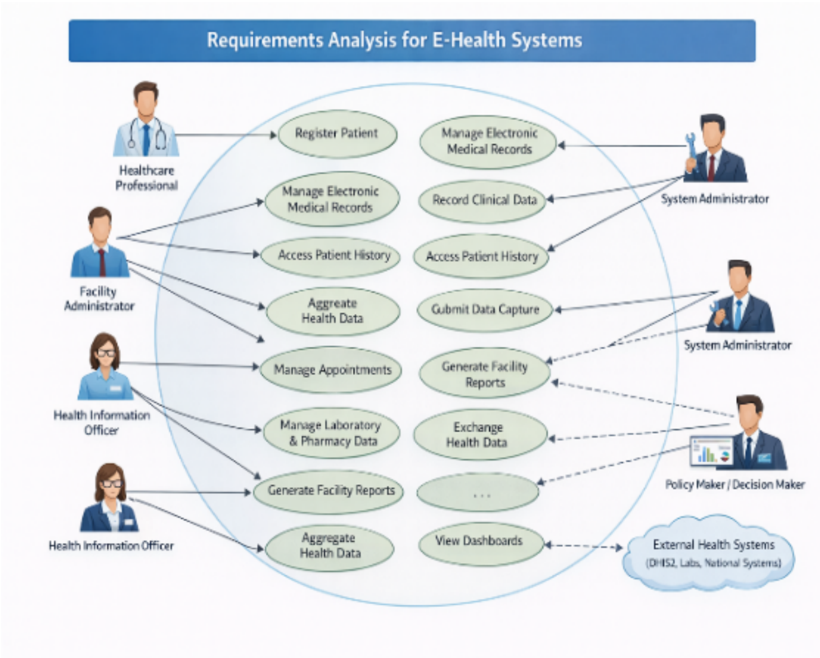

Fig. 6. Requirements Analysis for E-Health Systems

6 Implementation Considerations

6.1 Integration with Existing Health Information Systems

Successful implementation of the proposed e-health architecture requires seamless integration with existing health information systems already deployed within healthcare institutions. In the Democratic Republic of Congo, many facilities operate heterogeneous systems developed independently for specific programs such as disease surveillance, patient management, or administrative reporting. These systems often lack interoperability and standardized data structures, leading to fragmentation of health information.

The proposed architecture addresses this challenge by incorporating an interoperability layer that enables data exchange through standardized protocols and application programming interfaces. Rather than replacing existing systems, the architecture supports incremental integration, allowing institutions to preserve prior investments while improving overall system coherence.

Data migration strategies must also be carefully planned to ensure continuity of operations and preservation of historical records. Where legacy systems rely on paper-based documentation, digitization processes should be implemented gradually to avoid disruption of clinical workflows. Training programs are essential to help healthcare professionals adapt to integrated digital environments

6.2 Scalability and Sustainability

Scalability is a critical requirement for digital health systems in resource-constrained environments. The proposed architecture is designed to support phased deployment, beginning with pilot implementations in selected healthcare facilities and expanding progressively as infrastructure and capacity improve.

A modular design enables the addition of new services without requiring major system redesign. This flexibility allows the architecture to accommodate emerging technologies, increasing user demand, and evolving healthcare priorities. Cloud-based components provide additional scalability by enabling dynamic allocation of storage and computing resources.

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Sustainability depends not only on technical factors but also on financial and institutional support. Long-term system operation requires reliable funding mechanisms for infrastructure maintenance, software updates, technical support, and capacity building. Partnerships with governmental agencies, international organizations, and private stakeholders can contribute to sustainable financing models.

Capacity development is equally important. Continuous training programs should be established to enhance digital competencies among healthcare workers and technical staff, ensuring effective system utilization over time.

6.3 Governance and Policy Requirements

Robust governance structures are essential for ensuring the effective and ethical use of e-health systems. Governance encompasses regulatory frameworks, institutional policies, accountability mechanisms, and oversight bodies responsible for guiding digital health initiatives.

In the context of the Democratic Republic of Congo, the development of comprehensive national standards for health information systems is crucial. These standards should address data management practices, interoperability requirements, security protocols, and system certification procedures. Clear policies regarding data ownership, consent, and access rights are necessary to protect patient privacy and build trust among users.

Institutional governance mechanisms should define roles and responsibilities for system management, including maintenance, monitoring, and incident response. Coordination between ministries, healthcare institutions, and regulatory authorities is required to ensure alignment of digital health initiatives with national health strategies.

Ethical considerations must also be incorporated into governance frameworks. Safeguards should be implemented to prevent misuse of health data and to ensure equitable access to digital health services across different population groups.

7 Discussion

7.1 Implications for Health Informatics Research

The proposed context-aware e-health information systems architecture contributes to health informatics research by addressing a critical gap between theoretical models and practical implementation in resource-constrained environments. While prior studies have extensively examined technology adoption determinants, fewer have translated these findings into concrete architectural frameworks tailored to fragile healthcare systems.

This study demonstrates that effective digital health implementation requires the integration of socio-technical factors into system design. By aligning architectural components with empirically identified adoption determinants—such as perceived usefulness, infrastructure availability, institutional support, and trust—the proposed framework advances the concept of user-centered health information systems.

Furthermore, the architecture extends traditional enterprise architecture models by incorporating resilience and adaptability as core design principles. In contexts characterized by intermittent connectivity, limited resources, and organizational constraints, conventional high-resource architectures may be impractical. The proposed model therefore contributes to the emerging field of context-aware digital health design, emphasizing that technological solutions must reflect local realities rather than replicate models developed for high-income settings.

The research also highlights the importance of interdisciplinary approaches combining information systems, public health, and policy perspectives. Such integration is essential for developing sustainable digital health solutions capable of supporting healthcare transformation in developing countries.

7.2 Practical Implications for Healthcare Systems

From a practical perspective, the proposed architecture provides a structured roadmap for healthcare institutions seeking to implement or upgrade e-health systems. By adopting a layered design, healthcare organizations can prioritize critical components based on available resources and operational needs.

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The modular nature of the framework facilitates phased deployment, enabling institutions to begin with essential services such as electronic health records and progressively integrate advanced functionalities like telemedicine and decision support systems. This approach reduces financial risk and implementation complexity while allowing continuous improvement.

The architecture also supports improved coordination of healthcare services through enhanced data sharing and interoperability. Integrated information systems can reduce duplication of efforts, minimize medical errors, and improve continuity of care across different facilities. Additionally, the incorporation of mobile health solutions extends service delivery to underserved and remote populations, thereby improving healthcare accessibility.

Security and privacy provisions embedded within the architecture are particularly important for building trust among healthcare professionals and patients. Trust is a key determinant of technology adoption, especially in environments where concerns about data misuse may hinder digital transformation initiatives.

For policymakers and health system planners, the framework offers guidance for aligning technological investments with national health priorities. It underscores the necessity of complementary actions such as workforce training, infrastructure development, and regulatory reform to ensure successful implementation.

7.3 Comparison with Existing E-Health Architectures

Existing e-health architectures developed in high-income countries typically assume reliable infrastructure, stable connectivity, and advanced institutional capacity. While these architectures emphasize interoperability, data analytics, and sophisticated clinical decision support, they may not adequately address the constraints faced by developing healthcare systems.

The proposed architecture differs in several important respects. First, it explicitly incorporates infrastructural limitations as a design parameter, advocating hybrid solutions that combine local and cloud-based resources to ensure system resilience. Second, it emphasizes scalability and modularity, enabling gradual implementation rather than large-scale deployment.

Third, the architecture integrates governance and policy considerations more explicitly than many technical frameworks. In fragile healthcare systems, institutional factors play a decisive role in determining the success or failure of digital health initiatives. By embedding governance mechanisms within the architectural design, the framework acknowledges the socio-political dimensions of technology implementation.

Compared with other context-oriented models proposed for developing countries, the present architecture offers a comprehensive approach that simultaneously addresses technical, organizational, and environmental factors. Its layered structure ensures flexibility while maintaining coherence across system components.

Overall, the comparison highlights that effective e-health implementation requires architectures specifically tailored to local contexts rather than direct transplantation of solutions from technologically advanced settings. The proposed framework therefore represents a step toward more inclusive and sustainable digital health development.

8 Conclusion

8.1 Summary of Contributions

This study proposed a context-aware information systems architecture to support sustainable e-health implementation in the healthcare sector of the Democratic Republic of Congo. Recognizing that digital health transformation in resource-constrained environments requires more than technological solutions, the research integrated infrastructural, organizational, and institutional considerations into a comprehensive architectural framework.

The proposed architecture contributes to the literature by translating empirically identified adoption determinants into a practical system design. Its layered structure—comprising infrastructure, application, data management, interoperability, and security components—ensures flexibility, scalability, and resilience under challenging conditions such as limited connectivity and unstable power supply.

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From a theoretical perspective, the study advances health informatics research by bridging the gap between technology adoption models and information systems architecture design. From a practical standpoint, it provides policymakers, healthcare institutions, and system developers with actionable guidance for planning and implementing digital health solutions adapted to fragile healthcare systems.

Overall, the framework supports a sustainable pathway for digital transformation, enabling improved healthcare accessibility, efficiency, and quality of services.

8.2 Limitations

Despite its contributions, the study has several limitations. First, the architecture was developed as a conceptual framework and has not yet been implemented or empirically validated through large-scale real-world deployment. Practical implementation may reveal operational challenges not fully captured in the design phase.

Second, the research focused primarily on healthcare professionals' perspectives and institutional factors, potentially overlooking the views of patients, community health workers, and other stakeholders. Including these perspectives could provide a more comprehensive understanding of system requirements.

Third, the study is context-specific to the Democratic Republic of Congo. While many findings may be applicable to other developing countries, differences in policy environments, technological capacity, and healthcare structures may limit direct generalization.

Finally, rapid technological evolution in digital health may require continuous adaptation of the proposed architecture to accommodate emerging innovations such as artificial intelligence, advanced analytics, and Internet-of-Things medical devices.

8.3 Future Research

Future research should focus on empirical validation of the proposed architecture through pilot implementations in healthcare facilities. Such studies would provide valuable insights into system performance, usability, cost-effectiveness, and impact on healthcare delivery outcomes.

Further investigations could also explore patient-centered perspectives on digital health adoption, particularly in rural and underserved communities. Understanding user experiences across different stakeholder groups would enhance the design of inclusive e-health solutions.

Additionally, comparative studies across multiple developing countries could identify context-specific and universal factors influencing successful implementation. This would contribute to the development of adaptable frameworks applicable to diverse healthcare environments.

Finally, future work may examine the integration of emerging technologies, including artificial intelligence, mobile health innovations, and data-driven decision support systems, to enhance the capabilities of digital health architectures while maintaining security, privacy, and ethical standards.

Statement on conflicts of interest

None

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The Use of Machine Learning and Internet of Things Technologies in Maternal Healthcare: A Systematic Review

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Background and Purpose: There has been a recent increase in the use of the Internet of Things (IoT) and machine learning (ML) technologies in maternal healthcare. These technologies have enabled the design of wearable medical devices that can remotely monitor pregnant women's vital signs, predict impending pregnancy complications, and provide early warnings. This would necessitate timely, appropriate, and personalized care to improve the health of pregnant women. This review examines current trends and gaps in integrated IoT and machine learning technologies in maternal healthcare and provides recommendations for designing suitable models to improve personalized maternal healthcare.
Methods: We adopted the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines for systematic reviews to analyse 50 articles published between 2017 and 2024 covering the use of IoT and ML in maternal healthcare. The risk of bias of the included studies was evaluated using the Prediction Model of Bias Assessment Tool (PROBAST).
Results: We established the need for further studies to guide the design of IoT and ML frameworks that can capture both fetal and maternal vitals and transmit them directly to the cloud for analysis without an intermediary such as a smartphone. Furthermore, the use of tinyML technology for on-device sensor data analytics in real-time monitoring requires further consideration in maternal healthcare applications.
Conclusions: This review followed PRISMA guidelines to analyse trends in the use of integrated ML and IoT technologies in maternal healthcare. The evaluation highlighted gaps in the design of the devices for continuous monitoring of maternal and fetal vitals and predicting pregnancy complications. The review provides recommendations for further research work in the design of these intelligent devices.

Keywords: Machine Learning, Internet of Things, Pre-eclampsia, Pregnancy complications, Maternal healthcare.

1 Introduction

Pregnancy complications have continued to be a critical global health challenge, and it is estimated that they affect approximately 8% of all pregnancies [1]. The complications often result in increased rates of morbidity and mortality for both the mother and unborn child. Early diagnosis and prompt intervention can reduce the risk of severe complications, which, if not diagnosed in good time, are associated with poor birth outcomes such as miscarriage, pre-term birth, stillbirth, low birth weight, or birth deformities [2]. Every day, eight hundred women die due to preventable causes related to pregnancy and childbirth [3]. With the help of technology, some of these fatalities can be averted. In 2020, the maternal mortality rate was 223 deaths per 100,000 live births in low-income countries [4]. The use of advanced technologies can enable the development and implementation of tools for enhancing early detection of these pregnancy complications [5]. One of the main goals of the United Nations Sustainable Development Goals is to reduce the global maternal mortality ratio to fewer than 70 per 100,000 live births by 2030 [6]. The use of the Internet of Things (IoT) and advancements in machine learning (ML) and deep learning can help achieve this goal by enhancing

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real-time monitoring of health status and predicting pregnancy complications, enabling timely, appropriate intervention. However, optimizing models for early prediction and identification of maternal complications remains a major challenge in real-time pregnancy monitoring [7]. A decrease in self-perception of clinical signs related to maternal complications, challenges in accessing the healthcare system, and poor quality of healthcare leads to delays in the diagnosis of the complications and poor prognosis as well [8]. Developing a non-invasive ANC tool to identify maternal signs and symptoms of illness during pregnancy can provide a significant opportunity to detect abnormal patterns early and manage them, thereby minimizing severe complications [2].

Health information systems in many African countries face various challenges that hinder their ability to deliver evidence-based healthcare effectively. According to [9], challenges include reliance on paper-based record-keeping, inadequate ICT infrastructure, poor internet connectivity, and limited electrical supply, especially in rural areas. Additionally, inadequate numbers of qualified health informatics personnel and fragmented, non-interoperable digital platforms that limit real-time data capture and sharing. This results in fragmented, unreliable, insecure, and poor-quality data, which impedes informed clinical decisions, leading to missed diagnoses and repeated testing that are costly and time-consuming [10]. These challenges can be addressed by integrating ML and IoT technologies, especially in maternal healthcare, to improve maternal and neonatal outcomes in limited-resource settings. The technologies can be harnessed to implement a real-time monitoring system that continuously collects patient vitals to facilitate data-driven decisions, early risk detection, early warning of impending complications, and timely, personalized interventions [11]. These systems would transform African health systems from reactive, paper-based systems to a proactive, data-driven, patient-centered approach.

Easy access to personalized information related to pregnancy, high-quality health services, and effective interaction with healthcare providers is necessary for all pregnant women. To facilitate these services for pregnant women quickly and efficiently, intelligent devices, communication systems, and e-health applications should be implemented and used to help prevent many pregnancy-related complications [12]. The potential for global e-health growth has increased as communication and information technologies advance. In Rwanda, for example, a monitoring system for pregnancy and newborn information was implemented using a mobile application. The project tracks the number of pregnancies and their associated complications through instant messaging in the community [13].

The adoption of emerging technologies such as IoT and machine learning in maternal healthcare can improve maternal and fetal health outcomes. The technologies have been utilized extensively in implementing information systems tools for early detection of complications, identification of pregnant women who are at high risk, and provision of continuous data on the health status of pregnant women and their unborn child to make informed decisions on appropriate and timely intervention to reduce maternal health risk [14].

This review aims to present a systematic review of the literature on the integration of Internet of Things (IoT) and machine learning (ML) technologies in maternal healthcare to gain a better understanding of the research trends and critical research concerns in this area by analyzing the common ML algorithms, features, and IoT frameworks used in remote monitoring and prediction of pregnancy complications. Additionally, we seek to provide a roadmap for future research on the effective integration of technologies to address complex pregnancy complications by proposing a conceptual model for maternal healthcare monitoring. The remainder of this article is organized as follows: Section 1.1 presents the machine learning process and the algorithms used for predicting pregnancy complications. Section 1.2 provides the IoT technologies used in maternal healthcare. Section 2 compares this study with other related previous reviews. Section 3 explains the systematic review methodology used to answer the research questions, while Sections 4 and 5 present the results and discussion. Sections 6 and 7 provide limitations, a summary of the study, and opportunities for future research.

1.1 Machine learning in maternal healthcare

Machine learning is an artificial intelligence branch that enables machines, through the use of smart software, to perform their jobs skillfully [15]. Statistical learning methods are the backbone of intelligent machines. The machine learning technique is based on mathematical procedures and algorithms that describe the relationships between variables [16]. The technique is used to extract complex patterns from existing datasets to make predictions or decisions. In the healthcare system, machine learning algorithms provide an efficient means to extract knowledge by constructing predictive models from diagnostic medical datasets. For instance, extracting knowledge from data collected from diabetic patients can help predict diabetic progression [17]. Machine learning comprises the following phases: data collection, data preprocessing, model training, model evaluation, and model deployment and performance monitoring [18]. The machine learning steps are iterative and vary based on the problem being solved and the data set being used, as illustrated in Figure 1.

Obtaining the dataset needed to train the models is the first step in the machine learning process. Since this affects the model's correctness, the data set gathered ought to be accurate and relevant. An important aspect to consider is where the data is collected, as it should come from a reliable source, as this can affect the model's outcome. For instance, in maternal healthcare, data can be collected from e-health records, wearable devices such as sensors and wristwatches, and surveys [19].

The data preprocessing phase involves data cleaning, including handling missing values, inconsistent data, and duplicate data. Additional tasks include combining data from different sources, converting the dataset into a suitable format, reducing dimensionality, and extracting relevant features. Understanding the data and the issue to be solved is part of the problem definition phase, for instance, in maternal healthcare, determining the specific maternal health issues like gestational diabetes, pre-eclampsia, or pre-term birth.

During the model development phase, the training data set is split into training and test sets, and the appropriate algorithm for the particular problem is evaluated. Then the model is trained on the training data set to extract hidden patterns; for example, training a model to predict the risk of pre-eclampsia based on the selected features [20].

The next phase is the model evaluation phase, in which the model's hyperparameters are fine-tuned on a validation dataset to avoid overfitting. The model's performance is evaluated using appropriate metrics such as sensitivity, accuracy, precision, and F1 score [19].

The last phase is model deployment, which involves using the model to predict unseen data. It can include integrating the model into a maternal healthcare system. Then, continuously monitor the model and retrain it periodically to ensure its accuracy and relevance [20].

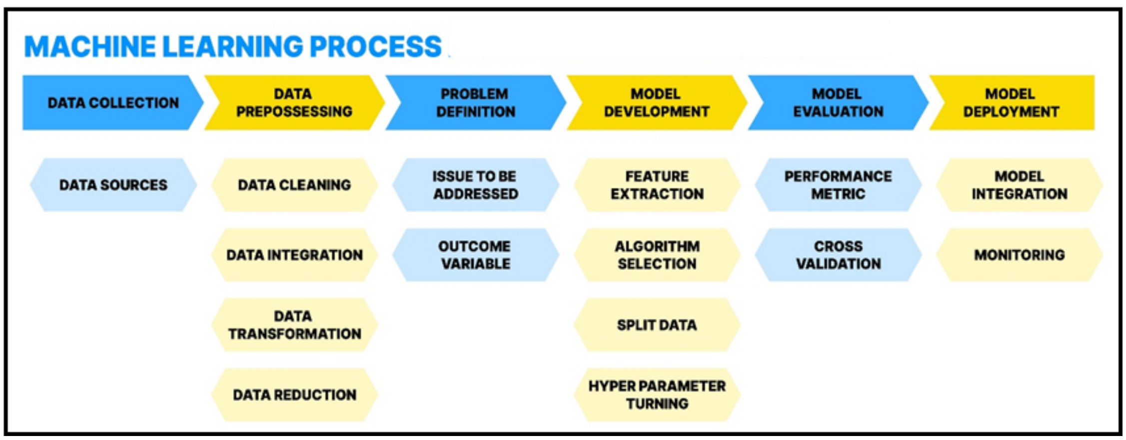

Figure 1. Machine-learning process

Deep learning models have shown higher predictive performance when using electronic health record data, which has increased massively. Due to the lack of transparency in deep learning models, it is difficult to interpret their patterns; as a result, there is a lack of trust in using them for real-world decision-making, since it is difficult to explain how predictions are generated. This problem may be solved by using Bayesian neural networks to predict the effects of data noise. The uncertainty is initiated to ensure the provision of model prediction, which

also provides an extra level of confidence [21]. However, high uncertainty may undermine model predictions. Furthermore, investigating the distributions of model predictions and uncertainties enables the identification of patient groups to ensure timely intervention, such as reducing data noise, thereby improving predictive accuracy [22].

Some of the machine-learning techniques used for predicting pregnancy complications include artificial neural networks (ANNs), deep learning, naïve Bayes, support vector machines (SVMs), k-nearest neighbors (KNNs), decision trees, random forests, and gradient-boosted decision trees [23].

The ANN algorithm usually mimics how the brain's cell tissue works, with the computational trick lying in the relationships among the neurons. This algorithm consists of at least two layers, namely: the input layer and the output layer. The input layer consists of the input value nodes, while the output layer consists of the output value nodes after processing using the activation function. In a multivariate neural network, hidden layers contain output-value nodes that serve as inputs to the other side nodes [24]. An artificial neural network is a biologically inspired computer simulation that performs particular tasks such as clustering, classification, and design recognition [25].

Deep learning is an advanced machine learning subfield that enables computational models structured into multiple layers to analyse data at various levels of abstraction. The layers are represented by a neural network structure, stacked in a literal layer-by-layer manner. In contrast, deep learning has several hidden layers, each representing a higher level of abstraction, unlike neural networks and multiple-layer perceptrons. The technique is used to extract additional hidden features that may not be visible to the human eye, thereby increasing its predictive accuracy. The technique is widely used across domains such as image processing, image identification and retrieval, natural language processing, and search engine information retrieval [26]. Commonly used deep learning approaches include multilayer perceptron (MLP), recurrent neural networks (RNN), and convolutional neural networks (CNN) [27].

Naïve Bayes is a supervised learning method that is adaptable and uses conditional probabilities to classify an instance based on the characteristics of the test data set and assign it to the same class [28]. Naïve Bayes is a simple classifier that uses probabilistic techniques based on the application of Bayes' theorem and is independent of assumptions about the relationships between the characteristics used for classification. The algorithm calculates probabilistic outcomes and matches dataset values by computing frequencies. The Bayesian theorem assumes that all attributes are independent. The conditional independence assumption is seldom correct in real-world applications and yields better, more advanced classification results [17].

The support vector machine (SVM) is a supervised algorithm used for classification and regression analysis, though it is primarily used for classification. In this algorithm, every data element is represented as a point within an n-dimensional space, where n is the number of characteristics, with each characteristic corresponding to a specific coordinate [29]. This algorithm is a popular classification method that categorizes data into multiple classes using binary classification. Unlike other machine learning algorithms, SVMs use a hyperplane as a decision boundary between classes. The algorithm searches for the hyperplane with the highest range. It is an exclusionary classifier that formally characterizes the data by separating a hyperplane between specific classes and isolating entities. It is also involved in identifying and classifying instances that are not data-supported but do not involve distributing data collected for each class [17].

K-Nearest Neighbor (KNN) is a simple algorithm for classification and regression that uses a non-parametric method, where the input comprises k closest training instances in the parameter space to give an output t, depending on whether the algorithm is geared towards classification or regression. The algorithm searches for the nearest data neighbors, records each logical element, and categorizes the current elements according to their similarity. The value of k is always a positive integer representing the number of nearest neighbors in a classification technique. Class or object property values are selected from the closest neighbors [17]. The KNN algorithm assumes that similar things exist near one another. The advantages of KNN are that its implementation is simple and straightforward, and that no model needs to be built; only features need to be tuned or additional assumptions made; however, it becomes slower as the number of parameters increases [30]. The decision tree algorithm consists of an internal node and one class-labeled node. The classification issues in this algorithm are addressed by repeatedly splitting the input space to create a tree with pure, straightforward node points associated with a single class. Moving down the tree, the classification of new data elements is performed by selecting a single branch at each point. Developing a decision tree is dependent on the type of target in the current model. This algorithm uses a reduction-in-variance approach to build a tree model for continuous target variables at the test point, rather than the Gini impurity approach used for categorical target variables. In the Decision tree technique, initiation occurs at the root node and termination at the last node, which is the leaf node of the tree. Internal nodes are located between the root and leaf nodes and are used to test data-point features; each internal node has one possible outcome. This algorithm is used in real-world applications across sectors. For instance, the health sector is used for early diagnosis of cognitive disability, which increases the efficiency of screening positive cases as well as predicting pregnancy complications for pregnant women. The advantage of this algorithm is that it is easy to interpret, handles both continuous and categorical attributes, and requires little or no information processing. In addition, it is highly significant for classification and prediction. However, when the data set is imbalanced, this algorithm shows poor overall performance and is noise-sensitive, which can lead to overfitting if the training dataset contains noise [27].

Random forests are ensemble models that integrate multiple models and are compatible with a wide range of data sets for classification or regression. The random forest model overcomes high conflict even beyond the decision trees. In a random forest model, there are several decision trees, each with a slight disparity from the others. Integration of the outcomes from each decision tree is performed for a specific data point. During the integration process, a majority vote is used for classification, and the average value is used for regression tasks. The performance of the combined trees is better than that of a single tree when it comes to predictions. This is because separate training is used for all the decision trees on a random sample drawn from the training data set. This model is called a random tree because it builds random trees, ensuring that all trees are different [27]. Although complex and time-consuming, the model is suitable for feature importance analysis and has been successfully applied to the early detection of various pregnancy complications.

A gradient-boosted decision tree is another ensemble model, similar to a random forest, because it uses multiple decision trees and supports both classification and regression. However, this model differs from the random forest in that it doesn't use randomization when developing model trees. Instead, pre-pruning is used, in which trees are constructed serially and each attempts to rectify the mistake of the preceding tree. In this model, the death of the trees is small, with depth values ranging from 1 to 5. The basic concept of this algorithm is to mix several simple models. The most extensive application of this model is in supervised learning, where it is naturally robust. The main drawback of this model is that it requires carefully standardized parameters, typically takes longer to train, and is ineffective when the data points are in high-dimensional space [27]. The model has been widely used in building predictive models in maternal healthcare. The algorithm was used by [31] to implement a perinatal mortality prediction model that had an accuracy of 90.24%

1.2 TinyML

TinyML is a machine learning subdomain involving developing and deploying machine learning models on small, low-power devices such as microcontrollers, embedded systems, and sensors. This is a fast-expanding research area, driven by a growing demand for intelligent devices that can process data at the edge rather than relying on cloud or remote servers. The main aim of TinyML is to bring the power of machine learning to a wide range of edge devices, enhancing their ability to handle complex tasks such as voice recognition, object detection, and predictive maintenance. The recent proliferation of TinyML can largely be credited to improvements in the hardware and software ecosystems that support its implementation. With the prospect of deploying low-energy systems such as sensors and microcontrollers, machine learning can be effectively brought to the edge, enabling these applications to operate in real time and allowing machine learning practitioners to achieve more with less. As pointed out by Warden & Situnayake [32], the tinyML technology has several advantages, particularly

- Reduced latency: Data transmission to the server is unnecessary because the model runs on the edge device. In a typical data transfer, there is latency; hence, avoiding the transfer to the server reduces latency.
- Saves Energy: The microcontrollers require low power, enabling them to run for a long time without charging. No vast infrastructure is needed either, since there's no data transfer.
- Improved security and data privacy: - Since the data is kept on the model that runs on the edge, there is no need to transfer the data to servers, and this increases the guarantee of data privacy
- Reduction of bandwidth: The on-device sensors read and process the data locally, so no raw sensor data needs to be transmitted to the server.

1.3 Monitoring Pregnancy Complications Using IoT Technology

Internet of Things (IoT) technology enables smart devices to gather and share data by communicating with one another. However, these smart devices face challenges in data storage, processing power, and power shortages, among others. To overcome these challenges, IoT technologies are implemented using different communication protocols based on factors like data rate, power consumption, and communication range. According to [33], communication protocols are classified into low-power wide-area networks (LPWAN) and short-range networks. LPWAN is a cost-effective wireless technology that can use licensed or unlicensed frequencies. It provides long-range connectivity with low power consumption and low data rates. The LPWAN protocols include Sigfox, long-range (LoRa), and Narrow-band IoT, among others. Short-range networks provide reliable, low-power connectivity that supports high data rates over short distances. Some short-range network protocols that can be used include Bluetooth, which provides a secure short-range low-power device connection; others are Zigbee, Z-Wave, RFID, and near-field communication NFC [34].

Monitoring women's vital signs during pregnancy and labor is very important. It helps in the early identification of high-risk pregnancies for the caregivers to provide more targeted and appropriate treatment, follow-up care, and monitor fetal well-being in both low and high-risk pregnancies. Proper management of maternal and fetal risk and labor complications detected in pregnancy can prevent 3.2 million deaths and reduce maternal and neonatal morbidity and mortality to a large degree throughout the world [35]. The prenatal supervision of intrauterine growth enhances the detection of growth-restricted fetuses, which are exposed to an increased risk of death [36].

Ninety-nine percent of maternal deaths occur in developing countries. This is mainly attributed to the inability of the majority of pregnant women to undergo customary checkups at the onset of their pregnancies, increasing the chances of infant deaths, especially in rural areas [37]. With the use of IoT technologies, this can be minimized; for instance, the researchers proposed using sensors to measure vital parameters of the pregnant woman and the baby, such as temperature, fetal movement, blood pressure, and heart rate. The measured parameters were then transferred through IoT and viewed on a mobile phone. These sensors provide high-quality, timely health care for the mother and the unborn child, thereby enabling regular monitoring that reduces infant mortality [38].

A 24-hour monitoring system for pre-eclampsia was developed by [39]. They used a smartwatch in conjunction with a mobile device and a cloud-based application. The smartwatch measures the pregnant mother's blood pressure and sends real-time data to the caregiver for appropriate action. The target population was women at 20 weeks or more into their pregnancy. The researchers sampled 30 pregnant women from two level-five hospitals in Kenya. The system was based on Internet of Things architectures, which comprised a FI smart wristwatch, a pregnant mother's smartphone, a blood pressure monitoring application, a cloud data center, and the caregiver's smartphone. Various parameters were used to evaluate the system, including content richness, perceived usefulness, user satisfaction, and perceived ease of use. The use of a smartwatch integrated with mobile and cloud applications showed great potential for being adopted in health systems, especially in developing countries.

Maternal mortality for women living in rural areas and poor communities is very high [3]. The ultrasounds used in these areas are insufficient; additionally, there are inadequately skilled personnel to use and interpret the scans, leading to high scan costs and potentially undetected pregnancy complications [40]. Thus, there is a need for continuous monitoring using IoT-based technology. An IoT-based healthcare monitoring system for rural pregnant women was proposed by [37]. They used sensors to measure parameters such as fetal temperature and fetal heart rate in their study.

Additionally, an Arduino controller board was used to integrate the temperature and the accelerometer sensor. The controller analyzed the sensor data, and the results were then simulated. The regular monitoring of the vital parameters of the fetus and the pregnant woman in rural areas greatly reduced infant mortality, with IoT providing quality and timely health assistance for both fetus and woman [37].

A routine checkup for pregnant women is vital, as it ensures that women receive appropriate maternal health care services, and it reduces maternal morbidity and mortality rate to a great extent [40]. A real-time monitoring system using IoT techniques to monitor the fetus's heart rate, temperature, and motion, as well as labor symptoms, was proposed by [41]. The parameters are measured using sensors such as an accelerometer to monitor fetal motion, a temperature sensor to measure temperature, and a pulse rate sensor to measure heart rate. Other sensors and devices used included a force sensor, a microcontroller, and a sweat sensor. The device is designed as an abdominal belt with the mentioned sensors, which are connected to the microcontroller. The microcontroller is programmed to send an alert message via GSM when the set threshold parameters are exceeded, and to store all measured data in the cloud using IoT [41].

Maternal health requires a comprehensive framework that enables continuous monitoring of pregnant women. The framework is essential in addressing the diverse health needs of pregnant women, which differ from pregnancy to pregnancy and from woman to woman [42]. Additionally, the monitoring framework assists in early identification of pregnancy complications and provides an opportunity for appropriate intervention to minimize the risks associated

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with them. Moreover, continuous monitoring offers pregnant women support and informational empowerment, leading to improved outcomes for both the mother and her unborn child. To support this monitoring framework, [43] presented an IoT-based system for ubiquitous maternal health monitoring during pregnancy and the postpartum period. The system consisted of multiple data collectors to track the mother's condition, including stress, sleep, and physical activity. The researchers sampled 28 women from southern Finland with high-risk pregnancies who were monitored during pregnancy and three months postpartum using the system. The women had smartphones with the study app installed and wore a smartwatch for three months after delivery. They were required to measure their blood pressure at least once a week and send the data through the mobile application to the server. The system's feasibility, energy, and data reliability were also evaluated, whereby the results indicated that the system implementation was feasible in terms of system usage over the nine months. It was also concluded that the smartwatch used had acceptable energy efficiency for long-term monitoring, enabling the collection of photoplethysmography data [43].

For any pregnant woman, it is a good practice to perform routine screening for hypertensive disease; certain parameters need to be monitored during pregnancy, such as blood pressure, respiratory rate, glucose levels, and fetal heart sounds, to ensure they remain within normal limits [44]. Ansari & Ansari [45] proposed a smart system for monitoring pregnant women and analyzing the biological factors during pregnancy. The system enabled fast decision-making and treatment by enabling high-speed transfers of medical information to doctors and over mobile devices for consultation and remote medical examinations. Various sensors were used to capture parameters such as blood pressure, temperature, hemoglobin level, heart rate, and kicking rate, enabling real-time monitoring of the pregnant woman.

Remote, continuous monitoring during pregnancy provides healthcare professionals with significant opportunities to observe key parameters and detect pathological signs at an early stage. Grym et al. [46] conducted a study to evaluate the feasibility of continuous monitoring of health parameters, including physical activity, sleep, and heart rate, in nulliparous women throughout the nine months and one month postpartum. During pregnancy, a smart wristband connected to a cloud server was used to measure parameters in a sample of 20 women. The physical activity, sleep, and heart rate were collected with a smart wristband, which was integrated with a photoplethysmogram bio-sensor to measure the heart rate and an inertial measurement unit for tracking physical activity and sleep. The study confirmed that the IoT-based system was feasible for monitoring health parameters during pregnancy when large amounts of data were collected. The study concluded that a smart wristband with an IoT solution was a feasible system for collecting representative data on continuous variables such as sleep, physical activity, and heart rate.

When a pregnant woman is under too much stress, it can have negative effects on both her and her unborn child. These prolonged high levels of stress can lead to high blood pressure, heart disease, pre-term birth, or low birth weight, as well as disrupt the normal maternal adaptation process [47]. Oti et al. [48] developed a personalized, automated health system for real-time stress monitoring based on IoT technology to support conventional clinical methods for maternal stress management. The researchers suggested a stress-level estimation algorithm based on heart rate and heart rate variations during pregnancy. The algorithm was distributed in an edge-based IoT system. The algorithm was tested using supervised and unsupervised learning on an unlabeled dataset for 7 months. A sample of twenty pregnant women was used. The women wore a wearable smart wristband for seven months. Data was collected in two categories, first using a Garmin vivosmart 2 device, capturing heart rate, activity, and sleep information with 60,000 data points. The second data set was obtained using a Garmin vivosmart 3 device, which has a stress level classification ranging from 0 to 100. Heart rate, sleep activity, and stress classification were extracted with 600 data points. An online k-means clustering algorithm was used classification of the stress levels. The edge-based IoT architecture consisted of sensors, edge devices, and a cloud server. A 97.9 % accuracy was obtained using a 10-cross-fold validation.

2 Previous Review Studies

Recent reviews and meta-analyses have greatly contributed to the domain knowledge of using Machine learning and the Internet of Things (IoT) in maternal healthcare. This section highlights the recent systematic reviews related to the current study. A summary of the previous reviews is shown in Table 1.

Based on these reviews, it is evident that IoT and machine learning technologies have garnered substantial attention in recent years, primarily aimed at enhancing the overall health of a mother and her unborn child. Reviews of studies on the application of ML and IoT technologies in maternal healthcare have been conducted. Nevertheless, the framework of integrating ML IoT technologies to facilitate early diagnosis of pregnancy complications has not been the main focus of the evaluation. Thus, this research endeavors to provide a systematic evaluation of the existing frameworks that integrate ML and IoT technologies in maternal healthcare. The review focuses on the features, ML algorithms, and IoT frameworks used to identify existing gaps and to provide a roadmap for future research. It is also worth noting that most previous reviews used the PRISMA methodology and that databases such as PubMed, Springer, and Emerald were frequently used. This information has significantly informed the conceptualization of the current review paper.

Table 1. Previous Review

Study	Methodology	Database	Machine learning	IoT	Contribution	Relationship with current research
[49]	PRISMA	PubMed, Africa Journal Online(AJOL), Google Scholar, Scopus	Yes	Yes	Researchers noted that there were no data-driven models for emerging technologies in maternal care.	The review focused on the existing data model, whereas current research focuses on frameworks for integrated IoT and ML technologies in maternal healthcare.
[50]	Systematic literature review	ACM, Emerald, Hindawi, Science Direct, IEEE, SAGE, Springer	No	Yes	Provided a comprehensive taxonomy of IoT in healthcare	The review focused on the application of IoT in healthcare; our review focuses on maternal healthcare
[51]	Not mentioned	PubMed, IEEE, Science Direct, Springer,	No	Yes	Research provided a taxonomy of IoT-based sensors in healthcare	Review focused on IoT in healthcare, our research is on both IoT and machine learning in healthcare
[52]	RISMA	Scopus, Science Direct, Google scholar, web of science, ACM	No	Yes	Reviewed the state of the art in the adoption of 4.0 technologies in maternal healthcare	The review focused on the application of 4.0 technologies in mental healthcare, whereas our research focused only on IoT and ML technologies.
[53]	Not mentioned	PubMed, Semantic Scholar, National Center of Biotechnology Information(NCBI)	Yes	Yes	Reviewed the sensors and AI algorithms for maternal health.	The review focused on issues common in the use of AI and IoT in maternal health, such as security and energy. The current review focuses on the framework of integrated technologies in maternal healthcare.
[54]	Systematic review, design with a narrative method	PubMed, EMBASE, Scopus, Cochrane database	Yes	No	The review focused on issues in wearable devices in healthcare	The review did not provide the application of AI in maternal healthcare
[55]	PRISMA	Google Scholar, IEEE Xplore, MDPI, Science Direct, IOP Science, PubMed, and ACM	Yes	Yes	Reviewed description, data processing, and performance of sensors used in maternal healthcare.	The review did not focus on appropriate features and IoT frameworks in maternal healthcare.

3 Materials and methods

The review was conducted according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [56]. The framework for categorization and coding was borrowed from [57] and [58]. Four major research phases: Article identification, Inclusion and exclusion, Quality check, and classification and coding were carried out. The review sought to answer the following research questions (RQs)

- RQ1: What is the trend in the use of IoT and ML in maternal healthcare?
- RQ2: What are the commonly used machine learning algorithms in the prediction of pregnancy complications?
- RQ3: Which model specifications are most suitable for developing prediction models of pregnancy complications?
- RQ4: Which IoT frameworks are commonly used in maternal healthcare?
- RQ5: What are the best practices for transmitting data from IoT devices to cloud storage?

3.1 Article Identification

The initial stage of this review was to identify relevant research studies using the terms IoT, Machine learning, and maternal healthcare, guided by the research questions. Based on the availability and thorough coverage of the systematic review objectives, five electronic databases were selected: PubMed, Emerald, Springer, IEEE, ScienceDirect, and BioMed, to provide access to a range of relevant articles. These electronic databases were selected because they contain peer-reviewed research and are commonly used by diverse scholars.

The following search string was used, the string was made as broad as possible to capture all the relevant articles:

(Iot[All Fields] AND Machine Learning[All Fields] AND ("mothers"[MeSH Terms] OR "mothers"[All Fields] OR "maternal"[All Fields]) AND ("delivery of health care"[MeSH Terms] OR ("delivery"[All Fields] AND "health"[All Fields] AND "care"[All Fields]) OR "delivery of health care"[All Fields] OR "healthcare"

3.2 Inclusion and Exclusion Criteria

A total of 527 articles were retrieved from all selected databases, with 313 from PubMed (the highest percentage), 114 from ScienceDirect, 5 from Emerald, 21 from IEEE Explorer, and 74 from Springer, as illustrated in Figure 2.

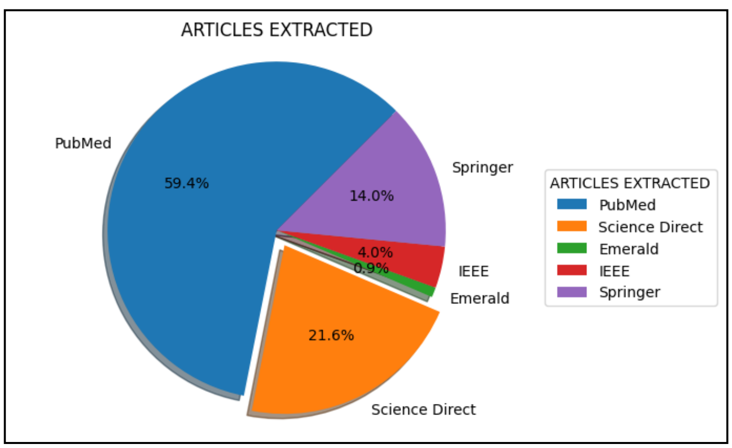

Figure 2: Articles extracted

The inclusion criteria adopted in this research were based on:

- English language as the original publication
- Access to the full-text
- Research employing machine learning and IoT approaches to monitor and predict pregnancy complications.
- Experiment-based articles.
- Papers published between 2017 and 2024 because research focused on recent trends

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Duplicated articles from the databases were excluded in the second phase based on a review of the titles and abstracts. If the abstract was unclear, the introduction and conclusion were read. The articles were excluded based on the following criteria:

- Book chapters
- Articles on comparative studies
- Articles that were not accessible
- Case reports and systematic reviews
- Articles on medical image detection
- Articles that discussed impact assessment studies

The initial search retrieved 527 articles. After checking for duplicate studies, 78 articles were excluded, leaving 449. A further 399 irrelevant articles were excluded. Finally, only 50 articles were analyzed in the study. The summary of the findings after excluding the articles is presented in a PRISMA flow chart Figure 3.

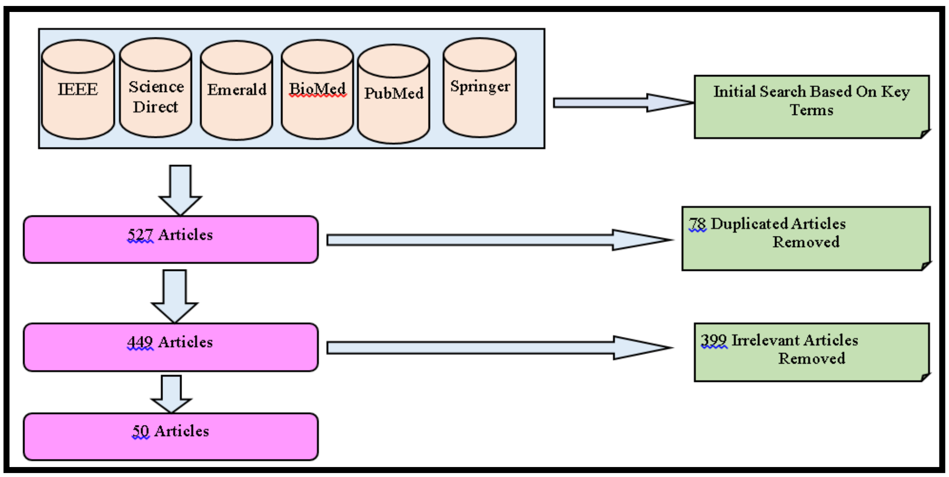

Figure 3: Research resources and article screening

3.3 Quality Check

The quality of the studies was assessed based on whether they addressed the use of IoT and machine learning in maternal healthcare, the clarity of the research objectives and questions, and the clarity of the methodology used. The risk of bias of the included articles was assessed independently by two reviewers (MMM) and (EMM) using the Prediction Model Risk Tool (PROBAST). The conflicts were resolved through discussion and consultations with the third reviewer (AW). The bias in each article was reported per domain and summarized in a risk-of-bias table (Table 2). Based on the risk and bias evaluation, most studies had low risk for participants, predictors, and outcomes. However, 46.8% of the studies had a high risk of analysis, mainly because most studies didn't discuss preprocessing, handling missing data, normalizing data to avoid dominance by some features in machine learning algorithms, and handling categorical values. The overall risk of bias for the selected articles was 50%.

Table 2: Risk of bias table based on PROBAST.

Study	Participants	Predictors	Outcome	Analysis	Overall
[59]	Low	Low	Low	Low	Low
[60]	High	High	High	High	High
[61]	High	High	High	High	High
[62]	Low	High	High	High	High
[63]	Low	High	Low	High	High
[64]	High	Low	High	High	High
[65]	Low	Low	Low	High	High

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[66]	High	Low	High	High	High
[48]	Low	Low	Low	Low	Low
[67]	Low	Low	Low	Low	Low
[68]	Low	Low	Low	Low	Low
[26]	Low	Low	Low	Low	Low
[24]	Low	Low	Low	Low	Low
[69]	Low	Low	Low	Low	Low
[70]	High	Low	Low	Low	High
[71]	Low	Low	Low	Low	Low
[72]	Low	Low	Low	Low	Low
[73]	Low	Low	Low	Low	Low
[74]	Low	Low	Low	High	High
[75]	Low	Low	Low	High	High
[76]	Low	Low	Low	Low	Low
[77]	Low	Low	Low	Low	Low
[78]	Low	Low	Low	Low	Low
[79]	High	Low	High	High	High
[80]	Low	Low	Low	High	High
[81]	Low	Low	Low	Low	Low
[82]	Low	High	Low	High	High
[83]	Low	Low	Low	High	High
[84]	Low	Low	Low	High	High
[85]	Low	Low	Low	High	High
[86]	Low	Low	Low	Low	Low
[87]	Low	Low	Low	Low	Low

3.4 Classification and Coding Frameworks

To improve the display of the systematic review results, a table was created based on the search terms, illustrating the input features for training the ML algorithm, the types of ML algorithms used, the performance metrics, and the IoT frameworks used in maternal healthcare.

4 Results

The selected studies were analyzed, and the results were presented in tabular format. The main focus was on IoT frameworks, including the data communication modules and the features/parameters used, the ML algorithm, and the evaluation metric. Table 3 summarizes the analyzed papers by whether IoT and ML technologies were integrated, the ML algorithms and parameters used, and the performance metrics.

Table 3: A summary of all the reviewed studies between 2017 and 2024

Study	Year	IoT/ML-Integrated	ML Algorithm used	Features captured using sensors	Wearables and embedded IoT	Evaluation metrics
[59]	2022	No	Decision Tree, Random Forest, SVM, KNN, Naïve Bayes, and Multilayer Perceptron	Static features	None	Accuracy Sensitivity Specificity
[43]	2021	No	None	Pregnant activities include; stress, sleep, and physical activity.	smart rings, smartwatches, Holter monitors, and PPG sensors	system's feasibility, energy efficiency and data reliability
[46]	2019	No	None	Heart rate	Biosensor, Activity tracer Smart wristband	Accuracy
[60]	2022	Yes	-Decision Trees -Naïve Bayes, -SVM, -Random forest, -Stochastic Gradient Boosting -Logistic Regression	Maternal parameters -Abdominal pain -Visual disturbances -Hyperreflexia - BP, Fetal parameter -Amniotic fluid volume -Feto-placental unit	Wireless CTG Blood pressure sensors Smartphones	-Sensitivity -Accuracy -Area Under curve (AUC)
[61]	2022	Yes	KNN Decision Tree	Blood pressure Heart rate Body temperature	PIC microcontroller (PIC16F877A Blood pressure sensor Heartbeat sensor, Temperature sensor	Not specified
[88]	2021	No	None	-fetal heart rate, -Blood glucose/sugar, -Uterine contraction, -Blood pressure	-Blood pressure sensors- GIS -Smartphone	Not specified
[62]	2020	Yes	Modified Decision Tree Algorithm	Blood sugar Blood pressure,	Not Implemented	Accuracy.
[89]	2018	No	None	Body temperature, glucose level, pulse rate, fetal movement	LoRa technology to interface the maternal monitoring system in the ambulance	Not specified
[90]	2022	No	None	Temperature, heart rate	Arduino microcontroller, pulse sensor, temperature sensor, GSM module	Not specified
[91]	2024	No	None	Fetal heart rate	FHR detector	Accuracy, Sensitivity, Specificity
[92]	2018	No	None	Blood pressure, heart rate, and patient steps	The V07 smart wristwatch used Bluetooth technology to transmit data to a mobile application.	Not specified

Study	year	IoT/ML-Integrated	Algorithm used	Features captured using sensors	Wearables and embedded IoT	Evaluation metrics
[63]	2021	Yes	SVM, boosted decision tree, logistic regression, Bayes point machines, decision forest	Static	Proposed to use Arduino with a heartbeat sensor, temperature sensor, blood sugar sensor, and Wi-Fi module	AUC, accuracy, recall, f1-measure
[93]	2017	No	None	Not mentioned	Proposed portable medical devices with multiple sensors, mobile devices, and cloud.	Not specified
[94]	2020	No	None	Body temperature, blood pressure, heart rate, pulse rate,	Arduino microcontroller, wireless RFID	Not specified
[64]	2021	Yes	Support Vector Machines	Heart rate, blood sugar, temperature, and uterine contraction	Sensor devices, smartwatches.	Not specified
[65]	2021	Yes	1-D convolutional neural network (CNN) classifier	uterine tonus activity, blood pressure, heart rate, temperature and oxygen saturation	IoT module to monitor FHR IoT module - (heart rate, oxygen saturation, blood pressure, and temperature) signs	Accuracy of F1- score
[39]	2019	No	None	Blood pressure	F1 smart wristwatch, IoT technology Mobile device	Not specified
[37]	2018	No	None	Temperature, blood pressure, fetal heart rate	Temperature sensor, blood pressure sensor, Accelerometer sensor, Arduino controller, Mobile technology	Not specified
[41]	2020	No	None	Heart rate, temperature, fetal motion, labor pain symptoms, excessive sweat	Abdomen belt with a temperature sensor, pulse rate sensor, sweat sensor, accelerometer, force sensor, and MPU 6050. Microcontroller, GSM, and cloud computing	Not Specified
[46]	2019	No	None	Physical activity, sleep, and heart rate	Smart wristband, cloud technology, IoT technology, photoplethysmogram biosensors, and an inertial measurement unit	Not specified
[66]	2023	Yes	Decision tree	Blood pressure, blood glucose level, ECG, temperature	Arduino Nano, ESP32 microcontroller module	Accuracy
[45]	2020	No	None	Blood pressure, Temperature Haemoglobin level,	Sensors, Cloud	Not specified

Study	Year	IoT/ML-Integrated	Algorithm used	Features captured using sensors	Wearables and embedded IoT	Evaluation metrics
[48]	2019	Yes	K-means clustering algorithm Random forest	Heart rate, sleep information	Garmin Vivismart 2, IoT, Edge computing, cloud computing	Accuracy
[67]	2018	No	Naïve Bayes and Logistic Regression	None	None	ROC Curve, Accuracy, Sensitivity, Specificity
[68]	2020	No	ANN, Logistic regression, Decision tree, SVM, Random forest, and ensemble method	None	None	Precision, sensitivity, Specificity, ROC, and AUROC
[26]	2018	No	ANN, Naïve Bayes, KNN, Linear regression, and SVM	None	None	Accuracy
[24]	2018	No	ANN and Deep learning	None	None	Accuracy
[69]	2019	No	Decision tree	None	None	Accuracy, Precision, Recall, and F-Score.
[70]	2019	No	C4.5 Decision Tree and K Nearest Neighbor	None	None	Accuracy, precision, Specificity
[71]	2020	No	Logistic regression, ANN, Gradient boosting decision tree (GBDT), and ensemble learning were experimented with.	None	None	Accuracy
[72]	2024	No	Convolutional Neural Networks	None	None	Accuracy
[73]	2023	Yes	Random forest classifier	Heart Rate (HR), Systolic/Diastolic BP, Fetal Movements, and Temperature	a wearable device that consists of different sensing modules that collect data, i.e., BP, Temperature, Heartbeat	Accuracy
[74]	2024	Yes	ANN	Temperature, Heart rate, Blood pressure	Wearable sensing technology, Arduino Mega 2560, Smartphone	Sensitivity
[75]	2017	No	Random forest, Naïve Bayes, decision tree	None	None	Accuracy, averaged one-dependence estimator, true positive rate, positive rate.
[76]	2021	No	Gradient boosting, Logistic regression	None	None	Area under the curve, Specificity, sensitivity, positive predicted value.
[77]	2018	N0	SVM, Bayesian networks, Naïve Bayes, Neural Network, Random forest, C4.5 decision tree, Adaptive regression spline, Logistic regression	None	None	ROC, Accuracy, Sensitivity, Specificity, F1 score

Study	Year	IoT/ML-Integrated	Algorithm used	Features captured using sensors	Wearables and embedded IoT	Evaluation metrics
[78]	2019	No	Logistic regression, decision tree, naïve Bayes, SVM, random forest, stochastic gradient boosting.	None	None	ROC Curve, Area Under Curve, Accuracy, sensitivity, and Specificity
[79]	2019	Yes	Viterbi Machine learning algorithm	Blood pressure.	Smart Bracelet	Accuracy, Sensitivity, Specificity
[80]	2018	No	A hybrid of Multivariate adaptive regression splines (MARS) and Support Vector Machine	None	None	Accuracy, Sensitivity, and Specificity
[81]	2020	No	Naïve Bayes	None	None	Accuracy, AUC, and ROC curve sensitivity
[82]	2020	No	ANN, Random Forest, Naïve Bayes, Bagged Tree, Boosting, Linear regression	None	None	Accuracy Random forest had the highest accuracy of 87%.
[83]	2017	No	ANN with 50 hidden layers	None	None	The accuracy of the ANN
[84]	2019	No	Backpropagation ANN with 11 neurons	None	None	Not Specified
[85]	2020	No	Support vector machines (SVM)	None	None	Accuracy
[86]	2023	Yes	optimized single-dimensional Convolutional Neural Network KNN, Random forest(RF), SVM, Convolutional neural networks(CNN) and Extreme learning machines (ELM)	heart rate, temperature, blood pressure, blood glucose, oxygen saturation, and fetal heart rate	Accelerometers, respiration sensors, temperature sensors, heart rate sensors (Maternal and Fetus), Pulse Oximeters, esp8266 WIFI handsets	Accuracy, Precision Recall, Sensitivity F1-score
[87]	2024	Yes	Decision tree, K nearest neighbors, Extreme Gradient Boosting, Random Forest Adaptive boosting Multilayer perceptron	temperature, blood pressure, glucose levels, and heart rate	Raspberry Pi 4 Model B single-board computer, including heart rate, blood pressure, glucometer (HbA1c, Fasting hour-m), and temperature sensors	Accuracy, ROC, AUC

5 Discussion

Integrated IoT and machine learning technologies can be used to implement systems capable of continuously monitoring maternal and fetal vitals and predicting the occurrence of pregnancy complications. This would aid early warning and prompt appropriate, timely intervention measures to improve the health of expectant women and their fetuses. Additionally, the technologies can support data-driven intervention and individualized maternal care. The use of these technologies can make maternal healthcare more proactive, accessible, and effective, ultimately improving birth outcomes. The goal of this review was to understand recent trends and gaps in the use of these integrated technologies in maternal healthcare and to provide recommendations for future design considerations. In the discussion that follows, we explore our findings guided by the review questions. The first research question sought to understand cutting-edge technologies commonly used in the early diagnosis of pregnancy complications to improve pregnant women's health. From the analysis, the research interest in the integration of IoT and ML in maternal healthcare began in 2019, marking the start of efforts to integrate IoT and Machine learning technologies to monitor pregnant women and predict pregnancy complications in real time. For the years 2023 and 2024, this review found only 3 and 4 research articles, respectively, that integrated the two technologies in maternal healthcare. This clearly shows that research on integrating these technologies into maternal healthcare is in its early stages and that there is significant potential for further research in this area. There is a great opportunity for innovations that involve monitoring pregnant women and predicting pregnancy complications, thus further studies in this field are necessary. Figure 4 shows the trends in the use of IoT and ML in pregnancy complications between 2017 and 2024. Table 4 contains details of the commonly used IoT frameworks in maternal healthcare.

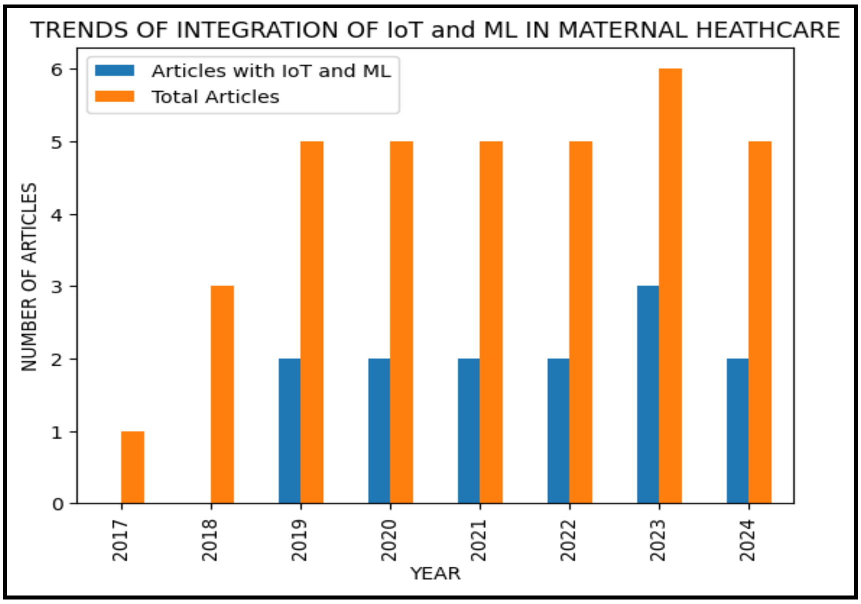

Figure 4: Trends of integration of IoT and ML in maternal healthcare

Table 4. Wearable and embedded IoT

Wearable and embedded IoT	Research article	Frequency
None	[59], [91]	2
Existing smart device	[43], [46], [92], [64], [48], [79], [39], [46], [73]	9
Arduino microcontroller,	[90], [63], [94], [37], [45], [66]	6
Microcontroller	[61],[41], [93], [89]	4

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Not Implemented	[62], [88], [72]	3
IoT module	[65], [86], [87]	3

The answer to the second research question would guide the selection of appropriate machine learning algorithms to experiment with when designing pregnancy complication prediction models, as well as the evaluation metrics to use. This research found that decision tree algorithms were most commonly used to implement predictive models for pregnancy complications, followed closely by random forests and support vector machines. We observed that 65 pregnancy complication prediction models had been developed and implemented across the 50 articles we reviewed. Of the 65 models, 15 used the decision tree technique, 11 used the random forest algorithm, and 10 used the support vector machine algorithm. Decision trees are widely used for predicting pregnancy complications due to their ease of use and interpretability; they are also adaptable to both categorical and numerical datasets because they do not require data scaling or encoding [95]. Moreover, decision trees require minimal data preprocessing because they do not require data normalization. Furthermore, they successfully capture complex nonlinear inputs and output features, making them ideal for real-world applications [96]. These aspects make them suitable for use as a researcher can easily verify their decision-making process.

Random forests have also been widely used in predicting pregnancy complications. They work by averaging the decisions of multiple trees, thereby reducing the risk of overfitting and increasing the forest's accuracy. They are suitable for managing large datasets and data with missing values [97]. SVMs have the advantage of handling small datasets; they are ideal for high-dimensional datasets and are not prone to overfitting [98]. From the review, only a few studies integrated deep learning models with IoT technologies. Figure 5 summarizes the commonly used machine learning algorithms in maternal healthcare.

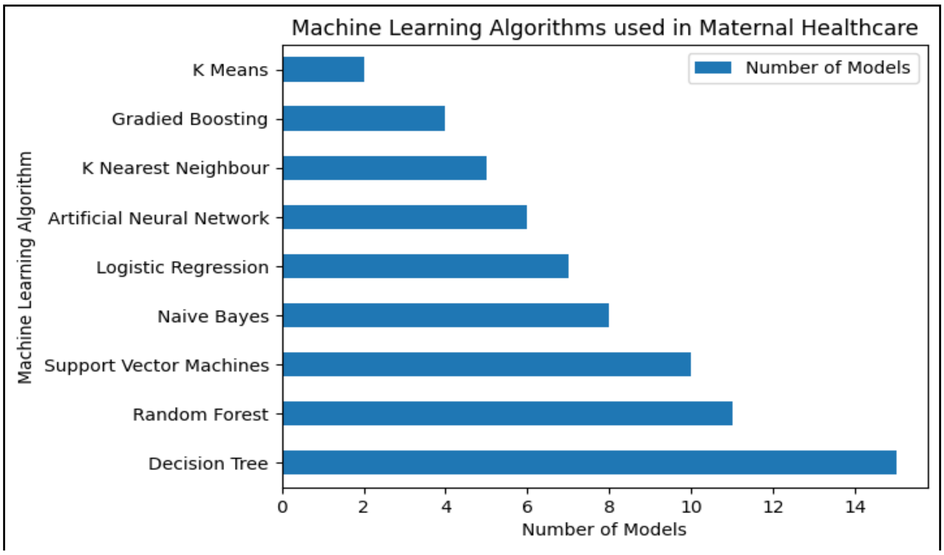

Figure 5: Machine Learning algorithms used in maternal healthcare

The review further established that the accuracy metric, a measure of correct predictions, is the most commonly used, as 26 of the 50 studies reviewed used it. The recall metrics followed this. The least-used evaluation metric for predicting pregnancy complications is precision, as shown in Figure 6. Although the accuracy metric is simple to understand, it can provide a quick overview of a predictive model's performance and is commonly used in predicting pregnancy complications, it has some challenges. The metric is not suitable for use with imbalanced data sets and doesn't account for the consequences of false positives or false negatives [99]. The sensitivity, or recall, metric focuses on the actual positive cases. It is a measure of the predictive model's ability to minimize false negatives. A high recall (sensitivity) implies that the predictive model doesn't miss women with pregnancy complications. The metric is appropriate because the cost of a false negative can be deadly. Aggregate metrics such as area under the curve, F1-score, and receiver operating characteristic (ROC) have also been used in maternal healthcare. The metrics combine various performance characteristics into a single figure [99] and provide a comprehensive

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understanding of the models' performance. The precision metric is the model's ability to minimize false positives among predicted positives, that is, incorrectly predicting a complication that does not exist; it measures the model's ability to avoid raising false alarms. The specificity metric emphasizes actual negative cases, that is, correctly identifying pregnant women without pregnancy complications, which is ideal for avoiding unnecessary interventions.

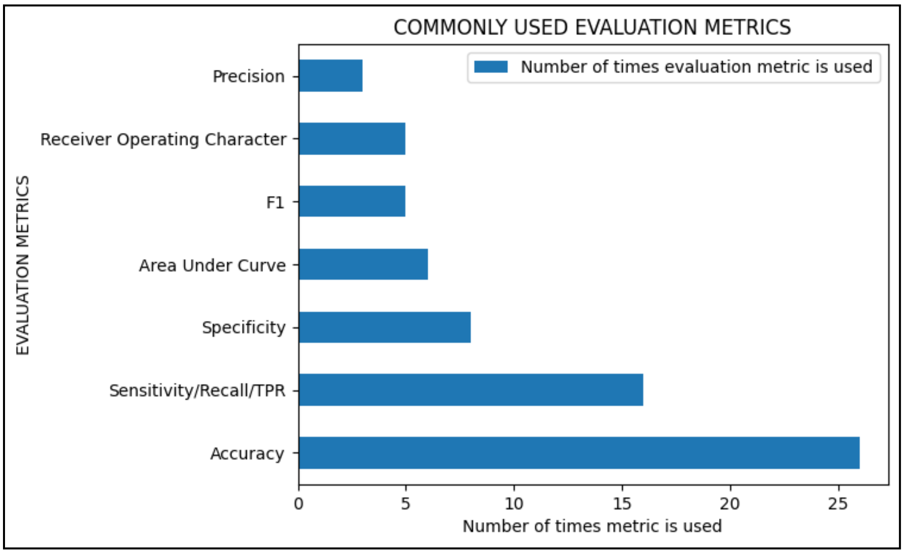

Figure 6: Commonly used evaluation metrics

The third research question aims to identify the most suitable features used in the design of an IoT framework for the remote monitoring of pregnant women's vital signs. The researchers established that the most commonly used features in monitoring pregnancy complications are blood pressure, temperature, and maternal heart rate. Additionally, initial research used blood pressure measurements. The researchers also found that, due to advancements in IoT technologies, other features such as blood oxygen levels, fetal heart rate, and uterine contraction values have recently been used to monitor the health status of pregnant women. Patients' steps and sleep patterns are the least used feature in monitoring the health status of pregnant women. Figure 7 shows the trends in the features used to monitor pregnancy complications.

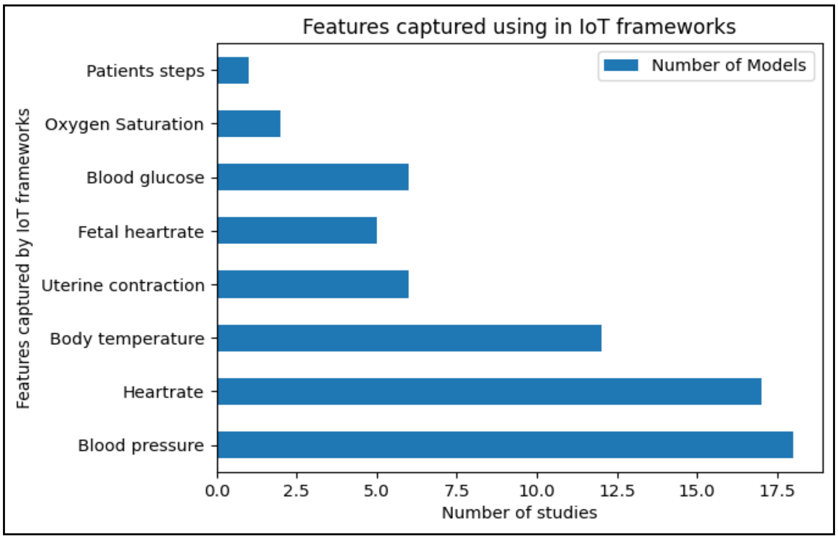

Figure 7: Features captured using IoT frameworks

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The fourth research question would help in understanding the research gap in the design and implementation of models that integrate ML and IoT technologies in maternal healthcare. As shown in Figure 8, this review found that 47% of the studies examined did not monitor the vital signs of pregnant women. Further analysis of the studies revealed that 21% used existing smart devices, such as smartwatches, while 16% used Arduino, which is likely inappropriate given its size. Only about 10% of the studies used microcontrollers to design a custom-made PCB-based monitoring device. This implies that further research is necessary on appropriate IoT frameworks for real-time monitoring of pregnant women using suitable biosensors, powerful microcontrollers, and integrating them with ML. Additionally, the analysis revealed that none of the reviewed studies used tinyML models to predict pregnancy complications. Consequently, there is a need to explore further the use of tinyML technology to build lightweight predictive models that can be embedded in IoT devices to predict pregnancy complications in real time.

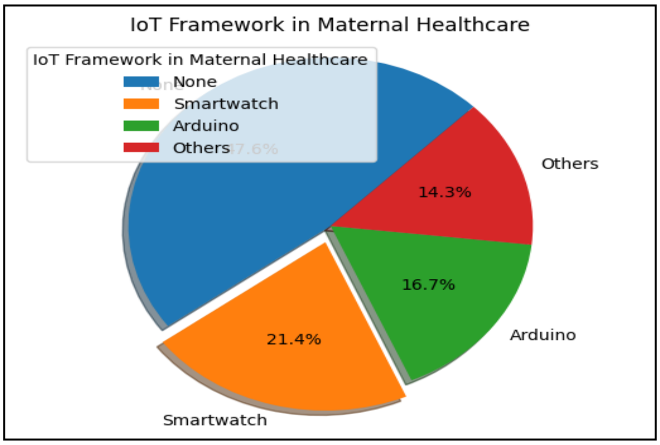

Figure 8: IoT frameworks in maternal healthcare

The last research question sought to understand how data from IoT monitoring devices in maternal healthcare was transmitted to the cloud for analysis and storage. The question focused on the communication modules used in the devices for monitoring the vital signs of pregnant women. The research found that 44% of the studies relied on smartphones as intermediaries to transmit the captured vital sign values to the cloud for analysis and storage. In 36% of the studies, the data transmission model was not mentioned. Data transmission was done using a Wi-Fi communication module in only 12% of the studies, while LoRa technology was implemented in monitoring devices in 4% of the studies, as shown in Table 5. Though most of the reviewed studies used smartphones as intermediaries for data transmission, smartphones are costly and difficult to access in lower- and middle-income countries, and it is also not easy to customize their firmware to suit specific research needs. Moreover, they may be difficult to integrate with existing electronic healthcare systems, and, above all, users may lack technical support for device use, and data security is not guaranteed [100].

Table 5. Data transmission module

Data transmission module	Research articles	Frequency
Smartphone Intermediary	[43], [46], [61], [88], [92], [93], [64],[41], [90], [48], [79]	11
LoRa	[89]	1
Wi-Fi	[63], [66], [86],	3
Not mentioned	[62], [94], [45], [45], [91], [101], [73], [74], [87]	9

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Fog computing	[65]	1

This demonstrates the need to empirically evaluate appropriate microcontrollers, biosensors, communication modules, and ML-based maternal risk prediction models. This can be used to design and develop a custom-made maternal health monitoring device with edge computing capabilities to preprocess captured vital signs and securely transmit the vital data directly to the cloud for analysis and storage, without the need for intermediaries such as smartphones. This model can be integrated with a mobile application to provide timely user alerts, feedback, and personalized recommendations. Further, a clinical dashboard for remote monitoring that is accessible to clinicians could also be developed. Large language models can also be used to generate clinician-friendly messages for expectant women. A proposed conceptual model for maternal health monitoring is shown in Figure 9.

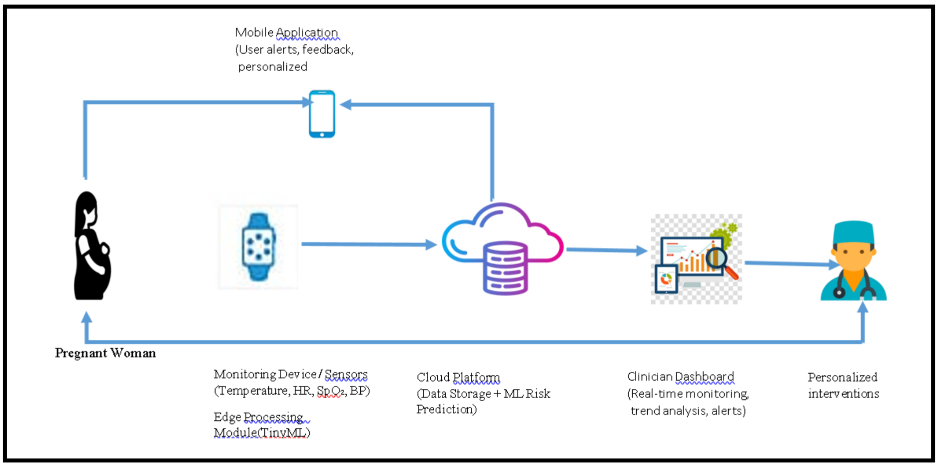

Figure 9: IoT ML Maternal Health Monitoring Conceptual Model

6 Limitations of the Study

The limitations of the study included the following:

1. Whereas the 50 articles analyzed in this study were carefully selected, a few studies on the use of machine learning and IoT in maternal healthcare might have been missed. This oversight might be due to several reasons, including but not limited to the inclusion criteria selected for this study.
2. The examined studies demonstrated different performances of the same machine learning technique, making it difficult to determine the best-performing technique.

7 Conclusion

In recent years, the integration of IoT and ML technologies has demonstrated tremendous potential in transforming maternal healthcare. These technologies have enabled the implementation of applications for remote monitoring and forecasting pregnancy complications. The rising number of pregnancy-related problems is still a major concern, with serious consequences for both maternal and fetal health. This review explores the integration of IoT and ML, examining their collaborative role in maternal healthcare by enabling continuous and remote monitoring of vital signs to enhance early diagnosis of pregnancy complications. This would allow for timely intervention measures to be put in place to improve the health status of pregnant women. The review focuses on existing gaps in integrating these technologies into maternal healthcare. It explores appropriate features, an IoT framework, ML algorithms, and evaluation metrics, and provides recommendations for further research work.

The ability of IoT devices to gather more detailed physiological data, such as blood oxygen levels, fetal heart rate, and uterine contractions, enhances remote monitoring. Despite these advances, there are still

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challenges in developing comprehensive frameworks that can capture the entire range of maternal and fetal vital signs and securely transmit the values to cloud storage for analysis. Previously, ML studies on maternal health were distinct from studies on maternal health monitoring. This review has established that the integration of IoT and machine learning in healthcare has recently become a focus for many researchers. Nonetheless, further research can be carried out on IoT frameworks that capture both fetal and maternal vital signs using powerful microcontrollers that integrate multiple communication modules, allowing the captured values to be transmitted directly to the cloud without the use of intermediary expensive smartwatches. These IoT ML frameworks may also be integrated with the pregnancy complication ML prediction model to monitor and classify pregnant women at risk of pregnancy complications in real time. This would ensure that appropriate and timely intervention is implemented in maternal healthcare to reduce poor birth outcomes. The gathered vitals can be analyzed using ML techniques to design a personalized care plan for different pregnant women. Furthermore, the evaluation of tinyML for on-device sensor data processing, which offers promise for real-time monitoring, requires further research.

Acknowledgments

None

Statement on conflicts of interest

No conflict of interest

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Journal of Health Informatics in Africa

A User Experience Model for Health Data Visualization for Managerial Decision Support

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Background and Purpose: In public health management, decision-making is heavily reliant on data derived from routine health information systems (RHIS). However, the increasing volume of data necessitates the development of decision-support tools to facilitate data visualisation (DataViz). Despite the availability of several tools, the varying requirements of health managers, based on their respective decision-spaces, contexts, content needs and personal attributes, pose a challenge. Drawing on a public health medicine perspective, this study aims to develop a User Experience (UX) model for the Western Cape Department of Health and Wellness to improve the design of RHIS DataViz systems.
Methods: The study involved a comprehensive description of the RHIS policy landscape, structures, and processes to understand the regulatory context. A literature review was conducted to investigate the theories and application of UX in RHIS. A Proposed UX model for RHIS DataViz was developed based on the International Organisation for Standardization's definition of UX, and components from other UX models. The model was tested through a case study involving interviews with 15 health managers, which were subsequently analysed thematically. A focus group was conducted to refine the model, and its final version was evaluated by external subject-matter experts.
Results: The final UX Model for RHIS DataViz emphasises the importance of purposeful storytelling of RHIS data content. However, it also recommends mindfulness of the cognitive load placed on health managers and the range of contextual factors affecting their UX.
Conclusions: The UX Model for RHIS DataViz can be a useful guide for UX practitioners and business analysts while exploring health manager RHIS DataViz requirements. Moreover, the multi-method study, rooted in the design science research paradigm, demonstrates the agility of public health medicine in assimilating innovative research methods.

Keywords: user-centred design, health information systems, routinely collected health data, decision support, design science

1 Introduction

In public health management, decision-making is significantly reliant on data, particularly from Routine Health Information Systems (RHIS) [1]. These systems are designed to support health managers by providing timely, accurate, and comprehensive data to inform decisions on service delivery, resource allocation, and health outcomes improvement. However, as the volume of data collected by RHIS increases so does the complexity of interpreting and utilizing it effectively. Health managers must navigate a wide range of data points, often without adequate decision-support tools to visualize or contextualize this information, making the process overwhelming and time-consuming [2, 3].
Data visualisation (DataViz) helps to convert complex health data into forms that are easier to interpret and use [4]. By providing visual representations of patterns and trends, DataViz can support health managers in drawing insights that may not be immediately evident in raw data [5]. Yet the process of interacting with data is not always straightforward. In the context of RHIS, the usability of DataViz tools plays a significant role in shaping how information is interpreted and whether it informs practical action. Tools that are poorly aligned with users' cognitive processes or decision-making contexts may hinder rather than assist [6].

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Within the Western Cape Department of Health and Wellness (WCDHW), this problem is compounded by the wide range of decisions that managers face. These range from immediate operational responses to long-term service planning, each requiring different forms of data interaction [3]. The entities and facilities under managerial oversight are themselves heterogeneous, ranging from primary health care clinics through district and regional hospitals to central academic hospital complexes, each with distinct scale, case mix, and information requirements. Moreover, the diversity of the management workforce adds another layer of complexity. Not all managers are equally comfortable with digital tools, and levels of data literacy vary considerably across the system. A tool that supports one user group well may present barriers to another. There is a need to better understand how DataViz design choices interact with these varying contexts and capacities, so that RHIS tools can more effectively support managerial work.

One of the persistent challenges in developing RHIS DataViz tools lies in the lack of a deliberate user-centred design approach, particularly in how these tools support the user experience (UX). The ISO 9241-210 standard defines UX as encompassing the perceptions and responses that arise from both the actual and anticipated use of a product, system, or service [7]. These responses extend beyond technical functionality, encompassing a wide range of elements such as emotions, beliefs, preferences, perceptions, and even physical and psychological reactions during use. At its core, UX speaks to how users engage with a system, including dimensions of usability, accessibility, and satisfaction [8]. In practice, when the UX of a DataViz tool is poor, health managers may struggle to interpret the information presented to them or to act on it in a timely manner. The result can be a missed opportunity to improve services or address emerging issues [9]. For this reason, a considerable argument can be made for the development of a UX model that is specifically attuned to the daily realities and challenges of health managers in the WCDHW. Tools that are both practical and intuitive are more likely to be adopted and used in ways that genuinely support data-driven decision-making [9].

RHIS DataViz tools, when well designed, can support more effective decision-making among health managers [5]. A central aim of these tools is to present information in ways that are clear, interpretable, and actionable within the constraints of managers' work environments. In practice, however, many existing tools do not achieve this. Managers are often presented with large volumes of data or complex visual layouts that make it difficult to extract relevant insights [10]. This can reduce the practical value of the information, leaving it underutilised in daily decision-making. The diversity of decision contexts across the health system further complicates tool design. Managers at provincial, district, and facility levels each operate within distinct decision-spaces that require different forms of data support [3]. A district manager, for example, may need high-level population trends to guide strategic resource allocation, while a facility manager may focus on more granular clinical or operational indicators to inform service delivery [9]. Designing DataViz tools that can accommodate such varied needs remains an ongoing challenge.

Existing research has shown that health managers are more likely to adopt RHIS DataViz tools when these systems are aligned with their specific decision-making contexts [9]. However, a lack of user-centred design often results in low adoption rates, with health managers opting to rely on traditional data interpretation methods rather than adopting new technologies [9]. This challenge is further compounded by the varying levels of data literacy among health managers in the WCDHW. A successful UX model must consider these varying levels of familiarity with data analytics tools and provide intuitive, easy-to-use interfaces that minimize the learning curve for users [5].

Despite the growing availability of RHIS DataViz tools, many of these systems have been developed without a nuanced understanding of the user experience of those expected to use them [9]. In the WCDHW, increasing digitisation and harmonisation of RHIS processes have made more data accessible to health managers. Yet this abundance of information, often spread across multiple dashboards, can become overwhelming. Rather than enhancing decision-making, it risks introducing confusion and fragmentation, especially when the design of these tools lacks coherence or alignment with users' cognitive and contextual needs. There is, therefore, a need for a conceptual model that clarifies the factors shaping user experience in RHIS DataViz and can guide the design of more usable, meaningful visualisation tools. The aim of this study is to develop a UX model that will inform the design of routine health information visualisation systems for managerial decision support in the WCDHW.

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2 Methods

2.1 Research Design

This study employed a Design Science Research (DSR) approach to investigate and iteratively refine a conceptual model of UX in the context of RHIS DataViz for managerial decision-making. DSR was selected for its focus on problem-solving through artefact development, making it well-suited for addressing the gap between RHIS tool functionality and user experience in a public health setting [11, 12]. In DSR, an artefact is a constructed output (a construct, model, method, instantiation, or design proposition) that addresses a real-world problem [11]. The artefact developed in this study is the UX model itself, which evolved iteratively through the four DSR phases. The research was situated within the WCDHW, a provincial health system. The system includes 6 districts, 33 sub-districts, 53 hospitals, and over 270 fixed primary care facilities, supported by a layered managerial structure operating at sub-district, district, and provincial levels. This organisational arrangement provided an ideal environment for exploring the intersection between data systems and the decision-making needs of health managers.

The DSR process [Fig. 1] included four iterative phases: problem awareness, suggestion, development, and evaluation. These phases guided the creation of a novel UX model grounded in the real-world experiences of health managers. A mixed-methods design was used to generate, refine, and validate the model. This included qualitative case study methods and structured expert evaluation to ensure both theoretical soundness and practical applicability [12].

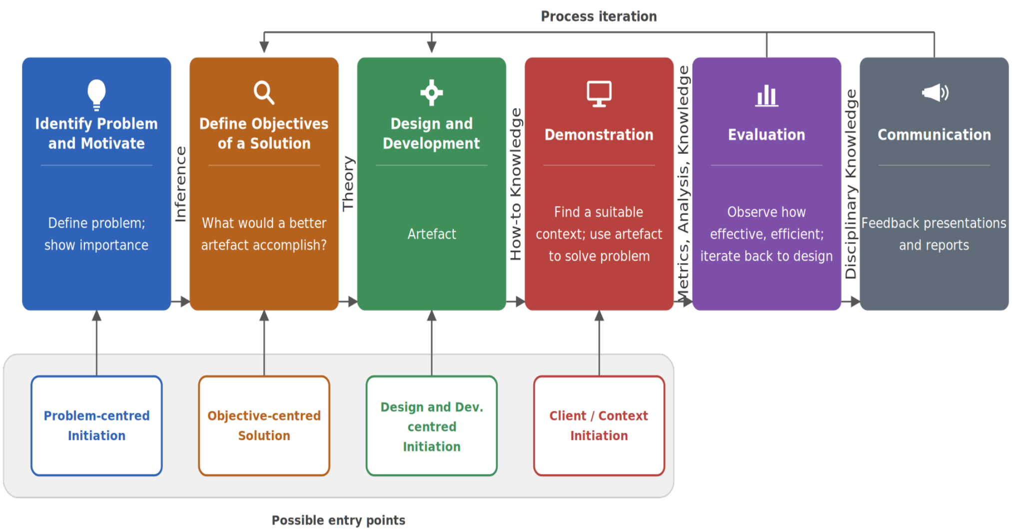

Figure 1: Design Science Research Process. Source: Adapted from Peffers et al.[12]

The study was grounded in an interpretivist epistemological stance, recognising that UX is shaped by users' perceptions, professional values, and contextual realities. The research acknowledged that health managers' experiences with RHIS DataViz are situated, meaning-laden, and shaped by operational constraints. Ontological and epistemological assumptions aligned with the view that these subjective accounts constitute valid knowledge and are essential for designing usable, relevant health information tools. Axiologically, the study aligned with the WCDHW's organisational values of accountability, innovation, and competence, reflecting its strategic commitment to evidence-based service delivery [3, 13].

2.2 Data Collection Methods

Data were collected using multiple qualitative methods to capture a holistic view of managers' UX with RHIS DataViz. These included direct observation, key informant interviews, and a focus group discussion (FGD) in 2020. A purposive sampling strategy was applied to ensure representation across the various levels of management, including participants from both rural and urban settings within the WCDHW.

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Direct observations were conducted during routine meetings such as district executive, and facility performance review meetings. These occasions offered opportunities to see the use of RHIS DataViz for service monitoring and decision-making. Observations provided insight into real-time use of dashboards, the social dynamics of data interpretation, and contextual factors influencing UX.

Semi-structured interviews were held with 15 health managers. Eligible participants were line managers with direct responsibility for clinical service delivery; corporate or support-function managers (finance, human resources, supply chain, infrastructure, information management) were excluded. These interviews explored experiences of using RHIS DataViz tools, factors that supported or hindered their use, and participants' views on what model components were most relevant. The sample size was guided by data saturation, which was reached after 15 interviews. All direct observations and key informant interviews were conducted by the principal investigator, a public health medicine specialist employed within the WCDHW at the time of fieldwork, in order to maintain consistency of interview technique, prompts, and observational lens across the case study group. Reflexive notes were maintained throughout fieldwork to surface potential biases arising from this insider-researcher role, and these are revisited in the Discussion.

FGDs served to cross-check emerging findings and contributed to the co-refinement of the model. Participants reflected on draft model components, shared feedback, and suggested revisions. This iterative process allowed the study to incorporate perspectives from users who engage with RHIS DataViz in everyday practice.

Interview data were collected over a six-month period and were triangulated with relevant policy documents, internal reports, and strategic frameworks from the WCDHW. This ensured alignment with the organisational context and strengthened the credibility of the UX model.

2.3 Case Study Approach

This study was conducted within the WCDHW, a provincial health system in South Africa with a longstanding emphasis on health information systems innovation [14]. A case study approach was adopted to provide an in-depth understanding of health managers' experiences with RHIS DataViz in this context. This method allowed detailed analysis within a specific, real-world context, offering insight into the model's practical relevance and applicability. The framework by Rashid et al. guided this case study, providing a structured approach that included foundational preparations, pre-fieldwork, fieldwork, and reporting [15].

The case was set in a provincial health system with a mix of urban and rural service platforms, a defined operational hierarchy, and an established digital health reporting infrastructure. This made it a relevant and information-rich context for examining how DataViz tools are used by health managers to support routine decision-making. Pre-fieldwork included obtaining ethical and operational approvals, developing a case protocol, and defining the unit of analysis. The case focused on collective managerial experience rather than individual perspectives, reflecting how RHIS DataViz is typically discussed and applied during team meetings and strategic planning.

The case study findings informed the iterative refinement of the UX model. Triangulation with policy documents and strategic plans added depth and credibility to the interpretation process. The case also served as a practical environment for assessing the model's relevance and for eliciting user feedback on preliminary components prior to expert evaluation.

2.4 Model Development and Evaluation

Model development followed the iterative process outlined in Figure 2, drawing on the approach by Becker et al. [16, 17]. An initial UX model was synthesised from the literature, incorporating constructs relevant to RHIS DataViz and UX design. This preliminary model was iteratively refined through user feedback obtained during interviews and focus group discussions with health managers.

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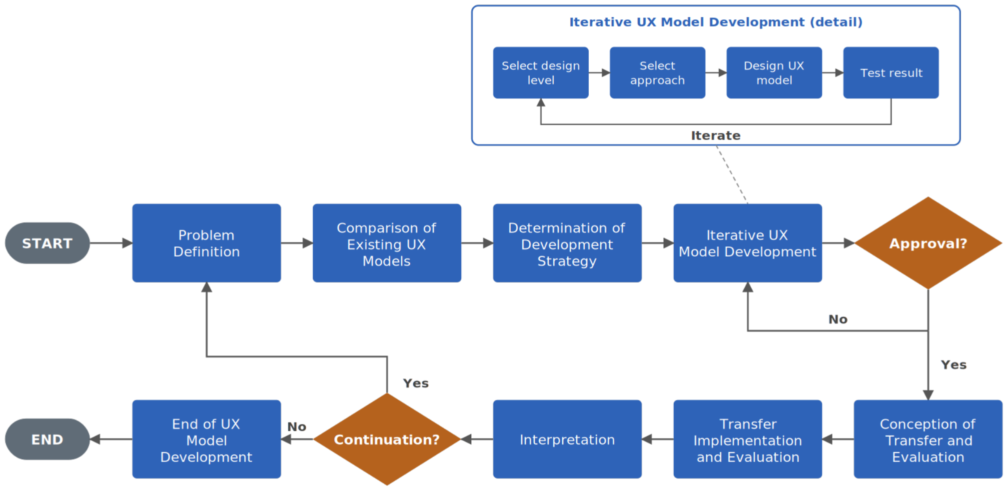

Figure 2: Procedure for Developing a Model for RHIS DataViz. Source: Adapted from Becker, Knackstedt, Pöppelbuß [16, 17]

After a pause in research activities caused by the COVID-19 pandemic, the refined model underwent evaluation in 2022 by eight external experts specializing in user experience, routine health information systems, and data visualisation. Using a structured digital instrument, reviewers rated the usefulness of each component and provided qualitative commentary. Their feedback informed further refinements, resulting in a final UX model tailored to RHIS DataViz in managerial decision-making contexts [16]. The expert evaluators were selected for their independence from earlier research phases and their demonstrated expertise in areas such as UX, health information systems, data visualisation, health management, and decision support. They included public health professionals, policy analysts, human-computer interaction scholars, and business analysts with experience in the South African health system context.

2.5 Data Analysis

The data collected during this study were analysed through both thematic analysis and expert evaluation methods, providing a robust foundation for refining the UX model for RHIS DataViz.

2.5.1 Thematic Analysis of Case Study Data.

Thematic analysis was applied to the data gathered from direct observations, key informant interviews, and focus group discussions with health managers, following the six-step framework outlined by Kiger and Varpio [18]. The steps involved familiarization with the data through repeated readings of interview transcripts and observation notes, generating initial codes using ATLAS.ti™ software, and identifying significant themes related to UX in RHIS DataViz. These themes were reviewed and refined, with names assigned to encapsulate key aspects of managers' experiences. Themes that emerged from this analysis were directly mapped to components of the proposed UX model and provided insights that guided the model's iterative development.

2.5.2 Model Evaluation Analysis.

The refined UX model was then subjected to expert evaluation by eight external reviewers with backgrounds in UX, RHIS, and Data Visualization. Each expert was asked to assess the model's components using a 3-point Likert scale (Useful, Neutral, Not Useful) and provide narrative feedback. Responses were analysed qualitatively by categorizing expert recommendations and comments, focusing on their alignment or divergence from the model's components.

The distribution of responses across the Likert scale was reviewed to identify components rated as particularly useful or needing adjustment. Key insights were extracted from the experts' narrative comments to inform final modifications to the model. This feedback process allowed the integration of

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expert perspectives on RHIS and decision-support contexts, enhancing the model's relevance and practical applicability for health managers.

Together, these analyses contributed to a well-rounded evaluation of the UX model, incorporating both in-depth thematic insights from case study data and validation from expert reviewers.

2.6 Ethical Considerations

This research was approved by the Stellenbosch University Health Research Ethics Committee (Reference No: S18/05/095) and adhered to national and international ethical guidelines, including the Declaration of Helsinki 2013. Written informed consent was obtained from all participants, and efforts were made to minimize disruption to routine managerial duties during data collection sessions. Access to interviewees was arranged through WCDHW's senior management to ensure minimal operational impact.

3 Results

3.1 Case Study Findings on RHIS Data Visualization for Health Management

3.1.1 Organizational Structure and Participant Characteristics.

This study was conducted within the WCDHW, a provincial health system in South Africa with a longstanding emphasis on health information systems innovation. At the time of the study, the WCDHW had implemented a number of digital tools for routine health information, including public- and manager-facing dashboards, yet faced persistent challenges in translating these data into improved service delivery at facility and district levels.

Health managers in this context operated within a complex, multi-tiered governance environment. Their responsibilities spanned from responding to immediate operational issues, such as medicine stock-outs or human resource shortfalls, to aligning services with provincial targets and strategic priorities. These decision-making responsibilities unfolded under pressure from resource constraints, performance mandates, and service delivery expectations, all of which shaped how managers engaged with RHIS data and visualisations.

Fifteen health managers were purposively sampled to represent a range of roles and decision-making levels, including facility-, subdistrict-, district-, and provincial-level management. All 15 participants were line managers with direct responsibility for clinical service delivery; corporate or support-function managers (finance, human resources, supply chain, infrastructure, information management) were excluded by design, as their data needs and information systems differ materially from those of service line managers. Participants were drawn from both urban and rural substructures. Most were experienced users of RHIS tools and had prior exposure to dashboard visualisations, although their technical literacy and comfort with data interpretation varied. The sample included 10 female and 5 male participants, reflecting the gender composition of the provincial management workforce at the time.

Rather than being passive recipients of data, these managers were observed to be active interpreters, interrogating the meaning of indicators, assessing implications for their services, and using visualisations to justify actions or identify gaps. Their feedback revealed a range of contextual, cognitive, and emotional factors that shaped the UX of RHIS DataViz tools. These real-world experiences provided a critical empirical foundation for the iterative development of the UX model.

3.1.2 User Perceptions and Responses to RHIS Data.

RHIS DataViz was consistently valued as a core tool for evidence-based decision-making across all managerial levels. However, participants emphasized that the trustworthiness of the data was paramount for fostering constructive decision-making processes and collaborative relationships. For instance, district-level managers articulated how data-driven accountability forms a cornerstone of WCDHW's ethos. As one participant explained:

"Our intention is to be a recognized leader in health system strengthening and health systems development. To meet that commitment and to influence other systems, it very often comes back to the relationships with people. But you must build that relationship. We need to have a deeper understanding

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of the issues and tap into making the connections with other people. This is based on the fact that everybody is accountable for something." – **Participant 10**

The case study indicated that RHIS data plays a dual role: on one hand, it reinforces accountability by documenting service performance; on the other hand, it can foster or undermine relationships depending on its perceived purpose. Several managers expressed concern that RHIS data might sometimes be perceived as punitive, as it could be used to critique performance rather than facilitate shared problem-solving. As one manager noted:

"In one example, the HbA1c data of diabetic patients was problematic. When I highlighted this to health care workers on site visits, they felt threatened. 'She's coming here to find something wrong and not listen to us first!' So how do I make sure that the data doesn't become a hindrance in relationships? Data should just be one of the inputs for your understanding the system performance." – **Participant 10**

These findings underscore the importance of transparency and support within the RHIS DataViz systems to enable managers to interpret data without fearing repercussions, thereby fostering a data culture focused on mutual understanding and service improvement.

3.1.3 Task Context: Managing Service Delivery and Corporate Functions.

The WCDHW requires managers to engage with RHIS data across a range of responsibilities, from direct patient service delivery to corporate functions like finance and HR. This dual focus created unique task demands that shaped participants' interactions with RHIS DataViz tools. At the facility and district levels, managers cited substantial challenges in accessing data needed to fully understand the local burden of disease. This was particularly evident among managers responsible for developing business cases for service expansion or improvement, where data was often incomplete or required a patchwork of information from multiple sources.

"*We knew the burden of disease in our community was really heavy. We did not previously have access to public health specialists when building the business case, but I knew it was a community with significant burden of disease both in infectious diseases such as HIV and TB as well as high interpersonal violence, and substance use mainly alcohol-driven violence based on EMS [Emergency Medical Services] data*." **– Participant 15**

In contrast, corporate functions such as *people management* and *finance* required managers to adopt a different analytical lens, which some participants found challenging given their clinical backgrounds. For example, Participant 4 described feeling underprepared for analyzing people management and finance data:

"*My staff are not actually skilled and equipped to analyse that data for me. I am struggling with other datasets like finance and HR. They're on top of the Quality Assurance data. But finance and HR data is a bit of a struggle for me. And to make decisions on that, I only have the APL [Approved Post Listing] which is numbers… I struggle actually to make sense of HR data."* **– Participant 4**

The findings suggest that RHIS DataViz tools must be versatile and accommodate both clinical and corporate data analysis to meet the varied needs of health managers effectively.

3.1.4 Social and Organizational Contexts.

The role of RHIS data in promoting transparency and collaboration was repeatedly emphasized by participants, who highlighted that data transparency can bolster trust across different management levels and with external stakeholders. However, managers expressed concerns that data misuse could strain relationships within the health system, especially when data is perceived as a means of oversight rather than improvement.

Participant 2 illustrated this trust-building potential by discussing how community stakeholders viewed data as an "equalizer" in establishing shared goals:

"*The Health Committee can also engage the data and say that 'Wow, now we have a narrative between us to say that we really are happy with what you guys have been doing.' And I think data can actually play a very important role as being the equalizer especially with the conflict-ridden space like Health."* **– Participant 2**

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Participant 10 echoed this sentiment, emphasizing that while data is essential for fostering accountability, it should be positioned as one of many inputs in decision-making rather than as a performance metric that could strain relationships.

3.1.5 Presentation, Data Quality, and Data Storytelling.

The presentation of data and its storytelling capacity were key themes in participants' experiences with RHIS DataViz. Several participants emphasised that data must "tell a story" to effectively support decision-making, suggesting that raw numbers alone are insufficient. Managers, particularly at the district and provincial levels, underscored the importance of following a coherent narrative, referred to as the "golden thread", to ensure that data insights align with the WCDHW's strategic goals.

"C*ertain data elements are more important than others. These tell a more strategic story. One needs to discover that story. And whether that story is linked to the strategy of the Department."* **– Participant 10**

Furthermore, data quality was highlighted as a concern, with participants indicating that inconsistent or fragmented data undermines decision-making and hinders trust. Managers were often cautious when assessing data quality and would cross-reference information to verify accuracy before making critical decisions.

3.1.6 Cognitive Load and Interactive Flexibility.

Participants repeatedly expressed concerns regarding the cognitive load imposed by the volume and complexity of data indicators required for routine reporting. While the Provincial Indicator Workgroup had made efforts to streamline these indicators, managers still found the sheer volume of information to be overwhelming.

"*I come from an office space where you work with data, where you see data, you're sitting in these types of meetings. But I think clinicians can only..., for the large part, most managers are old clinicians. They can only take in a certain amount of information*." **– Participant 2**

Additionally, participants noted that RHIS DataViz tools would benefit from interactive features allowing them to tailor data presentations to suit specific reporting needs. For example, managers expressed a desire for functionality that enables them to calculate indicators directly within RHIS tools to reduce manual data handling.

"Why can't they work on an indicator report where you don't have to do that [calculate manually]? Although I think it's a good exercise because then you will understand how the indicator is built. You need to know what must be divided by what to get the information." **– Participant 8**

3.2 Adjustments to the UX Model for RHIS DataViz based on the Case Study Findings

3.2.1 Managers' Insights on Model Components.

The UX Model's components resonated with participants across several dimensions, including User Perceptions and Responses, Context of Use, Interaction with RHIS DataViz, and User Internal & Physical State. Key themes that emerged as crucial to managers' RHIS DataViz experiences included Emotions and Comfort, Cognitive Load, Social and Organizational Contexts, and Data Quality. Participants provided feedback suggesting that the model accurately reflected their interactions with RHIS DataViz but recommended additional elements, such as data storytelling, to better capture the complexities of managerial decision-making.

3.2.2 Recommendations for Model Refinement based on the Case Study Findings.

Based on the case study findings, specific refinements to the Proposed UX Model were suggested:

a) Incorporate Data Storytelling: Develop a narrative element that guides managers through data insights to support cohesive decision-making.
b) Prioritize Cognitive Load Reduction: Limit data indicators to essential metrics, with options to drill down selectively, thereby minimizing cognitive strain.

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c) Highlight Data Quality Assurance: Ensure that RHIS DataViz tools enable managers to access high-quality, integrated data sources to build trust in the decision-making process.
d) Enhance Interactivity: Incorporate functionality that allows managers to customize data presentations, including automated calculations and the option to generate tailored reports.

These refinements aimed to enhance the utility of the UX Model for RHIS DataViz and better align it with WCDHW's unique operational needs, as voiced by the participants.

3.3 Evaluation of the Refined Model

A total of eight expert evaluators were invited to participate, of whom six provided informed consent and completed the evaluation.

The four main branches of the model: (1) User Attributes, (2) Interaction with RHIS DataViz., (3) User Perceptions & Responses, and (4) Context of Use, were generally evaluated as useful. Five of the six responding evaluators affirmed the overall usefulness of these components. For instance, Evaluator 1 said, *"All four components of the UX are important and will impact on the UX and thus the benefit of the information to the manager and therefore ultimately to the health system as a whole."* Similarly, Evaluator 5 remarked, *"The main components of the model are useful … exactly what will be needed when developing a tool to assist managers who are making the decisions."*

There was, however, critical engagement with certain subcomponents. The "Brand Image" subcomponent received neutral to negative feedback and was ultimately removed from the model. Evaluator 1 commented, *"The brand image doesn't fit in … and could well be left out without any negative impact."*

Conversely, support was strong for the inclusion of "Cognitive Load." Evaluator 3 emphasised, *"'Cognitive load' brings to mind 'Less is more'—it is true for art and data presentation alike."*

The evaluation process led to targeted refinements, including the renaming of "Big Picture" to "Level of Abstraction" and the removal of overlapping or less clearly defined subcomponents such as "Situational" and "Training."

Finally, all six respondents endorsed the model in its entirety. Evaluator 3 stated, *"This is an extremely comprehensive model … the research generated by implementing this model could lead to the development of guidelines that could transform the eHealth software space."* Evaluator 6 added, *"It does not replace the need for input from knowledgeable domain experts … but it does provide the potential for improved communication between developers and domain experts."*

This expert evaluation affirmed the relevance and applicability of the model and informed the final iteration of the UX Model for RHIS DataViz., marking the conclusion of the model development process.

3.4 Final UX Model for RHIS DataViz

The final UX model [Fig. 3] defines UX as health managers' perceptions and responses that arise from interacting with RHIS Data Visualisation tools. These experiences are influenced by four main components: User Attributes, Context of Use, Interaction with RHIS DataViz, and User Perceptions and Responses.

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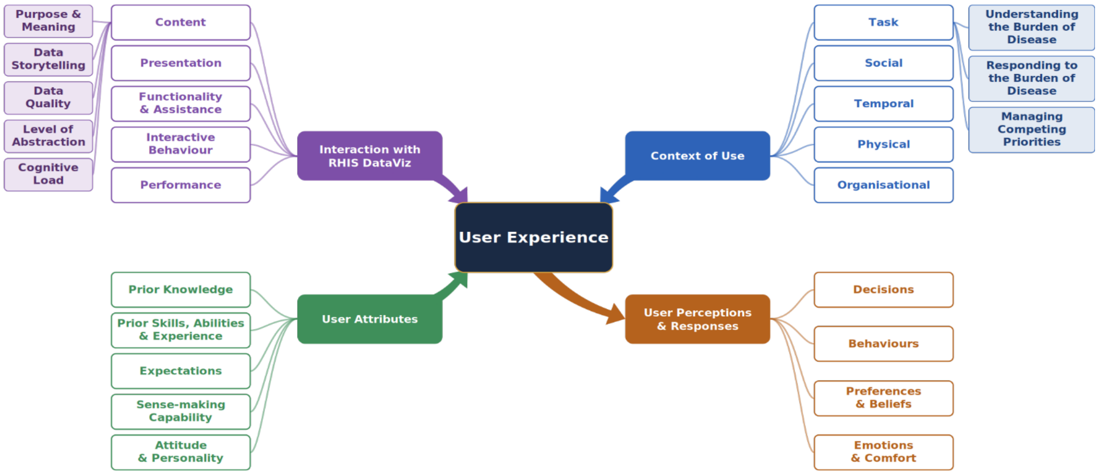

Figure 3: User Experience Model for Health Data Visualization for Managerial Decision Support

3.4.1 User Perceptions and Responses.

These refer to the outcomes before, during, or after interacting with RHIS DataViz.

- *Decisions*: Actions taken after interpreting data, such as allocating resources or adjusting priorities.
- *Behaviours*: Changes in managerial habits (e.g. increased engagement with staff or reports).
- *Preferences and Beliefs*: Evolving views about visual design or trust in data sources.
- *Emotions and Comfort*: Feelings ranging from frustration to reassurance during interaction.

3.4.2 Interaction with RHIS DataViz.

This includes the design and functional elements of the system that shape the user's experience.

- *Content*: The indicators or data elements visualised, including:
  - *Purpose and Meaning*: Clear rationale for data visualisation.
  - *Data Storytelling*: The narrative quality of the information.
  - *Data Quality*: Completeness, accuracy, and reliability.
  - *Level of Abstraction*: Ability to drill up/down through data layers.
  - *Cognitive Load*: The mental effort needed to interpret the visuals.
- *Presentation*: How data is displayed (e.g. charts, maps, infographics).
- *Functionality and Assistance*: Features that support use, such as filters or tooltips.
- *Interactive Behaviour*: How the system responds to user actions.
- *Performance*: Speed and responsiveness under typical working conditions.

3.4.3 Context of Use.

This refers to the broader setting in which the tool is used.

- *Task Context*: The work involved in understanding and responding to the burden of disease, and in balancing competing service priorities.
- *Social Context*: The interpersonal dynamics that shape interaction with data in team or oversight settings.
- *Temporal Context*: How long the user has been exposed to the tool, influencing comfort and ability.
- *Physical Context*: The physical environment and devices used (e.g. office desktop vs tablet in clinic).
- *Organisational Context*: The values, policies, and strategic imperatives that influence the user's framing of data.

3.4.4 User Attributes.

These refer to characteristics that influence how users interpret and interact with data.

- *Prior Knowledge*: Familiarity with indicators, systems, and decision-making roles.
- *Prior Skills, Abilities and Experience*: Tacit or practical knowledge relevant to RHIS data use.

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- *Expectations*: Expected functionality based on previous digital tools.
- *Sense-making Capability*: Capacity to derive meaning from diverse data inputs.
- *Attitude and Personality*: Individual differences in engagement, trust, and analytical preference.

4 Discussion

4.1 Insights from Iterative Model Development in a Public Health System Context

The application of the UX model to RHIS DataViz surfaced valuable insights about the realities of managerial data use in a provincial public health system. The case study revealed that health managers work within a context shaped by competing priorities, fluctuating workloads, and differing levels of data literacy. These contextual nuances had direct implications for how users engaged with visualised information, how they derived meaning from data stories, and how they acted upon insights. For instance, health managers found that features such as interactive drilldowns and layered data summaries enhanced usability, but only when aligned with their information needs and cognitive bandwidth. These findings affirm the need for user-centred RHIS design that is not only technically functional but also cognitively ergonomic [6, 10].

The concept of “cognitive load” emerged as a recurring theme. Several managers reported feeling overwhelmed when presented with dashboards that included large volumes of data or lacked narrative structure. This finding supports the inclusion of “data storytelling” and “level of abstraction” as core model components [19, 20]. Moreover, emotional responses to data, ranging from frustration to pride, highlighted the affective dimensions of UX in health systems, echoing earlier literature that calls for a broader conceptualisation of UX beyond mere usability [8, 21].

Evaluation feedback from expert reviewers further reinforced the model’s practical relevance. Reviewers highlighted that contextual subcomponents, such as organisational priorities and physical environment, were often overlooked in existing health IT implementations. The refined model’s attention to these aspects was viewed as an important corrective. For example, the component “managing competing priorities” was praised for capturing the dilemma of balancing local service needs with provincial or national targets, a reality previously documented in South African PHC contexts [3].

The usability of the model itself also came under scrutiny. Reviewers appreciated the layered structure and the descriptive clarity of components but recommended refinements in terminology to make the model more accessible to non-specialist users. Consequently, several terms were revised. For instance, “Big Picture” was renamed to “Level of Abstraction”, to improve resonance with target users. These adaptations illustrate the iterative nature of DSR and the importance of continuous user feedback in artefact refinement [11, 12].

Overall, the model proved useful in bridging the gap between technical data design and managerial decision-making practice. It clarified how users make sense of visual data under real-world constraints and illuminated factors that promote or hinder effective use. These insights confirm the value of integrating UX theory into RHIS design and suggest that the model has utility beyond the specific case setting, particularly in other LMIC health systems undergoing digital transformation.

A further consideration concerns the relationship between trust in DataViz and trust in upstream data collection. Well-designed visualisations cannot generate confidence in decision support if managers doubt the accuracy or completeness of the underlying records. Visualisation features such as data lineage display, quality flags, and drill-down to source records can support trust at the point of use, but their effect is contingent on a functioning data assurance ecosystem upstream of the dashboard. The UX model therefore needs to be read as one component within a broader information quality system rather than a stand-alone solution.

A second consideration concerns the practical tension between standardisation and context-specific visualisation. Dedicated UX support for each manager is impractical at scale within a public health system. Generative AI and natural language query interfaces offer one possible direction, allowing managers to interrogate a common dataset through plain-language questions and receive visualisations shaped to their specific decision context. Realising this potential will depend on careful attention to UX design principles, governance arrangements, and data privacy safeguards, and warrants further investigation.

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4.2 Contribution to Theory and Practice

This study contributes a novel theoretical model of UX tailored to the RHIS data visualisation needs of health service managers. While existing UX models tend to emerge from consumer, web-based, or product design contexts [8], this model foregrounds the cognitive, contextual, and managerial demands of decision-making in public health systems. The model draws on the ISO definition of UX [7] but extends it by including context-specific subcomponents such as “managing competing priorities,” “sense-making capability,” and “level of abstraction.” These elements were confirmed to be important by evaluators and distinguish the model from general UX frameworks.

Theoretical value lies in the way this model bridges the fields of UX, health informatics, and systems thinking. It integrates both human-computer interaction (HCI) principles [22] and health governance [3, 13], presenting UX as an emergent phenomenon situated in complex, resource-constrained environments. This is especially pertinent for low- and middle-income countries (LMICs), where managerial decisions must often be made with imperfect data, limited time, and competing demands [23].

In practical terms, the model provides development teams and public health stakeholders with a structured yet flexible framework to assess, design, and procure RHIS data visualisation tools. Its language, refined through expert feedback, supports better alignment between software design and managerial workflow. For instance, the revision of “Big Picture” to “Level of Abstraction” made the concept more intuitive and technically applicable for both users and developers. Moreover, the model can inform procurement specifications, design requirements, and formative evaluation during RHIS dashboard development. The removal of less relevant components (such as “Brand Image”) shows the importance of contextual relevance and responsiveness in model development. These practical implications underscore the value of DSR in producing artefacts that are not only theoretically rigorous but also aligned with real-world implementation needs [11, 16].

The model also complements emerging local research on the UX of digital health systems in the Western Cape. Recent work on the UX of electronic medical records in the Western Cape public health sector highlights similar challenges of cognitive burden, contextual complexity, and the need for user-centred design [24]. Together, these studies suggest that UX theory can offer a unifying perspective for advancing the design of both RHIS and clinical information tools in this setting. The present model extends this agenda by providing a structured framework specifically tailored to RHIS DataViz and decision-support contexts, with potential application across other LMIC health systems.

4.3 Study Limitations

This study’s scope and method present several limitations that should be considered when interpreting the findings. The empirical component was limited to a single provincial health system in South Africa. Although WCDHW has demonstrated significant investment in health information systems and digital initiatives [14, 25], the organisational arrangements, levels of digital maturity, and governance structures in this setting may differ from those in other South African provinces or low- and middle-income countries (LMICs). While the study offers in-depth contextual insights, the broader applicability of the findings would require additional adaptation and validation in diverse settings [6, 9].

The case study and model evaluation primarily involved operational and strategic health service managers. While this user group was appropriate for the RHIS DataViz use case, perspectives from other potential users such as policymakers, data capturers, analysts, or clinical teams were not explored in depth. Similarly, patients and community stakeholders were excluded, even though their inclusion is increasingly valued in user-centred digital health design [23].

Although the expert evaluation confirmed the model’s relevance, face validity, and clarity, it relied on structured survey instruments rather than real-world implementation or usability testing. The model was not instantiated into a working prototype, and its application to live RHIS dashboards remains to be evaluated. Future studies should empirically assess how applying the model influences users’ comprehension, decision-making quality, or system usability [26].

Although cognitive load and contextual complexity were recognised as influential components of UX, this study did not systematically quantify these constructs during evaluation. Their influence was inferred from qualitative interviews and expert feedback. Further research could benefit from incorporating validated instruments for measuring these dimensions [10].

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The principal investigator's insider position offered familiarity with the organisational context, established relationships of trust with participants, and an understanding of the operational pressures under which managers worked. It also carried the risk of confirmation bias and of participants moderating their responses in the presence of a fellow employee. These risks were mitigated by maintaining reflexive notes throughout fieldwork, by triangulating observational and interview findings against the policy review and the subsequent expert evaluation, and by securing access to participants through senior management rather than through the principal investigator's own service relationships.

Despite these limitations, the study offers a rigorous and contextually grounded contribution to understanding UX in RHIS Data Visualisation for managerial use, and a foundation for future applied research and design.

5 Conclusion

This study contributes a novel, theory-informed, and contextually grounded model of UX RHIS data visualisation, designed to support managerial decision-making in a public health setting. By applying DSR methodology, the model was iteratively developed, refined, and evaluated through empirical engagement with health managers and expert reviewers. It advances current understanding of UX in RHIS applications by explicitly incorporating the contextual realities, user attributes, and cognitive processes unique to public sector decision-making.

The model's strength lies in its relevance to operational and strategic health managers who must interpret complex health data while navigating multiple organisational demands. It provides a practical and theoretically robust foundation for improving data use in health governance, offering value not only to system designers but also to implementation teams seeking to enhance dashboard usability, policy alignment, and service responsiveness. While the model is rooted in a specific provincial context, its components reflect broader challenges and dynamics present across many health systems globally, particularly in low- and middle-income countries. Future work should explore its application in different digital maturity settings, assess its influence on decision quality, and examine its adaptability to participatory or patient-facing RHIS tools.

In an era of increasing data availability, strengthening the usability and uptake of health data remains a strategic imperative. This model represents a step toward more human-centred, context-aware digital health systems that enable meaningful engagement with data for better health outcomes.

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Statement on conflicts of interest

RD and HM were employed by the WCDHW at the time of the study, which constitutes a potential conflict of interest. Mitigation measures are described in the Study Limitations. DvG declares no competing interests.

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Improving Tuberculosis Detection with Deep Learning in X-Ray Imaging

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Background and Purpose: Tuberculosis (TB) continues to pose a major global health burden, particularly in low-resource settings, where timely and accurate diagnosis remains a challenge. Conventional diagnostic methods such as sputum smear microscopy and bacterial culture are often slow, labour-intensive, and susceptible to human error. Although several studies have explored alternative diagnostic tools, there remains a critical need for efficient, accurate, and scalable solutions. This study aimed to address this gap by developing a deep learning (DL)-based diagnostic model using chest X-ray images to detect TB with high precision and speed in a resource-limited setting.
Methods: A Convolutional Neural Network (CNN) model based on the VGG19 architecture was developed and trained on a dataset of labelled chest X-ray images. The model was optimized to identify the radiographic features indicative of TB. Performance metrics, including precision, recall, F1-score, and overall accuracy, were used to evaluate the diagnostic effectiveness of the model.
Results: The proposed DL model demonstrated strong diagnostic performance, achieving a precision of 96%, recall of 96%, F1-score of 96% and an overall accuracy of 96%. These results indicate the robustness of the model in identifying TB cases from chest X-ray images with minimal false positives and false negatives.
Conclusions: The findings underscore the potential of AI-driven diagnostic tools to significantly enhance TB detection, particularly in settings with limited access to laboratory facilities. The VGG19-based model offers a promising pathway toward faster, more reliable, and scalable TB diagnosis, contributing to improved disease management and global control efforts.

Keywords: Medical imaging, Tuberculosis (TB) detection, Deep learning, Computer-aided diagnosis, Chest X-ray analysis, VGG19 architecture.

1 Introduction

Tuberculosis (TB) is a life-threatening infectious disease caused by *Mycobacterium tuberculosis*, primarily affecting the lungs and transmitted through airborne droplets released when infected individuals cough, sneeze or speak [1]. Despite decades of global control efforts, TB remains one of the leading causes of death from infectious diseases, with an estimated 10 million new cases and approximately 1.5 million deaths reported annually[2]. The burden of TB is disproportionately high in low- and middle-income countries, where healthcare systems often face significant diagnostic and infrastructural constraints.

Early and accurate diagnosis remains the most effective strategy for controlling and preventing TB [3]. Conventional TB diagnostic approaches include chest radiography, sputum smear microscopy, and bacterial culture testing [4]. Chest X-ray examinations rely heavily on the expertise of trained radiologists, making the process time-consuming and prone to inter-observer variability, particularly in resource-limited settings. Bacterial culture, although considered the gold standard, is slow, typically requiring three to four weeks to yield results [5]. Sputum smear microscopy is the most widely used diagnostic method because of its low cost and simplicity; however, its sensitivity decreases significantly in patients with low bacterial loads or TB–HIV co-infection [2], [6], [7]. These limitations often delay the initiation of treatment and increase the risk of disease transmission.

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Advances in digital health technologies have introduced automated approaches to TB diagnosis, aimed at supporting clinical decision-making and reducing diagnostic delays. Computer-Aided Diagnosis (CAD) systems leverage image processing, machine learning (ML), and, more recently, deep learning (DL) techniques to analyze medical images and identify patterns associated with TB [6], [8], [9]. CAD systems have demonstrated promising results in the analysis of chest radiography and computed tomography (CT) images, offering rapid and scalable screening solutions. In parallel, radiomics-based approaches have emerged as an alternative automated strategy for extracting quantitative features from medical images to support TB classification and diagnosis [10]. However, radiomics pipelines are often complex, requiring specialized expertise for implementation and interpretation, which limits their practical adoption in routine clinical settings.

Despite their technical promise, the adoption of AI-powered TB diagnostic systems remains uneven across different regions. While several high-income countries have successfully integrated CAD solutions into clinical workflows, their implementation in Africa is still at an early stage [11]. Pilot deployments have been reported in countries such as South Africa, Kenya, and Tanzania; however, widespread uptake is constrained by insufficient clinical infrastructure, restricted access to advanced technologies, high licensing costs associated with proprietary software, unreliable Internet connectivity, and a shortage of skilled personnel [12]. In Tanzania, TB screening at peripheral healthcare facilities often relies on TB score charts to guide referrals to specialized centers. Although useful, these tools are subjective and prone to misclassification, necessitating confirmation through laboratory-based testing [13], [14].

Simultaneously, many hospitals in Tanzania have transitioned to digital medical record systems and routinely acquire digital chest X-ray images, creating an opportunity for the integration of AI-driven diagnostic support tools. For TB diagnosis to be clinically effective in such environments, diagnostic systems must be fast, accurate, affordable, and usable with minimal equipment and expertise [5]. Ideally, these systems should operate with limited computational resources, deliver results within hours, and provide outputs that frontline clinicians can interpret. However, existing diagnostic techniques which include microscopy, culture, and rapid diagnostic tests remain limited by low sensitivity, high costs, and delayed turnaround times, particularly in rural and resource-constrained facilities [7].

Against this background, there is a clear need for deployment-aware, deep learning–based diagnostic tools that not only achieve high diagnostic accuracy but are also tailored to the infrastructural, technological, and human resource realities of low-resource settings such as Tanzania. This study responds to that need by proposing and evaluating a deep learning model for TB detection from chest X-ray images, designed with contextual feasibility and clinical usability in mind.

2 Related Work in Deep Learning–Based Medical Image Analysis

Deep learning, particularly through convolutional neural networks (CNNs), has become the dominant paradigm in medical image analysis owing to its ability to automatically learn complex hierarchical features from raw imaging data. CNN-based models have demonstrated state-of-the-art performance in disease detection, classification, and prognosis in diverse medical imaging domains. Among the widely adopted CNN architectures, the Visual Geometry Group (VGG) family, which includes VGG16 and VGG19, remains influential owing to its simple and modular design, strong feature extraction capability, and reproducibility across datasets and applications.

2.1 VGG Architectures in General Medical Image Diagnosis

Globally, VGG-based architectures have been successfully applied to a wide range of medical-image analysis tasks. The foundational work by Simonyan and Zisserman demonstrated that increasing the network depth using small, uniform convolutional kernels significantly improves the image classification performance. Building on this architecture, [15] applied CNNs, including VGG variants, to dermatological image classification and achieved a performance comparable to that of expert dermatologists in skin cancer detection. Similarly, [16] employed VGG-inspired deep learning models for diabetic retinopathy screening and reported high sensitivity and specificity suitable for large-scale clinical deployment.

During the COVID-19 pandemic, VGG-based transfer learning models have been extensively explored for thoracic image analysis. [17] demonstrated that VGG architectures achieved competitive accuracy in detecting COVID-19 from chest radiographs, reinforcing their suitability for lung disease classification

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tasks. The continued relevance of VGG networks in medical imaging is largely attributed to their sequential architecture and use of 3×3 convolutional filters, which enable stable training and effective extraction of fine-grained pathological features from images. These characteristics are particularly valuable in medical contexts, where disease manifestations may be subtle and spatially localized.

2.2 Global Studies on VGG-Based Tuberculosis Detection

Several studies, in the global context, have specifically investigated the use of VGG architectures for TB detection from chest X-ray images. [18] conducted one of the earliest large-scale evaluations of deep CNNs for pulmonary TB detection, reporting classification accuracies exceeding 90% and demonstrating the feasibility of automated screening for TB. [5] proposed a VGG-based framework that combined lung segmentation, feature extraction, and visualization techniques, achieving robust diagnostic performance while improving model interpretability through heatmap analysis. Similarly, scholars compared multiple CNN architectures, including VGG, for TB screening and found that transfer learning significantly enhanced performance, particularly when the annotated training data were limited [19].

These studies consistently show that VGG-based models remain competitive with deeper and more complex architectures, such as ResNet and Inception. Their effectiveness is particularly evident in scenarios characterized by moderate dataset sizes, limited computational resources, and a need for transparent and reproducible models, which are also the conditions that closely align with TB screening requirements in low- and middle-income countries.

2.3 African Studies on AI and Deep Learning for TB Diagnosis

In the African context, the application of AI and deep learning to TB diagnosis has gained increasing attention due to the high disease prevalence and chronic shortage of radiological expertise. [4] evaluated computer-aided TB screening systems in Zambia and demonstrated that automated chest X-ray analysis could achieve a sensitivity comparable to that of expert radiologists, supporting the feasibility of CAD tools in sub-Saharan Africa. The other study examined the integration of AI in medical imaging practice across multiple African countries and highlighted the potential of CNN-based systems to alleviate workforce shortages, particularly in rural healthcare settings [8].

More recently, a study conducted a systematic review of deep learning approaches for TB detection from chest radiographs and reported consistently high diagnostic accuracies across African datasets [20]. However, they emphasized that many existing models fail to account for contextual challenges, such as infrastructural limitations, data heterogeneity, and limited technical expertise. These findings underscore the need for context-aware AI solutions that are not only accurate but also deployable in real-world African healthcare settings.

2.4 Studies Related to Tanzania and Comparable Settings

Research on AI-assisted TB diagnosis in Tanzania is still emerging but demonstrates a growing potential. Pilot deployments of AI-powered TB screening tools in East African countries, including Tanzania, noted improvements in screening efficiency and case detection rates, particularly in peripheral facilities [12]. Other studies conducted in Tanzanian healthcare settings have highlighted the persistent challenges associated with conventional TB diagnostic workflows, including reliance on sputum microscopy, delayed laboratory results, and limited access to expert radiologists [21], [22], [23], [24].

Although most Tanzanian studies focus on feasibility assessments and pilot implementations rather than algorithm development, they provide a strong justification for locally adaptable deep learning artifacts. By leveraging a VGG19-based architecture trained on chest X-ray images and designed with infrastructural and human resource constraints in mind, this study contributes to bridging the gap between technical innovation and practical deployment in Tanzania.

Overall, the existing literature demonstrates that VGG-based deep learning models are effective for medical image analysis and TB detection across global, African, and regional contexts. However, many prior studies emphasize algorithmic performance without explicitly addressing the feasibility of deployment in low-resource environments. Few studies have integrated considerations such as offline operation, low-cost hardware compatibility, and reduced dependence on specialized personnel into model

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design. This study addresses these gaps by combining a proven VGG19 architecture with a deployment-aware experimental setup, offering a technically robust and contextually appropriate solution for TB diagnosis in Tanzania and in similar settings.

3 Materials and methods

3.1 Study Design

This study used an experimental research design to develop a deep learning model for TB detection. In this design, the dataset was divided into two distinct groups: the training and testing datasets. The input chest X-ray images constituted the independent (cause) variables, whereas the model's TB classification outcomes represented the dependent (effect) variables. The Design Science Research (DSR) methodology was employed to create a practical artifact in the form of a deep learning model for TB detection. The study followed established DSR guidelines, progressing through problem identification, objective definition, artifact design and development, demonstration, evaluation, and communication, as detailed in Table 1.

Table 1 Summary of Design Science Research (DSR) Process

DSR Process	Techniques / Methods Used	Outputs / Outcomes
Problem Identification	Systematic literature review using Scopus, Google Scholar, ScienceDirect, and WHO reports; analysis of TB diagnostic workflows in Tanzania; review of existing CAD and AI-based TB detection systems. In this study, the independent variable is the set of features extracted from chest X-ray images, while the dependent variable is the predicted tuberculosis classification outcome (TB-positive or TB-negative)	Clearly defined research problem highlighting limitations of existing TB diagnostic methods and CAD systems in low-resource settings (infrastructure constraints, limited accessibility, shortage of skilled personnel)
Definition of Objectives and Requirements	The requirements analysis phase was conducted through a literature study, which involved reviewing existing research on computer-aided diagnosis (CAD) systems for tuberculosis detection, deep learning applications in medical imaging, and challenges associated with TB diagnosis in low-resource settings. Key sources included peer-reviewed articles, WHO reports, and prior studies such as Rahman et al.[5] .	Defined artefact objectives and requirements: use of standard chest X-ray images, low computational cost, offline operability, high diagnostic accuracy, and interpretability for clinicians [5].
Artefact Design and Development	Dataset acquisition from Benjamin Mkapa Hospital and public datasets; image preprocessing (resizing, normalization, noise filtering); data augmentation; CNN architecture selection (VGG16, VGG19, ResNet50); transfer learning; hyperparameter tuning using TensorFlow and Keras	Developed and optimized VGG19-based TB detection model capable of extracting discriminative radiological features from chest X-ray images
Demonstration	Application of trained model to unseen chest X-ray images; classification into TB-positive and TB-negative cases; visualization of prediction probabilities	Functional demonstration of the artefact's ability to classify TB cases using standard digital chest X-ray inputs
Evaluation	Quantitative model evaluation using accuracy, sensitivity, specificity, precision, recall, and F1-score. Usability evaluation using structured Likert-scale questionnaires administered to 21 healthcare professionals (medical doctors, clinical officers, and radiologists) from Benjamin Mkapa Hospital, selected through purposive sampling based on their experience in interpreting chest X-rays.	Empirical evidence of model performance and usability. Questionnaire results indicated high user acceptance, with 90.5% agreement on model performance, 85.7% on clinical relevance, and 95.2% on system reliability, confirming the system's clinical applicability.

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Communication	Scientific documentation and dissemination through peer-reviewed publication	Contribution of a validated, deployment-aware AI artefact and methodological knowledge to the health informatics community

3.2 Data Collection

To develop a successful deep learning model, the training data must possess several key qualities. The data should be representative, properly labeled, resistant to noise, and contain specific patterns [8]. Three primary methods for obtaining data are described in the literature: data discovery, data augmentation, and data generation. The first method, data discovery, involves searching for new datasets. Data augmentation enhances the data discovery phase by providing new data from external sources when the discovered datasets are insufficient [5]. Data synthesis is necessary when external datasets are limited or unavailable; it involves generating artificial data that mimic real-world data. The sample dataset of the chest x-ray images used in this study is shown in Figure 1.

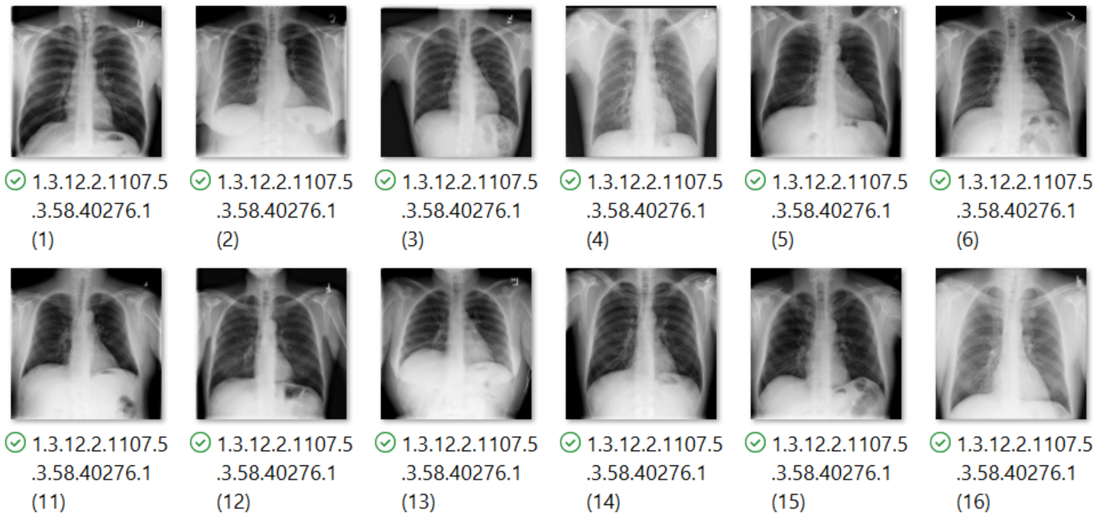

Figure 1 Collected chest X-ray images

To meet the study's objectives, the dataset included 401 TB-negative and 531 TB-positive images collected from Benjamin Mkapa Hospital, along with 6,012 TB-negative and 6,851 TB-positive images from the Kaggle repository, resulting in a total of 6,413 TB-negative and 7,382 TB-positive images. Before addressing the class imbalance, initial data preprocessing was conducted, which involved removing images with artifacts, such as medical devices and text overlays, to ensure data quality. After preprocessing, random undersampling was applied a technique that reduces the size of the majority class to match the minority class. A final sample size of 10,674 images was obtained through a structured preprocessing and class-balancing procedure. Initially, 13,795 chest X-ray images were collected from two sources. Images containing medical devices, annotations, or severe artifacts were excluded to enhance the data quality during preprocessing.

To address the class imbalance and reduce the model bias, random undersampling was applied to the majority classes in both datasets. As a result, 337 TB-positive and 337 TB-negative images were retained from the Benjamin Mkapa Hospital dataset, whereas 5,000 TB-positive and 5,000 TB-negative images were selected from the Kaggle dataset, yielding a total of 10,674 images used for model development.

The two datasets were combined through a structured integration process. First, class labels were harmonized to ensure consistent binary categorization of tuberculosis-positive and tuberculosis-negative cases across sources. All images were resized to a uniform spatial resolution and normalized to standardize pixel intensity distributions. Duplicate patient records and overlapping images were removed to prevent data leakage. Finally, stratified sampling was applied to preserve class balance after merging. This approach enabled the construction of a unified and representative dataset suitable for robust deep learning model development.

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The study included presumptive and confirmed cases of TB aged 2 years or older, regardless of sex, with symptoms such as cough, fever, weight loss, loss of appetite, night sweats, or a history of TB, as well as drug or alcohol use. Pregnant women were not included as they were not eligible for X-ray image examination.

3.3 Experimental Setup

To ensure the practical deployment of the proposed system in low-resource healthcare environments, the model was designed to operate on low-cost hardware commonly available in Tanzanian healthcare facilities in which they operate with limited ICT infrastructure and shared computing resources [25]. In this context, a standard laptop refers to a device with minimum specifications in the range of:

- Intel Core i5 (or equivalent) processor
- 8 GB RAM
- At least 256 GB storage
- Optional entry-level GPU such as NVIDIA GTX 1050 or equivalent

During model development and training, Google Colab with NVIDIA Tesla T4 GPU (12 GB VRAM), 12.7 GB RAM, and approximately 33 GB temporary storage was used to accelerate training processes. However, once trained, the model can run on standard laptops without requiring high-performance computing infrastructure.

This configuration reflects the typical computing infrastructure available in many district hospitals and diagnostic centers in Tanzania [26].

The software stack consisted of TensorFlow and Keras, which offer high-level application programming interfaces (APIs) that support the efficient construction, training, and optimization of deep learning models.

Beyond computational considerations, the experimental setup was intentionally designed to address the contextual challenges associated with deploying computer-aided diagnostic (CAD) systems in low-resource settings, such as Tanzania. The VGG19-based model was trained and validated using standard two-dimensional chest X-ray images, which are widely available even in district and peripheral health facilities, thereby eliminating the need for specialized imaging modalities, such as computed tomography. To ensure feasibility within constrained environments, the model was developed to operate on low-cost hardware, including standard laptops and entry-level GPUs, which require minimal computational infrastructure. Furthermore, unlike many existing CAD solutions that depend on continuous Internet connectivity, the proposed system can operate offline once trained, making it suitable for healthcare facilities with intermittent or unreliable network access.

The artifact was designed to be deployable either as a standalone application or through integration with existing Picture Archiving and Communication Systems (PACS), enhancing accessibility without reliance on cloud-based services. In addition, the system minimizes dependence on specialized personnel by employing automated image preprocessing and classification pipelines, supported by intuitive outputs, such as probability scores and heatmap visualizations, that enable frontline clinicians to interpret results without advanced expertise in artificial intelligence. Finally, the model and accompanying documentation are intended for open-source release, supporting scalability, local customization, and capacity building through knowledge transfer and training initiatives aimed at strengthening human resources in medical imaging and artificial intelligence.

3.4 Image Preprocessing and Labelling

The acquired digital X-rays from Benjamin Mkapa Hospital were labeled as TB positive or negative to facilitate proper model training, and also the Kaggle dataset was downloaded already labelled. Labeling was based on clinical symptoms and radiological features, with the guidance of a radiologist. Factors such as malnutrition, HIV, alcoholism, smoking, and diabetes contribute to TB susceptibility [27]. The radiological features that were considered included the presence of cavities in lung tissues, which are commonly seen in advanced TB, the presence of infiltrates, which are areas with increased density suggesting the presence of an acute infection or inflammation caused by TB, and the presence of nodules on X-ray images indicating TB, which are small rounded opacities scattered throughout the lungs [18]. Images were labeled as positive if the patient's history and X-ray image indicated susceptibility to TB, and

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negative otherwise. A range of pre-processing approaches were performed to improve the image brightness and contrast, including noise reduction, smoothing irregularities, and geometric transformation.

Data normalization was essential in ensuring the viability of the deep learning model for TB detection [28]. This technique involves normalizing pixel values in X-ray images, resulting in a faster training process and improved stability during learning. In addition, data augmentation techniques were incorporated into the workflow. Techniques like rotation, flipping, and zooming were used to enhance the dataset's diversity and improve the model's ability to generalize effectively.

3.5 Architecture Selection

Using CNN architecture, this study developed a model to correctly classify TB-positive and TB-negative images. A CNN is a network architecture designed for pixel data processing and image recognition [29]. CNNs have the ability to analyze digital images, assign importance to different elements and objects within the image, and distinguish between them. When it comes to classification techniques, a CNN requires minimal pre-processing [30]. This study employed VGG19 (Visual Geometry Group), a CNN architecture, to develop a model for TB detection. Further, compared to deeper architectures such as ResNet and Inception, VGG19 offers a favorable balance between performance, interpretability, and computational efficiency, which is critical for low-resource clinical environments.

The VGG architecture was chosen for its strong generalization to unseen data, thanks to its deep convolutional layers that progressively capture hierarchical features. Its use of smaller 3x3 filters reduces parameters while retaining the ability to extract fine details, making it effective for image recognition [31]. VGG balances good performance with moderate computational demands, making it more accessible than deeper models like ResNet or Inception. Its straightforward, sequential design is easier to understand and interpret, supporting transparency, with tools like Grad-CAM helping to visualize and explain predictions.

3.6 Model Development with VGG19

The VGG19 architecture was first presented in 2014 by Simonyan and Zisserman in their influential publication titled "Very Deep Learning CNN for Large-Scale Image Recognition" [32]. The researchers successfully showed that a deep neural network could be trained effectively by utilizing 3x3 filters. which allowed the network to reach a considerable depth of 19 layers, this approach enabled the network to achieve a significant depth of 19 layers, resulting in outstanding performance on the complex ImageNet dataset [33]. VGG19, unlike prior architectures, consistently used 3x3 kernels in all of its layers, instead of using a combination of different filter sizes [34]. This architecture of VGG19 is fundamental for its ability to effectively classify tasks that go beyond its original training scope.

To develop a better predictive model using VGG19 architecture, the dataset comprising 674 chest X-ray images, was prepared to aid in the model's development. The finalized dataset was divided into training (80%), validation (15%), and testing (15%) subsets using stratified sampling to maintain class distribution consistency and to ensure that no patient-level overlap occurred across the subsets. The training data played a crucial role in enabling the model to learn and distinguish between patterns associated with TB-positive and TB-negative cases. The remaining 536 images were set aside for validation purposes equating to 5% of the entire dataset, serving as a continuous monitoring tool that provided an unbiased evaluation of the model's performance.

The following formula was used for each convolutional layer to perform a discrete convolution operation in feature extraction. This shows how the model extracts hierarchical features (edges, textures, patterns) from the images.

$$F_{i,j}^{(l)} = \sum_{m=1}^{M} \sum_{n=1}^{N} X_{i+m,j+n}^{(l-1)} \cdot K_{m,n}^{(l)} + b^{(l)}$$

where:

- $X^{(l-1)}$is the input feature map from the previous layer
- $K^{(l)}$is the convolution kernel
- $b^{(l)}$is the bias term

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- $F^{(l)}$ is the resulting feature map at layer l

This operation allows the network to learn spatial patterns associated with TB-related abnormalities.

A modified VGG19-like architecture was adopted for model development. The network is characterized by a series of convolutional layers (Conv2d), each followed by batch normalization (BatchNorm2d) and ReLU activation. Max pooling layers (MaxPool2d) are used to reduce spatial dimensions at several points in the network.

The architecture consists of:

- initial Conv2d-BatchNorm2d-ReLU blocks with 64 filters
- Conv2d-BatchNorm2d-ReLU blocks with 128 filters
- Conv2d-BatchNorm2d-ReLU blocks with 256 filters
- 8 Conv2d-BatchNorm2d-ReLU blocks with 512 filters

After the convolutional layers, the network uses both adaptive average pooling and adaptive max pooling, followed by flattening. The classifier part of the network consists of a series of fully connected layers (Linear), batch normalization, ReLU activation, and dropout, culminating in a final output layer with 2 units.

All convolutional layers use 3x3 filters, and all 20,563,776 parameters in the network are trainable. The network maintains spatial dim3ensions through the convolutional layers and reduces dimensions through max pooling. This architecture has no non-trainable parameters, allowing for full control of the entire network during training.

Table 1 indicates a comprehensive breakdown of the network architecture with the initial input shape being 32 x 3 x 256 x 256. Also, Table 2 provides the VGG19 architecture, which includes output volume sizes for each layer and relevant information about convolutional filter sizes and pooling sizes.

Table 2: Overview of the VGG19 architecture

Layer Type	Output Size	Filter Size
INPUT IMAGE	256×256×3	
Conv2d +BatchNorm2d+ReLU	256×256×64	3×3, K = 64
Conv2d +BatchNorm2d+ReLU	256×256×64	3×3, K = 64
MaxPool2d	128×128×64	2×2
Conv2d +BatchNorm2d+ReLU	128×128×128	3×3, K = 128
Conv2d +BatchNorm2d+ReLU	128×128×128	3×3, K = 128
MaxPool2d	64×64×128	2×2
Conv2d +BatchNorm2d+ReLU	64×64×256	3×3, K = 256
Conv2d +BatchNorm2d+ReLU	64×64×256	3×3, K = 256
Conv2d +BatchNorm2d+ReLU	64×64×256	3×3, K = 256
Conv2d +BatchNorm2d+ReLU	64×64×256	3×3, K = 256
MaxPool2d	32×32×256	2×2
Conv2d +BatchNorm2d+ReLU	32×32×512	3×3, K = 512
Conv2d +BatchNorm2d+ReLU	32×32×512	3×3, K = 512
Conv2d +BatchNorm2d+ReLU	32×32×512	3×3, K = 512
Conv2d +BatchNorm2d+ReLU	32×32×512	3×3, K = 512
MaxPool2d	16×16×512	2×2
Conv2d +BatchNorm2d+ReLU	16×16×512	3×3, K = 512
Conv2d +BatchNorm2d+ReLU	16×16×512	3×3, K = 512
Conv2d +BatchNorm2d+ReLU	16×16×512	3×3, K = 512
Conv2d +BatchNorm2d+ReLU	16×16×512	3×3, K = 512
MaxPool2d	8×8×512	2×2
AdaptiveAvgPool2d+AdaptiveMaxPool2d	1×1×512	
Flatten	1024	
BatchNorm1d + Dropout	1024	
Linear + ReLU	512	
BatchNorm1d + Dropout	512	
Linear	2	

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The development of TB detection model combined VGG19 architectural strengths with the essential components of a CNN This integration leveraged VGG19's efficient use of 3×3 kernels throughout its architecture while incorporating the core functions of CNN layers. This blending empowered the model to analyze chest X-ray images efficiently, transforming raw pixel data into a detailed understanding of TB-related patterns.

3.7 Model Optimization

To optimize the model's performance hyperparameter tuning was employed with key parameters including learning rate, batch size, dropout rate, number of epochs, and the choice of optimization algorithm. The systematic approach involved iterative experimentation using a grid-based search strategy, where one hyperparameter was varied at a time while others were held constant. Model performance was evaluated on the validation set using accuracy and loss metrics. Configurations that minimized validation loss and improved generalization were selected, leading to the final hyperparameter values reported in this study. The learning rate of range of 0.0001(1^{e-4}) to 0.01(1^{e-2}) was employed to minimize validation loss while optimizing accuracy, as presented in Figure 2.

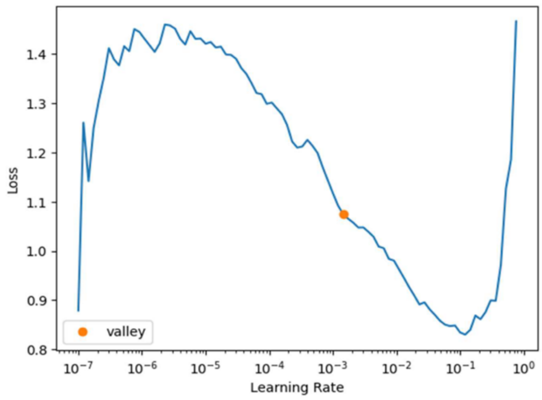

Figure 2 Finding of the Learning Rate

Various batch sizes were tested, with 32 chosen to balance computational efficiency and model accuracy, given hardware constraints. Although larger sizes like 64 have been optimal in other studies [6], the VGG19 architecture required a smaller batch size for stable performance. A 20% dropout rate was used to reduce overfitting by deactivating neurons randomly, maintaining model performance by balancing dropout and avoiding reliance on specific neurons.

To further enhance the model's performance, 50 training epochs were used, influencing the trade-off between better performance on training data and the potential risks of overfitting. The Adam optimizer [35] was chosen for its adaptive learning rate and ability to handle sparse gradients, which were critical for achieving accelerated convergence and improved accuracy in TB detection.

3.8 Model Evaluation

The process of evaluation began at the initial stage of model development, where data was divided into three distinct groups: the training set, the validation set, and the test set. To ensure a thorough evaluation, the validation set played a crucial role in the development of the DL model. The validation set acted as an ongoing monitoring tool, enabling continuous evaluation of the model's performance. The dataset was split into training (80%), validation (5%), and testing (15%) sets, corresponding to 8,538, 536, and 1,600 images respectively.

The effectiveness of the model was assessed to determine its performance in detecting TB by using various metrics and techniques to evaluate the ability of the model in detecting TB through the study of X-ray images. The performance metrics used were Accuracy, Precision, Recall, and F1-Score. Which were computed based on the following mathematical formulars as shown in Table 3:

- TP (True Positive): Indicates the instances where TB images were correctly detected as TB cases.
- TN (True Negative): Indicates the instances where normal images were correctly detected as non-TB cases.
- FP (False Positive): Indicates the instances where normal images were falsely classified as TB cases.
- FN (False Negative): Indicates the instances where TB images were falsely classified as normal cases.

Further, the proposed artifact was subjected to usability evaluation which involved 21 healthcare professionals from Benjamin Mkapa Hospital, including medical doctors, clinical officers, and radiologists who are routinely involved in TB diagnosis using chest X-ray images. Participants were selected using purposive sampling, ensuring that only professionals with relevant expertise in interpreting radiological images were included.

Table 3: Performance metrics and their corresponding formula

Performance Metric	Formula
Accuracy is the ratio of correctly classified predictions out of the total number of predictions generated from the test set.	$Accuracy\ (A) = \frac{(TP+TN)}{(TP+FN)+\ (FP+TN)}$
A model's recall is the number of positive cases it correctly detected,	$Recall\ (R) = \frac{TP}{(TP+FN)}$
precision is the accuracy of the model in positive predictions.	$Precision\ (P) = \frac{TP}{(TP+FP)}$
The F1 score is a performance evaluation metric that measures the accuracy of a model by taking into account both its precision and recall values	$F1\ Score = \frac{(2*TP)}{(2*TP+FN+FP)}$

The validation of the developed TB detection system was conducted in real clinical settings at Benjamin Mkapa Hospital (BMH) in Dodoma, Tanzania. During this phase, healthcare professionals interacted with the system by uploading chest X-ray images, reviewing the model's predictions, and assessing the usability of the web-based interface. The evaluation followed a naturalistic validation approach, allowing the system to be tested within the real clinical workflow of the hospital environment. This approach ensured that the results reflect the practical applicability of the model in real healthcare settings.

The evaluation was conducted using structured questionnaires based on a Likert scale, allowing respondents to rate different aspects of the system, including model performance, clinical relevance, reliability, security, and overall usability.

The results indicated strong positive feedback regarding the system's usability and effectiveness. Specifically, 90.5% of respondents agreed that the model performs well in distinguishing TB-positive and TB-negative cases, 85.7% agreed on its clinical relevance, and 95.2% confirmed the reliability of the system. These findings suggest that the proposed system has strong potential to support healthcare professionals in TB diagnosis.

3.9 Ethical Consideration

The ethical considerations of research must be considered before, during, and after the research process, encompassing all stages of the research, such as data collection, data storage, processing, and sharing (Ishtiaq, 2019). The researcher obtained research permit and ethical clearance from the University of Dodoma Review Board to ensure compliance with all University ethical and legal regulations. The study has also obtained a research permit from Benjamin Mkapa Hospital to ensure compliance with relevant national regulations and ethical standards. The privacy and confidentiality of participants have been protected by storing data securely. The study is inclusive, and no gender-based discrimination was tolerated. On the other hand, participants were not offered any incentives that may unduly influence their decision to participate.

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4 Results

The DL model for TB detection achieved a remarkable accuracy of 96%, with a precision of 95% and a recall of 98% for the TB-negative class, leading to an F1-Score of 96%. This indicates the model's strong ability to correctly identify all TB-negative instances. For the TB-positive class, the model recorded a precision of 98% and a recall of 95%, resulting in an F1-Score of 96%. Table 4 illustrates more of the performance of the model. Overall, the performance of the model highlights the high effectiveness in distinguishing between TB and non-TB cases, potentially enhancing clinical diagnostic accuracy.

Table 4 Results of Model Development Using VGG19

	Precision	Recall	F1-score	Support
Negative class	95%	98%	96%	800
Positive class	98%	95%	96%	800
Macro average	96%	96%	96%	1600
Weighted average	96%	96%	96%	1600
Accuracy	96%			1600

The confusion matrix, in Table 5, for the TB detection model shows that it correctly identified 783 instances as negative (TN = 783), and misclassify 41 instances as positive (FP-17) indicating a strong accuracy in recognizing negative cases. However, the model did misclassify 7 positive instances as negative (FN = 41), reflecting a minor shortfall in detecting some positive cases. Despite this, the model successfully identified 43 positive instances as positive (TP = 759), demonstrating a solid ability to detect positive cases accurately.

Table 5 Confusion Matrix for VGG19 Model

		Predicted Values	
		Negative	**Positive**
Actual Values	**Negative**	783	17
	Positive	41	759

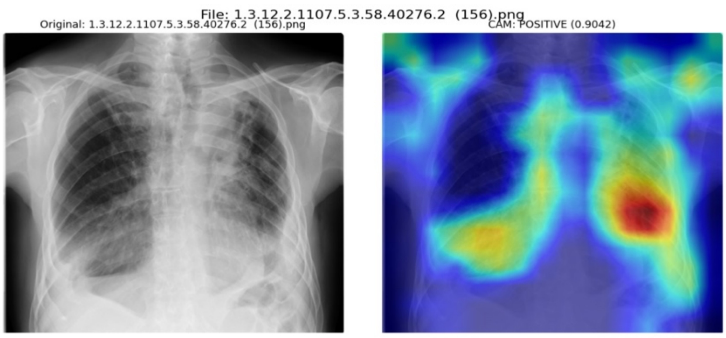

Figure 2 Showing heat map of an X-ray image detected by the model as TB positive.

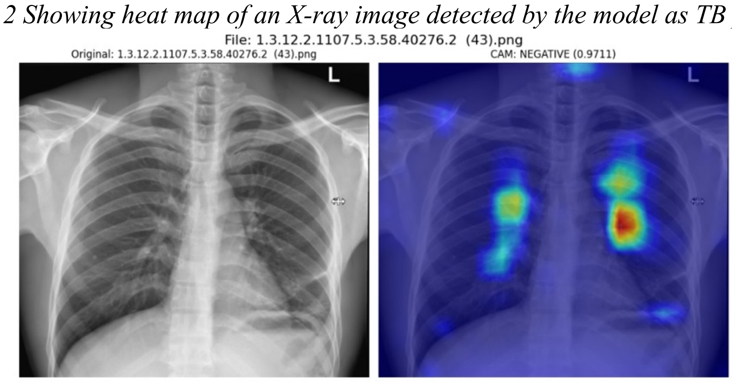

Figure 3 Showing heat map of an X-ray image detected by the model as TB negative.

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The output of the X ray images after being analyzed by deep learning model for TB detection has been indicated in Figures 2 and 3 using heatmaps to visually represent how the deep learning model focuses on specific areas of the X-ray images to make its predictions for TB detection.

In Figure 2, the heat map highlights regions with higher color concentration, indicating the areas the model prioritized when classifying the X-ray image as TB-positive. In contrast, Figure 3 shows the heat map for a TB-negative classification, where the model focused on different regions of the X-ray image and the color concentration shows the area where the model prioritized when making such decision. These visualizations provide insight into the decision-making process of the model, helping to explain how it distinguishes between TB-positive and TB-negative cases based on image features.

5 Discussion

The performance of the VGG19-based deep learning (DL) model in this study in terms of 96% accuracy, 96% F1-score, and balanced precision-recall across TB-positive and TB-negative classesaligns with and in some cases exceeds benchmarks reported in recent literature. For instance, Hansun et al. [27] noted that DL models using chest X-rays often achieve accuracy rates between 85% and 95%, but performance varies significantly depending on dataset quality and model architecture. The high recall for TB-negative cases (98%) and high precision for TB-positive cases (98%) in this study suggest that the model is particularly effective at minimizing both false negatives and false positives, which is critical in TB screening contexts where misdiagnosis can lead to delayed treatment or unnecessary isolation.

A study by Lakhani and Sundaram evaluated several deep CNN architectures, including VGG variants, for TB classification from chest X-rays [18]. Using transfer learning, they reported classification accuracies exceeding 90% on public TB datasets, affirming the feasibility of CNN-based TB detection. The current model exhibits similar performance levels while being tailored for deployment under constrained infrastructure, which was not the primary focus in Lakhani and Sundaram's work.

Further, a study by Rahman et al**.** extended this line of research by incorporating lung segmentation and visualization methods into a VGG-based TB detection framework [5]. Their approach achieved robust classification performance, particularly in scenarios where unauthorized image regions could confound predictions. In contrast, this study emphasizes the importance of infrastructural feasibility and clinician interpretability under real-world constraints (e.g., offline operation and low-cost hardware). While Rahman et al. focused on segmentation-assisted improvements, the present model achieves strong diagnostic results with a simpler pipeline, making it more practical for environments with limited computational resources.

In a comparative evaluation, Hwang et al. analyzed multiple CNN architectures, including VGG19, ResNet50, and Inception networks, for TB screening tasks [19]. They found that models using transfer learning achieved better performance than those trained from scratch, particularly when dataset sizes were moderate. Consistent with their findings, our model benefits from transfer learning, but further distinguishes itself by optimizing for deployment feasibility and interpretability which are key considerations for clinical adoption in low-resource regions.

Moreover, the use of class activation maps (CAMs) to visualize model attention enhances interpretability which is an essential factor for clinical adoption. This aligns with findings by Rahman et al. [28], who emphasized that heatmap visualizations can increase clinician trust in AI systems by revealing the decision-making process. The model's ability to focus on diagnostically relevant regions in TB-positive and TB-negative cases, as shown in Figures 2 and Figure 3, supports its potential as a decision-support tool.

The current study's results not only align with established performance benchmarks but also address practical limitations that have hindered the adoption of AI-based TB diagnostics in low-resource settings. Unlike many prior studies that prioritize maximizing accuracy within controlled experimental environments, this work explicitly integrates deployment-aware design principles such as offline capability, low-cost hardware compatibility, and outputs that clinicians can interpret without advanced technical training.

For example, heatmap-based visualization of model predictions provides clinicians with intuitive insight into model reasoning, thereby addressing a major barrier to trust and adoption identified in the broader literature.

The proposed artefact addresses key challenges in Tanzania by leveraging low-cost digital X-ray systems, requiring minimal additional infrastructure, and operating with limited computational resources.

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Its automated nature reduces reliance on highly specialized personnel, making it suitable for deployment in peripheral healthcare facilities.

However, the study's reliance on a limited dataset introduces concerns about generalizability. As highlighted by Oloko-Oba and Viriri, DL models trained on homogeneous datasets may underperform when exposed to images from different populations or imaging protocols [20]. Future work should incorporate multi-institutional datasets and explore domain adaptation techniques to enhance robustness. The model's performance should be prospectively validated in operational clinical settings to assess external generalizability. Additionally, integration with existing hospital information systems and workflow evaluation remains an important step toward translation into practice.

6 Conclusion

The study has successfully developed and validated a deep learning model using a VGG19 architecture to detect tuberculosis (TB) from chest X-ray images. The model demonstrated exceptional accuracy in distinguishing TB-positive from TB-negative cases, The findings indicate that deep learning approaches, particularly those based on CNN, can greatly enhance TB detection, offering a rapid, cost-effective, and accessible diagnostic tool. This technology holds promise for improving TB management, especially in resource-limited settings where traditional diagnostic methods may be inadequate.

Despite achieving high accuracy, the study has several limitations. First, the dataset primarily consisted of X-ray images from a limited number of sources, which may not represent all potential variations seen in different populations or healthcare settings. Additionally, the model's performance is influenced by the quality and characteristics of the input images, meaning that poor-quality or heavily artifact-laden images could degrade the model's effectiveness.

The research paves the way for broader applications in other areas of medical imaging. Future research should focus on integrating other imaging modalities, such as CT scans or MRI to further enhance the model's accuracy. Lastly developing mobile applications that can incorporate this TB detection model would increase accessibility in low-resource areas, while ensuring compatibility with existing healthcare systems.

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Statement on conflicts of interest

Not Applicable.

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A Digital Counter-Gambling Intervention for Online Gambling Students Using Interactive Mobile Application Messaging

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Background and Purpose: Gambling Disorder (GD), particularly in its online form, presents a significant public health concern, especially among young university students in contexts like Kenya. This study aimed to develop and evaluate a strategy for promoting responsible online gambling among second- and third-year students at Kisii University.
Methods: Utilizing a diagnostic design across three phases, the research first investigated the prevalence and patterns of Online Gambling Disorder (OGD) among a randomly selected sample of 500 students (429 respondents, 86% response rate) using the South Oaks Gambling Screen (SOGS) and Problem Gambling Severity Index (PGSI). Based on this diagnosis, a structured digital intervention framework, named the ICGIM system, was designed and developed. The system's creation followed an iterative methodology grounded in User-Centered Design (UCD) and Agile principles, incorporating insights from behavioural psychology and stakeholder consultations. The intervention was then implemented over 12 weeks with students identified as pathological or high-risk gamblers. A post-intervention evaluation assessed the system's effectiveness and usability.
Results: Results indicated that the ICGIM system was effective in reducing gambling frequency. Key features, including daily motivational messages, a call sponsor function, and chat support, were highly valued for providing emotional and psychological support, reinforcing positive behavioural change, and enhancing accountability.
Conclusions: The findings underscore the potential of a tailored digital intervention, integrating automated and human-centered support mechanisms, to mitigate online gambling disorder within a university student population.

Keywords: Online Gambling, Problematic Gambling, Responsible Gambling, University Students, Digital Intervention

1 Introduction and Background

Gambling disorder (GD) is a public health concern, and more so online gambling among university students. Diagnostic and Statistical Manual (DSM V) by Sharma, et al. [1] defines GD as a condition that describes a gambler's inability to control their gambling despite the detrimental consequences of the behavior. University administrators are increasingly getting concerned with online gambling among university students who spend most of their time on online gaming ad gambling, leading to problematic gambling, hence the need to address poor student outcomes (e.g. debt, mental health concerns, failure of courses, withdrawal from programs) due to excessive and high prevalence of gambling behavior, that has led to psychosocial and financial distress. Gambling was legalized in Kenya in 1966 [2] and currently, there has been proliferation of online gambling options that have made gambling an easy activity.

Most Kenyan online gamblers are young (18-25 years) and are either students or come from a low-income background, and see online gambling not only as a chance to relax but as a way to create a source of supplementary income [3]. According to Statistica [4], the revenue from the online gambling market in

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Kenya reached US$87m in 2023, and is projected to get to US$121m by 2027, and the average revenue per user was projected to be US$326.30 in 2023. This is driven by the massive and aggressive online gambling campaigns leveraging social media, internet adverts, and traditional platforms including radio, television, and billboards. As a result, Kenya reported the highest number of youths participating in online gambling in Sub-Saharan Africa (SSA) in 2021, with at least 80 percent of respondents indicating that they had gambled or betted at least once. According to Bitanihirwe and Ssewanyana [5], youths who indulge in gambling were found to perform poorly in their studies, lose their school/tuition fees in gambling related activities, and to engage in risky behavior, such as alcohol and drug abuse and high-risk sexual behavior and some end up having gambling disorders. With the expansion of the gambling industry in Kenya, opportunities to engage in gambling are numerous. Given the high level of youth unemployment and the low wages in Kenya, an increasing number of youths find themselves participating in gambling-related activities without being aware of the potential undesirable effects that may culminate from gambling addiction

In Kenya, like in many other African countries, gambling is classified and positioned as a legitimate recreational and leisure activity, regulated by the Betting, Lotteries and Gaming Act Cap 131 of 1966 which does not mention online gambling in any form. Although Kenyan laws set the minimum age to gamble at 18 years, access to gambling has rapidly evolved recently. The seamless integration of mobile money wallets and sports betting platforms, opening up of new markets as well as the innovative marketing campaigns has made gambling very easy. The growth of gambling industry has been on the rise, hence the high rate of disordered gambling among the youth. According to Kisambe [6] nearly 300,000 Kenyans play the multi-shilling jackpot each week. Most of these players are the youth who do not have strategies to guide them on responsible gambling. Based on the fast growth of gambling, the project sought to focus on the use of technology to address the online gambling impact. The technology referred to as the Internet-based Counter-Gambling Interactive Messages (ICGIM) intervention was built on the premise that media coverage is used by the gambling and betting industry to encourage the youth to use their services. The same media coverage through the intervention could therefore be used to promote responsible gambling. ICGIM was envisaged as a robust strategy to increase youth education and awareness regarding online gambling disorder.

The goal of this project was to develop a strategy for promoting responsible online gambling among second- and third-year students at Kisii University, Kenya. To achieve this, the project focused on the following specific objectives:

i. To investigate the prevalence and patterns of online gambling disorder among second- and third-year students at Kisii University.
ii. To design a structured digital intervention framework, named ICGIM, aimed at addressing online gambling disorder among the target student population.
iii. To develop and implement the ICGIM digital intervention system tailored to support second- and third-year students struggling with online gambling disorder at Kisii University.
iv. To evaluate the effectiveness and usability of the ICGIM intervention system in mitigating online gambling disorder among second- and third-year students at Kisii University.

2 Literature Review

In an exploratory analysis of a randomized controlled trial, Grahlher, et al. [7] investigated the "Meine Zeit ohne" (MZo) mobile app, a voluntary commitment program aimed at reducing substance use, gambling, and digital media use among vocational school students. Their study found the intervention's effectiveness was domain-specific, with no spillover effects between behaviors; success was primarily driven by "congruent use," where participants selected a challenge directly aligned with their personal high-risk behavior. The authors concluded that this low-threshold app shows promise in reaching adolescents and raising awareness before habits solidify into addictions [7].

In a systematic review, Giroux, et al. [8] examined the characteristics and efficacy of online and mobile interventions for problem gambling, alcohol, and drug use, noting a significant gap as no study addressed gambling. Their analysis of 18 studies found that most interventions were grounded in motivational or cognitive-behavioral approaches and demonstrated short-term reductions in substance use, which were generally maintained at six-month follow-ups. The review concluded that such digital interventions are

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promising for reaching a workforce-integrated adult population seeking initial help but underscored the need for more long-term efficacy studies with follow-ups extending to 12 months [8].

A study by Merkouris, et al. [9] developed and evaluated the usability of a smartphone-based Ecological Momentary Intervention (EMI) designed to help manage gambling cravings in real-time. The app, which delivered brief, self-directed activities (e.g., urge surfing, breathing exercises) triggered by Ecological Momentary Assessment (EMA) prompts, was tested with a sample of people who gamble, clinicians, and researchers over seven days. Results indicated that the intervention was rated as acceptable and helpful, with participants reporting they would recommend it and that it could effectively reduce short-term cravings; however, feedback suggested improvements were needed in visual appeal, engagement, and personalization options. The findings demonstrate the feasibility and potential of EMI delivered via smartphone as a tool for managing gambling urges and supporting harm reduction [9].

In a content analysis, St Quinton and Morris [10] systematically reviewed the inclusion of Behaviour Change Techniques (BCTs) in 40 freely available gambling prevention mobile applications sourced from the Apple and Google Play stores. Their analysis, using the BCTTv1 taxonomy, revealed that apps incorporated a limited range of BCTs (mean = 2.82 per app), with the most prevalent being "Social support (unspecified)," "Self-monitoring of behaviour," and "Remove access to the reward." The authors concluded that while these apps are a popular tool, their current design draws upon a narrow set of change strategies and recommended that future developers utilize a greater variety of evidence-based BCTs to enhance their potential effectiveness [10].

In a systematic evaluation of publicly available mobile health applications, McCurdy, et al. [11] et al. (2024) assessed the quality of 14 problem-gambling-specific apps using the Mobile App Rating Scale (MARS). The study found that while app functionality was generally well-rated, overall engagement scores were low; however, the inclusion of specific evidence-based features was associated with higher quality ratings. Apps incorporating cognitive-behavioral therapy (CBT) content demonstrated significantly better information quality and aesthetics, and those featuring in-app communities showed improved engagement, aesthetics, and information scores. The authors concluded that to enhance the public health impact of these tools, future app development should prioritize the integration of engaging, evidence-based features like CBT and social support communities to improve user experience and potential efficacy.

In a review of mobile health applications for problem gambling available in Australia, Brownlow [12] identified and analyzed 17 apps from the Google Play and Apple iTunes stores. The study found that while these apps were generally low-cost or free, they suffered from low popularity in terms of downloads and ratings, infrequent updates, and offered a limited range of in-app functions. The author concluded that although these apps provide a foundational intervention tool, there is significant room for improvement in their quality, functional diversity, and update frequency to enhance user engagement and effectiveness, and that a greater number of competing apps could foster market improvements [12].

In an evaluation of Australian mobile applications for problem gambling, Ridley, et al. [13] examined apps from major app stores and found a significant disparity, with apps promoting gambling far outnumbering those designed for treatment. Their analysis revealed that the available treatment apps primarily aimed for total cessation but rarely employed recognizable therapeutic models, most frequently offering only a single tool such as a "sober time tracker." The authors concluded that while mobile apps present a novel and accessible treatment avenue, their current design is limited and requires more thoughtful, evidence-based development—ideally in association with reputable services—to be effective and compete with the more appealing design of gambling-promotion apps.

Building upon this analysis, the present research was motivated by the critical opportunity to synthesize these observed gaps into a cohesive intervention. The literature revealed a consistent absence of key supportive features in existing tools: namely, integrated peer communities, direct sponsor access, financial tracking, AI-driven motivational messaging, recovery story repositories, site-blocking functionality, and personal journaling capabilities. By engaging directly with the student population, it was further confirmed that these are not merely technical omissions but represent unmet psychosocial and behavioral support needs. Therefore, to address this significant shortfall in comprehensive, user-centered support, this study proposed the development and evaluation of a holistic mobile application designed dubbed ICGIM specifically to empower college students in mitigating gambling-related harms through a multifaceted, supportive digital ecosystem.

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It should be noted that we came across no literature testing gambling apps among African university students, indicating a clear gap. Furthermore, the lack of qualitative feedback on gambling app features is rarely discussed, representing another gap that motivates this study.

2.1 Conceptual Framework

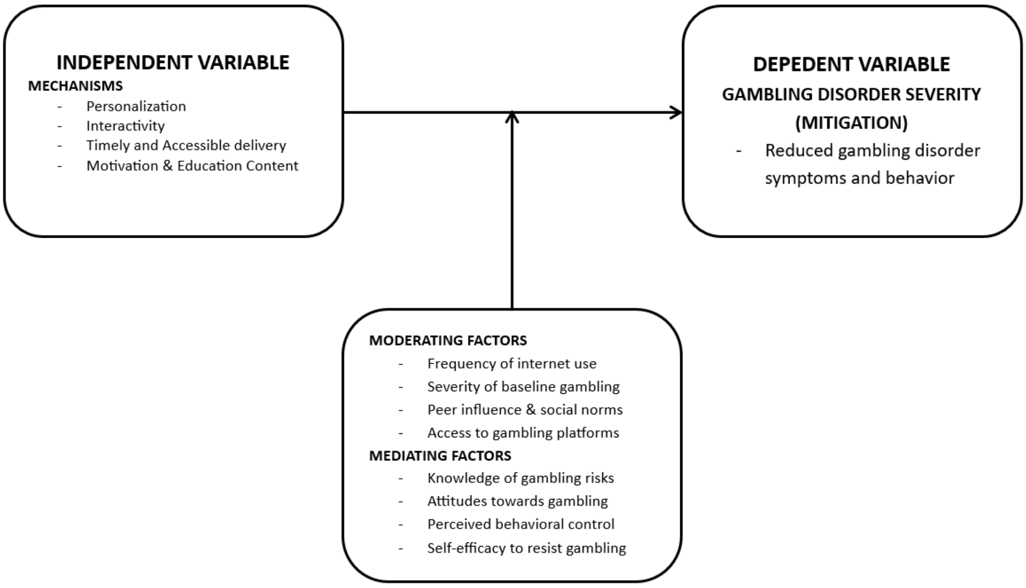

Figure 1: Conceptual Framework of the study

The conceptual framework (Figure 1) guides the methodological design of this study by illustrating the hypothesized relationships among the study variables. It postulates that internet-based interactive counter-gambling messages, delivered through accessible digital platforms such as mobile phones, tablets, and computers, influence specific psychological, behavioral, and technological factors among online gambling students in Kenyan universities, thereby leading to a reduction in the severity of gambling disorder.

In this study, the independent variable is the internet-based counter-gambling interactive messages delivered through the Internet-Based Counter Gambling Interactive Messages (ICGIM) mobile application. The intervention comprises personalized and frequent interactive messages presented in the form of questions, quizzes, motivational prompts, recovery journals, daily check-ins, chat-based support, financial tracking tools, recovery goal-setting features, reflective exercises, and related digital content. These components are systematically delivered over the intervention period to ensure consistent exposure and engagement.

The mediating variables include psychological and technological factors that are expected to explain the mechanism through which the intervention influences gambling behavior. These mediators include attitudes toward reducing gambling, perceived behavioral control, self-efficacy, perceived ease of use and accessibility of the digital intervention, level of digital literacy, and the frequency and intensity of baseline online gambling behavior. These variables are measured using structured questionnaires and in-app usage metrics at baseline and post-intervention.

The moderating variables account for individual and contextual differences that may influence the strength or direction of the relationship between the intervention and the outcome. These include frequency of internet use, baseline severity of gambling behavior, peer influence and social norms, and access to online gambling platforms.

The dependent variable, which represents the primary outcome of the study, is the severity of gambling disorder. This outcome is operationalized through changes in participants' self-reported gambling behavior, including reduced frequency and intensity of gambling activities, increased intention to reduce or cease

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gambling, and improved self-reported self-control over gambling behavior following exposure to the intervention.

3 Methodology

The project design was a diagnostic design that explored the problem of online gambling among Kisii University students and developed an intervention to address it. This research design addressed the problem in a structured form divided into three phases - the issue's inception, diagnosis of the issue, and solution through the ICGIM App. The target population comprised of 2,645 second and third-year students from Kisii University's eight schools. This population did not include the fourth and first-year students due to the fact that the fourth-year students were at the tail end of their studies, while the first years were newly admitted into the university and were still acclimatizing with the university environment.

To begin with, from each school, 10% of the population was randomly selected. This gave a total of 500 students. The 500 students were surveyed at baseline using the SOGS and PGSI tools so as to identify the severity of the gambling disorder. The students whose scores from the SOGS tool were or more were categorized as pathological gamblers, while those whose scores were from 8 to 27 under the PGSI were categorized as high-risk gamblers who might be experiencing gambling related problems. The students identified were then exposed to the ICGIM intervention for 12 weeks. After that period, an assessment was done to check for any changes after using intervention.

A post-intervention assessment was done to help evaluate the ICGIM digital intervention system. It enabled the research team to gather critical insights into both the effectiveness and usability of the solution developed to address online gambling disorder among second- and third-year students at Kisii University. One of the primary purposes of the assessment was to determine whether the intervention had a meaningful impact on students' behavior, awareness, and attitudes toward online gambling. This evaluation was essential in verifying if the system achieved its intended outcomes.

4 Results

Out of the 500 questionnaires that were given to students, 429 were filled and returned. This was a response rate of 86%, which was adequate and excellent to yield reliable and consistent results [14]. Additionally, during sampling, all schools in the university were represented. From the responses, most students were from the School of Business 78 (15.9%), followed by Agriculture 120 (24%), the School of Law 44 (8.9%), Education 51 (10%), Applied Sciences 46 (9%), the School of Health 53 (10.8%), and the School of Information Technology 37 (7.5%). This indicated the varied nature of the students' academic interests. The study utilized the South Oaks Gambling (SOGS) tool that identifies helps identify how often one engages in gambling. Table 1 below presents the information on how often university students engage in different types of gambling, broken down by whether they "not at all," "less than once a week," or "once a week/more."

Table 1: Online Betting and Gambling Type Among University Students

Gambling Activity	Not at all (%)	A week or less (%)	A week or more (%)
Play cards for money	81 (16.5%)	182 (37.0%)	229 (46.5%)
Bet on horses, dogs, or other animals	424 (86.2%)	51 (10.4%)	17 (3.4%)
Bet on sports	21 (4.3%)	142 (28.7%)	329 (66.9%)
Play dice games	123 (25.0%)	177 (36.0%)	192 (39.0%)
Play casino games	39 (7.9%)	108 (22.0%)	345 (70.1%)
Play numbers on lotteries	52 (10.6%)	207 (42.1%)	233 (47.3%)
Play bingo	319 (64.8%)	102 (20.7%)	71 (14.5%)
Play stock/market games	245 (49.8%)	154 (31.3%)	93 (18.9%)
Play slot/poker machines	87 (17.7%)	229 (46.5%)	176 (35.8%)
Bowled/pool/golf for money	73 (14.8%)	218 (44.3%)	201 (40.9%)
Play pull tabs/paper games	194 (39.4%)	247 (50.2%)	51 (10.4%)

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Other gambling activities	79 (16.1%)	265 (53.8%)	148 (30.1%)

4.1 Prevalence of Gambling Disorder

The prevalence of different behaviors and emotions associated to gambling disorders are as presented in Table 2.

Table 2: Prevalence of Online Gambling Disorder

Symptom	**Yes (%)**	**No (%)**
Have problems with betting and gambling	423 (86.0%)	69 (14.0%)
Gamble more than you intend to	389 (79.1%)	103 (20.9%)
Have people criticize you for betting	287 (58.3%)	205 (41.7%)
Feel guilty when betting	292 (59.3%)	200 (40.7%)
Want to stop betting but cannot	308 (62.6%)	184 (37.4%)
Hide betting slips from others	181 (36.8%)	311 (63.2%)
Argue with people about how to handle money	267 (54.3%)	225 (45.7%)
Lost a lot of time due to betting	431 (87.6%)	61 (12.4%)
Borrow money to bet and fail to repay	359 (73.0%)	133 (27.0%)

From the findings, a substantial majority 423 (86%) admit to having a problem with gambling or betting. Much of the population 389 (79.1%) gambles more than they plan to. More than half of the participants 287 (58.3%) stated that they receive criticism for their betting practices. Following a wager, a sizable portion 292 (59.3%) experience guilt. The majority (62.6%) say they would like to quit betting but are unable to do so. More than one-third (36.8%) keep their betting slips secret. Moreover half 267 (54.3%) disagree with others about their financial management practices. The majority of people 431 (87.6%) bet a lot of time. Nearly three-quarters 359 (73%) of those who borrow money to wager find it difficult to repay. This forms the basis of the present study, which focuses on the creation, design, and implementation of an innovative digital application intended to support students by tracking their behaviors and actively engaging them. The application aims to enhance students' self-awareness and motivation, ultimately encouraging responsible gambling behaviors or supporting complete cessation of gambling in the long term.

4.2 Intervention Design and Development

The development of the ICGIM system was guided by a rigorous, iterative methodology rooted in the principles of User-Centered Design (UCD) and the Agile development framework. This approach was selected to ensure that the final product was not merely a theoretical intervention but rather a practical, accessible, and effective tool tailored to the complex needs of individuals struggling with gambling disorder. The methodology was interconnected with several other phases and feedback loops to ensure continuous development. The process commenced with a foundational research phase that included a proper understanding of the problem domain. This happened through a thorough literature review on behavioral psychology, Cognitive-Behavior Therapy, and Transtheoretical Model of Change, to ground the system's interactive components in establishing therapeutic principles. Different stakeholders were met and interviews with potential users and clinicians were undertaken and data collected informed the design and development of the ICGIM intervention system. As more stakeholders were met, their data catalyzed the redesigning and development of the system resulting in an improved system that accommodated the needs of all the stakeholders resulting in a User-Centered Design Framework for the development of ICGIM.

Once the prototype of the ICGIM application was completed, a group of 30 participants was given the opportunity to interact with the system over a period of several weeks. Participants received brief training on how to use the various features of the application. Following this usability testing phase, they provided extensive feedback and suggestions aimed at improving the system. All suggestions were carefully

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considered, and the application was subsequently redesigned, incorporating additional insights from domain experts, including medical psychologists and other healthcare practitioners. Among the features most frequently used and positively received by participants were the interactive motivational messages, which were delivered daily to encourage responsible gambling behavior, as illustrated in Figure 3.

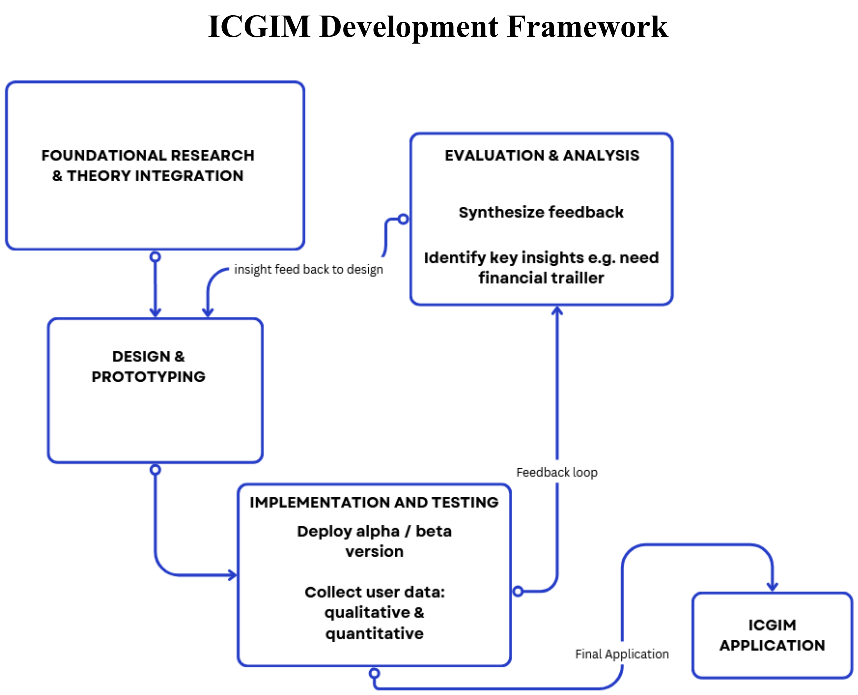

Figure 2: ICGIM Development Framework.

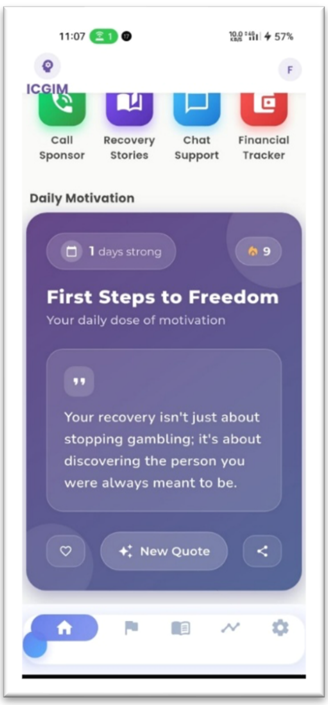

Figure 3: Personalized interactive messages sent to user of the ICGIM application

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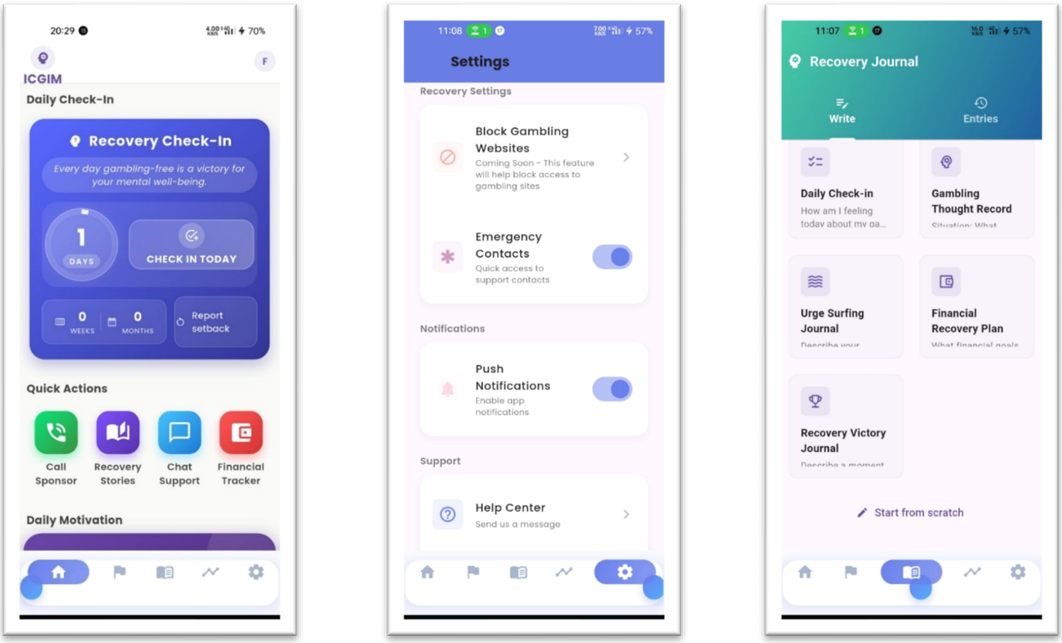

Figure 4: Snapshots of the different interactive interfaces of the ICGIM mobile App

4.3 Effectiveness of ICGIM digital intervention

After the system was updated and upgraded, five students were purposively selected to use the improved Internet-Based Counter Gambling Interactive Messaging (ICGIM) system over a period of several weeks to evaluate whether the application was fully optimized and had effectively incorporated the key suggestions provided by earlier participants. At the end of the intervention period, the participants completed a post-intervention survey designed to assess system usability and features, as well as perceived impact and well-being outcomes. Responses were captured using a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), and the results are presented in the subsequent figures.

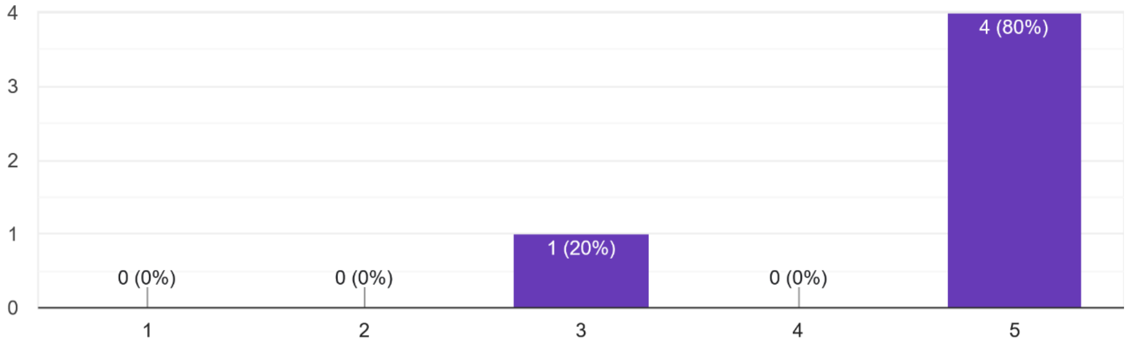

Figure 5: Response on how chat feature was supportive in providing emotional assistance

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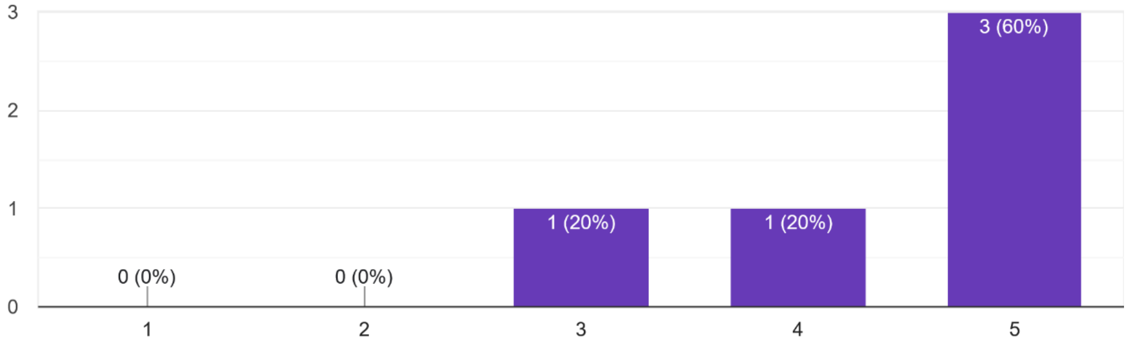

Figure 6: Response on how the call sponsor feature made them feel supported and accountable

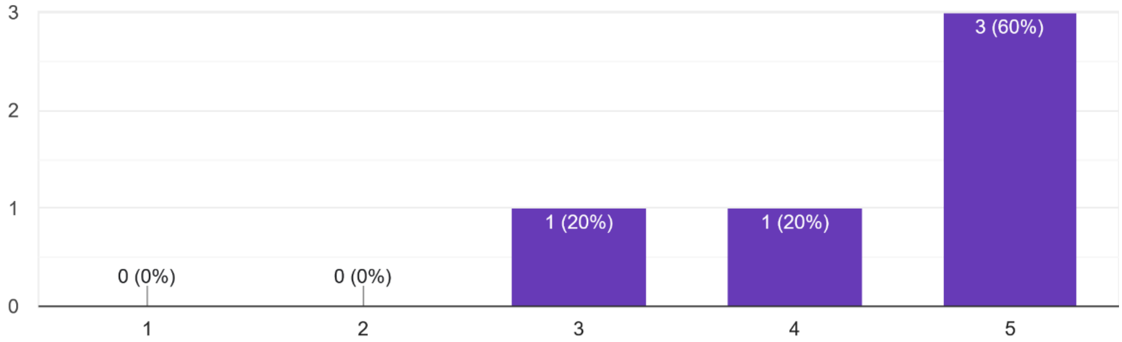

Figure 7: Response on how daily motivational messages helped reduce their urge of gambling

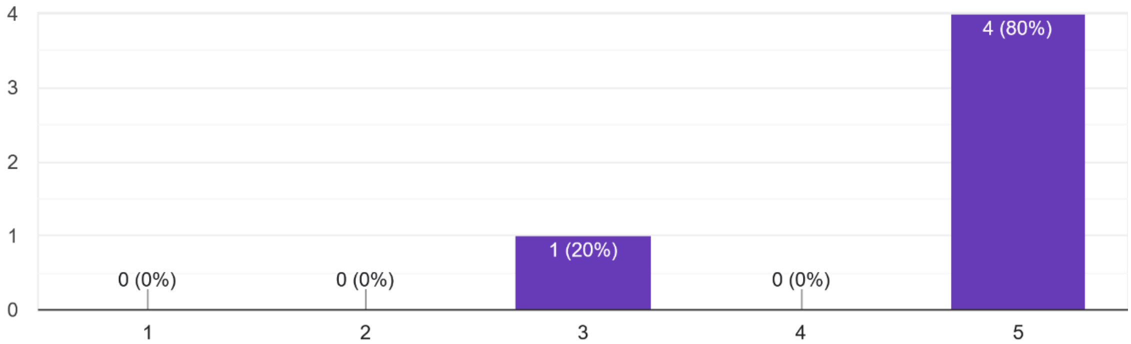

Figure 8: Response on how gambling frequency has reduced since using the ICGIM system

The post-intervention survey results indicate that the ICGIM system was effective in reducing the frequency of gambling among participants. Users reported that the daily motivational messages played a significant role in reducing gambling urges by reinforcing positive behavioral change and self-awareness. In addition, the call sponsor feature was highly valued, as it enhanced participants' sense of accountability and provided consistent social support throughout the intervention period. The chat support feature was also positively received, with participants noting that it offered timely emotional assistance from experts and trained champions, particularly during periods of heightened vulnerability. The findings demonstrated that the ICGIM system provided strong emotional and psychological support through its interactive messaging features, highlighting the importance of integrating both automated and human-centered support mechanisms in digital interventions aimed at mitigating gambling disorder among university students.

The qualitative feedback from participants indicates that the improved ICGIM system contributed positively to users' efforts to reduce or stop gambling. Several users reported that the system provided

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factual information, real-life stories, and timely advice that inspired behavior change and helped them manage gambling urges, with some noting that they chose to engage with the application instead of visiting gambling websites when tempted.

"It has given me more facts and stories that have inspired me"

Others highlighted the value of progress tracking, particularly in relation to financial stability, with one participant emphasizing that the system supported a gradual return to healthier financial habits.

"*I began using the app with no hopes of being helped to stop gambling but as time goes by, there were fruits of regaining a healthy financial stability*"

Regarding new and improved features, users most frequently cited the enhanced navigation and user interface, as well as the introduction of financial tracking tools, which were perceived as critical in promoting accountability and awareness of personal spending. Participants also acknowledged that their earlier recommendations had been incorporated, noting improvements in accessibility, visual appeal, and the inclusion of financial trackers and testimonials, all of which made the system more engaging and motivating.

"Our recommendations were incorporated"

5 Discussion

5.1 Sociodemographic and Behavioral Correlates of Gambling Disorder Among University Students

The results of this study shows that university students' gambling habits are highly influenced by sociodemographic characteristics. The study's gender gap (79.5% male vs. 20.5% female) is consistent with earlier research showing that men are more likely to gamble at greater stakes [15]. Students between the ages of 19 and 25 are especially vulnerable to gambling disorders, making age another important consideration. This result supports research that indicates a higher risk of gambling-related problems for younger people [16]. Findings that show financial instability can worsen gambling disorders are in line with the research's emphasis on financial help, especially from the Higher Education Loans Board (HELB) [17]. Echoing findings from Hing Hing, et al. [18] that imply family dynamics can influence gambling problems, the study also finds a substantial association between gambling behaviors and family type. In the work done by Suomi, et al. [19], they found that gambling behaviors are strongly influenced by familial support systems, and students from single-parent families showed higher gambling disorder scores.

According to the current study, students are likely to play casino games and wager on sports, which is in line with Valenciano-Mendoza, et al. [20] findings about comparable patterns in their demographic. The propensity to "chase losses," as observed in this study, is consistent with the findings of Yau and Potenza [21], who found that this behaviour is suggestive of problem gambling. Findings by Estévez, et al. [22], who connected gambling difficulties with mental health issues, are supported by the significant prevalence of anxiety and depression among students with gambling disorders in this study. Interestingly, the regression analysis showing that depression is significantly predicted by income source is consistent with earlier studies showing that financial stress is a factor in psychological discomfort [23].

The findings of the current study are consistent with those of Mofatteh [24], who discovered that psychological distress is more prevalent among younger students. The intricate relationship between sociodemographic characteristics and gambling behaviors is highlighted by this study overall, highlighting the necessity of focused interventions for populations that are at risk. It emphasizes how crucial it is to treat gambling addiction and related mental health conditions in order to lessen their negative effects on students' life [25].

The hallmarks of gambling illness include a developing obsession with gambling and a need to place more frequent and larger bets [21]. More so than the severity of the overall gambling disorder, the style of gambling can influence how frequently a person gambles. Compared to other forms of gambling, including

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playing bingo or placing bets on animals, sports betting and casino games seem to be more popular (participation rates are higher) [20]. Since up to 5% of teenagers and young adults who gamble go on to have a problem, young people are particularly vulnerable. It is believed that 96% of individuals with gambling disorders also suffer from at least one other mental illness [16]. Research indicates that between 1.2% and 6.0% of people globally suffer from gambling addiction. Up to 90% or more of those who struggle with gambling never ask for assistance [15].

5.2 ICGIM Intervention Outcomes: Engagement, Feature Feedback, and Preliminary Behavioral Changes

The ICGIM's daily motivational messages were effective in helping users manage and reduce gambling urges, reinforcing positive behavioral change on a consistent basis. Most participants also agreed that the system contributed to a noticeable reduction in the frequency of their gambling activities. Collectively, these outcomes demonstrate that the integrated support structure of the system—combining emotional support, accountability mechanisms, and motivational reinforcement—was instrumental in influencing healthier decision-making and promoting sustained behavioral change among users.

The ICGIM app operationalizes the four independent constructs on the conceptual framework as follows: Personalization through iterative user-centered design and stakeholder feedback; Interactivity via chat, sponsor calls, and two-way motivational messages; Timely & Accessible delivery through daily push notifications on mobile devices; and Motivation & Education Content using CBT and Transtheoretical Model-based messaging. The dependent variable (gambling disorder mitigation) is assessed through self-reported behavioral changes, though we acknowledge the small sample as a limitation.

While the sociodemographic correlates above provide important contextual background, the primary contribution of this study is the ICGIM mobile app itself. During the usability testing phase (n=30), the most frequently used and positively received features were the interactive motivational messages, delivered daily based on the Transtheoretical Model of Change. Of the 30 participants, 27 (90%) reported opening the motivational messages consistently throughout the testing period. The chat feature was used by 18 participants (60%), while the call sponsor feature was used less frequently (n=8, 27%), potentially due to perceived discomfort with directly contacting a sponsor. In the post-intervention evaluation (n=5, purposively selected), all five participants confirmed that the motivational messages were "helpful" or "very helpful" in recognizing gambling triggers.

Regarding gambling disorder severity mitigation (the dependent variable in our framework), two of the five post-intervention participants reported a self-perceived reduction in gambling frequency from daily episodes to 2–3 times per week. One participant reported complete abstinence during the final week of the study. While these results are not statistically generalizable due to the small sample size (n=5) and purposive sampling, they provide preliminary evidence that the ICGIM mechanisms (personalization, interactivity, timely delivery, and motivational content) may contribute to symptom reduction.

Participants also provided constructive feedback for future iterations. Three participants requested additional educational content on financial management. Two participants suggested integrating a self-exclusion timer that locks the app during high-risk hours (e.g., late night). These suggestions have been documented for Version 2.0 of ICGIM.

6 Conclusion

This study demonstrates that sociodemographic factors play a critical role in shaping gambling behaviors and the prevalence of gambling disorders among university students. Male students, those aged 19–25 years, individuals with financial dependency—particularly loan reliance—and students from single-parent households were found to be more vulnerable to problematic gambling. The strong associations between gambling disorder, financial stress, anxiety, and depressive symptoms highlight the need for holistic interventions that integrate mental health and economic support. These findings underscore the importance of targeted, context-sensitive prevention and intervention strategies within university settings, alongside institutional efforts to raise awareness, strengthen support systems, and mitigate the adverse effects of gambling on students' well-being.

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The study further concludes that the Internet-Based Counter Gambling Interactive Messages (ICGIM) system is a highly promising and effective digital intervention for supporting recovery from gambling addiction. Through a co-development and iterative refinement process, the system demonstrated high usability, effectiveness, and positive behavioral impact, achieving a very high user satisfaction rate among participants. Users particularly valued the financial tracking feature for enhancing accountability, as well as the integrated emotional and social support components, including inspirational content and real-time assistance. In conclusion, the ICGIM's multi-faceted, user-centered design provides a robust framework for reducing gambling behaviors and supporting sustained recovery, with future refinements expected to further enhance its relevance and scalability.

Ethical Considerations

Ethical approval for the study was obtained from the Kisii University Institutional Scientific and Ethics Review Committee (ISERC) under reference number KSU/ISERC/0034/04/25. All participants provided written informed consent, confirming their voluntary participation and their willingness for their involvement to contribute to the development and evaluation of the Internet-Based Counter Gambling Interactive Messages (ICGIM) digital intervention.

Acknowledgement

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Statement on conflicts of interest

No conflict of interest.

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Journal of Health Informatics in Africa

Enhancing Diabetes Mellitus Diagnosis and Management in Ghana through Supervised Learning: A Predictive Modeling Approach

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Background: Diabetes mellitus is an emerging public health problem in Ghana where delayed diagnosis, limited specialized services and budget limitations may hinder patients from accessing prompt therapy. Machine learning based clinical decision support systems can help clinical judgement by recognizing patterns within routinely gathered patient data to provide timely diagnostic support based on evidence.
Purpose: In this work supervised machine learning models for the prediction of diabetes mellitus were created using clinical data from a healthcare institution in Ghana and the models were internally validated and their potential clinical decision support application discussed.
Methods: We acquired a retrospective data set of 3407 patient records from St Michael's Hospital, Jachie-Pramso, Ghana. The dataset contained eight predictor variables, including age, sex, fasting plasma glucose, glycated haemoglobin, nocturia, polyuria, weight loss and body mass index and ultimately a binary diabetes outcome. The data pre-processing includes removal of duplicate and missing entries, encoding of categorical variables and setting up the data set for modeling. The Random Forest, Gaussian Naive Bayes and Extreme Gradient Boosting models were constructed using 80:20 training-test split. The model performance was assessed by accuracy, class-specific precision, recall, F1-score and confusion matrices.
Results: The best accuracy (99.5%) was obtained by XGBoost, followed by Random Forest (98.9%) and Gaussian Naive Bayes (94.5%) on the held-out test dataset. XGBoost also presented the best blend of class-specific accuracy, recall and F1-score. These data revealed XGBoost as the best candidate model among the three algorithms studied. However, results are internal validation of a single healthcare center and need external confirmation before clinical adoption.
Conclusion: XGBoost provided the best internal prediction performance and may offer the computational basis for a diabetes-centric clinical decision support system in Ghana. However, before the model can be integrated into normal patient treatment, it has to be externally verified in geographically and clinically varied groups and prospectively examined for calibration, usability, fairness, and therapeutic utility.

Keywords: Diabetes Mellitus, Predictive Modeling, Supervised Learning, Healthcare Decision-making, Treatment Outcomes.

1 Introduction

Computer applications have become vital instruments to address human demands especially in public health [1]. Among these applications, Artificial Intelligence (AI) is one of the major forces pushing the growth and innovation in a variety of fields including healthcare [2]. Specifically, the incorporation of AI into Clinical Decision Support Systems (CDSS) has changed healthcare delivery, providing timely and tailored support to both physicians and patients [1]. Although affluent nations have made headway towards CDSS implementation this is not the case in resource restricted situations like Ghana [1]. In such scenario there is

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no doubt that there is an urgent need for intelligent decision-making tools to improve the delivery of healthcare. Diabetes mellitus is a chronic disease characterized by either deficient production of insulin or poor usage of insulin and is a major public health problem worldwide [3]. Diabetes is a growing burden with increasing incidence, particularly in sub-Saharan Africa, where access to specialist healthcare services is restricted [4].

The rising burden of diabetes in Ghana emphasizes the need for novel approaches to enhance its diagnosis and management [5, 6]. Although there is research on software-based treatments for diabetes management, there is a significant gap in the use of expert driven decision support systems for diagnosis [7, 8]. Furthermore, most of the research efforts have been directed to general prenatal care and not to the issues related to the diagnosis of diabetes [8]. This work seeks to fill these gaps by proposing, creating and deploying a Diagnostic Decision Support System (DSS) for the Ghanaian setting. The suggested system utilizes expert knowledge and clinical data to increase the accuracy, speed and efficiency of diabetes diagnosis, especially in the disadvantaged areas with limited access to specialized care. Importantly, this study goes beyond prior treatments by highlighting the incorporation of Clinical Practice Guidelines (CPGs) and expert opinions into the design of the CDSS, assuring its relevance and efficacy in the Ghanaian healthcare setting.

1.1 Clinical Decision Support and Predictive Modelling for Diabetes

Clinical decision support systems combine patient-specific information with clinical expertise to help offer healthcare workers with evaluations, warnings, forecasts or suggestions that may assist clinical decision-making [9]. Traditional CDSSs are often rule-based and predetermined, while modern systems increasingly include machine-learning algorithms that can detect complicated and nonlinear associations in electronic health data [10]. Machine learning-supported CDSSs in diabetes care have been examined for disease-risk prediction, screening, diagnosis, therapy selection, glycaemic monitoring and prediction of complications [11]. The potential relevance of such applications is high in scenarios where expert services are restricted and routinely acquired clinical information might be utilized to help frontline healthcare personnel.

Supervised machine-learning algorithms develop correlations between labeled predictor factors and a known clinical result [12]. Random Forest employs several decision trees and aggregated voting to increase the stability of the prediction and to lessen the danger of overfitting of decision trees [13]. Gaussian Naive Bayes estimates class membership by applying Bayes' theorem and conditional independence assumptions, whereas XGBoost creates decision trees in a sequential manner, where later trees fix errors caused by previous trees [14]. Studies on machine learning methods for diabetes prediction have revealed that ensemble methods like Random Forest and gradient boosting models usually surpass single classifiers [15, 16]. However, its documented performance is highly dependent on the population studied, specification of outcomes, sample size, preprocessing steps, validation method and class imbalance [17].

Previous studies highlighted the promise of machine learning for clinical decision assistance in diabetes. Islam et al. built a CDSS to predict type 2 diabetes and shown that the combination of clinical features and machine learning classification might assist in the early identification of patients at risk [18]. Similarly, Tasin et al. tested multiple algorithms using a privately gathered diabetes dataset and found that the prediction performance was highly dependent on feature selection, data quality, and the demographic represented in the dataset [19]. While such research shows the technical promise of machine learning, many of them are based on datasets that are regularly reused or populations outside sub-Saharan Africa. Therefore, their results cannot be automatically generalized to Ghana because of variations in patient characteristics, clinical practices, illness distribution, healthcare access and data-recording methods that may impact model performance.

In Ghana, digital interventions have focused mostly on diabetes education, lifestyle change, self-management, and patient-health care provider communication [20, 21]. Other Ghanaian research have focused on decision assistance tools in areas such as prenatal care [22]. However, information on supervised machine learning models constructed utilizing routinely obtained Ghanaian clinical data particularly for diabetes diagnosis is quite few. In addition, published predictive studies tend to focus just on accuracy and do not sufficiently evaluate class-specific sensitivity, precision, F1-score, model calibration, external validity or impact of false-negative predictions. This is significant because a model with a high overall accuracy might nevertheless miss clinically relevant cases, especially when the outcome classes are uneven.

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The primary research gap that the current work addresses is the little knowledge on the comparative efficacy of supervised machine-learning algorithms trained on locally generated Ghanaian clinical data for diabetes prediction. In this study, the Gaussian Naive Bayes, Random Forest and XGBoost are compared using accuracy, precision, recall, F1-score and confusion matrices. It also determines the top performing candidate algorithm for additional validation and possible implementation into a Ghanaian diabetic CDSS. The study does not assess real clinical uptake or patient outcome but provides an internally validated prediction basis that needs external, prospective confirmation before deployment.

1.2 Theoretical and Conceptual framework

The Technology Acceptance Model gives a theory-based implementation perspective to understand the possible acceptance of the proposed CDSS [23]. The model indicates that users' adoption of a technology is mostly affected by two factors, perceived utility and perceived ease of use. Perceived utility in this context is defined as the degree to which healthcare professionals feel a predictive CDSS may enhance the timeliness, consistency and accuracy of diabetes-related clinical choices. Perceived ease of use was related to the extent to which doctors felt the system could be controlled and understood without undue effort or disruption to clinical workflow. These views may affect clinicians' attitudes, desire to utilize the system and ultimately routine use.

In the present study, the Technology Acceptance Model was not empirically tested, as the focus was on model creation and internal predictive performance, not on clinician conduct. The concept has consequences for future development of CDSS, nonetheless. However, a technically sound model may not provide therapeutic advantages if its predictions are hard to comprehend, inadequately embedded in the workflow or not accepted by healthcare personnel. Therefore, future implementation studies should measure perceived utility, convenience of use, trust, interpretability, fit with workflow and intention to use by potential healthcare consumers.

Conceptually, the investigation starts with regular demographic, biochemical, anthropometric and symptom-related information. These variables are preprocessed and three supervised learning algorithms are trained. The algorithms make binary predictions that are compared to the reported diabetes result using accuracy, precision, recall, F1-score and confusion matrices. The top performing candidate model may then be implemented in a CDSS which can offer risk estimations or diagnostic cues to health care practitioners (figure 1). The ultimate choice must always be made by clinical judgement and approved diagnostic protocols. The model is meant to help qualified healthcare professionals, not to substitute them.

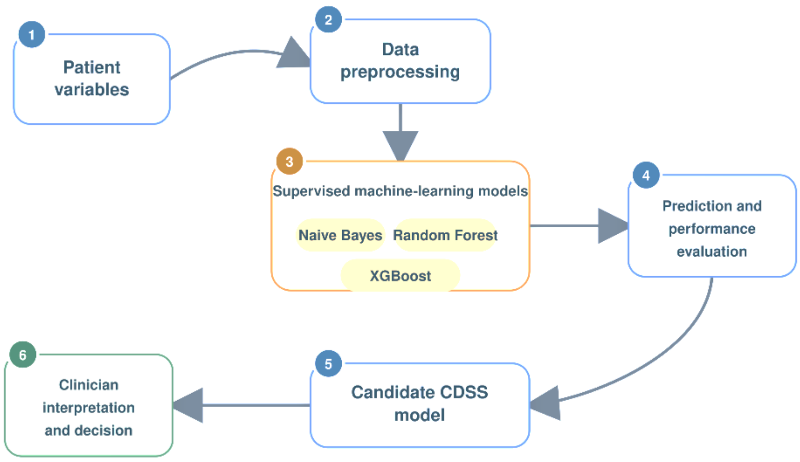

Fig. 1. Conceptual framework for supervised machine-learning-supported diabetes decision support.

The relevance of this study is more than academic questioning and practical use for healthcare professionals as well as patients. The proposed CDSS would provide general practitioners with enhanced decision-making tools and has the potential to fill the gap in diabetes treatment, particularly in rural locations with limited medical resources [24]. Ultimately this research helps to the continuing efforts to enhance healthcare delivery and decrease the socioeconomic burden of diabetes in Ghana and comparable

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resource restricted contexts. The main purpose of this work was to create and internally validate supervised machine learning models for prediction of diabetes mellitus using clinical data collected from St. Michael's Hospital, Jachie-Pramso, Ghana. The specific aims of the present study were to (1) preprocess routinely collected clinical data for diabetes prediction, (2) build Gaussian Naive Bayes, Random Forest and XGBoost classification models, (3) compare the models using accuracy, precision, recall, F1-score and confusion matrices, and (4) identify the best-performing candidate model for further external validation and possible future integration into a diabetes-focused CDSS.

2 Methodology

2.1 Dataset Collection

In this study, the dataset used was collected from the St. Michael hospital from a community in the Ashanti region of Ghana called Jachie Pramso. The dataset contained 3407 instances with 2232 diabetic and the remaining 1175 being non-diabetic. The dataset has nine attributes with one as an output class with binary value indicating if a person is diabetic or not.

2.2 Data Preprocessing

The data was first preprocessed using an open-source data cleaning tool called openRefine to remove null values and redundant rows. It was further preprocessed by converting the True/False values to a binary 0 and 1 to allow it to be used for training by the model.

This is needed to train models like logistic regression, random forest, and xgb since they cannot use words for training. After all irrelevant and imbalanced features are dropped to prevent overfitting and increase the model's robustness.

2.3 Study Design

This research work is aimed at finding out the benefits of using clinical decision support to diagnose and manage diabetes in Ghana and getting the best model that can predict diabetes in people, Following the gathering and pre-processing of data, the dataset will be trained using supervised machine learning techniques to obtain the best model capable of predicting diabetes in people. The best model would be chosen and used to predict occurrence on the dataset. Figure 2 depicts how the desired outcome will be attained.

2.4 Data Description

The dataset used in this study was gathered from the St. Michael Hospital in Jachie Pramso, Ghana, in the Ashanti area. These data amounted to a total of three thousand four hundred and seven (3407) samples, divided into two groups: non-diabetic people and diabetes people. The dataset comprises physical examination indicators such as age, gender, fasting blood glucose level, glycated hemoglobin level, body mass index, and patient signs and symptoms (figure 3).

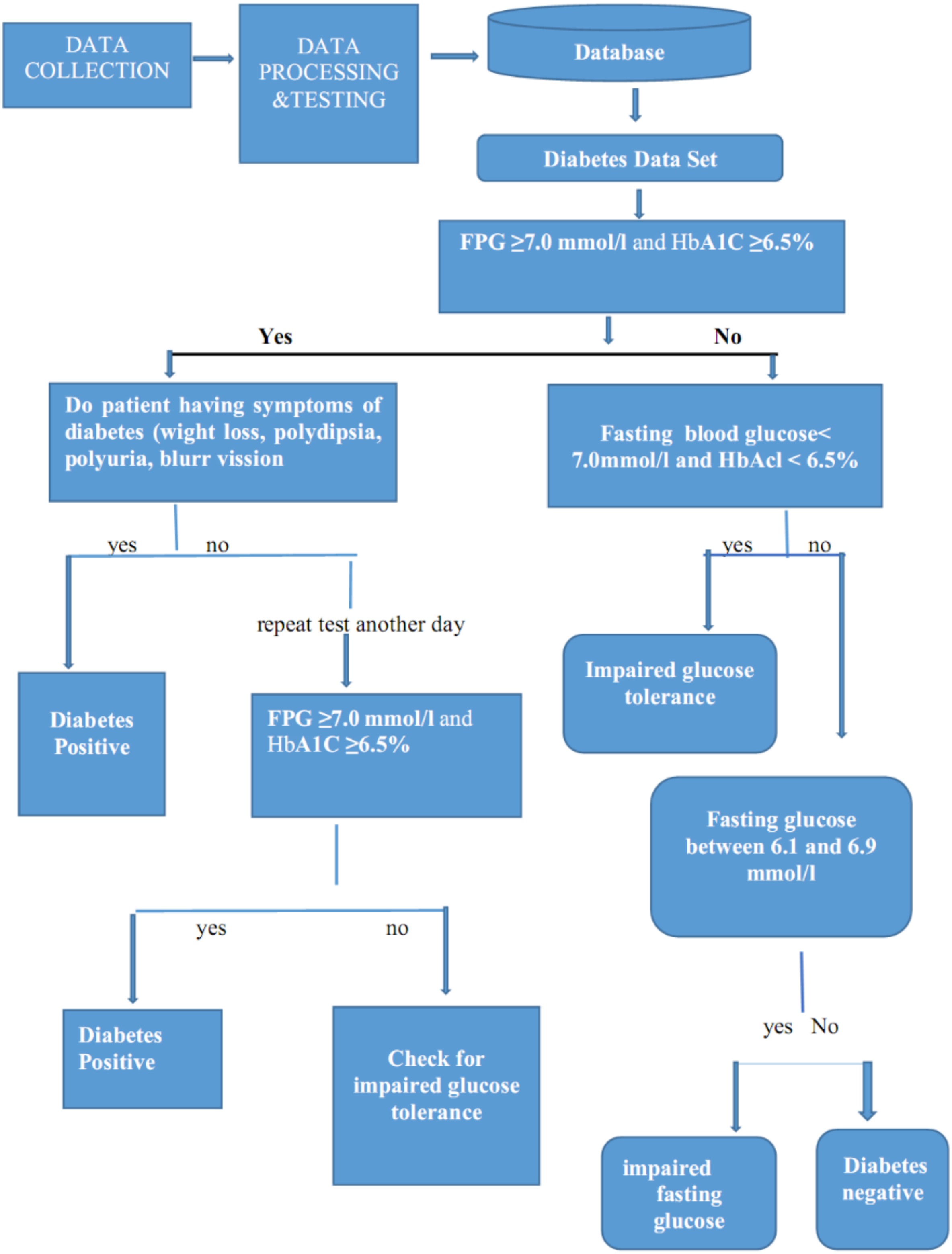

Fig. 2. Flow Chart for the Diagnostic Model

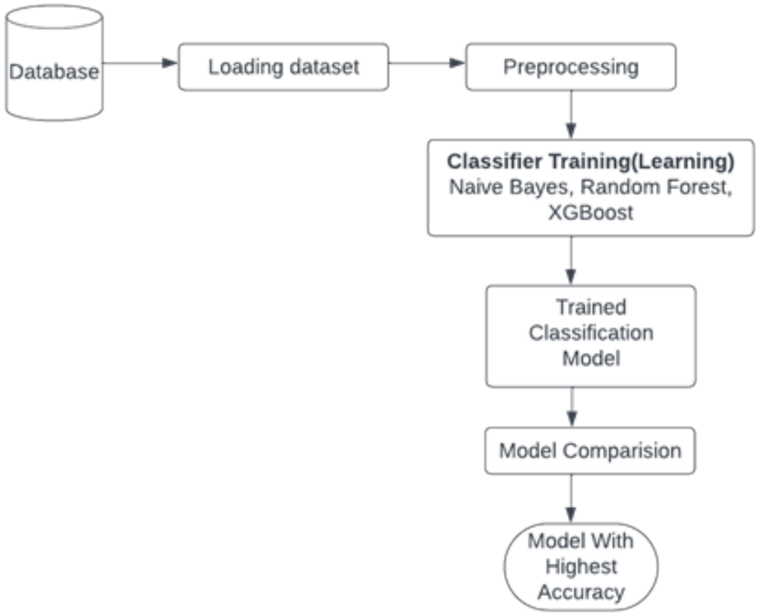

Fig. 3. Data Flow Diagram for the diagnostic model

2.5 Model Design Algorithms

2.5.1 The Naive Bayes algorithm

Naive Bayes is a probabilistic method based on Bayes theory. It is a Supervised Learning algorithm i.e. it trains on labeled data. Assumes features are independent. For example, the likelihood of a class label is independent of the values of all other attributes. This assumption is typically not true with real data but can be beneficial in many circumstances. It is an efficient and simple algorithm. It's capable of big data sets. It is also resistant to noise and outliers. This makes it ideally suited for medical data which is frequently inadequate and noisy. In our situation, we have employed the technique of Gaussian naive bayes which is more sensitive to data. The accuracy of the model for real-valued data was 94.57%.

2.5.2 Random Forest

The Random Forest is one of the most accurate and widely used ensemble machine learning methods. It operates by creating a huge number of decision trees throughout the training phase. Each tree is constructed using a random portion of the training data and a random subset of the features, which adds variety and helps prevent overfitting. During the prediction phase, the algorithm calculates the predictions of all the individual trees. It does this via majority voting in the case of classifying tasks and by averaging in the case of regressive tasks. The ensemble method enhances the prediction performance of the model, and generalizes to unknown data. Random Forest also gives you an idea of the relevance of features. It assesses how much each attribute contributes to the model's accuracy. This helps us comprehend the relationships in the data. The Random Forest is judged to be around 98.97% accurate. Random Forest finds use in banking, healthcare, natural language processing and many other domains.

2.5.3 XGBoost (Extreme Gradient Boosting)

Extreme gradient boosting (XGBoost) is a high-performance and high-efficiency machine learning technique for classification and regression, especially for structured data. XGB belongs to the gradient-boosting family and became famous because of its excellent predictive power and flexibility. XGBoost generates an ensemble of decision trees iteratively. The objective is to reduce mistakes in prediction by integrating predictions of already created trees to improve accuracy with each tree that is produced. This iterative process is built upon the optimization of gradient descent. XGB has built-in regularization to

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prevent over-fitting. This provides XGBoost with robustness to noisy or difficult datasets. XGB has L1 and L2 regularization terms in objective function. The best accuracy of XGBoost is 99.56 %.

3 Results and Discussion

This work generated predictive models for diabetes mellitus categorization utilizing the Gaussian Naive Bayes, Random Forest and XGBoost algorithms. The dataset consisted of 3407 patient records and eight predictor variables: age, sex, fasting plasma glucose, glycated hemoglobin, nocturia, polyuria, weight loss and body mass index. The binary outcome variable was diabetes status and hence not included in the predictor factors. The dataset was preprocessed and then divided into training and test sets in an 80:20 ratio. Each method was trained on the identical training dataset and assessed individually on the held-out test dataset using accuracy, class-specific precision, recall, F1-score and confusion matrices. Figure 4 shows an example of the pre-processed data that was utilized to create the model.

	AGE	Gender	FPG	HbA1c	Noctouria	Polyuria	Weight_loss	BMI	Outcome
0	52	F	7.0	6.7	True	True	True	31.0	positive
1	57	M	10.8	8.0	False	False	False	32.0	positive
2	56	F	3.6	5.0	False	False	False	23.0	negative
3	32	F	7.5	6.8	False	False	False	31.0	positive
4	51	M	5.7	6.2	False	False	False	20.0	negative

Fig. 4. Sample of the pre-processed data using Python libraries in the Google Colab environment

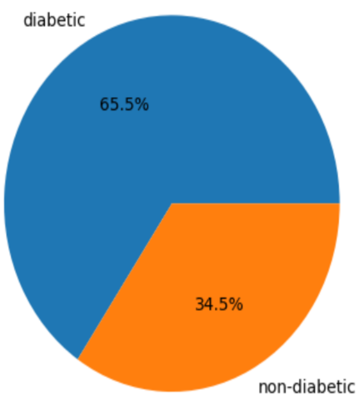

Fig. 5. Pie Chart showing a distribution of Diabetic and Non-Diabetic Patients

The pie chart visually represents the distribution of health conditions within the studied population (figure 5). It illustrates two main categories: "Diabetic" and "Non-Diabetic."

- Diabetic: This category occupies the majority of the chart, representing approximately 65.5% of the total population. It signifies individuals who have been diagnosed with diabetes.
- Non-diabetic: The remaining portion of the chart, accounting for approximately 34.5%, represents individuals who do not have diabetes.

This pie chart offers a clear and concise overview of the prevalence of diabetes within the research cohort, highlighting the significance of this health condition in the context of your study.

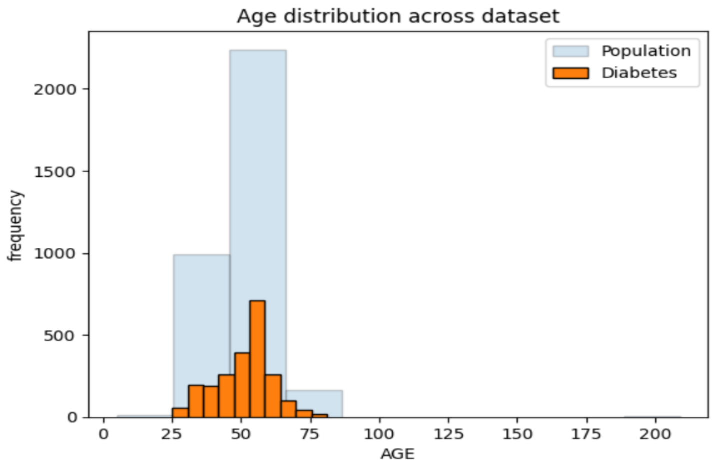

Fig. 6. Bar Chart showing Age distribution across Diabetic Patients

The figure 6 shows the age distribution of the people with diabetes across the dataset. The x-axis shows age in years, and the y-axis shows frequency, or the number of people in each age group.

The chart shows that the most common age group for people with diabetes is 65-74 years old. There is a gradual increase in the frequency of diabetes with age. The frequency of diabetes then declines slightly in the 75-84 age group and then more sharply in the 85+ age group.

Overall, the chart shows that diabetes is a more common condition in older adults. This is likely due to several factors, including age-related changes in metabolism, hormone levels, and immune function.

Summary of the age distribution of people with diabetes:

Most common age group: 65-74 years old

Slight decline in frequency in the 75-84 age group and a sharper decline in the 85+ age group

Diabetes is more common in older adults.

3.1 Results of Random Forest Algorithm

This model achieved an accuracy of 98.9%. The algorithm contained 100 trees improving the predictive accuracy and generalization of the model. The model's precision is 100% for non-diabetic patients and 99% for diabetic patients, the recall was 97% for non-diabetic and 100% for diabetic patients and an f1-score of 98% for non-diabetic and 99% for diabetic patients (figure 7).

```
Accuracy of model:  0.9897360703812317
              precision    recall  f1-score   support

           0       1.00      0.97      0.98       223
           1       0.99      1.00      0.99       459

    accuracy                           0.99       682
   macro avg       0.99      0.99      0.99       682
weighted avg       0.99      0.99      0.99       682
```

Fig. 7. Results from Random Forest Algorithm

The confusion matrix of the Random Forest algorithm shows that out of the 20% of data used as test data, 217/218 non-diabetic patients were correctly predicted with 1 non-diabetic predicted as diabetic. Out of 464 diabetic patients, 6 were predicted to be non-diabetic and the remaining 458 correctly predicted as diabetic (figure 8).

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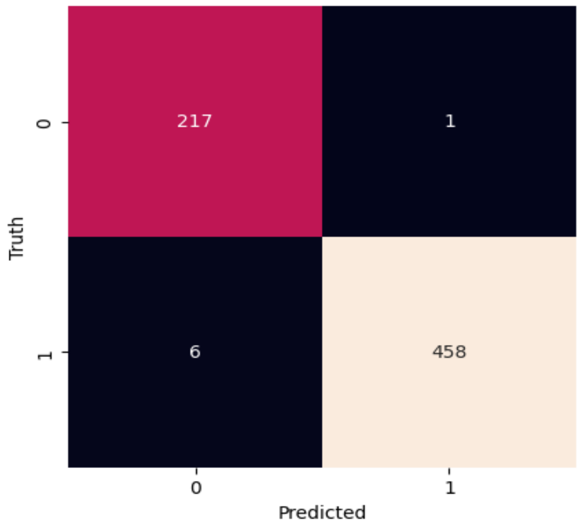

Fig. 8. Confusion Matrix for Random Forest Algorithm

3.2 Results of Naive Bayesian Algorithm

This model achieved an accuracy of 94.5%. The model's precision is 95% for non-diabetic patients and 94% for diabetic patients, the recall is 89% for non-diabetic and 98% for diabetic patients and an f1-score with 92% for non-diabetic and 96% for diabetic patients (figure 9).

```
Accuracy of model:  0.9457478005865103
              precision    recall  f1-score   support

           0       0.95      0.89      0.92       235
           1       0.94      0.98      0.96       447

    accuracy                           0.95       682
   macro avg       0.95      0.93      0.94       682
weighted avg       0.95      0.95      0.95       682
```

Fig. 9. Results from Naive Bayesian Algorithm

The confusion matrix of the Gaussian Naive Bayes algorithm shows that out of the 20% of data used as test data, 208/218 non-diabetic patients were correctly predicted with 10 non-diabetic predicted as diabetic. Out of 464 diabetic patients, 27 were predicted to be non-diabetic and the remaining 437 correctly predicted as diabetic (figure 10).

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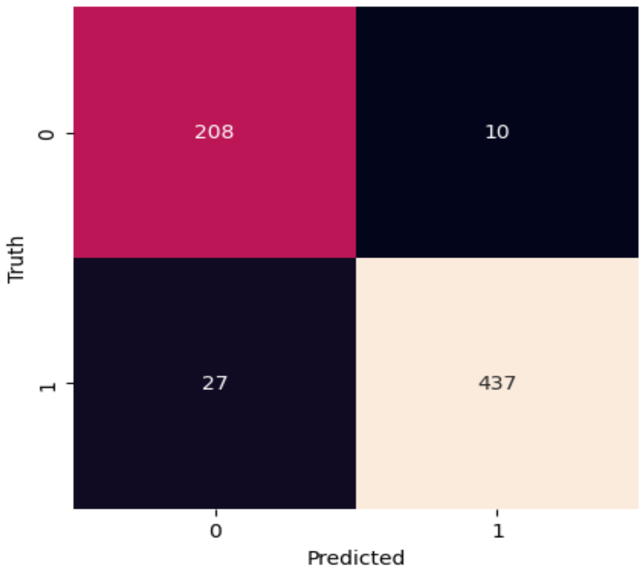

Fig. 10. Confusion Matrix for Naive Bayes Algorithm

3.3 Results of the XGBOOST Algorithm

This model achieved an accuracy of 99.5% by using 1000 estimators, a learning rate of 0.05% and 4 number of jobs. The model's precision is 100% for non-diabetic patients and 99% for diabetic patients, the recall is 98% for non-diabetic and 100% for diabetic patients and an f1-score with 99% for non-diabetic and 100% for diabetic patients (figure 11 and 12).

```
Accuracy of model:  0.9956011730205279
              precision    recall  f1-score   support

           0       1.00      0.98      0.99       223
           1       0.99      1.00      1.00       459

    accuracy                           0.99       682
   macro avg       1.00      0.99      0.99       682
weighted avg       0.99      0.99      0.99       682
```

Fig. 11. Results from the XGboost Algorithm

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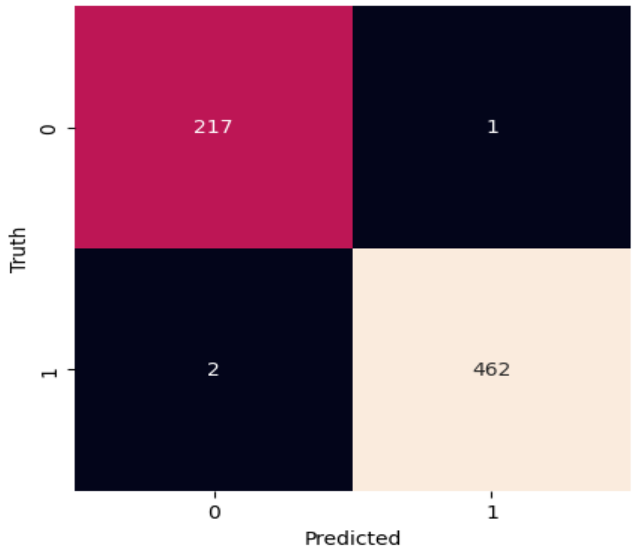

Fig. 12. Confusion Matrix for XGboost Algorithm

3.4 Comparison of Results for Algorithm Models

Table 1 examines the performance of 3 independently constructed candidate models on the identical held-out test dataset. The models were not ensembled together in single ensemble voting, stacking or averaging. Instead, Gaussian Naive Bayes and Random Forest were used as comparator models and the highest performing algorithm was chosen as the computational foundation of the proposed CDSS.

The total test accuracy of XGBoost was 99.5% which was more than Random Forest (98.9%) and Gaussian Naive Bayes (94.5%) . XGBoost also showed the greatest balanced performance per class. For non-diabetic class, it attained an accuracy of 100%, recall of 98% and F1-score of 99%. Precision, recall and F1-score for Diabetic class were 99%, 100% and 100% correspondingly. Random Forest showed similar performance with a little lower overall accuracy and non-diabetic recall. Gaussian Naive Bayes had the lowest accuracy and the lowest recall for non-diabetic patients, meaning it was more likely to misclassify non-diabetic patients.

Given these comparable results, XGBoost was selected as the final candidate prediction model for future validation and possible inclusion into a diabetes-oriented CDSS. In the proposed application, the model would take the eight patient characteristics and produce a binary prediction of diabetes or a risk indication linked with it for physician assessment. Random Forest and Gaussian Naive Bayes were kept as benchmark algorithms and no more predictions were added to the chosen XGBoost model. Hence, the "final model" refers only to the XGBoost candidate, not to a combination of the three techniques.

Table 1. Comparison of Results for Algorithm Models

Model	*Class of diabetes*	*Accuracy*	*Precision*	*Recall*	*F1 Score*
Random Forest	Non-Diabetic	98.9%	100%	97%	98%
	Diabetic		99%	100%	99%
XGBoost	Non-Diabetic	99.5%	100%	98%	99%
	Diabetic		99%	100%	100%
Naive Bayes	Non-Diabetic	94.5%	95%	89%	92%
	Diabetic		94%	98%	96%

Therefore, the link between the individual algorithm outcomes and the proposed CDSS is sequential, not additive. First, we trained and evaluated the three algorithms separately. Second, we analyzed their performance indicators to identify which algorithm most consistently differentiated between diabetes and

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non-diabetic individuals. Third, XGBoost was picked as the candidate prediction engine for the greatest accuracy and the best trade-off between class-specific precision, recall and F1-score. The selected model, if externally verified, may be implemented in a CDSS interface that takes as input routinely gathered patient data, generates a prediction about diabetes and communicates the outcome to a trained physician. The output would inform screening and diagnostic prioritizing and judgments on confirmatory evaluation; it would not determine a diagnosis in its own right or replace authorized diagnostic criteria and professional judgement.

3.5 Comparison with prior diabetes prediction studies

The better performance of XGBoost in the current study is consistent with prior findings that tree-based ensemble and boosting algorithms tend to perform well on structured clinical data. XGBoost, unlike Gaussian Naive Bayes, does not assume conditional independence of predictors and may model non-linear connections and interactions between biochemical, anthropometric and symptom-related variables. Random Forest can also represent complicated interactions with the use of many decision trees, which may account for its near-accuracy to XGBoost and far higher accuracy than Gaussian Naive Bayes.

The XGBoost accuracy of 99.5% obtained in the present study was greater than the accuracy (81%), F1-score (0.81), and area under the curve (0.84) reported by Tasin et al. [19] for an XGBoost model created using a private diabetes dataset using an adaptive synthetic-sampling strategy. Supervised machine learning techniques can help type 2 diabetes prediction in a CDSS framework, however performance varies depending on the methodology, feature set and validation approach, as shown by Islam et al. These studies suggest the promise of supervised learning for diabetes-related decision assistance but also highlight that performance estimates are very dataset- and analysis design-dependent.

In a comprehensive review, Fregoso-Aparicio et al. [17] reported a high level of variation in diabetes-prediction studies with respect to demographics, predictor factors, algorithms and validation techniques. The research also found poor interpretability and inconsistent reporting as impediments to therapeutic applicability. Hence, the increased accuracy seen in the present investigation should not be construed as conclusive indication that the model would outperform previously reported models in other populations. The current dataset was collected from a single health institution in Ghana and consisted of very relevant indicators directly related to the clinical diagnosis of diabetes, i.e., fasting plasma glucose and HbA1c. Their inclusion may partly account for the very high performance.

Differences in diabetes prevalence, demographic makeup, sample size, missing data handling, feature selection, class imbalance and reference outcome definition between the current and prior research may potentially contribute to the observed differences. Moreover, the current estimations were based on a single 80:20 hold-out split, while several earlier research employed cross-validation or independent external validation. The results therefore give an optimistic internal evidence for the selection of XGBoost as a candidate model but require external and prospective validation before any inferences regarding generalisability or clinical superiority can be drawn.

3.6 Advantages of using clinical decision support to diagnose and manage diabetic patients

The performance measures reflect many attributes that would impact the potential utility and safety of the selected model in a CDSS. Accuracy measures the total proportion of properly categorized test observations, although accuracy alone is not sufficient for clinical assessment, especially given 65.5% of the research records were from patients classified as diabetes. Therefore, class-specific accuracy, recall and F1-score are more therapeutically meaningful data. The rounded reported result of 100% diabetes-class recalls shows that the XGBoost model was able to identify all, or almost all, diabetic instances in the held-out test dataset. High diabetic-class recall is particularly critical in a screening or diagnostic-support system, because false negative findings might delay confirmatory testing, treatment, and risk-factor management. The 99% diabetes-class precision shows that almost 99% of the records expected to be diabetic were classified as diabetic in the test dataset, indicating a low number of false-positive alarms. It may decrease unwanted referrals and further testing. A diabetic-class F1-score of 100% indicates a good mix of accuracy and recall.

For the non-diabetic class, XGBoost reached 100% accuracy, 98% recall and 99% F1 score. These results show considerable discrimination between the two outcome groups in the internal test sample. The balanced

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class-specific performance of XGBoost is the key empirical reason for picking it as the potential predictive component of the proposed CDSS above Random Forest and Gaussian Naive Bayes. If these findings are confirmed by external data, the model might be used by doctors to identify patients who may need confirmatory examination, to prioritise individuals for additional review and to promote more uniform interpretation of routinely provided clinical information. However, the stated metrics assess predictive performance under retrospective internal testing settings. They do not show that the system improves patient outcomes, lowers waiting time, decreases death or improves diabetes control. Prospective studies are needed to analyze the clinical impact, workflow, usability and safety to assess such advantages.

3.7 Proposed integration of the candidate model into a CDSS

The present study identified XGBoost as a possible predictive component of a future diabetes-focused CDSS; it did not examine a fully implemented clinical system. In a future deployment, the relevant demographic, biochemical, anthropometric and symptom-related characteristics would be entered or retrieved by the physician using an electronic interface. The verified XGBoost model would then produce a prediction or indication of risk associated to diabetes, with the same pre-processing processes that were employed during model building. The system might show the prediction with important patient factors and cues for confirmation examination.

The forecast should be used in conjunction with recognized diagnostic criteria, clinical practice standards, the patient's medical history, and professional judgment. Thus, the suggested CDSS would act as a helpful tool rather than an independent diagnostic system. Before clinical deployment, the model needs to undergo external validation in other Ghanaian health settings, calibration assessment, performance evaluation across demographic and clinical subgroups, explainability analysis, prospective workflow testing, and assessment of its impact on improving clinical decisions and patient outcomes.

3.8 Testing and validating of decision support model

All three techniques were assessed internally on a held-out test subset of 20% of the available data, with the remaining 80% used for model training. All three models employed the same eight predictor variables and definition of binary outcome. The performance was evaluated by accuracy, precision, recall, F1-score and confusion matrices. XGBoost had the best performance on these criteria and was thus chosen as the potential prediction model.

This approach is an internal hold-out validation, and shows that the model worked well on records that were not used for training the model. However, it does not provide external validity across various hospitals, geographies or African people. Before the model can be regarded reliable for normal clinical application, the performance of the model has to be evaluated using independent datasets from healthcare institutions with various patient profiles, illness prevalence, clinical procedures and data-recording methods. Calibration, workflow compatibility, clinician acceptability, patient safety and clinical value also need prospective study.

4 Limitations of Study

There are various drawbacks to this study. First, a retrospective dataset was collected from one health center in Ghana. Thus, the sample may be reflective of the characteristics of the patients, clinical practices, illness prevalence and data collection techniques of that facility, and may not be representative of other hospitals, areas or populations. This restricts the generalisability of the findings outside and opens the risk of selection bias.

Secondly, the study was conducted using routinely collected clinical information. Information bias may have arisen from errors in measurement, data entry, diagnostic coding or documentation. Variables that could affect diabetes risk or diagnosis were not accessible for inclusion. These include family history, nutrition, physical activity, medication usage, comorbidities and socioeconomic features. There was also an imbalance between the diabetic and non-diabetic classifications, with the diabetes records comprising about 65.5% of the sample. Overall accuracy was recorded, but the imbalance could have impacted class-specific data.

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Third, we added fasting plasma glucose and HbA1c as predictors. Including these parameters may have helped greatly to the very high prediction accuracy because the measurements are crucial to the clinical diagnosis of diabetes. There is a possibility of incorporation bias or target leakage if the recorded outcome was obtained using these tests. Future research should provide the definition of the reference diabetic outcome and consider models with and without variables used to determine that outcome.

Fourth, an internal review was carried out on a single 80:20 train-test split. The performance estimates from one split could be dependent on how the data are allocated. More robust estimates of model performance might be obtained using repeated stratified cross-validation, bootstrapping and independent external validation. Moreover, discrimination was not reported in the study employing area under the receiver operating characteristic curve, probability calibration, calibration plots, decision-curve analysis or clinically defined decision thresholds.

Finally, the study assessed predicting algorithms, not a fully deployed CDSS. It did not analyze model explainability, subgroup fairness, clinician acceptability, workflow integration, usability, cost effectiveness, patient safety, or impacts on clinical decision-making and health outcomes. Thus, the data should be seen as supportive evidence for selecting a candidate model for future validation and development, rather than as proof for a clinically successful CDSS.

5 Conclusion

In this work we created and internally validated Gaussian Naive Bayes, Random Forest and XGBoost models for the classification of diabetes mellitus using clinical data from St. Michael's Hospital, Jachie-Pramso, Ghana. The best held-out test accuracy was attained by XGBoost (99.5%), followed by Random Forest (98.9%) and Gaussian Naive Bayes (94.5%). XGBoost had the best overall mix of class-specific accuracy, recall and F1-score and was thus selected as the candidate prediction model for further validation and potential future incorporation into a diabetes-focused CDSS. The results reveal good internal predictive performance, but little clinical efficacy or generalisability. Before deployment, the XGBoost model must undergo recurrent internal validation, independent external validation, calibration and explainability assessment, subgroup fairness review, and prospective testing within normal clinical procedures. If the studies confirm its safety and efficacy, the model might help doctors identify patients who need additional examination and promote more consistent use of routinely obtained clinical information. Its output is intended to supplement, not replace, established diagnostic criteria, confirmatory testing, and expert clinical judgment.

6 Recommendations

- Healthcare institutions in Ghana should consider integrating the developed predictive models, particularly those utilizing XGBoost and Random Forest algorithms, into their clinical workflows. This integration can facilitate more accurate and timely diagnosis of diabetes mellitus, leading to improved patient outcomes.
- To maximize the potential of predictive modelling in healthcare decision-making, ongoing training and capacity-building programs should be provided to healthcare professionals. This includes training on how to interpret and utilize the output of predictive models effectively in clinical practice.
- Continuous efforts should be made to expand the availability and quality of healthcare data, particularly in the context of diabetes diagnosis and management. This may involve collaborations with healthcare facilities, research institutions, and government agencies to collect comprehensive and standardized datasets for model development and validation.
- Further validation and external evaluation of the developed predictive models are necessary to ensure their generalizability and reliability across different healthcare settings and populations. Collaborative studies with other healthcare institutions in Ghana and similar regions can provide valuable insights into the performance of these models in diverse contexts.
- Building upon the success of predictive modelling, the development and implementation of a robust Decision Support System (DSS) tailored to diabetes diagnosis and management in Ghana

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should be prioritized. This DSS should incorporate the validated predictive models as well as clinical guidelines to provide actionable insights to healthcare providers at the point of care.
- Community engagement and education initiatives should be established to raise awareness about the importance of early detection and management of diabetes mellitus. This includes educational campaigns targeting both healthcare professionals and the general public to promote preventive measures and lifestyle modifications.

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Conflict of Interest Statement

The authors declare that there are no conflicts of interest, financial or otherwise, regarding the publication of this paper. All authors have read, approved, and agreed to the submission of the final manuscript.

Author Contributions

- **Moses Peter Teye Ofoe :** Conceptualization, methodology, data collection, conduct of the study, investigation, and formal analysis.
- **Kate Takyi:** Resources, supervision, and project administration.
- **Gadafi Iddrisu Balali:** Drafting, critical review, and substantive revision of the manuscript, including response to reviewer comments.
- **Boadu-Acheampong Samuelson:** Data curation, methodological support, and draft review.
- **Rose-Mary Owusuaa Mensah Gyening:** Writing (original draft preparation), software, visualization, and
- formal analysis.

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Factors influencing User Acceptance of Electronic Health Records Systems in Low Resource Settings: The Case of Ghana

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Background and Purpose: Electronic Health Records (EHR) Systems play a vital role in improving healthcare globally, particularly in low resource settings. Their adoption however remains challenging in developing countries although they have been shown empirically to be superior to traditional paper records. The Lightwave Health Information Management System, an EHR, was deployed in the Tamale Teaching Hospital in December, 2020. Unfortunately, no evaluation has ever been done to ascertain staff attitudes and perceptions of the system. We investigated user acceptance and factors influencing user acceptance among healthcare workers in the Tamale Teaching Hospital, in Ghana.
Methods: A quantitative cross-sectional design was used to study 373 randomly selected health care workers. A Z-test for proportion was used to examine differences in staff attitudes pre- and post-implementation of the system. Further, logistic regression analysis was used to identify factors influencing acceptance of the system.
Results: The study revealed a high acceptance rate (97%) with the application. We observed significant improvement in the overall positive attitude pre-implementation (65%) compared with post-implementation (77%) towards electronic health records system (z=-3.07; p-value=0.007; 95% C.I.-.19 - -.04). Predictors of user acceptance were workers with at least 20 years' experience in computer use (OR=6.307, p=0.032), and being a medical doctor (OR=7.443, p=0.048). The study identified complex software interface, lack of dedicated power supply, poor internet connectivity, and inadequate training as key challenges to the acceptance of the system.
Conclusions: To avoid dissatisfaction among workers, management should organize training sessions to improve computer skills, and make sufficient budgetary allocation for planned maintenance, stable power supply, and reliable internet connectivity.

Keywords: Electronic health records, electronic medical records, eHealth, Ghana, User acceptance, Attitude

1 Introduction

The deployment of Electronic health records (EHR) systems across healthcare institutions in developing countries has grown rapidly, impacting on health outcomes including access to medical information and evidence based treatment decision making [1][2][3]. An electronic health record (EHR) is described as a digital record of health-related information on an individual that complies with nationally recognized interoperability standards and that can be created, managed, and consulted by authorized clinicians and staff across more than one health care organization [4]. Rolling out EHRs offers several benefits such as enhancing the security of patient records and promoting efficient patient care [2][5]. These systems minimize patient waiting times and maintain continuity of care by ensuring that patient information is easily available across sister healthcare institutions [2]. Despite these benefits, implementation of EHRs across

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health facilities face multiple challenges. These challenges can be classified into technical factors (security and privacy concerns), infrastructural factors (unstable internet and unreliable power supply), organizational factors (high software and hardware costs), and human factors (inadequate compliance with data security and privacy practices) [6]. These factors affect worker morale leading to dissatisfaction and low acceptance towards electronic health records systems among health professionals. A major barrier to implementing these systems successfully lies in getting users to embrace and effectively utilize the new system [7]. User acceptance signifies the degree to which the system meets the expectations of users about the tasks it is supposed to facilitate [7]. However, user expectations of electronic health records have been affected by perceptions including fear of job losses and disruptions to workflow [8][9].

The Tamale Teaching Hospital (TTH) serving as the major referral centre for Northern Ghana had challenges with paper-based records in the past due to factors including limited storage space and increasing rate of missing records resulting in patient delay and sometimes absence of previous patient records to facilitate continuity of care [7]. The first health information system used by the hospital was an Electronic Medical Records (EMR) system known as the Hospital Administration and Management Services [8][10]. An Electronic Medical Record (EMR) refers to a digital record system used by healthcare professionals to document, manage, and monitor patient care within a single healthcare facility. Unlike an Electronic Health Record (EHR) system, which enables the secure exchange of patient information across multiple healthcare organizations, an EMR system is owned and maintained by a single institution and is limited to that facility. Thus, interoperability is the key feature that distinguishes EHRs from EMR systems [11]. Lack of interoperability and low user acceptance were the main challenges to the use of this new system in the Tamale Teaching Hospital [8][10]. To mitigate these barriers and in response to the World Health Organization's (WHO) advocacy for the adoption of EHR systems to enhance healthcare delivery, the government of Ghana through its Ministry of Health released an electronic health strategic framework in 2010 known as the eHealth strategic framework [12]. Four primary strategic concepts were presented in the framework: First, to simplify the rules governing the administration of health information and data. The second goal was to increase sector capacity so that eHealth solutions may be used more widely in the healthcare industry. Third, to use eHealth to close equity gaps and widen access within the healthcare industry. Lastly to finally transition to electronic reporting and record-keeping systems [12][13]. Subsequently, in 2017, Ghana's Ministry of Health deployed an EHR system known as the Lightwave Health Information Management System (LHIMS) [8][14]. This EHR system, developed by Lightwave Healthcare Solutions, is an interoperable system that provides integrated patient management, real-time disease surveillance, and timely data to support clinical and administrative decision-making. It also enables secure sharing of information, improves billing and National Health Insurance Scheme (NHIS) claims processing, reduces paper-based costs, and enhances efficiency, patient safety, quality of care, and overall health service delivery [15][16][17]. Following the launch in 2017, the LHIMS has fully been adopted by all Teaching Hospitals and regional hospitals in Ghana and is currently being rolled out in other health facilities nationwide [8][18]. The Tamale Teaching Hospital adopted the LHIMS in December 2020 [10].

From an earlier study in two hospitals including the Tamale Teaching Hospital to assess health workers' preparedness for the LHIMS implementation, workers expressed fears about the possible impact of the system on workflow and were therefore reluctant to accept the new technology [6]. Unfortunately, no evaluation has ever been conducted to ascertain staff attitudes and perceptions of the system since its implementation in 2020 [8]. The objectives of the study were to assess user attitudes and the factors affecting acceptance of the electronic health records system pre- and post-implementation. The perceptions of healthcare workers regarding this new system are essential for future implementations and sustainability [19]. The findings would act as a guide to improve acceptance for other hospitals in the ongoing implementation of the LHIMS throughout the country.

2 Materials and methods

2.1 Study setting

The study was conducted in the Tamale Teaching Hospital, a tertiary health facility situated in the Northern Region of Ghana, positioned at latitude 9° 24' 0" north and longitude 0° 50' 0" west [8][20][21][22]. For a period of thirty-four (34) years, the hospital previously functioned as a Regional Referral Hospital but was

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upgraded to the status of a Teaching Hospital in 2008 to provide advanced services and support to neighboring health facilities [8][21]. The hospital provides generalized and specialized services including internal medicine, surgery, obstetrics and gynaecology, pediatrics and child welfare, accident and emergency [8][10]. It was the first hospital in the northern part of Ghana to adopt and implement the Light wave health information system in December 2020 [8][10]. The study was conducted in the hospital because there has not been any evaluation of the Light wave Health Information System to determine its impact on workers.

2.2 Study design

This study applied a hospital-based quantitative cross-sectional design because it allows for the assessment of multiple health related variables simultaneously [23]. Such studies are particularly useful in exploring attitudes, perceptions and behaviours and identifying associations between key factors and outcomes within a defined timeframe [8][23]. The design was well-suited to the objective of examining healthcare workers' acceptance of the LHIMS within a limited timeframe, a necessary consideration in busy healthcare environments [23]. Cross-sectional methods are frequently used in health research to analyze technology adoption and user acceptance within a specified period [8][23].

2.3 Inclusion and exclusion Criteria

The population of interest was healthcare workers specifically, doctors, nurses, laboratory technologists, pharmacists, IT personnel, radiologist, and physiotherapists who use the software in their daily activities and have been working for at least a year in the facility. The study assumed that extended exposure to the new system would allow individuals to provide an objective assessment of the system. Excluded from the study were administrative personnel, staff on annual leave, temporary staff specifically national service personnel, and clinical students.

2.4 Sample size and sampling technique

A sample of 373 participants after adjusting for a 10% non-response rate, was computed using the Yamane's formula, n = N / (1+ N (e)2), from a total population of workers of 2217 [10], a level of precision of 5%, and a confidence level of 95% [24][25]. Participants were selected from each health professional grade using a stratified sampling approach. Each health professional group was considered a stratum, therefore, sample sizes for each cadre were calculated using the proportionate sampling approach. From the calculations, 46 medical doctors, 290 nurses and midwives, 24 laboratory scientists, 8 records officers, 3 radiologists, one IT officer, and one physiotherapist were selected. Subsequently, lists of the healthcare workers in each professional group were compiled from the hospital administration, using their staff identity and contact number. Participants were then selected based on the specific sample sizes, using both systematic and the simple random sampling methods. The systematic approach was used to select Nurses, doctors and laboratory scientists who had large number of workers. The selection for records, radiology, IT and the physiotherapists were done randomly due to the smaller number of workers in these units.

2.5 Data collection tool and procedure

A pretested, self-administered structured questionnaire was used for data collection [26]. The questionnaire was extracted from a validated instrument of the Davis' Technology Acceptance Model [27]. Section A encompassed questions relating to the socio-demographic characteristics of the respondents, section B included questions pertaining to attitudes before and after implementation of the system, while section C contained a series of questions addressing the challenges with the new system [8]. All items in Sections B and C were examined using a 5-point Likert scale [8]. Section D contained binary questions with "Yes" or "No" responses to determine whether users accept the system. The questionnaire was designed electronically using google forms to ensure the principal investigator had real time access to correct errors as data collection was ongoing. After obtaining permission from the institution and respondents, they were

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provided with a link to the questionnaire hosted on Google Forms - this approach was adopted because all respondents were computer literates [8]. We collected data from 13th November 2023 to 13 January 2024.

2.6 Variables

The outcome variable was user acceptance, measured using a binary (yes or no) question to eliminate the possibility of a neutral answer, as is typical in most Likert scales [7][28]. Studies have shown that the inclusion of a "neutral or no opinion" response category as seen in most Likert scales can significantly increase the number of respondents selecting it, thereby masking genuine opinions that respondents may hold [28]. The predictors included age, sex, profession/health cadre, years of experience as a healthcare worker, years of experience with EHRs, duration of computer usage, history of formal computer training, frequency of EHRs use [8]. Additional variables, including respondents' attitudes toward the use of EHRs, were assessed using a 5-point Likert scale [8].

2.7 Data processing and analysis

Responses obtained through Google Forms were exported and organized in a Microsoft Excel worksheet. Data was cleaned and analyzed using IBM's Statistical Product and Service Solutions (SPSS) version 26 [8]. The data were summarized using descriptive statistics such as median, standard deviation, frequencies, and percentages. The Z-test for proportion was applied to test user attitude prior to and following implementation of the system, and the multiple logistic regressions to determine significant associations between the outcome variable and the predictors of EHR acceptance [8]. All tests were two-sided with a p-value less than 0.05 interpreted as significant.

2.8 Ethical Considerations

Ethical approval for the study was obtained from the Committee on Human Research, Publications and Ethics (CHRPE) of the Kwame Nkrumah University of Science and Technology (Approval No. CHRPE/AP/1004/23). Authorities of the Tamale Teaching Hospital granted approval for the study. Participant informed consent was obtained by agreement and signing the consent form. The study was conducted according to the tenets of the Helsinki declaration.

3 Results

3.1 Socio-Demographic Characteristics of Respondents

Overall, 373 health professionals, 47% female and 53% male participated in the study [8]. The mean age of the workers was 32 years (± 4 years). The majority of workers were nurses and midwives (78%), followed by medical doctors (12%) and other categories of staff (10%). More than half of the workers (54%) had less than five years of professional experience in healthcare. Most (63%) had used the LHIMS for 3 years while 78% indicated regular use of LHIMS in their work. About 65% of workers indicated computer usage experience spanning 10 to 19 years, 59% had formal computer training, while 41% learned to use computers on the job (Table 1).

Table 1. Background characteristics of respondents.

Variable	Frequency n=373	Percentage %=100
Age Group		
Less than 30	125	33.5
30 to 39	220	59.0
40 and above	28	7.5
Mean age (years)	31.88 (SD ± 4)	
Gender		
Male	199	53.4
Female	174	46.6
Profession/Health Cadre		

Nurse/Midwife	290	77.7
Medical Doctor	46	12.3
Laboratory Staff	24	6.4
Records Staff	8	2.2
Radiology	3	0.8
ICT Staff	1	0.3
Physiotherapist	1	0.3
Level of Education		
Certificate	15	4.0
Diploma	96	25.7
Bachelor's Degree	197	52.8
MBchB	46	12.3
Master's Degree	19	5.2
Years In Healthcare Practice (years)		
Less than 5	202	54.2
5 to 9	96	25.7
10 and above	75	20.1
Years of Using LHIMS		
1 year	37	9.9
2 years	102	27.4
3 years	234	62.7
Years of Computer Use in Life		
Less than 10	69	18.5
10 to 19	243	65.1
20 and above	61	16.4
History of Formal Computer Training		
Yes	220	59.0
No	153	41.0
Frequency of LHIMS Usage		
Never	0	0
Rarely	5	1.3
Often	76	20.4
Every time	292	78.3

Source: Adapted from author's thesis available from udsspace.uds.edu.gh [8]
* LHIMS-Light wave health information management system

3.2 Level of User Acceptance

In general, 97% of the workers expressed acceptance of the LHIMS, suggesting majority were satisfied with the application (Figure 1) [8].

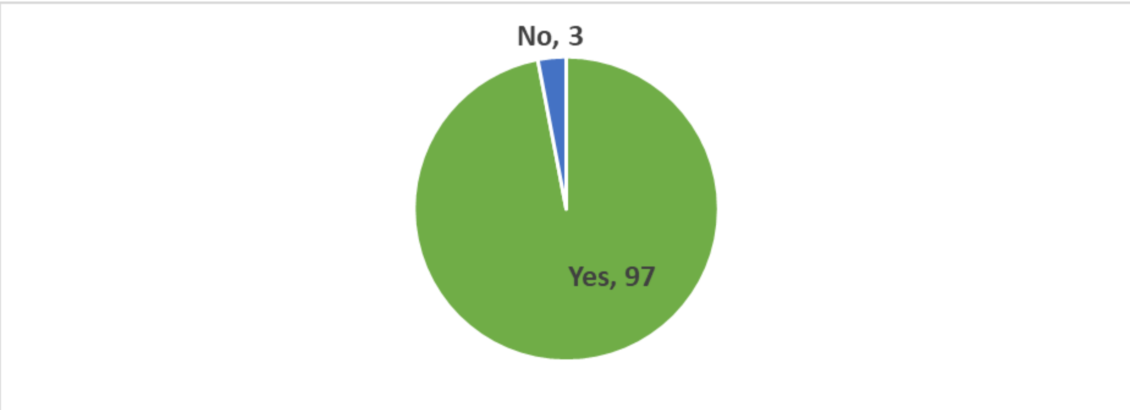

Fig. 1. Level of User Acceptance

3.3 Attitude before and after implementation of the LHIMS EHR

Attitudes of healthcare workers were examined to determine if there were any significant differences in their attitudes pre- and post-implementation of the LHIMS [8]. The study employed a Z-Test for

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Proportions to test the null hypothesis that no significant difference existed in the attitudes of healthcare workers prior to and following the implementation of the LHIMS [8]. This analysis was limited to staff who indicated agreement with each attitude-related item in Table 2 pre- and post-implementation of the system [8]. Significant differences were observed across the following factors: favorable attitude for LHIMS (p=0.001), LHIMS being a good idea (p=0.001), expecting LHIMS use in the future (p=0.008), satisfaction with LHIMS (p=0.007), all staff encouraged to use LHIMS (p=0.002), and overall positive attitude towards LHIMS (p=0.002) [8].

Table 2. Z-Tests for Proportions of attitudes before and after the implementation of LHIMS

Factor (Agree)	Pre-implementation %	Post-implementation %	z-value	P-value	95% C.I.
Favorable attitude for LHIMS	171 (45.8)	245 (65.7)	-4.04	0.001	-.29- -.10
LHIMS use is a good idea	226 (60.6)	288 (77.2)	-4.07	0.001	-.25 - -.09
Expect to use LHIMS in the future	256 (68.6)	293 (78.5)	-2.63	0.008	-.18 - -.03
Expect LHIMS use to be satisfying	207 (55.5)	253 (67.8)	-2.71	0.007	-.21- -.03
Believed LHIMS would ensure better care	257 (68.9)	283 (75.9)	-1.82	0.069	-.15 - .01
Never satisfied with paper-based patient records	149 (39.9)	176 (47.2)	-1.32	0.186	-.18 – 0.03
Believed all staff should learn to use LHIMS	252 (67.6)	305 (81.5)	-3.78	0.002	-.21 - -.07
Overall my attitude about LHIMS is positive	244 (65.5)	289 (77.5)	-3.07	0.002	-.19 - -.04

Source: Adapted from author's thesis available from udsspace.uds.edu.gh [8]
LHIMS-Lightwave health information management system

3.4 Challenges with the LHIMS in Tamale Teaching Hospital

The study evaluated perceptions of respondents regarding the challenges encountered using the Lightwave health information system at the hospital. The major challenges reported were frequent power interruptions and absence of a reliable backup power system (79%), inadequate essential logistics particularly computers and laptops (75%), equipment malfunctioning (74%), and poor internet or network connectivity (70%). Other difficulties included inadequate training or support (63%), technical issues including difficulties using the LHIMS interface (57%), lengthy data entry procedures (55%), and concerns over data security and privacy (53%) [8].

3.5 Predictors of User acceptance of the LHIMS

To assess the independent predictors of the User Acceptance of the LHIMS, the logistic regression model was used. We found significant associations between workers with at least 20 years of computer use (OR = 6.307, 95 % CI, 1.17-33.89, p = 0.032), being a medical doctor (OR = 7.443, 95% CI, 1.019-54.378, p = 0.048) and user acceptance. However, age, frequency of LHIMS utilization, and formal training in information and communication technology were not found to be statistically significant predictors of user acceptance (Table 3) [8].

Table 3. Multivariable logistic regression of factors influencing user acceptance

Variable	OR	95% CI	P-value
Age Group (years)			
Less than 30	Ref		
30 to 39	2.072	0.243-17.683	0.506

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40 and above	2.470	0.439-13.909	0.305
Profession			
Allied Staff	Ref		
Nurse/Midwife	4.116	0.097-174.864	0.459
Medical Doctor	**7.443**	**1.019-54.378**	**0.048**
Laboratory Staff	3.134	0.338-29.054	0.315
Years of Computer Use			
Less than 10	Ref		
10 to 19	2.913	0.419-20.263	0.280
20 and above	**6.307**	**1.174-33.897**	**0.032**
Frequency of LHIMS Usage			
Every time	Ref		
Often	15.118	0.443-516.142	0.132
Rarely	14.740	0.439-495.180	0.133
History of Formal Training			
No	Ref		
Yes	0.361	0.084-1.544	0.170

Source: Adapted from author's thesis available from udsspace.uds.edu.gh [8] *Ref- Reference Category, OR-Odds Ratio, C.I- Confidence Interval

4 Discussion

The study assessed user attitude and acceptance of an EHR system in the Tamale Teaching Hospital [8]. The findings indicated a high level of user acceptance of the LHIMS, and a positive user attitude towards the system after implementation despite the operational challenges. Workers with 20 years' computer experience, and medical doctors were significantly associated with user acceptance.

Contrary to the pre-implementation findings by Abdulai et al., in 2020 [6], when the health workers were reluctant to accept the Light wave Health Information System, a high level of user acceptance (97%) suggest that most healthcare workers have come to appreciate the system's usefulness in facilitating their duties and have expressed approval of the system. The overwhelming acceptance of the LHIMS suggest that workers found the system beneficial and were highly motivated to adopt it. This reflects a strong foundation for its successful integration and improvement of healthcare delivery. Staff approval of the system is likely to lead to sustained use which ultimately could contribute to improved healthcare outcomes. We found that the high acceptance rate of the system was influenced by a generally positive staff attitude after implementation. The findings indicate a marked improvement in overall attitudes toward the LHIMS, with 77% of respondents expressing positive views compared to 65% before its introduction (Table 2). Majority of workers see the system as a good initiative and satisfying compared to the manual system. This improvement reflects the system's beneficial impact on staff performance and their growing confidence in its long-term usefulness. Our findings are consistent with other studies conducted in the Philippines, United Kingdom and Netherlands where 97%, 96% and 99% of healthcare workers respectively, reported acceptance of EHRs [8][25][29]. The acceptance rate observed in this study exceeds those reported in other African contexts, including Ghana (59%) [25], Ethiopia (72.2%) and Nigeria (78.1%) [30]. Lower acceptance rates in these countries has been linked to high installation costs, insufficient institutional commitment and recurrent system-related issues [25]. Although the user acceptance rate observed in this study was higher than those reported in Ethiopia and Nigeria, this comparison should be interpreted with caution because of methodological differences. The Ethiopian and Nigerian studies measured their outcome (acceptance) using composite Likert-scale items that were subsequently dichotomized, whereas the present study employed a direct binary (Yes/No) outcome measure of acceptance, which may have influenced the observed differences.

Findings from our study suggest that health workers with longer years of experience using computers were more receptive to the LHIMS application. Length of computer use refers to the duration of experience with computer applications, which has been found to predict successful implementation of electronic health information systems [8][31]. Health professionals with longer computer experience are likely to adapt more

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readily to new digital applications because of their familiarity with computer use. It is therefore plausible that the high proportion of workers (65%) with 10–19 years of computer experience contributed to the successful implementation and acceptance of the LHIMS. Additionally, previous studies have suggested that greater computer familiarity may reduce concerns about technology-related job losses, although this was not directly assessed in the present study [8]. Our finding aligns with results from other studies, which reported that the duration of computer use significantly influences user acceptance among nurses [7][32], and that health workers with computer expertise were more likely to express readiness for electronic health records use [6]. On the contrary health workers without adequate exposure to computer technology struggle to use electronic records systems [33]. We suggest to the management of the hospital to focus on regular computer training and on-the-job practices to equip workers with needed skills to adapt quickly to the new system, rather than dependence on staff with long duration of computer use.

In our study, medical doctors demonstrated a higher level of acceptance of the LHIMS compared to all other professional categories. This is encouraging, given that physicians have historically been reluctant to integrate electronic record systems into their workflows [34]. Physicians have raised concerns about electronic record systems, including issues such as the time-consuming nature of data entry, fears that they are complex to use, and that computers are disruptive to workflow [34]. Despite these challenges, the finding suggests that physicians in the Tamale teaching hospital recognize the benefits of the application [8]. This suggests that acceptance by the doctors at the teaching hospital has a positive impact on the workflow since they provide the critical information for patient care.

The major barriers associated with using the LHIMS system at the Tamale Teaching Hospital were infrastructural and usability-related issues [8]. Usability concerns such as the complex user interface and inadequate training and support affected staff ability to freely navigate the LHIMS resulting in complaints of lengthy data entry processes. Complex interfaces that lack integration with clinical workflow affect patient care process. Some studies have reported the difficulties clinicians experience with poorly designed software interfaces which often disrupt workflow due to prolonged screen navigation [35]. There is the need to make system procedures more friendly to health workers since information technology is not their core competency. Additionally, this highlights the need for continuous user training, technical support and collaboration with developers to improve system usability. Furthermore, constraints including frequent power interruptions and lack of a backup power supply, inadequate computers, equipment malfunction and poor internet connectivity are major infrastructural challenges which are characteristic of Low- and Middle-Income Countries such as Ghana [6][8]. Mensah, et al., 2024 [36] similarly reported that unstable power supply had negative effects on LHIMS in some major hospitals in Ghana. This suggests the need for institutional investment in reliable power supply, ICT infrastructure, and equipment maintenance. A planned budgetary allocation for administrative overheads by the hospital management would ensure sustainability of the LHIMS EHR. Addressing these distinct challenges is essential to optimize LHIMS performance and promote sustained user acceptance.

The findings of this study support the applicability of the Technology Acceptance Model (TAM) in explaining LHIMS acceptance among healthcare workers. Challenges related to interface complexity and lengthy data entry processes may negatively influence Perceived Ease of Use, while the perceived benefits of LHIMS, including improved access to patient information, documentation, and clinical decision-making, enhance Perceived Usefulness. The high acceptance observed among users, particularly clinicians, may therefore reflect the value they derive from the system in supporting healthcare delivery. Strengthening system usability, user training, and functional improvements will be essential to further enhance acceptance and a sustained use of LHIMS.

4.1 Conclusion

Our study revealed a successful acceptance and integration of the Light wave Health Information System among healthcare workers at the Tamale Teaching Hospital [8]. The favorable attitudes expressed by staff following its implementation indicate a growing professional readiness to transition from manual to digital records systems. Despite usability and infrastructural challenges, the LHIMS demonstrates considerable potential to significantly improve healthcare efficiency and patient outcomes in similar contexts. Management of the Tamale Teaching Hospital should therefore organize comprehensive training programmes that would enhance the computer skills of workers, and make sufficient budgetary allocation for planned maintenance, procurement of ICT infrastructure, and a sustainable internet supply. This study

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shows that acceptability and usage of EHRs has improved across low resourced settings in recent years. A wider implementation is recommended across similar sub regions.

4.2 Limitations and Future Research

This research was limited to a single tertiary healthcare institution, which may restrict the generalizability of the findings to primary and secondary health centers that differ in context and staff composition [8]. Also, the retrospective assessment of pre-implementation attitudes conducted several years after LHIMS implementation may have introduced recall bias, as participants' current experiences with the system could have influenced their recollection of initial perceptions.

Additionally, the cross-sectional design provides a snapshot of user acceptance and satisfaction at a single point in time and does not allow assessment of changes over time or causal relationships.

The study also did not evaluate the long-term impact of LHIMS on patient outcomes, quality of care, or healthcare quality and outcomes. Future research should therefore adopt longitudinal and multi-institutional approaches to examine the broader clinical impact and operational effects of EHR implementation.

4.3 What is already known on this topic

Health workers of the Tamale teaching hospital faced anxiety prior to the introduction of the electronic records application [6].

4.4 What this study adds

Workers have favorable attitude towards the LHIMS application post implementation. Experience with computer use contributed significantly to acceptance of the EHR system. Medical doctors at the hospital are more accommodating to the use of the LHIMS

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Credit authorship contribution statement

- Elijah Bawa Mishio: Conceptualization, Methodology, Formal analysis, Writing – original draft.
- Julius Waamsasiko Adong: Writing – review & editing, Supervision.
- David Nana Adjei: Analysis, Review & editing.

Statement on conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Relational Mechanism in Community-Based Health Information System Governance: Implications for Alignment and Community Health Outcomes

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Background and Purpose: Effective governance of Health Information Systems (HIS) is critical to improving health outcomes, yet the practices underlying the CBHIS governance relational mechanism and their relationship with alignment and community health outcomes remain poorly understood. This study sought to identify these practices and examine their interrelationships with alignment and community health outcomes.
Methods: A mixed-methods study employing a convergent parallel design was conducted across two purposively selected sites with established experience in CBHIS implementation and use. Quantitative data were collected using 164 semi-structured questionnaires and analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). Qualitative data were thematically analysed using ATLAS.ti (v24).
Results: Validity and reliability testing identified nine practices associated with the CBHIS governance relational mechanism, while qualitative analysis revealed two additional practices, collectively constituting core governance practices required for alignment. The study also validated six indicators measuring community health outcomes. Results showed a positive and statistically significant relationship between the CBHIS governance relational mechanism and community health outcomes, with the exogenous construct exerting a positive influence on the endogenous construct, confirming the model's predictive relevance.
Conclusions: This study identified key practices associated with the CBHIS governance relational mechanism that support alignment between the Community-Based Health Information System (CBHIS) and community health outcomes. Notable practices include stakeholder engagement, data review meetings, dialogue days, community health chalkboards, and the use of Information, Education, and Communication (IEC) materials, which enhance collaboration and information sharing within community health systems. These practices show potential to improve community health outcomes. However, the findings should be interpreted cautiously due to the use of purposive sampling and the inclusion of only two study sites. The results therefore provide preliminary insights and highlight the need for further validation across broader contexts using more representative sampling approaches.

Keywords: Alignment, Community-Based Health Information System Governance Relational Mechanism, Community Health Outcomes, Health Information System, Governance

1 Introduction

The use of Health Information Systems (HIS) is increasingly prevalent across various tiers of healthcare, including community healthcare settings. Community-level HIS encompass Electronic Community Health Information Systems (eCHIS), Mobile-Jamii Afya Link (MJali), Integrated Community Health Information System (iCHIS), and the Smart Health application, among others. These applications are commonly known as Community-Based Health Information Systems (CBHIS). They enable the collection, analysis, and reporting of community health data.

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Although the implementation of CBHIS applications is on the rise, existing literature has reported suboptimal performance and limited value derived from digital health integrations. Several interventions aimed at reversing these trends have been tabled. Developing and implementing a context-specific HIS governance is one of them. Evidence collectively suggests that effective governance of HIS is crucial for the successful integration and use of HIS systems. It is also an essential determinant of positive health outcomes and proper health system functioning [1], [2], [3], [4], [5], [6]. HIS Governance is operationalised through the implementation of structures, processes, relational mechanisms, and their corresponding context-specific practices, which are necessary for alignment to occur [5], [7], [8], [9], [10]. Research indicates that organisations with effective IT governance programs achieve a minimum of 20% higher earnings than those with less effective governance, even when pursuing identical strategies [11].

Over the past decade, several Community-Based Health Information Systems (CBHISs) have been implemented in Kenya, including the electronic Community Health Information System (eCHIS), which is currently being rolled out across all 47 counties. The literature reflects ongoing efforts to examine CBHIS governance. While some studies such as [12] have addressed general aspects of CBHIS governance, research to date [13] has primarily focused on the structural mechanism and its relationship with alignment and community health outcomes. In contrast, the governance processes and relational mechanisms remain underexplored. This study, therefore, investigates the specific practices underpinning the relational mechanism and their interactions with CBHIS–community health alignment, referred to as the alignment, and outcomes. There is therefore a need to identify these practices and examine their interrelationships with health outcomes, consistent with prior research calling for deeper examination of the "how" and "why" of relationships between health IT governance mechanisms and health performance [8], [14], [15].

This study pursued two objectives: (1) to identify the practices associated with the CBHIS governance relational mechanism that are essential for achieving alignment, and (2) to examine the interrelationships among the CBHIS governance relational mechanism, alignment, and community health outcomes. To enhance contextual understanding, a pre-study involving key informants from the Department of Health in Nairobi City County was conducted to explore and identify relevant governance practices. Insights from this pre-study informed both the selection of practices and the focus of the literature review. The following section, therefore, reviews existing literature on HIS governance and health outcomes.

2 Literature Review

2.1 Health Information System (HIS) Governance

Information Technology (IT) governance entails the establishment of practices across structural, process, and relational mechanisms to ensure alignment between IT and an organisation's vision, mission, strategy, and objectives, thereby promoting value creation and sustainability [16]. In the healthcare context, effective governance of Health Information Systems (HIS) is critical to achieving improved health system performance and health outcomes. HIS governance is operationalised through governance structures, processes, and relational mechanisms, together with their associated practices. The following section, therefore, reviews existing literature on practices associated with the HIS governance relational mechanism.

2.2 Practices Associated with the HIS Governance Relational Mechanism

The CBHIS governance relational mechanism encompasses active stakeholder engagement, collaborative interactions, and the communication practices used to convey governance decisions. While communication is recognised as vital for HIS implementation, its specific mechanisms and effectiveness remain underexplored in community-based contexts. [15] highlight the role of timely, accurate, bidirectional communication, such as prompt emails, in supporting Health Information Exchange (HIE) and broader health system initiatives. Yet, their analysis focuses on formal organisational settings, leaving questions about adaptation and responsiveness at the community level.

Building on this, existing literature identifies a range of practices associated with the HIS governance relational mechanism, including informal IT–business executive interactions, enterprise-wide communications, co-location of IT and business functions, leadership messaging, and capacity-building initiatives [17]. Although these practices are credited with fostering shared understanding, executive

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support, and organisational coordination, existing literature often assumes a straightforward, uniform impact on alignment, overlooking the complex, context-dependent factors that may influence their effectiveness. This perspective neglects contextual complexities, such as organisational culture, stakeholder heterogeneity, and resource constraints, that may mediate or moderate outcomes. Similarly, [18], [19] highlight the role of effective communication and stakeholder engagement in data warehouse initiatives; yet, these studies focus on structured enterprise environments, which may not reflect the informal dynamics and social norms critical to the success of community-based health systems.

In community health settings, inclusive dialogues and stakeholder participation are increasingly recognised as central to success. [20] emphasise the importance of community consultations in implementing Ward-Based Outreach Teams (WBOTs), illustrating that relational practices must extend beyond formal organisational hierarchies. Similarly, [21] demonstrates that disseminating IT policies and guidelines through multiple channels, including low-tech solutions such as community ‘chalkboards’, can enhance adoption and compliance, highlighting the need to adapt relational practices to the realities of local contexts. These findings collectively suggest that while traditional governance frameworks provide valuable guidance, they may be insufficient to capture the nuanced relational dynamics in community-based health systems.

To address these gaps, the present study conducted pre-study interviews with key community health informants, resulting in the identification of three additional practices that complement those reported in the literature. These findings underscore the importance of contextualised, adaptive, and multi-level relational governance practices in supporting CBHIS alignment and use. By synthesising prior research with empirical insights, this study contributes a more nuanced understanding of the CBHIS governance relational mechanism, emphasising that effective governance is not solely a function of formal structures and processes but is contingent upon ongoing communication, collaboration, and stakeholder engagement tailored to the community context. Table 1 summarises the full set of practices and their sources, integrating both literature and pre-study findings.

Table 1. HIS Governance Practices and their Sources

S.No.	**Indicator**	**Source**
1	CBHIS stakeholders’ identification	[22], [5], [12], [20], [17], [23], [24]
2	CBHIS executive-level communication	[15], [17]
3	Data Use & Review Meetings	[25]
4	Dialogue days	[20], [25]
5	Action days	This study’s pre-study (January-February 2024)
6	Community Meetings (Barazas)	[20], [24], [25]
7	Community Health Digital Scorecard	This study’s pre-study (January-February 2024)
8	Community 'chalkboard’	[21], [25], [26]
9	Information Education Communication (IEC) materials	This study’s pre-study (January-February 2024)

2.3 Outcomes of Health Information Systems

Existing literature highlights several healthcare benefits associated with the utilisation of Health Information Systems (HIS) across different levels of care. Community-Based Health Information Systems (CBHIS) have been shown to enhance healthcare coordination and management in critical contexts, such as monitoring and treatment of tuberculosis, tracking drug defaulters, including Continuing Complex Care (CCC) patients, providing antenatal care (ANC) information, and reporting immunisation coverage for children under five [25]. Implementation of eCHIS, for instance, has been associated with a reduction in errors during house-to-house registration by Community Health Workers (CHWs), improving data quality and lowering operational costs [23], [27], [28]. Studies also indicate that community health HIS interventions increase engagement and utilisation of health services, evidenced by rises in hospital deliveries, immunisation coverage, effective distribution of medications (e.g., analgesics, deworming agents, multivitamins), and dissemination of treated bed nets [24] [25]. Furthermore, CBHIS has been shown to strengthen accountability and performance management at the community level [12]. Table 2 summarises these HIS outcomes alongside their corresponding literature sources.

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Table 2. HIS Outcomes and their Sources

S.No.	Indicator	Source
1	Improved community healthcare coordination	[12], [25], [28], [29]
2	Improved community health data, information quality and availability.	[27], [28]
3	Reduced community health operational costs	[23], [27]
4	Increase in efficiency and effectiveness in delivering community health services	[24], [25], [27], [30]
5	Improvement in community health engagement in health	[5], [12], [25], [27], [28], [31]
6	Improved accountability and performance management	[12], [25], [32]

2.4 Research Conceptual Model

CBHIS governance mechanisms comprises of structures, processes, and relational mechanisms, as and their associated practices are considered essential for achieving alignment between community health initiatives and CBHIS, ultimately enhancing community health outcomes. This perspective is supported by prior studies such as [2], [5], [6], [8], [8], [23], [33].

This study focuses specifically on the interrelationship between the CBHIS governance relational mechanism and community health outcomes. Existing research highlights that relational mechanisms of health IT governance are critical for achieving and sustaining alignment [15], while organisational communication is key to improving healthcare and IT alignment [33]. Furthermore, implementing practices associated with the HIS governance relational mechanism is widely regarded as a prerequisite for deriving value from HIS investments [17].

Building on this evidence, the study hypothesises that the practices linked to the CBHIS governance relational mechanism are necessary for alignment to occur, and that once alignment is established, the relational mechanism (exogenous construct) positively influences community health outcomes (endogenous construct) (link c). To capture this dynamic, the study integrates the IT Governance Theory with the Strategic Alignment Model (SAM), as neither framework alone adequately addresses the research problem. The conceptual model is presented in Figure 1.

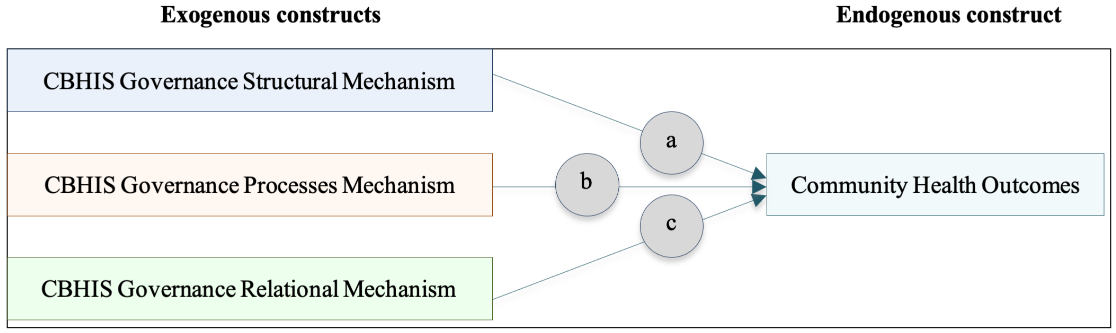

Fig. 1. Research conceptual model

3 Research Methodology

3.1 Pre-study

Before the main data collection, a pre-study was conducted in Kibra Sub-County, Nairobi County, between January and February 2024. The primary aim of this pre-study was to refine the research questionnaire and identify potential ambiguities in the study design. A total of 28 participants took part in the exercise, comprising the County Community Health Focal Person (CCHFP), County Health Records and Information Officers (CHRIOs), County Health IT Officers, the Sub-County Community Health Focal Person (S-

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CCHFP), Sub-County Health Records and Information Officers (S-CHRIOs), and Community Health Assistants (CHAs).

3.2 Data collection and survey instrument

This study, informed by a pragmatic perspective, utilised a mixed-method research strategy with a convergent parallel research design. Kisumu County and Makueni County were deliberately selected from a total of 47 counties based on their experience in the establishment and utilisation of CBHIS. The study population comprised 321 officers selected from various strata. The research utilised Yamane's formula by taking a 95% confidence interval and a +/- 5% margin of error, resulting in a sample size of 179 respondents. Both probability and non-probability sampling methods were employed to select respondents from various strata. The study utilised semi-structured questionnaires for data collection.

The data collection instrument consisted of a semi-structured questionnaire organized into several structured sections to ensure clarity, ethical compliance, and comprehensive data capture. Section A provided a general introduction to the study, including the researchers' contact details (email and mobile phone number) for any inquiries or clarification. Section B focused on informed consent, giving respondents the option to either agree or decline participation in the study. Section C contained a respondent information sheet, which offered clear definitions and explanations of key terms used in the research to promote a shared understanding. Section D captured respondents' demographic information, including variables such as county, sub-county, level of education, and age bracket. Section E was divided into two parts: Part 1 comprised closed-ended items designed to measure indicators of the CBHIS governance relational mechanism, while Part 2 included open-ended questions that allowed respondents to provide additional insights or information not captured in the structured items. Similarly, Section F focused on measuring community health outcomes, with Part 1 containing structured indicators and Part 2 providing an open-ended component for respondents to elaborate further on issues they considered relevant. This structured yet flexible design enabled the collection of both quantitative and qualitative data, thereby enhancing the depth and validity of the findings.

Ten research assistants (one in every sub-county) were trained and issued with printed semi-structured questionaires. A total of 179 printed data collection instruments were issued to study respondents between February and June 2024. Table 3 presents the study population, sampling strategies employed, and sample sizes.

Table 3. Study population, sampling techniques and sample sizes

Project	Stratum	Population	Sampling Method	Sample
Kisumu County	County Executive Committee Member – Health	1	Purposive	1
	County Executive Committee Member – IT	1	Purposive	1
	Chief Officer – Health	1	Purposive	1
	Chief Officer – IT	1	Purposive	1
	Directors of Health Services	3	Purposive	1
	IT Directors	3	Purposive	1
	County Health Records & Information Officers (CHRIOs)	1	Purposive	1
	Sub-County Health Records & Information Officers (S-CHRIOs)	7	Purposive	7
	County Community Health Focal Persons (CCHFPs)	1	Purposive	1
	Sub-County Community Health Focal Persons (S-CCHFPs)	7	Purposive	7
	Community Health Assistants/Officers (CHAs/CHOs)	198	Random	101
	IT Officers	7	Purposive	7
Makueni County	County Executive Committee Member – Health	1	Purposive	1
	County Executive Committee Member – IT	1	Purposive	1
	Chief Officer – Health	1	Purposive	1
	Chief Officer – IT	1	Purposive	1
	Directors of Health	3	Purposive	1
	IT Directors	1	Purposive	1

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	County Health Records & Information Officers (CHRIOs)	1	Purposive	1
	Sub-County Health Records & Information Officers (S-CHRIOs)	6	Purposive	3
	County Community Health Focal Persons (CCHFPs)	1	Purposive	1
	Sub-County Community Health Focal Persons (S-CCHFPs)	6	Purposive	3
	Health IT officers	8	Purposive	4
	Community Health Assistants/Officers (CHAs/CHOs)	60	Random	30
	Total	**321**		**179**

3.3 Data Analysis (Tools, Type of Analysis, and Statistical Tests Used)

Prior to data analysis, the indicators measuring the CBHIS governance relational mechanism were coded as RM1 to RM9, while those assessing community health outcomes were coded as CHO1 to CHO6. The coding process was conducted using Microsoft Excel to ensure consistency and facilitate subsequent data handling.

Data analysis was conducted using SmartPLS software through Partial Least Squares Structural Equation Modelling (PLS-SEM) to analyse and validate the relationships between constructs associated with CBHIS governance relational mechanisms and community health outcomes. PLS-SEM was considered more appropriate than Covariance-Based Structural Equation Modelling (CB-SEM) because the primary objective of the study was prediction rather than theory confirmation, as supported by [34]. Furthermore, PLS-SEM is suitable for modelling complex relationships among latent constructs and can effectively handle both formative and reflective measurement models.

The analysis involved the estimation of both the measurement and structural models. In terms of measurement model specification, the CBHIS governance relational mechanism was conceptualised as a formative construct because its indicators collectively define the construct. In contrast, community health outcomes were modelled as a reflective construct, where the indicators are viewed as manifestations of the underlying latent variable. To assess the quality of the measurement model, the reliability of the reflective measurement scales was evaluated using Cronbach's alpha and composite reliability to ensure internal consistency. Convergent validity was assessed using Average Variance Extracted (AVE), while discriminant validity was examined using three widely accepted techniques: the Fornell-Larcker criterion, the Heterotrait–Monotrait (HTMT) ratio, and cross-loadings.

To determine the statistical significance of indicator weights and path coefficients, a bootstrapping procedure with 5,000 resamples was performed. This non-parametric approach enhanced the robustness of the results by providing confidence intervals and significance levels for the estimated parameters.

Furthermore, qualitative data collected during the study were analysed thematically using ATLAS.ti (Version 24). This involved coding textual data, identifying emerging patterns, and developing themes that complemented and enriched the quantitative findings.

4 Research Findings

Out of 179 distributed semi-structured surveys, 164 were completed and returned, yielding a response rate of 91.6%.

4.1 Identification and Validation of Construct Indicators

To begin with, the dependability and accuracy of the indicators and constructs were evaluated in conformity with previous research [35]. The researchers analysed the weights of the indicators on their corresponding constructs. The increased loadings indicated a greater shared variance between the construct and its corresponding indicator relative to error variance. Table 4 demonstrates that all items exhibited substantial and statistically significant loading ($P<0.05$) on their corresponding constructs. The t-statistics for the corresponding indicator weights were positive and significant.

The dependability of scales was evaluated through Cronbach's alpha and composite reliability (rho_c). The Cronbach alpha and composite reliability scores for the two constructs surpassed the minimum threshold of 0.70, as recommended by [34], thereby confirming the reliability of the study indicators. The convergent validities for the two constructs surpassed the minimal criterion of 0.5 (AVE>0.5). Table 4 presents the indicator loadings, construct reliabilities and convergent validity.

Table 4: Indicator loadings, construct's reliabilities, and convergent validity

Construct	Indicator	Indicator loading	T statistic	P values	Cronbach's alpha	Composite Reliability	Average Variance Extracted (AVE)
CBHIS Governance Relational Mechanism	RM1	0.726	11.588	0.000	0.882	0.906	0.521
	RM2	0.514	7.696	0.000			
	RM3	0.744	11.734	0.000			
	RM4	0.682	8.538	0.000			
	RM5	0.686	12.530	0.000			
	RM6	0.717	11.176	0.000			
	RM7	0.768	16.383	0.000			
	RM8	0.804	18.250	0.000			
	RM9	0.809	19.855	0.000			
Community Health Outcomes	CHO1	0.704	15.396	0.000	0.829	0.875	0.539
	CHO2	0.746	13.027	0.000			
	CHO3	0.724	12.598	0.000			
	CHO4	0.821	26.843	0.000			
	CHO5	0.626	8.981	0.000			
	CHO6	0.770	10.470	0.000			

RM1 = CBHIS stakeholders' identification and engagement; RM2 = CBHIS executive's level communication; RM3 = Data review meetings; RM4 = Dialogue days; RM5 = Action days; RM6 = Community Meetings (Barazas); RM7 = Community health digital scorecards; RM8 = Community health chalkboard; RM9 = Information Education Communication (IEC) materials. CHO1 = Improvement in community healthcare coordination; CHO2 = Improvement in community health data and information quality and availability; CHO3 = Reduction in community health operational costs; CHO4 = Efficiency and effectiveness in delivering community health services; CHO5 = Improvement in community engagement in health; CHO6 = Promotes accountability and performance management.

Three techniques are commonly used to assess a construct's discriminant validity: the Fornell-Larcker Criterion, Heterotrait-Monotrait Ratio (HTMT), and cross-loadings. The study findings indicated that all constructs satisfied discriminant validity according to the Fornell-Larcker Criterion, as each construct correlated more strongly with itself than with others. Similarly, the constructs met the HTMT criterion, with values below 0.85, consistent with the threshold recommended by [36]. The cross-loading technique was not applied, as both the Fornell-Larcker Criterion and HTMT results confirmed the absence of discriminant validity issues.

These analyses demonstrated that all constructs and their indicators met the established reliability and validity thresholds, thereby supporting the identification and validation of the practices associated with the CBHIS governance relational mechanism. Building on the validation of the CBHIS governance relational mechanism, the study identified the following key practices: active identification and engagement of CBHIS stakeholders; executive-level communication through emails, formal and informal meetings, and targeted announcements; regular data review meetings; organisation of dialogue days; action days; utilisation of community meetings (barazas); deployment of community health digital scorecards; provision and use of community health 'chalkboards' during dialogue days and community meetings; and the use of Information, Education, and Communication (IEC) materials to disseminate CBHIS-related information.

In addition to the quantitative findings, the qualitative analysis identified two additional practices related to the CBHIS governance relational mechanism. The first involves the use of social media platforms (WhatsApp, Facebook, X) and traditional media (radio and TV) to enhance communication. These channels provide benefits such as real-time updates, targeted messaging, and broader reach, thereby strengthening

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the dissemination of community health interventions, including CBHIS initiatives. The study found that multiple WhatsApp groups had been created to facilitate rapid and efficient information sharing among community segments. For instance, Community Health Assistants (CHAs) maintained groups connecting them with their leaders, Sub-County Community Health Focal Persons (S-CCHFPs), Sub-County Health Records and Information Officers (S-CHRIOs), CHRIOs, and CCHFPs. Similarly, S-CCHFPs, S-CHRIOs, CHRIOs, and CCHFPs had their own groups, while CHAs also used WhatsApp groups to interact directly with Community Health Promoters (CHPs), reflecting a structured, multi-tiered communication network. Highlighting the central role of these platforms in routine CBHIS communication, one respondent remarked:

"We mainly communicate through our Work-related WhatsApp group formed by our CHA." (Respondent 10)

Facebook pages and other social media groups were actively used to communicate and share health-related information. Dedicated pages and groups disseminated interventions, updates, resources, and success stories, for instance, a community health page posting daily health tips and upcoming events. Targeted advertisements were also used to reach specific demographics, such as promoting household registrations within communities. Similarly, X (formerly Twitter) facilitated regular updates and posts on health interventions, events, and tips. Respondents noted:

"Communication also happens through social platforms, e.g., WhatsApp, Facebook sharing, and Twitter." (Respondent 1, Respondent 5), and *"Communication also happens by sending SMS, using radio and television." (Respondent 31)*

Other innovative channels included the use of tikTok, skits, poems and dance performances, highlighting the diverse methods used to engage communities and disseminate CBHIS information effectively. A respondent noted:

"TikTok, skits, poems, and dance performances, as well as billboards along highways and roads." (Respondent 89)

Radio and television stations were also important channels for communicating CBHIS interventions and progress within communities. Radio programs and talk shows provided a platform for health experts to discuss topics such as maternal and child health, engage with listeners, and respond to queries - for example, through weekly radio segments on maternal and child health. Similarly, TV stations, such as Ramogi TV, were utilised to discuss community health interventions and run educational campaigns offering in-depth information on specific programs. Leveraging social media, radio, and TV enabled more effective dissemination of CBHIS information, contributing to improved community health outcomes. One respondent noted:

"Sometimes, local radio stations are used to pass critical information to county officials. They also inform community members about ongoing activities, facilitating CHPs, CHAs, and county officials in delivering services smoothly." (Respondent 65)

Analysis of qualitative data further revealed that community health conferences represent a highly effective communication and governance practice within the CBHIS relational mechanism. These conferences provide a structured and formal setting for knowledge exchange, collaboration, and stakeholder engagement across multiple levels. The study found that conferences serve as platforms for sharing community health interventions through expert presentations, workshops, training sessions, case studies, and success stories. They also facilitate resource sharing, capture community voices, and promote interactive discussions. Respondents consistently noted that the conferences organised offered valuable opportunities to learn from diverse experiences and replicate successful practices. Table 5 summarises the practices associated with the CBHIS governance relational mechanism.

Table 4. Practices associated with the CBHIS governance relational mechanism

S.No.	CBHIS governance practices
1	CBHIS stakeholders' identification and engagement
2	CBHIS executive's level of communication
3	Data review meetings
4	Dialogue days
5	Action days
6	Community meetings (Barazas)
7	Community Health Digital Scorecard
8	Community 'chalkboard'
9	Information Education Communication (IEC)
10	Social media platforms, radio and TV stations, SMSs and phone calls
11	Conferences

Consequently, the governance of CBHIS contributed to several positive community health outcomes, including improved healthcare coordination, enhanced quality and availability of community health data, reduced operational costs, increased efficiency and effectiveness in service delivery, greater community engagement in health initiatives, and strengthened accountability and performance oversight.

4.2 Results of testing the structural model

The structural model was evaluated in multiple stages, beginning with an assessment of multicollinearity in the inner model. The collinearity statistics indicated a variance inflation factor (VIF) of 1 for the path from the relational mechanism to community health outcomes (RM → CHO), well below the commonly accepted threshold of 5. This result confirms the absence of collinearity issues in the model.

Following the identification of multicollinearity of the inner model, the research results indicated that the beta coefficient (β) for the original sample (O) was 0.629, whereas the sample mean (M) was 0.642. This suggested that a one-unit increase in the CBHIS governance relational mechanism correlated with a positive increase of 0.629 units in community health outcomes, assuming all other factors remained constant. The relationship was characterised by a T statistic (t) of 9.600***. The t-statistic demonstrated that the beta coefficient was statistically distinct from zero, hence, enhancing confidence in its validity and suggesting that it was not attributable to arbitrary occurrence or fluctuation. The beneficial correlation was statistically significant, with a P-value of 0.000. A p-value of 0.000 (or < 0.001) signified a minimal likelihood that the measured beta coefficient rose from an arbitrary occurrence, indicating that the beta coefficient was statistically significant. The results indicated a significant positive relationship between the CBHIS governance relational mechanism and community health outcomes. Table 6 presents the structural model results.

Table 5. Path Coefficients - Mean, STDEV, T Values, p values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
RM -> CHO	0.629	0.642	0.066	9.600	0.000

The study additionally employed the coefficient of determination (R^2) [37] and the predictive relevance (Q^2) [38]. They were used to evaluate the structural model's predictability. The coefficient of determination (R^2) quantifies the ratio of variation in the endogenous construct attributable to the influence of the exogenous factors. It assesses the model's explanatory capability [39]. The research findings indicated that the CBHIS governance relational mechanism accounted for 39.6% of the variance in community health outcomes. Moreover, the research employed predictive relevance (Q2) to ascertain the predictive significance of the endogenous construct. The findings indicated that the predictive significance stood at 0.360, or 36.0%. This value exceeded 0; therefore, the study deduced that the model possessed a significant degree of predictive relevance. Table 7 provides a concise overview of the coefficient of determination (R2), adjusted R2, and predictive relevance (Q2).

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Table 6. A summary table of all the techniques utilised to assess the structural model

Predictor(s)	Outcome	Beta values	T statistics	P-values	R^2	Adjusted R^2	Q^2
RM	**CHO**	0.629	9.600***	0.000	39.6%	39.2%	36.0%

5 Discussion

5.1 Practices associated with the CBHIS Governance Relational Mechanism

This research established the following governance practices associated with the CBHIS governance relational mechanism.

First, CBHIS stakeholders' identification and engagement involves recognising and including all parties who are either influencing or being influenced by the CBHIS initiative. According to this research, digital health stakeholders included the national and county government, development partners such as AMFREF Health Africa, Living Goods, community health workers, community members, digital health information systems developers, church and associated health facilities, and the administrative wing, which included both the Chiefs and Assistant Chiefs. This finding was in tandem with the arguments of previous studies such as [5], [6], [10], [22], [24], who opined that the healthcare sector had many actors that went beyond the healthcare organisation. As argued by [24] and [40], all these stakeholders need to be identified and engaged to foster involvement and collaboration amongst crucial digital health implementers. As such, the success of health interventions such as HISs significantly relies on the identification and participation of all stakeholders involved in health [12], [20], [41]. It is evident from the above arguments that stakeholder identification and engagement play a vital role, and hence, there is a need to identify them exhaustively when addressing the governance of CBHISs.

The CBHIS executive level of communication formed another CBHIS governance practice, which created an environment where the county executives communicated with their subordinates. This approach was utilised to convey vital messages, decisions, and other relevant information to CBHIS stakeholders at county, sub-county, ward and community health unit levels. Research findings revealed that the county executives utilised different approaches, such as e-mails, internal memos, as well as formal and informal meetings. This finding supported the arguments of previous studies such as [15], [17] who postulated that executive-level enterprise-wide communications and organisational top-level announcements, such as sending and receiving timely and accurate e-mails, constituted crucial communication approaches for the success of health information exchange (HIE).

Data review meetings formed another practice related to the CBHIS governance relational mechanism. It is a structured gathering where CHWs gathered to analyse, discuss, and interpret community health data related to a specific project or program. The purpose of such meetings was to evaluate the performance of CHWs, recognise trends in disease outbreaks, and utilise data to inform decisions that enhanced outcomes. In addition, such meetings were employed to develop community health targets, promote accountability and facilitate open communication and collaboration amongst the CHWs. The research findings revealed that CHWs frequently utilised data review meetings to deliberate on CBHIS data and information. This finding supported the arguments raised by previous studies, such as [25].

Dialogue days formed another practice associated with the CBHIS governance relational mechanism. According to the research findings, dialogue days happened every quarter of the year. This allowed CHWs, community members and community health stakeholders to discuss community health issues arising from community health data. Community health performance, community health scorecards, and performance of CBHIS were some of the issues of concern during the dialogue days. According to the research findings, such platforms allowed for exchanging community health views, ideas, and opinions to achieve a common plan and set of actions. This research finding agreed with arguments of [20], who pointed out that the success of CHW programs using the WBOTs strategy relied partly on community dialogues involving different stakeholders.

Action days, also referred to as community health outreach events, was another noted practice associated with the CBHIS governance relational mechanism. These events entailed activities and services, including health education workshops, information booths, and community resources aimed at promoting health and well-being within the community. The study findings revealed that the CBHIS decisions, activities and processes were communicated during the community health outreach events.

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Conducting community meetings (barazas) was a practice that was used to achieve the CBHIS governance relational mechanism. According to this research, community meetings provided an avenue for engaging with the community. It allowed members to discuss important community issues such as the CBHIS implementation and use. The Chief or the Assistant Chiefs always lead such gatherings. Such forums reflected the importance of communal decision-making and community cohesion. This finding supported those of previous studies [20], [24], [25] who pointed out the importance of community meetings commonly known as barazas.

A community health digital scorecard was also a practice that was also used to achieve CBHIS governance relational mechanism. This was utilised to assess and measure the progress of digital health integrations. It contained a set of Key Performance Indicators (KPIs) that helped to evaluate how well a community was leveraging CBHISs to support healthcare, improve health outcomes, and enhance overall quality of life. According to the research, the scorecard also helped in identifying and communicating areas for improvement, as well as tracking progress over time. Through the scorecard, community leaders, healthcare organisations, public health agencies, and policymakers would gauge the effectiveness of CBHIS initiatives and make data-driven decisions to enhance well-being of the communities.

Community 'chalkboard' was identified as another CBHIS governance practice in place. It was either through a physical or digital space where community members would share information, messages, and announcements using chalk or digital writing tools. It served as a platform for communication, creativity, and community engagement. In the case of a physical community chalkboard, mainly a blackboard or whiteboard placed in a public area, passersby were encouraged to write messages, share announcements, express creativity, or convey information relevant to the community. An online platform such as social media was used in the case of digital community chalkboards. This finding is in agreement with those of a study conducted by [26], which pointed out that the community 'chalkboard' can be applied as a communication model that carries the community health agenda and guides community dialogue and discussions.

The use of Information Education Communication (IEC) materials formed another practice related to the CBHIS governance relational mechanism. Such materials were used to inform and educate community members about specific community health interventions and programs such as CBHISs. This was conducted with a view of promoting behavioural change through communication. Among other interventions, IEC materials were utilised in community-based projects such as eCHIS to disseminate crucial information, raise awareness, and encourage positive behaviours. In addition, IEC materials could be used to create changes in attitude, provide skills and knowledge and mobilise communities. Some of the methods and tools used included printed materials, audio-visual media, interactive methods, and digital media, among others.

Social media platforms, radio and TV programs were also utilised to communicate CBHIS issues. Research findings revealed that social media platforms (WhatsApp, Facebook, and X) and radio and TV stations were utilised to enhance communication of community health interventions such as CBHIS initiatives. These mediums offered benefits such as broad reach, real-time updates, and targeted messaging, which could improve community engagement, awareness, and participation in health programs. The findings of this research are in agreement with the results of a study by [28], who observed that the creation of communication channels, such as the use of the Telegram social media channel, facilitates communication with eCHIS implementers.

The utilisation of conferences also serve as a channel or platform to communicate community health interventions. Conferences provide a structured and formal environment for exchanging knowledge, fostering collaboration, and engaging stakeholders at various levels. Expert presentations, workshops and training, case studies and success stories, stakeholder engagement, resource sharing, community voice, and interactive sessions are some of the ways that can be applied in conferences for community health interventions.

5.2 Interrelationships between the CBHIS Governance Relational Mechanism, Alignment and the Community Health Outcomes

The practices associated with the CBHIS governance relational mechanism constitute a critical component of the governance practices necessary for achieving alignment. Consistent with this view, prior studies [15], [17], [33] highlight the relational mechanism as pivotal in attaining alignment. [15] further emphasise that,

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even when appropriate structures and processes are in place, the relational mechanisms of HIT governance remain essential for achieving and sustaining alignment.

The study findings demonstrated a significant and positive relationship between the CBHIS governance relational mechanism and community health outcomes, with the relational mechanism explaining 39.6% of the variance ($R^2 = 0.396$) and exhibiting predictive relevance ($Q^2 = 0.360$), confirming the model's robustness. These results indicate that effective relational governance practices contribute substantially to enhancing community health outcomes.

This aligns with prior research emphasising the critical role of stakeholder identification and engagement in community health initiatives. For instance, [24] highlighted that recognising key community health stakeholders is fundamental for CHWs to create meaningful impact, while [20] observed that successful CHW programmes depend on including diverse actors within the community health ecosystem. Similarly, [12] and [41] underscored that the active participation of all relevant stakeholders is crucial for the effectiveness of health interventions, including HIS implementations.

The findings also underscore the importance of structured communication in supporting HIS success. Disseminating IT policies, guidelines, and procedures facilitates organisational adoption and maximises the value of HIS investments [42]. Executive-level communications and top-level organisational announcements further strengthen alignment, coordination, and value realisation [17]. Together, these insights suggest that stakeholder engagement and effective communication, which form the core elements of the CBHIS governance relational mechanism, are central drivers of improved community health outcomes.

Moreover, structured community dialogues were identified as an essential practice for translating governance mechanisms into tangible outcomes. [20] emphasised the role of dialogue in the success of the WBOTs strategy, while [26] observed that engaging communities through dialogue can lead to measurable improvements in health outcomes. Complementary tools such as community "chalkboards" further support these interactions by guiding discussions and fostering collective engagement in health promotion [26]. These findings reinforce the view that the implementation of relational governance practices is critical for deriving value from health information system (HIS) investments [17], and align with broader evidence that effective digital health governance is fundamental to achieving health system goals and outcomes [5], [11], [43].

5.3 Limitations of the Study

Several limitations should be considered when interpreting the findings of this study. First, the use of purposive sampling may have introduced sampling bias, since participants were intentionally selected based on characteristics relevant to the research objectives. As a result, the sample may not fully represent the broader population, thereby limiting the generalisability of the findings beyond the study context. Additionally, the sampling approach may have restricted the diversity of perspectives captured, which could have influenced the range of responses obtained.

Despite these limitations, purposive sampling was considered appropriate for the exploratory nature of the study because it facilitated the inclusion of participants with relevant knowledge and experience regarding CBHIS governance practices. Future studies could strengthen the robustness and generalisability of the findings by employing probability-based sampling techniques and larger, more diverse samples across different community health settings.

6 Conclusion and Practical Implications

This study identified several relational governance practices associated with the Community-Based Health Information System (CBHIS) that appear to support alignment between CBHIS implementation and community health processes. Specifically, practices such as stakeholder identification and engagement, data review meetings, dialogue days, community health chalkboards, and the use of Information, Education, and Communication (IEC) materials emerged as important relational mechanisms within the studied contexts. The findings suggest that these governance practices may contribute to improved community health outcomes by enhancing collaboration, stakeholder engagement, communication, and information sharing within community health systems.

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These findings provide important practical implications for health informatics practitioners, policymakers, and community health stakeholders by highlighting relational governance practices that may strengthen the effectiveness of CBHIS implementation and support community health system performance. However, the findings should be interpreted with caution in light of the study limitations outlined earlier. As such, the study offers preliminary rather than conclusive evidence regarding the role of relational governance mechanisms in CBHIS implementation.

To strengthen the empirical validation and generalisability of these findings, future research should test and apply the proposed tool and governance practices across additional contexts using more representative sampling approaches, including randomly selected communities. Such studies would provide more robust evidence regarding the applicability, scalability, and effectiveness of relational governance mechanisms in improving community health outcomes and overall community health system performance.

7 Recommendations

This study identified context-specific practices associated with the CBHIS governance relational mechanism, offering practical guidance for health informatics practitioners and policymakers. The findings underscore the importance of investing in relational approaches such as CBHIS community meetings (barazas), dialogue days, community health digital scorecards, and Information Education Communication (IEC) materials to strengthen governance and enhance community health outcomes.

For policy formulation, the results highlight the need to integrate these practices into CBHIS governance frameworks to support alignment and system effectiveness. Future research should explore practices linked to the processes governance mechanism to assess their influence on community health outcomes. Additionally, subsequent studies could investigate the combined effects of practices across CBHIS governance mechanisms on alignment and the variance in community health outcomes.

Declarations

Ethics approval

Ethical approval was unnecessary for this research since it did not include direct human data.

Research permit and consent to participate

The National Commission for Science, Technology and Innovation (NACOSTI) issued a research license (Ref. No: 929552) to carry out this research. The study's authorisation was secured from county administrations and all participating sub-counties. All research participants provided informed consent. Respondents were allocated numerical identifiers ranging from 1 to 164 to safeguard personal identity. All procedures were conducted following applicable norms and legislation.

Consent for publication

Not applicable.

Availability of data and materials

All relevant data are included in the manuscript. The data supporting these findings can be obtained from the corresponding author upon request.

Competing interests

The authors wish to affirm that they hold no financial or non-financial competing interests.

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Authors' contributions

HC: Conceptualised the study, carried out literature review, analysed the data, composed the text, and revised the manuscript; TW: Conceptualised the study, revised and sanctioned the manuscript, and provided oversight during the research process; DO: Conceptualised the study, revised the manuscript, endorsed its final version, and provided guidance throughout the research. All authors reviewed the manuscript.

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Strategic Implementation Framework for Sustainable E-Health Deployment in Fragile Healthcare Systems: Evidence from the Democratic Republic of Congo

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Background and Purpose: The successful adoption of e-health systems does not automatically translate into effective implementation, particularly in fragile healthcare environments characterized by limited infrastructure, institutional constraints, and resource shortages. While previous studies have largely focused on technology adoption, limited attention has been given to translating adoption findings into practical implementation strategies. This study aims to develop a comprehensive implementation framework for the sustainable deployment of e-health systems in the healthcare sector of the Democratic Republic of Congo (DRC).
Methods:. The study employed a design-oriented research approach informed by an empirically validated e-health adoption model and a context-aware information systems architecture. Findings from quantitative analyses of healthcare professionals' adoption behavior, combined with evidence from the literature and digital health implementation guidelines, were synthesized to develop a strategic implementation framework. The proposed framework integrates technological readiness, organizational capacity, stakeholder engagement, governance mechanisms, policy alignment, and phased implementation principles
Results: The study proposes a five-phase implementation framework consisting of (1) planning and stakeholder engagement, (2) system design and development, (3) pilot implementation and capacity building, (4) phased scale-up and national integration, and (5) continuous monitoring, evaluation, and sustainability. The framework addresses critical implementation barriers, including inadequate ICT infrastructure, fragmented health information systems, limited digital competencies among healthcare professionals, financial constraints, and weak institutional coordination. It further identifies governance structures, interoperability requirements, financing mechanisms, and continuous capacity development as key enablers of sustainable e-health implementation in fragile healthcare settings.
Conclusions: The proposed framework bridges the gap between e-health adoption research and practical implementation by providing a structured roadmap for sustainable digital health deployment. It contributes to the digital health and health informatics literature by integrating adoption determinants, architectural design principles, and implementation strategies into a unified framework. The findings offer practical guidance for policymakers, healthcare institutions, and system designers seeking to implement scalable and sustainable e-health systems in the Democratic Republic of Congo and other resource-constrained healthcare environments

Keywords: E-health systems; Digital health; Technology adoption; Sustainable implementation; Fragile healthcare systems; ICT infrastructure; Health information systems; Democratic Republic of Congo

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1 Introduction

The digital transformation of healthcare systems has become a global priority, driven by the rapid advancement of information and communication technologies (ICT). Digital health, commonly referred to as e-health, encompasses a wide range of technologies, including electronic health records (EHRs), telemedicine, mobile health (m-health), and health information systems. These innovations have significantly improved the efficiency, accessibility, and quality of healthcare delivery, particularly in high-income countries where digital infrastructures are well established [1] [2].

E-health technologies enable real-time data sharing, improved clinical decision-making, enhanced patient monitoring, and better coordination of care across healthcare providers [3]. As a result, digital health has been recognized as a key enabler for achieving universal health coverage and strengthening health system resilience. Governments and international organizations increasingly promote the adoption of digital health solutions to address growing healthcare demands and improve population health outcomes

However, despite these promising advancements, the implementation of e-health systems remains a complex and challenging process, especially in resource-constrained and fragile healthcare environments. The successful deployment of digital health technologies requires not only technological infrastructure but also organizational readiness, skilled human resources, supportive policy frameworks, and sustainable financing mechanisms [4].

In many developing countries, including the Democratic Republic of Congo, healthcare systems face significant barriers to digital transformation. These challenges include inadequate ICT infrastructure, unreliable electricity supply, limited internet connectivity, low levels of digital literacy among healthcare professionals, and fragmented health information systems [4]. Additionally, issues related to data privacy, security, and lack of interoperability further complicate implementation efforts [5].

Moreover, the absence of well-defined implementation strategies and context-adapted frameworks often leads to fragmented and unsustainable e-health initiatives. Many digital health projects fail to scale beyond pilot phases due to poor alignment with local needs, insufficient stakeholder engagement, and lack of institutional support [6].

Therefore, while digital health holds substantial potential to transform healthcare delivery, its successful implementation in fragile healthcare systems requires a comprehensive and context-aware approach that integrates technological, organizational, and policy dimensions.

While significant progress has been made in understanding the determinants of e-health adoption, the transition from initial adoption to sustainable deployment remains a critical challenge, particularly in fragile healthcare systems. Existing research has extensively focused on behavioral models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which explain how users perceive and accept digital health technologies. These models have provided valuable insights into factors such as perceived usefulness, ease of use, social influence, and facilitating conditions [7].

However, adoption alone does not guarantee successful implementation or long-term sustainability. Many e-health initiatives that achieve initial user acceptance fail to progress beyond pilot stages due to the absence of structured implementation strategies, inadequate infrastructure, and weak institutional support. This highlights a significant gap between theoretical adoption models and real-world system deployment [8].

In resource-constrained environments, sustainable e-health implementation requires a broader perspective that goes beyond user behavior. It involves the integration of technological readiness, organizational capacity, governance structures, and policy frameworks. Factors such as ICT infrastructure, data security, interoperability, regulatory compliance, and financial sustainability play a crucial role in determining whether e-health systems can be effectively scaled and maintained over time [9].

Furthermore, the complexity of healthcare systems necessitates a socio-technical approach that aligns human, technological, and institutional dimensions. Without such alignment, even well-designed systems may fail due to resistance to change, lack of training, or incompatibility with existing workflows [10].

In the context of the Democratic Republic of Congo, this gap between adoption and sustainable deployment is particularly evident. While healthcare professionals may recognize the potential benefits of e-health systems, practical constraints such as limited infrastructure, fragmented health information systems, and insufficient implementation frameworks hinder their effective utilization [4].

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Therefore, there is a pressing need for a strategic implementation framework that bridges the gap between adoption and sustainable deployment. Such a framework should be grounded in empirical evidence, aligned with contextual realities, and designed to guide the phased implementation, scaling, and long-term sustainability of e-health systems in fragile healthcare environments.

Despite the growing recognition of the potential of e-health technologies to improve healthcare delivery, their implementation in fragile healthcare systems remains limited and often unsustainable. In many developing countries, digital health initiatives are characterized by fragmentation, lack of interoperability, and poor scalability, which significantly reduce their long-term impact on healthcare systems [4].

In the Democratic Republic of Congo, these challenges are particularly pronounced. Although several efforts have been made to introduce digital health solutions [11], their adoption and effective use remain inconsistent across healthcare facilities. Existing systems are often implemented in isolation, without integration into a coherent national framework, leading to duplication of efforts, inefficiencies, and limited data sharing [5].

Furthermore, current approaches to e-health implementation tend to focus primarily on technological deployment or user adoption, without adequately addressing the broader systemic and contextual factors required for sustainability. The absence of a comprehensive implementation strategy that integrates technological, organizational, and institutional dimensions constitutes a major barrier to successful e-health deployment.

Another critical issue lies in the gap between empirical research on technology adoption and practical implementation strategies. While studies based on models such as TAM and UTAUT have identified key determinants influencing user acceptance, these insights are rarely translated into actionable frameworks that guide real-world system deployment, particularly in resource-constrained environments.

As a result, there is a lack of context-aware strategic frameworks capable of supporting the scalable and sustainable implementation of e-health systems in fragile healthcare settings. This gap limits the effectiveness of digital health investments and undermines efforts to improve healthcare accessibility, quality, and efficiency.

Therefore, the central research problem addressed in this study is the absence of a structured, empirically grounded, and context-adapted implementation framework that can guide the sustainable deployment of e-health systems in the Democratic Republic of Congo.

The main objective of this study is to develop a strategic implementation framework for the sustainable deployment of e-health systems in fragile healthcare environments, with a focus on the Democratic Republic of Congo.Specifically, the study aims to:

Develop a strategic framework for sustainable e-health implementation in fragile healthcare systems.The study bridges the gap between e-health adoption research and implementation practice by integrating empirically validated adoption factors into a strategic deployment framework tailored to fragile healthcare systems.

The study provides a context-aware implementation strategy that offers actionable guidance for policymakers, healthcare institutions, and system designers to support sustainable e-health deployment in resource-constrained environments.

2 Literature Review

2.1 E-Health Implementation in Developing Countries

The implementation of e-health systems in developing countries presents unique challenges that extend beyond technological considerations. While digital health initiatives have the potential to improve healthcare accessibility and efficiency, their success depends on a complex interplay of infrastructural, organizational, financial, and socio-cultural factors [4].

Many developing countries face significant barriers, including limited ICT infrastructure, unreliable electricity supply, inadequate funding, and shortages of skilled personnel. These constraints often lead to the partial or unsuccessful implementation of digital health projects. Additionally, weak regulatory frameworks and governance structures may complicate issues related to data protection, privacy, and system accountability [5].

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Another critical challenge is the sustainability of e-health initiatives. Projects implemented with external funding or pilot programs may fail to scale up or continue after initial support ends. Sustainable implementation requires long-term planning, local capacity building, and alignment with national health strategies [12].

Despite these challenges, developing countries also present opportunities for innovative digital health solutions tailored to local contexts. Mobile health technologies, for example, have shown significant potential in regions where mobile phone penetration exceeds access to traditional healthcare infrastructure. However, the effectiveness of such solutions depends on their integration into broader health information systems architectures [13].

In the case of the Democratic Republic of Congo, the healthcare system faces multiple structural constraints, including geographical barriers, limited infrastructure, and resource shortages. These conditions underscore the need for a context-aware architectural framework capable of supporting scalable, interoperable, and secure digital health systems adapted to local realities [5].

2.2 Implementation Science in Health Informatics

Implementation science has become an essential field for understanding how health innovations, including digital health technologies, can be effectively integrated into routine healthcare practice. In health informatics, it focuses on bridging the gap between the development of technological solutions and their sustainable use in real-world settings [14].

Rather than emphasizing system design alone, implementation science highlights the importance of contextual, organizational, and behavioral factors that influence the success of health information systems. Key determinants include organizational readiness, stakeholder engagement, leadership support, user training, resource availability, and governance structures. These elements are critical to ensuring that digital health interventions are not only adopted but also effectively utilized and sustained over time [15].

In the context of e-health, implementation science provides insights into the persistent challenges that limit scalability and long-term impact. Many digital health initiatives fail to progress beyond pilot stages due to inadequate infrastructure, misalignment with clinical workflows, insufficient capacity building, and weak institutional coordination. These challenges are particularly pronounced in fragile healthcare systems, where resource constraints and systemic inefficiencies further complicate implementation efforts [14].

Consequently, there is a growing need for structured and context-aware implementation approaches that integrate technological, organizational, and policy dimensions. Such approaches enable the translation of theoretical insights into practical strategies for sustainable deployment.

This study adopts an implementation science perspective to develop a strategic framework that links empirically validated adoption factors with actionable implementation strategies. By doing so, it contributes to advancing health informatics research and supports the sustainable deployment of e-health systems in resource-constrained environments.

2.3 Organizational Readiness for Digital Transformation

Organizational readiness is widely recognized as a critical determinant of successful digital transformation in healthcare systems. It refers to the extent to which an organization possesses the necessary capabilities, resources, and commitment to implement and sustain technological innovations such as e-health systems. In the context of health informatics, readiness goes beyond the mere availability of technology and encompasses structural, human, and managerial dimensions [16].

A key component of organizational readiness is leadership commitment. Strong leadership plays a central role in driving digital transformation by defining strategic priorities, mobilizing resources, and fostering a culture of innovation. Without active support from top management, e-health initiatives often lack direction and fail to achieve long-term sustainability [17].

Human capacity and digital skills also constitute a fundamental aspect of readiness. Healthcare professionals must be adequately trained and supported to effectively use digital systems. Limited digital literacy and resistance to change remain significant barriers, particularly in resource-constrained environments, where exposure to information technologies may be limited [18].

In addition, organizational processes and workflows must be aligned with digital systems to ensure seamless integration into routine practice [19]. Misalignment between system design and clinical

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workflows often leads to low utilization and user dissatisfaction. Therefore, successful implementation requires the adaptation of organizational structures and processes to accommodate new technologies.

Resource availability, including financial capacity, technical infrastructure, and maintenance support, further influences organizational readiness. In many developing countries, healthcare institutions operate under severe resource constraints, limiting their ability to invest in and sustain digital health systems.

Finally, governance mechanisms and institutional coordination are essential for ensuring coherent implementation. Clear roles, responsibilities, and accountability structures contribute to effective system management and sustainability [20].

In fragile healthcare systems such as those in the Democratic Republic of Congo, organizational readiness remains uneven across institutions, significantly affecting the success of e-health initiatives [21]. Therefore, assessing and strengthening organizational readiness is a crucial step toward sustainable digital health implementation.

This study incorporates organizational readiness as a central dimension of the proposed implementation framework, emphasizing its role in translating adoption potential into effective and sustainable system deployment.

2.4 Barriers to Digital Health Deployment

Despite the growing recognition of the transformative potential of digital health technologies, their large-scale deployment remains constrained by multiple interrelated barriers, particularly in resource-limited and fragile healthcare systems. These barriers are not only technological but also organizational, financial, and institutional in nature, requiring a comprehensive and integrated approach to implementation.

One of the most significant challenges is the inadequacy of ICT infrastructure. Reliable electricity supply, stable internet connectivity, and access to appropriate hardware are essential prerequisites for digital health systems [4]. In many developing countries, including the Democratic Republic of Congo, these infrastructural limitations significantly hinder the effective deployment and continuous operation of e-health solutions.

Human capacity constraints also represent a major barrier. Limited digital literacy among healthcare professionals, insufficient training programs, and resistance to change reduce the effective use of digital systems. Without adequate user competence and engagement, even well-designed systems fail to achieve their intended impact [22].

Financial constraints further complicate implementation efforts. The high costs associated with system development, deployment, maintenance, and training often exceed the available resources of healthcare institutions. In addition, the lack of sustainable funding models leads to interruptions in system operation and limits scalability [23].

Another critical barrier is the fragmentation of health information systems. Many digital health initiatives are implemented in isolation, resulting in poor interoperability and limited data sharing across institutions [24]. This fragmentation reduces system efficiency and undermines the potential benefits of integrated healthcare delivery.

Governance and policy-related challenges also play a significant role. The absence of clear regulatory frameworks, data governance policies, and national standards creates uncertainty and limits coordination among stakeholders. Weak institutional support and lack of strategic leadership further exacerbate these issues [4].

Finally, concerns related to data privacy and security affect user trust and willingness to adopt digital health systems. Ensuring the confidentiality, integrity, and availability of health data is essential for building confidence among healthcare professionals and patients.

In fragile healthcare systems, these barriers are often interconnected and mutually reinforcing, making implementation particularly complex. Addressing these challenges requires a strategic and context-aware approach that integrates infrastructure development, capacity building, governance mechanisms, and stakeholder engagement [25].

This study builds upon these insights by proposing a comprehensive implementation framework designed to overcome these barriers and support the sustainable deployment of e-health systems in the Democratic Republic of Congo.

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2.5 Research Gap

Despite the growing body of literature on digital health and e-health adoption, several critical gaps remain, particularly in the context of fragile and resource-constrained healthcare systems. Existing studies have made significant contributions to understanding the determinants of technology acceptance, primarily through theoretical models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). These models have been widely applied to explain user behavior and intention to adopt digital health technologies [25].

However, a major limitation of this body of research is its predominant focus on adoption at the individual level, with limited attention to the practical challenges of system implementation and long-term sustainability. While these models provide valuable insights into behavioral determinants, they do not offer sufficient guidance on how to translate adoption intentions into effective and scalable deployment strategies.

In parallel, research in health informatics and digital health architecture has emphasized system design, interoperability, and technological innovation. Nevertheless, these studies often overlook the contextual and organizational realities that influence implementation outcomes, particularly in developing countries. As a result, there is a disconnect between technically sound solutions and their practical applicability in real-world healthcare environments.

Furthermore, implementation science has highlighted the importance of organizational readiness, governance structures, and contextual adaptation. Yet, there is still a lack of integrated frameworks that combine empirical adoption evidence with structured implementation strategies tailored to fragile healthcare systems.

In the context of the Democratic Republic of Congo, this gap is even more pronounced. Existing e-health initiatives remain fragmented, with limited coordination, weak infrastructure, and insufficient policy support. The absence of a comprehensive and context-aware implementation framework hinders the scalability and sustainability of digital health solutions.

Therefore, this study addresses a critical research gap by proposing a strategic implementation framework that bridges the divide between technology adoption theory and real-world deployment. By integrating empirically validated adoption factors with implementation science principles and contextual considerations, the study provides a structured approach to support sustainable e-health deployment in fragile healthcare environments.

3 Context of the Study: Healthcare System in the DRC

The Democratic Republic of Congo (DRC) presents a complex and fragile healthcare environment characterized by structural, economic, and infrastructural challenges [26]. As one of the largest countries in Sub-Saharan Africa, the DRC faces significant disparities in healthcare access, particularly between urban and rural areas. The healthcare system is organized into a decentralized structure comprising central, provincial, and peripheral levels, with health zones serving as the primary units for healthcare delivery [5].

Despite ongoing efforts to strengthen the healthcare system, it continues to face persistent challenges, including limited financial resources, shortages of qualified healthcare personnel, and inadequate infrastructure. Healthcare facilities often operate under constrained conditions, with insufficient medical equipment, unreliable electricity supply, and limited access to digital technologies. These constraints significantly affect the quality and efficiency of healthcare service delivery [27].

In recent years, the government and development partners have shown increasing interest in leveraging digital health technologies to improve healthcare outcomes. Initiatives such as electronic health information systems, disease surveillance platforms, and mobile health applications have been introduced to enhance data collection, reporting, and decision-making processes. However, these initiatives are often implemented in a fragmented manner, lacking interoperability and integration within a unified national framework [4].

The current state of digital health infrastructure in the DRC remains underdeveloped. Internet connectivity is inconsistent, particularly in rural areas, and many healthcare facilities lack the necessary hardware and technical capacity to support digital systems [4] [28]. Additionally, the level of digital literacy among healthcare professionals varies significantly, posing challenges for effective system adoption and use.

Institutional and policy-related factors further complicate the implementation of e-health systems. While national strategies for digital health exist, their operationalization is often limited by weak governance structures, insufficient coordination among stakeholders, and lack of sustainable funding mechanisms. These challenges hinder the scalability and long-term sustainability of digital health initiatives [29].

Given these contextual realities, the DRC represents a relevant and critical case for examining the challenges and opportunities associated with e-health implementation in fragile healthcare systems. Understanding this context is essential for designing and implementing strategies that are both realistic and effective.

This study situates its analysis within this complex environment, using the DRC as a case study to develop a context-aware strategic framework for sustainable e-health deployment.

3.1 Structure of the Healthcare System

The healthcare system in the Democratic Republic of Congo (DRC) is organized according to a decentralized and hierarchical structure designed to ensure the delivery of healthcare services across different administrative levels. This structure is composed of three main tiers: the central level, the intermediate (provincial) level, and the peripheral (operational) level [30].

At the central level, the Ministry of Health is responsible for the formulation of national health policies, strategic planning, regulation, and overall coordination of the healthcare system. It defines standards, guidelines, and priorities for healthcare delivery and oversees the implementation of national health programs. This level also plays a critical role in mobilizing resources and coordinating with international partners and donors [31].

The intermediate level, represented by the provincial health divisions, acts as a link between the central and peripheral levels. It is responsible for adapting national policies to local contexts, supervising healthcare activities, and providing technical support to health zones. This level ensures the coordination of healthcare services within provinces and monitors the performance of health facilities [32].

The peripheral level constitutes the operational core of the healthcare system and is organized into health zones. Each health zone typically includes a network of primary healthcare centers and a general referral hospital [28]. Health centers provide basic healthcare services, including preventive, promotive, and curative care, while general referral hospitals handle more complex cases and provide specialized services. The health zone approach is designed to ensure accessibility and continuity of care for the population [22].

Despite this structured organization, the healthcare system faces several operational challenges. Coordination between levels is often weak, and resource allocation remains uneven across regions. Many health zones operate with limited infrastructure, insufficient staffing, and inadequate equipment, which affects service delivery [4].

In the context of digital health, this multi-level structure presents both opportunities and challenges. On the one hand, it provides a framework for scaling e-health solutions across different levels of care. On the other hand, it requires strong interoperability, coordination mechanisms, and governance structures to ensure effective system integration and data sharing.

Understanding the structure of the healthcare system is essential for designing and implementing e-health solutions that align with existing organizational frameworks. This study leverages this structural understanding to propose an implementation strategy that supports coordinated and scalable deployment across all levels of the healthcare system in the DRC.

3.2 Current State of Digital Health Initiatives

In recent years, the Democratic Republic of Congo (DRC) has witnessed a gradual emergence of digital health initiatives aimed at improving healthcare delivery through the use of information and communication technologies. These initiatives are particularly important in a context characterized by the predominance of paper-based systems, unequal distribution of resources, limited internet penetration, and underdeveloped health information systems [33].

A key component of digital health development in the DRC is the increasing use of mobile health (mHealth) applications. Mobile phones are widely utilized to disseminate health information, especially in remote and underserved areas [34]. Common interventions include SMS-based alerts for vaccination campaigns, maternal health reminders, and public health awareness messages. These initiatives have

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contributed to improving communication between healthcare providers and communities, thereby enhancing preventive healthcare practices.

Telemedicine is also gaining traction as a strategic tool to bridge the gap between urban healthcare facilities and rural populations. It has proven particularly useful during health emergencies, such as the COVID-19 pandemic, by enabling remote consultations and reducing the risk of disease transmission. Although still in its early stages, telemedicine represents a promising avenue for expanding access to specialized healthcare services in geographically isolated regions [35].

In addition, the DRC has made progress in implementing health information systems to support data collection, reporting, and disease surveillance. The District Health Information System (DHIS2) is one of the most widely used platforms, facilitating the aggregation and analysis of health data at national and subnational levels. While DHIS2 has improved data availability and reporting efficiency, it remains primarily focused on statistical data management and does not fully support core operational processes such as electronic medical records, patient management, scheduling, billing, and inventory control [35].

Several healthcare facilities have also begun integrating digital technologies into their operations to improve service delivery. For example, hospitals in cities such as Bukavu, Kananga, Kisangani, and Kinshasa have introduced computerized systems for managing patient records, appointments, and diagnostic procedures. Some institutions have adopted electronic medical record systems and digital platforms to enhance the quality, accuracy, and efficiency of healthcare services. However, these initiatives remain localized and are not yet standardized or interconnected at the national level [5].

Despite these advancements, the digital health landscape in the DRC is characterized by fragmentation and limited interoperability. Many initiatives are implemented in isolation, often driven by external partners, leading to duplication of efforts and inefficiencies in data management. Furthermore, infrastructural constraints such as unreliable electricity supply, poor internet connectivity, and limited access to digital equipment continue to hinder large-scale implementation [36].

Human capacity challenges also persist, as many healthcare professionals lack adequate digital skills and training to effectively use these systems. In addition, sustainability remains a major concern, as numerous initiatives rely heavily on donor funding and lack long-term financial and institutional support.

Compared to more advanced healthcare systems in high-income countries, where ICT is fully integrated into clinical and administrative processes, the DRC remains at an early stage of digital health implementation. Existing systems, including DHIS2, do not yet provide comprehensive support for the full spectrum of healthcare operations.

Overall, while current e-health initiatives in the DRC demonstrate a growing recognition of the role of digital technologies in strengthening healthcare systems, significant gaps remain. These limitations highlight the need for a comprehensive, integrated, and context-aware strategic framework to guide the sustainable deployment and scaling of e-health solutions across the country.

4 Methodological Approach

4.1 Research Design

This study adopts a design-oriented research approach combined with empirical analysis to develop a strategic implementation framework for sustainable e-health deployment in the Democratic Republic of Congo (DRC). The research design is grounded in the integration of quantitative evidence and system design principles to address both behavioral and structural dimensions of e-health implementation.

The empirical component of the study is based on a quantitative research design aimed at identifying the key determinants influencing the adoption and use of e-health systems among healthcare professionals. Data were collected through structured questionnaires administered to healthcare workers across selected healthcare facilities. The survey instrument was designed based on an integrated model combining constructs from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), including perceived usefulness, perceived ease of use, performance expectancy, social influence, facilitating conditions, and behavioral intention [25].

Statistical analysis techniques were employed to evaluate the relationships between these variables and to validate the proposed adoption model. The results provided empirical evidence on the key technological, organizational, and institutional factors influencing e-health adoption in the DRC context [25].

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Building on these findings, the study adopts a design science perspective to translate empirically validated determinants into actionable implementation strategies. Rather than focusing solely on system development, the research emphasizes the design of a strategic framework that integrates technological readiness, organizational capacity, governance mechanisms, and policy alignment [37] [38].

The research design follows a structured process comprising three main stages: (i) empirical analysis of e-health adoption factors, (ii) identification of implementation requirements based on empirical findings, and (iii) development of a context-aware strategic implementation framework. This approach ensures that the proposed framework is both evidence-based and practically applicable.

By combining quantitative analysis with a design-oriented methodology, the study provides a comprehensive approach to addressing the challenges of e-health implementation in resource-constrained environments. This integrated research design enables the bridging of the gap between theoretical models of technology adoption and real-world implementation strategies.

4.2 Data Sources and Requirements Analysis

This study relies on a quantitative data-driven approach to identify the key requirements for the effective implementation of e-health systems in the Democratic Republic of Congo (DRC). The primary data source consists of structured questionnaire responses collected from healthcare professionals working in various healthcare facilities.

A total of 393 valid responses were obtained, representing a diverse group of participants, including physicians, nurses, and administrative staff. The questionnaire was designed based on an integrated adoption model combining constructs from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). These constructs include perceived usefulness, perceived ease of use, social influence, facilitating conditions, behavioral intention, and actual use, as well as contextual factors such as ICT infrastructure, trust, privacy and security, and policy and regulatory environment.

The collected data were analyzed using statistical methods, including reliability analysis, correlation analysis, and regression modeling. These analyses enabled the identification of significant determinants influencing e-health adoption and use within the DRC healthcare context. The empirical results provided a robust foundation for understanding both technological and contextual factors affecting system implementation.

Based on these findings, a requirements analysis was conducted to translate the statistically significant factors into actionable system and implementation requirements. Technological factors such as ICT infrastructure and system usability informed the need for scalable, user-friendly, and resilient system architectures. Organizational factors, including facilitating conditions and social influence, highlighted the importance of training, stakeholder engagement, and institutional support mechanisms.

Furthermore, contextual and institutional factors such as trust, privacy, security, and policy environment were incorporated into the requirements to ensure compliance with data protection standards and alignment with national health strategies. These elements guided the integration of security protocols, governance frameworks, and interoperability standards into the proposed implementation strategy.

The requirements analysis follows a structured mapping process, linking empirical findings to specific design and implementation components. This approach ensures that the proposed strategic framework is not only theoretically grounded but also empirically validated and contextually relevant.

By deriving implementation requirements directly from quantitative evidence, this study strengthens the link between adoption research and practical system deployment. This evidence-based approach enhances the reliability and applicability of the proposed framework in addressing the real-world challenges of e-health implementation in resource-constrained healthcare environments.

4.3 Framework Development Process

The development of the proposed strategic implementation framework follows a structured design-oriented approach grounded in the principles of Design Science Research (DSR). This approach is particularly suitable for addressing complex socio-technical challenges, such as e-health implementation in fragile healthcare systems, by focusing on the creation of practical and context-aware solutions.

The framework development process is based on the integration of empirical evidence derived from the quantitative analysis and theoretical insights from implementation science and health informatics. It follows a multi-stage process designed to ensure both scientific rigor and practical relevance.

The first stage involves the identification of key determinants influencing e-health adoption, based on the results of the statistical analysis. Significant factors such as ICT infrastructure, facilitating conditions, social influence, trust, privacy and security, and policy environment are considered as critical inputs for the framework design.

The second stage consists of translating these determinants into implementation requirements. This mapping process enables the transformation of abstract constructs into actionable elements, including technological specifications, organizational interventions, governance mechanisms, and policy considerations. For example, the significance of ICT infrastructure informs the need for scalable and resilient systems, while trust and security concerns guide the integration of robust data protection measures.

The third stage focuses on the design of the strategic implementation framework itself. The framework is structured around key dimensions that reflect the core components of sustainable e-health deployment: technological readiness, organizational capacity, stakeholder engagement, governance and policy alignment, and continuous monitoring and evaluation. These dimensions are interrelated and collectively support the effective implementation and long-term sustainability of digital health systems.

The framework also incorporates a phased implementation approach, enabling gradual deployment and scalability. This includes stages such as planning, system design, pilot implementation, scale-up, and evaluation. This phased strategy ensures that implementation risks are minimized and that lessons learned at each stage can inform subsequent phases.

Finally, the framework is conceptually evaluated in terms of its alignment with the identified challenges and contextual realities of the DRC healthcare system. The design emphasizes adaptability, scalability, and sustainability, ensuring that it can be applied in other resource-constrained healthcare environments with similar characteristics.

By combining empirical findings, theoretical foundations, and design principles, this framework provides a comprehensive and actionable approach to bridging the gap between e-health adoption and sustainable implementation.

5 Results

5.1 Descriptive Statistics

A total of healthcare professionals participated in the study, representing various roles within the healthcare system. The sample included physicians, nurses, administrative staff, and health information officers. The demographic distribution indicates a diverse representation in terms of age, professional experience, and level of familiarity with digital technologies. Overall, the respondents demonstrated moderate to high exposure to e-health systems, although variations were observed depending on institutional capacity and infrastructure availability.

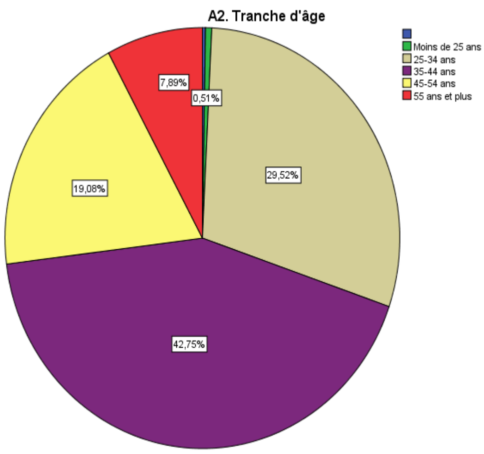

Fig. 1. Distribution of Respondents by Age Group

The pie chart (Fig 1) shows that most respondents fall within the 35–44 age group (42.75%), followed by those aged 25–34 (29.52%), meaning that over 72% of participants are in their most active professional years. Respondents aged 45–54 represent 19.08%, while those aged 55 and above account for 7.89%, reflecting experienced professionals likely involved in decision-making roles. In contrast, individuals under 25 are minimally represented (0.51%). Overall, the distribution indicates that the study mainly captures the perspectives of mature and professionally active healthcare workers, who are more likely to use and influence the adoption of e-health systems.

5.2 Measurement Model Assessment

The reliability and validity of the measurement model were assessed prior to hypothesis testing. Internal consistency was confirmed, with Cronbach's alpha and composite reliability values exceeding the recommended threshold of 0.70 for all constructs. Convergent validity was established as the average variance extracted (AVE) values were above 0.50. Discriminant validity was also confirmed using standard criteria, indicating that each construct was distinct and adequately measured.

These results confirm that the measurement model is robust and suitable for subsequent structural analysis.

Construct	*Cronbach's Alpha*	*Composite Reliability*	*AVE*
PEOU	0.90	0.86	0.72
PU	0.88	0.84	0.68
SI	0.86	0.78	0.54
FC	0.87	0.80	0.56
ICTI	0.91	0.82	0.61
TPS	0.89	0.85	0.65
PRE	0.85	0.76	0.52
BI	0.88	0.88	0.74
AU	0.89	0.83	0.69

Table 1: Reliability and Convergent Validity

5.3 Structural Model Results

The structural model was evaluated using path coefficients (β), significance levels (p-values), and explanatory power (R^2). The results are summarized in Fig 2.

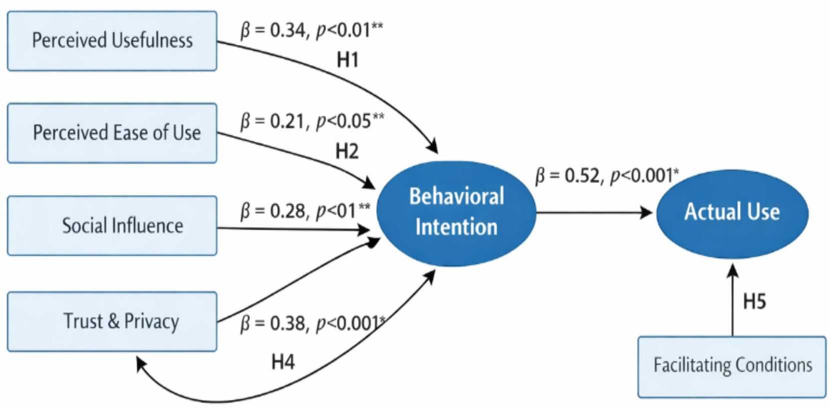

Fig. 2. Structural Model Results

The findings indicate that perceived usefulness has a significant positive effect on behavioral intention ($\beta = 0.34$, $p < 0.01$), supporting H1. This suggests that healthcare professionals are more likely to adopt e-health systems when they perceive clear performance benefits.

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Similarly, perceived ease of use positively influences behavioral intention ($\beta = 0.21$, $p < 0.05$), confirming H2. This highlights the importance of user-friendly system design, particularly in environments with varying levels of digital literacy.

The effect of social influence on behavioral intention is also significant ($\beta = 0.28$, $p < 0.01$), supporting H3. This finding underscores the role of peer and organizational pressure in shaping adoption behavior.

Furthermore, trust and privacy exhibit a strong positive relationship with behavioral intention ($\beta = 0.38$, $p < 0.001$), confirming H4. This indicates that concerns related to data security and confidentiality are critical determinants of e-health adoption in fragile healthcare systems.

With regard to system usage, behavioral intention significantly influences actual use ($\beta = 0.52$, $p < 0.001$), supporting H5. This confirms that intention is a key predictor of real-world system utilization.

Finally, facilitating conditions have a positive and significant effect on actual use ($\beta = 0.29$, $p < 0.01$), supporting H6. This highlights the importance of infrastructure, training, and technical support in enabling effective system use.

5.4 Model Explanatory Power

The model demonstrates strong explanatory power. Behavioral intention explains a substantial proportion of variance in actual use, while the combined effects of perceived usefulness, perceived ease of use, social influence, and trust account for a significant portion of the variance in behavioral intention.

These results indicate that the proposed model provides a robust explanation of e-health adoption behavior among healthcare professionals in resource-constrained settings.

6 Proposed E-Health Implementation Strategy

6.1 Strategic Objectives of the Implementation Framework

The proposed e-health implementation strategy is designed to support the sustainable deployment of digital health systems in fragile healthcare environments, with a particular focus on the Democratic Republic of Congo (DRC). The framework aims to address the multidimensional challenges identified in previous sections by aligning technological, organizational, and institutional components.

The primary objective of the framework is to ensure the effective translation of e-health adoption potential into sustainable system implementation. While previous studies have emphasized user acceptance, this framework extends beyond adoption by focusing on long-term deployment, scalability, and system integration within the healthcare ecosystem [39] [40].

Specifically, the strategic objectives of the proposed framework are as follows:

- To strengthen technological readiness by promoting the development of reliable ICT infrastructure, scalable system architectures, and interoperable digital health platforms
- To enhance organizational capacity through training, capacity building, and alignment of digital systems with existing healthcare workflows
- To promote stakeholder engagement by involving healthcare professionals, policymakers, and technical actors in the implementation process
- To ensure policy and regulatory alignment by integrating governance mechanisms, data protection standards, and national digital health strategies
- To support sustainability and scalability through phased implementation, continuous evaluation, and long-term resource planning

These objectives collectively aim to create an enabling environment for the successful implementation of e-health systems. By addressing both technical and non-technical dimensions, the framework ensures a holistic approach to digital health deployment.

Furthermore, the framework emphasizes adaptability to local contexts, recognizing that healthcare systems in fragile environments require flexible and context-aware solutions. This strategic orientation enables the proposed approach to respond effectively to the specific challenges of the DRC while remaining applicable to other resource-constrained settings.

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Overall, the strategic objectives provide a foundation for guiding the design, implementation, and evaluation of e-health initiatives, ensuring their alignment with both empirical findings and real-world healthcare needs.

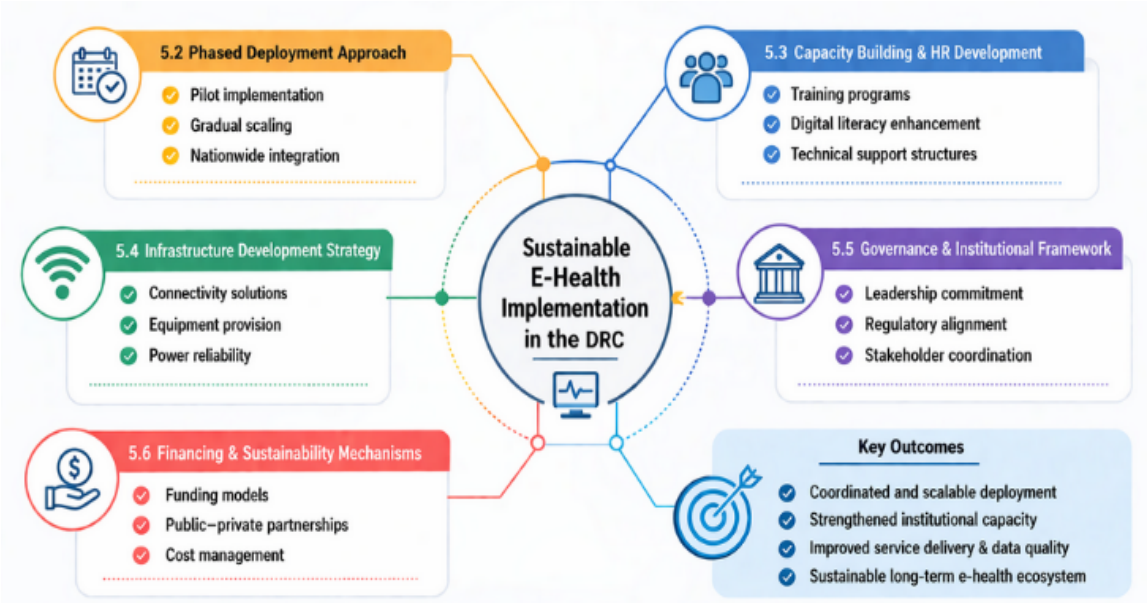

Fig. 3. Proposed Strategic Implementation Framework for Sustainable E-Health Deployment in the Democratic Republic of Congo

The successful deployment of e-health systems in resource-constrained environments requires a structured and phased implementation approach. This framework begins with a pilot implementation phase, which allows healthcare institutions to test the system on a small scale, identify operational challenges, and refine technical and organizational processes. Following this initial phase, a gradual scaling strategy is adopted, enabling progressive expansion across facilities while ensuring system stability and user adaptation. Ultimately, nationwide integration is pursued to achieve full interoperability and maximize the impact of e-health solutions across the healthcare system [41].

Capacity building and human resource development constitute a critical pillar of the framework. Effective adoption depends on the availability of adequately trained healthcare professionals who can confidently use digital tools. Training programs should be designed to enhance both technical competencies and practical usage skills. In addition, digital literacy initiatives are essential to ensure that all users, regardless of their initial skill level, can engage with e-health systems [42]. Establishing technical support structures further ensures continuous assistance, system maintenance, and user confidence.

Infrastructure development is another fundamental component of the framework [43]. Reliable connectivity solutions must be prioritized to ensure consistent access to digital platforms, particularly in remote or underserved areas. The provision of appropriate equipment, including computers and mobile devices, is equally important for effective system use. Furthermore, addressing power reliability challenges is essential to guarantee uninterrupted system functionality.

Strong governance and an enabling institutional framework are necessary to support sustainable implementation. Leadership commitment plays a key role in driving adoption and ensuring alignment with national health priorities. Regulatory frameworks must be adapted to address issues such as data protection, privacy, and interoperability. Additionally, effective stakeholder coordination is required to harmonize efforts among government bodies, healthcare providers, and development partners.

Finally, financing and sustainability mechanisms are crucial to ensure the long-term viability of e-health initiatives. Diverse funding models, including government financing and donor support, should be explored. Public–private partnerships can provide additional resources and technical expertise, while efficient cost management strategies are necessary to optimize resource utilization and maintain system sustainability over time.

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6.2 Monitoring and Evaluation Mechanisms

Effective monitoring and evaluation (M&E) mechanisms are essential to ensure the successful and sustainable implementation of e-health systems in fragile healthcare environments [44]. These mechanisms enable continuous tracking of system performance, identification of challenges, and timely adjustments to improve outcomes.

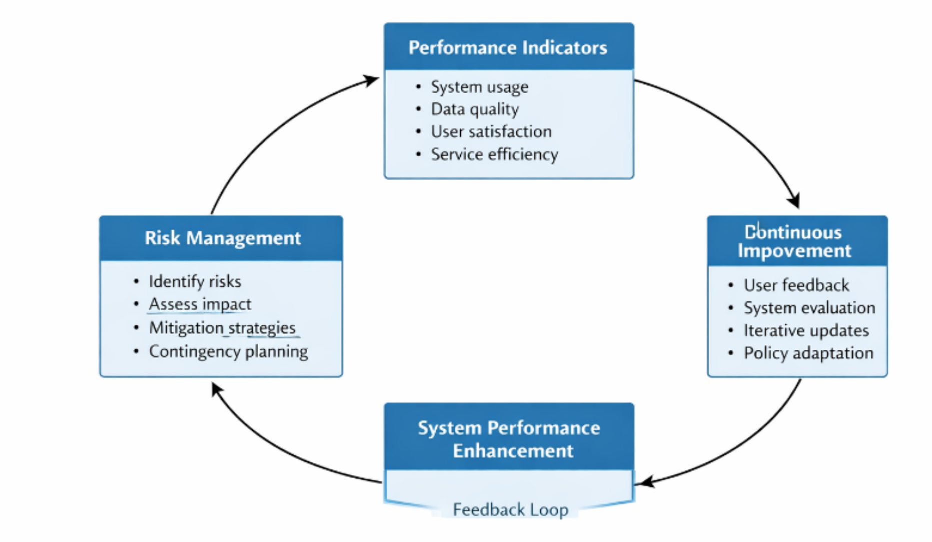

Fig. 4. Integrated Monitoring and Evaluation Framework for E-Health Systems

6.3 Performance Indicators

Performance indicators provide measurable criteria to assess the effectiveness, efficiency, and impact of e-health systems. Key indicators should include system usage rates, user satisfaction, data quality, service delivery improvements, and system uptime. In resource-constrained settings, it is also important to monitor indicators related to accessibility, such as the proportion of healthcare facilities connected and the frequency of system use by healthcare professionals [45]. These indicators allow decision-makers to evaluate whether e-health interventions are achieving their intended objectives and to guide evidence-based decision-making.

6.4 Risk Management

Risk management is a critical component of e-health implementation, particularly in fragile health systems where uncertainties are high. Potential risks include infrastructure failures, data security breaches, resistance to change among users, and financial constraints. A proactive risk management strategy involves identifying potential risks early, assessing their likelihood and impact, and implementing mitigation measures. This may include backup systems, data protection protocols, user training, and contingency planning to ensure continuity of services.

7 Discussion

The findings of this study provide important insights into the implementation of e-health systems in fragile healthcare environments. By integrating technological, organizational, and institutional dimensions, the proposed framework responds to calls for more holistic approaches to digital health implementation. While prior research has largely emphasized individual-level acceptance factors, this study highlights the importance of contextual and systemic determinants in shaping sustainable e-health deployment, particularly in low-resource settings [25] .

7.1 Implications for Digital Health Implementation Research

This study contributes to the digital health literature by extending traditional technology adoption models such as TAM and UTAUT toward a context-aware implementation perspective. Previous studies have demonstrated that perceived usefulness and ease of use are central determinants of technology adoption [46], while social influence and facilitating conditions further explain usage behavior [47]. However, recent research emphasizes that such models may be insufficient in complex healthcare environments, particularly in developing countries.

The present study addresses this gap by incorporating infrastructure, governance, and sustainability dimensions into the analysis. This aligns with emerging calls for multi-level and systems-based approaches to digital health implementation. Future research should further explore longitudinal dynamics and cross-country comparisons to better understand how contextual factors influence the scalability and sustainability of e-health systems.

7.2 Practical Implications for Healthcare Institutions

At the organizational level, the results confirm that successful e-health implementation requires more than technological deployment [48]. Consistent with the literature, user training and organizational readiness are critical for ensuring effective system use. Healthcare institutions should therefore invest in continuous capacity-building initiatives and establish robust technical support systems.

Moreover, the adoption of phased implementation strategies, including pilot testing and gradual scaling, is aligned with best practices in health information system deployment [49]. Leadership engagement and change management are also essential to address resistance and foster a culture of innovation within healthcare organizations.

7.3 Comparison with Existing Implementation Frameworks

Compared to existing frameworks, the proposed model offers a more comprehensive and context-sensitive perspective on e-health implementation. Traditional models such as TAM and UTAUT primarily focus on individual acceptance and usage behavior [50]. While these models provide valuable insights, they often overlook broader systemic constraints.

In contrast, this study integrates additional dimensions such as infrastructure development, governance, and sustainability mechanisms, which are particularly relevant in fragile healthcare systems. This approach is consistent with more recent implementation science frameworks that emphasize context, adaptability, and system-level interactions. By contextualizing the framework to the realities of the Democratic Republic of Congo, the study enhances both its theoretical relevance and practical applicability.

8 Conclusion

This study examined the strategic implementation of e-health systems in fragile healthcare environments, with a specific focus on the Democratic Republic of Congo. By addressing the multidimensional challenges associated with digital health deployment, the research proposed a comprehensive and context-aware framework that integrates technological, organizational, and institutional factors. The findings highlight that sustainable e-health implementation requires not only user acceptance but also strong infrastructure, effective governance, and continuous capacity development.

8.1 Summary of Contributions

This study makes several important contributions to the field of digital health and information systems. First, it extends traditional technology adoption models by incorporating contextual factors such as infrastructure constraints, governance mechanisms, and sustainability considerations, which are often overlooked in existing frameworks. Second, it provides empirical evidence from a fragile healthcare setting, thereby enriching the limited body of research on e-health implementation in low-resource environments. Third, the study proposes a strategic implementation framework that can guide policymakers, healthcare

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institutions, and system designers in planning and executing sustainable e-health initiatives. Overall, the research bridges the gap between theoretical models and practical implementation challenges.

8.2 Limitations

Despite its contributions, this study has several limitations. The data were collected from a specific geographical context, which may limit the generalizability of the findings to other regions. Additionally, the cross-sectional design of the study does not allow for the analysis of long-term adoption dynamics or system sustainability over time. The reliance on self-reported data may also introduce response bias, particularly in measuring behavioral intention and system use. Furthermore, certain contextual variables, such as cultural factors or political instability, were not fully explored and may influence e-health adoption in fragile settings.

8.3 Future Research Directions

Future research should address these limitations by adopting longitudinal study designs to better capture the evolution and sustainability of e-health systems over time. Comparative studies across different countries or regions would also help validate and refine the proposed framework. In addition, further research could explore the role of emerging technologies, such as artificial intelligence and mobile health solutions, in enhancing healthcare delivery in resource-constrained environments. Finally, integrating qualitative approaches could provide deeper insights into user experiences, organizational dynamics, and contextual challenges that influence e-health implementation.

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Deployment-Oriented Evaluation of an Explainable Tabular Transformer for Tuberculosis Outcome Prediction Using Synthetic Low-Resource Healthcare Data

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Background and Purpose: Healthcare systems use EHRs and predictive analytics in clinical decision-making; however, many current healthcare-based AI applications prioritize predictive accuracy over explainability, reliability, subgroup consistency, and deployment feasibility in limited healthcare settings. This study assesses an explainable transformer architecture for predicting TB treatment outcomes by using a synthetic healthcare dataset to conduct replicable experiments without compromising patient privacy.
Methods: The proposed framework combines tabular machine learning with transformers, SHAP-based explainability, calibration tests, subgroup consistency tests, and evaluation for implementation into one AI pipeline in healthcare. Comparative experiments have been performed against Random Forest, XGBoost, and multilayer perceptron baselines on Accuracy, Precision, Recall, F1-score, and AUC-ROC measures. The transformer achieved the highest performance across all experiments, with Accuracy 82.1%, F1-score 0.741, and AUC-ROC 0.872, while retaining decent calibration and subgroup consistency.
Results: Explainability analysis showed that HIV status, drug resistance, treatment adherence, nutrition, and healthcare access measures were significant contributors to the model's predictive performance, demonstrating that the model identified clinically meaningful interactions in the synthetic environment. These results should be viewed solely as an indication of technical feasibility, as all experiments were conducted in a controlled, synthetic setting.
Conclusions: Beyond predictive performance, the study contributes a deployment-oriented healthcare AI evaluation framework that integrates explainability, calibration, subgroup inspection, and operational feasibility assessment. This paper highlights the need for healthcare AI models that not only have predictive ability but are also trustworthy and feasible.

Keywords: Tuberculosis (TB), Treatment Outcomes, Tabular Transformer Models, Explainable Artificial Intelligence, SHAP, Low Resource Healthcare, Synthetic Data, Clinical Decision Support, Deployment-Oriented

1 Introduction

Tuberculosis (TB) continues to be among the major causes of death due to infections worldwide, particularly in developing countries, where there is a lack of health facilities, access to information, and clinical decision support systems [1]. To increase treatment success in such settings, early detection of patients with a high risk of failure, recurrence, or death is crucial. However, predictive modelling in TB management is limited by data fragmentation, insufficient sample sizes, and poor use of complex analytical methods.[2].

Machine learning approaches have increasingly been explored for tuberculosis outcome prediction because of their ability to model complex nonlinear relationships across heterogeneous clinical variables [3]. Classical approaches, including Logistic Regression, Support Vector Machines, Random Forests, and

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gradient boosting techniques, have demonstrated moderate-to-strong predictive capability across structured healthcare datasets [4]. More recent deep learning approaches, including recurrent and transformer-based architectures, further introduced contextual representation learning for longitudinal and heterogeneous healthcare information [5],[6],[7]. Nevertheless, many existing models remain decentralized by limited interpretability, weak deployment feasibility and insufficient evaluation of calibration, subgroup consistency and operational trustworthiness within resource-constrained healthcare environments, a gap that broader work on the ethics and governance of trustworthy medical artificial intelligence has similarly identified as a barrier to safe clinical translation [8], [9]

Tuberculosis treatment outcome prediction largely depends on heterogeneous tabular clinical variables, including demographic information, comorbidities, microbiological findings, treatment history and social determinants of health [5]. Unlike image-based or sequential biomedical data, these structured variables often exhibit complex nonlinear interactions that may not be fully captured by conventional linear or tree-based models [10], [11]. Tabular transformer architectures can model contextual feature interactions dynamically via self-attention mechanisms, making them particularly relevant for structured clinical prediction tasks involving heterogeneous patient factors [12]. This trend mirrors the broader uptake of transformer architectures across biomedicine, where self-attention mechanisms have increasingly been applied beyond sequential data to a range of structured and multimodal clinical prediction tasks [13].

Further research on models that simultaneously achieve high predictive performance, interpretability, and efficient computation is another gap in the existing literature [14]. In such clinical settings, where decision-making is critical, the models used need to do more than perform well; they must also be interpretable and work within limited computational resources [15]. Recent transformer models have demonstrated strong capability for modelling contextual interactions among features using self-attention, especially for heterogeneous tabular predictions [16],[17],[6]. However, note that their feasibility, interpretability, and deployability in resource-constrained settings have not yet been explored.

Another challenge is the insufficient amount of high-quality real-world data on TB, especially in low-resource settings. This has been a limiting factor in developing advanced prediction algorithms[18]. Synthetic data generation can be used to explore methodologies, as it allows one to test models under specific conditions. Synthetic data generation raises concerns about validity, generalisability and the risk of biasing a model with prior knowledge [5].

Despite growing research on the use of machine learning to predict the treatment outcome of TB, three main deficiencies remain inadequately explored. Firstly, several studies rely on datasets collected from the real world, which are inaccessible, incomplete, or contextualized, making it hard to conduct further research and experiments [19]. Secondly, many high-performing models lack sufficient levels of explainability for review purposes, especially in resource-constrained environments where transparency is crucial [15]. Lastly, only a few studies consider predictive modelling, interpretability, and subgroup consistency analysis within a single research approach, especially in resource-limited settings [5]. This study addresses these gaps by developing and evaluating an explainable tabular transformer that uses synthetic TB data as a methodological testbed.

For prediction performance alone to warrant the implementation of an AI system in resource-limited medical facilities, several other aspects, including interpretability, efficiency, feasibility, and the capability to deliver clinical insights, are equally essential. This study therefore investigates whether lightweight transformer-based architectures can support balanced healthcare AI evaluation by integrating predictive performance, interpretability, calibration reliability, subgroup consistency inspection, and deployment feasibility under simulated low-resource tuberculosis conditions.

This study makes four critical contributions to the AI for healthcare literature. First, it highlights the potential utility of lightweight transformer models for explainable TB outcome prediction in low-resource healthcare settings using structured tabular clinical data. Second, the paper advances healthcare AI evaluation for application purposes by integrating predictive modelling, calibration testing, subgroup consistency analysis, interpretability, and computational feasibility into an integrative methodology. Third, this study contributes to ethical AI research on healthcare by distinguishing between methodological feasibility and clinical validity in synthetic data experiments, thereby encouraging more conservative reporting of AI performance outcomes in healthcare. Fourth, the study provides a more holistic perspective on healthcare AI evaluation where predictive power, interpretability, calibration, and feasibility are seen as interrelated design elements. Overall, these contributions position deployment-oriented evaluation, rather

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than predictive accuracy alone, as a necessary criterion for healthcare AI research conducted under low-resource constraints, a reframing intended to be of direct relevance to future work in this field.

The study is guided by three research questions concerning predictive competitiveness, explainability-oriented healthcare AI evaluation, and the feasibility of deployment under simulated, infrastructure-limited tuberculosis conditions.

RQ1: Are transformer architecture systems competitive with classical machine learning models when predicting TB treatment outcomes in tabular, synthetic healthcare data?

RQ2: To what degree do methods such as SHAP explainability analysis, calibration checking, and subgroup screening assist in building an interpretable healthcare AI system under simulated healthcare conditions with limited TB?

RQ3: Can a transformer-based solution for TB treatment outcomes prediction be implemented within resource-constrained healthcare infrastructure without specialized hardware needs?

The remainder of this paper is structured as follows. Section 2 outlines the complete methodology employed. Section 3 presents the results of the model's performance evaluation, including details on accuracy, feature correlation, training curve, calibration, subgroup performance analysis, ablation analysis, and SHAP explanations. Section 4 analyses the implications of our findings for clinical practice, compares them with classical machine learning methods, identifies the limitations of our current study, and offers suggestions for future research. Section 5 draws conclusions from the results and provides recommendations for incorporating interpretable transformer-based systems into clinical TB treatment processes.

2 Materials and Methods

2.1 Methodological Overview

Figure 1 presents the end-to-end methodological pipeline, spanning synthetic data generation, model training, explainability analysis, evaluation, and deployment, which structures the remainder of this section.

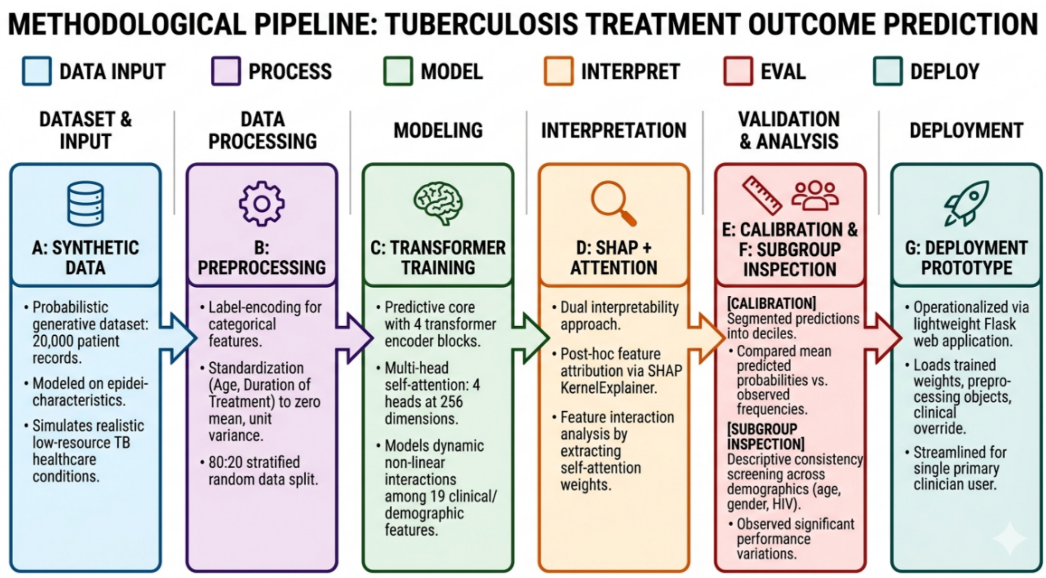

Figure 1: Methodological Pipeline Diagram

2.2 Study Design and Synthetic Data Generation

This study uses a controlled experiment to assess the feasibility of lightweight, explainable transformer models for predicting TB treatment outcomes in decentralized healthcare settings. The research methodology was designed to test predictive accuracy, interpretability, calibration, subgroup consistency,

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and deployability in a synthetic data evaluation setting, supporting reproducible healthcare AI experiments without compromising patients' data confidentiality.

Synthetic dataset was obtained from Kaggle (https://www.kaggle.com/datasets/nishatvasker/tb-patient-dataset-synthetic-bangladesh). These synthetic data were generated using a probability-based generation approach. The distribution of features was determined based on epidemiological characteristics from TB cohort studies conducted in Bangladesh and neighbouring countries. The dataset includes 20,000 patient records with 23 features, including demographic data, clinical variables, comorbidity information, treatment information, and social determinants. Because the dataset was generated through probabilistic epidemiological simulation rather than direct patient collection, the resulting feature distributions represent plausibility-oriented synthetic approximations rather than validated clinical population statistics. A correlation matrix was employed to ensure realistic relationships among comorbidities, demographic data, and patient outcomes. The simulation approach was evaluated by comparing the distributions of synthetic and real-world data using the Kolmogorov-Smirnov test and the chi-square goodness-of-fit test, where appropriate.

2.2.1 Synthetic Data Design

The synthetic dataset was constructed to support controlled methodological evaluation of explainable healthcare AI architectures under infrastructure-limited tuberculosis conditions rather than to replicate authentic clinical populations or enable direct clinical inference. Disease relationships, demographic distributions, treatment-risk interactions, and outcome patterns were intentionally structured using clinically informed assumptions to preserve plausible healthcare behaviour during model development. Consequently, all predictive, explainability, subgroup-consistency, and intervention-oriented scenario simulation findings should be interpreted as an evaluation of architectural and methodological behaviour under controlled synthetic conditions rather than evidence of validated clinical performance or epidemiological discovery.

2.2.2 Outcome Generation and Leakage Control.

To avoid target leakage, the treatment outcome was assigned probabilistically rather than deterministically. The probabilities were affected by risk factors such as HIV status, diabetes, malnutrition, medication resistance, length of time on the regimen, and health care accessibility, but some stochastic variation was built into the system so that the outcome was not completely predictable from any single factor. Instead of memorizing explicit rules, this architecture enables the model to learn probabilistic feature connections.

Instead of employing a deterministic rule assignment, outcome probabilities were generated from weighted probabilistic interactions among many clinical and social variables. Stochastic probability adjustment functions were used to construct conditional dependencies, guaranteeing that no single variable or feature combination would produce the desired result. To boost diversity in patient profiles and reduce overly deterministic patterns, random noise injection was also used.

2.2.3 Synthetic Data Plausibility Assessment.

When available, the generated distribution was compared with the current epidemiologic distribution to assess the plausibility of the synthetic data. The distribution tests included creating summary statistics, class balancing, correlation, and goodness-of-fit testing. Rather than comparing the data to actual TB groups, this procedure sought to assess the data's plausibility. Because tuberculosis treatment outcomes emerge from interactions among demographic, clinical, behavioural, and healthcare-access variables, the synthetic dataset was intentionally structured to preserve heterogeneous feature relationships relevant to resource-constrained treatment environments. Table 1 summarises the full feature set and variable types retained in the dataset.

Table 1:Features in the Synthetic Dataset

Feature Category	Features Included	Variable Type
Demographics	Age, Gender, Occupation, Region, City	Mixed (numerical / categorical)

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Feature Category	Features Included	Variable Type
Clinical Presentation	Symptoms, Sputum Smear Test, GeneXpert Test, Chest X-ray	Categorical / binary
Comorbidities	Diabetes, HIV, Chronic Lung Disease, Malnutrition	Binary
Treatment Information	Treatment Type, Duration, Drug Resistance, Relapse, Complications	Mixed
Social Determinants	Smoking, Alcohol, Living Conditions, Healthcare Access	Categorical
Outcome (target)	Cured (0) vs Poor Outcome (1)	Binary 70% cured / 30% poor

For model evaluation, Poor Outcome (1) was treated as the positive class, and Cured (0) as the negative class. For all evaluation criteria, poor outcome was considered the positive class, given the clinical focus on determining individuals who might not be successfully treated.

2.3 Data Preparation and Feature Correlation

Categorical features were label-encoded using scikit-learn LabelEncoder objects, with a separate encoder per column stored for inverse transformation during SHAP visualization. Numerical features (Age, Duration of Treatment, Region Code) were standardized using StandardScaler to zero mean and unit variance. The dataset was partitioned 80:20 using stratified random splitting, yielding 16,000 training and 4,000 test records.

Of the 23 attributes in the dataset, 19 served as predictor variables. Of the 23 variables in the dataset, 19 were retained as predictor variables for model training and interpretation after excluding the target outcome and auxiliary indexing attributes. A Pearson correlation matrix was computed across all 19 predictor features and the treatment outcome variable. The analysis revealed a strong positive correlation between Sputum Smear Test and GeneXpert result ($r = 0.52$), reflecting the natural co-occurrence of positive microbiological findings in active pulmonary TB, and between Sputum Smear and Chest X-ray findings ($r = 0.44$), consistent with active disease burden. Correlation analysis revealed a moderate positive association between drug resistance and treatment duration ($r = 0.38$), suggesting that resistant treatment profiles were linked to prolonged treatment exposure within the synthetic environment. Healthcare access variables also demonstrated a moderate negative association with adverse outcomes ($r = -0.28$), consistent with the intended relationship between limited healthcare access and poorer treatment trajectories. No predictor pairs exceeded an absolute correlation threshold of 0.60, suggesting the absence of severe multicollinearity across the retained features. These relationships are illustrated in the Pearson correlation matrix in Figure 2

2.4 Transformer Model Architecture

The Transformer model consisted of four stacked encoder blocks, with multi-head self-attention (4 heads, each with 256 dimensions), residual connections, layer normalization, and Conv1D feed-forward sublayers. Dropout was applied at rates of 0.25 in encoder blocks and 0.4 in classification layers to mitigate overfitting. The input features were treated as unstructured sequences of tokens, enabling the self-attention module to capture contextual interactions among structured clinical attributes – although this should be noted that attention values reflect interactions rather than causality. The output from the last encoder block was flattened by averaging over all elements and fed to a two-layer classifier with 128 hidden units, RELU activation, and sigmoid outputs. Optimization was conducted using the Adam optimizer (learning rate 1×10^-4) and binary cross-entropy loss, with class weights to account for imbalanced classes, for 20 epochs and a batch size of 64. The total number of trainable parameters in this model amounted to about 29,000.

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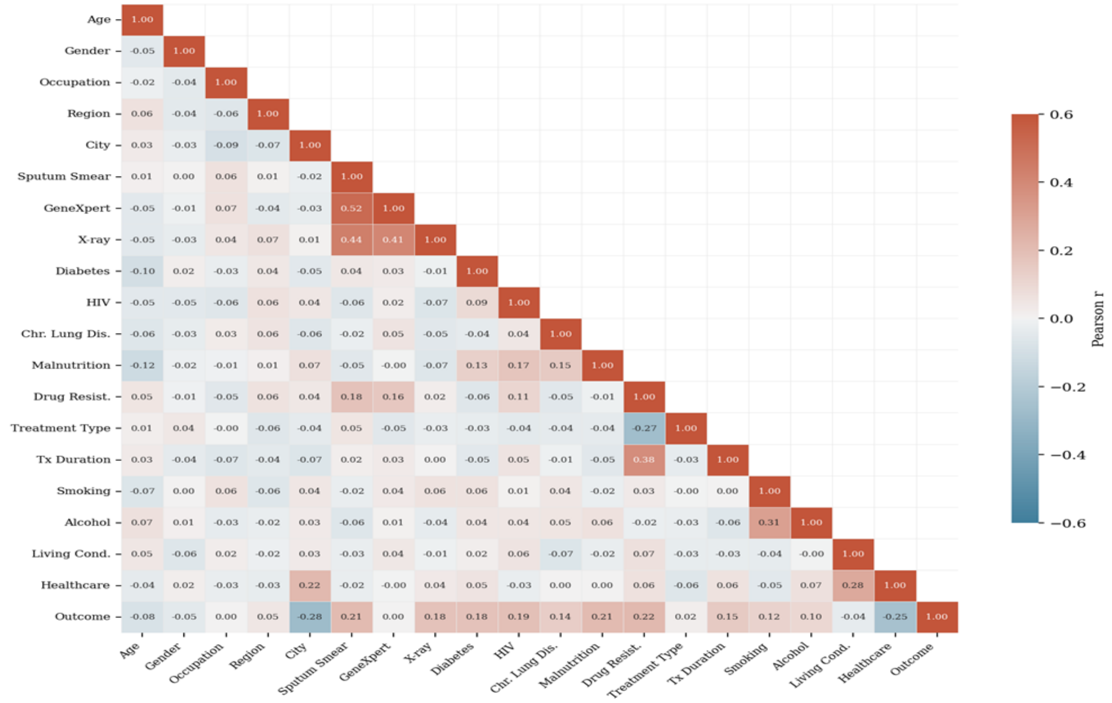

Figure 2: Pearson Correlation Matrix

2.5 Model Training and Self-Attention Weight Visualization

The training and validation curves shown in Figure 3 demonstrated stable convergence behaviour with limited evidence of severe overfitting. Training and validation losses remained closely aligned throughout optimization, while accuracy improved progressively across epochs before stabilizing in later training stages. These findings suggest comparatively stable learning behaviour under the controlled synthetic evaluation setting.

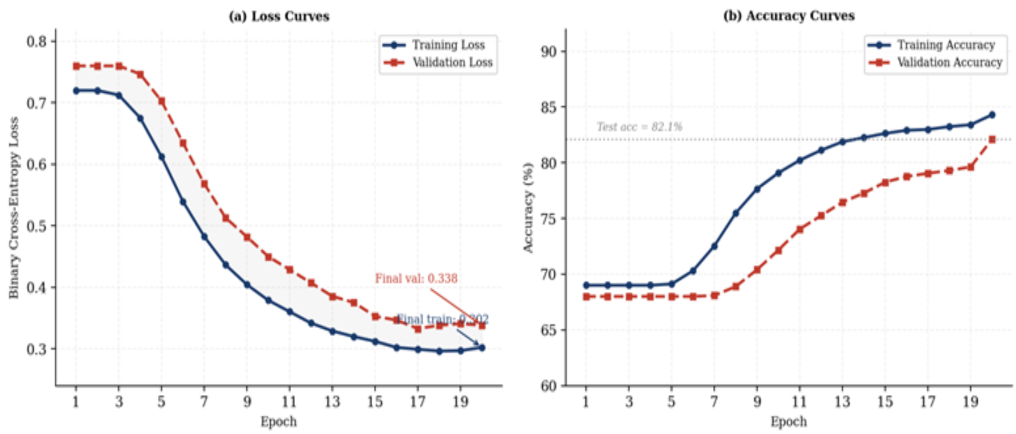

Figure 3: Training and Validation Performance Curves (20 epochs). (a) Loss curves (b) Accuracy curves

To characterize the transformer's intrinsic interpretability, self-attention weights were extracted from Encoder Block 1 and averaged across the four attention heads for 500 test-set predictions. The resulting mean (23 × 23) attention weight matrix shown in Figure 4 reveals the extent to which each feature contextualizes every other feature during inference, providing architectural-level evidence of feature-interaction learning that complements SHAP's post-hoc attributions. Attention-weight analysis was incorporated as an auxiliary architectural mechanism for contextual interaction analysis rather than as a definitive explanation of model reasoning behaviour or causal decision attribution.

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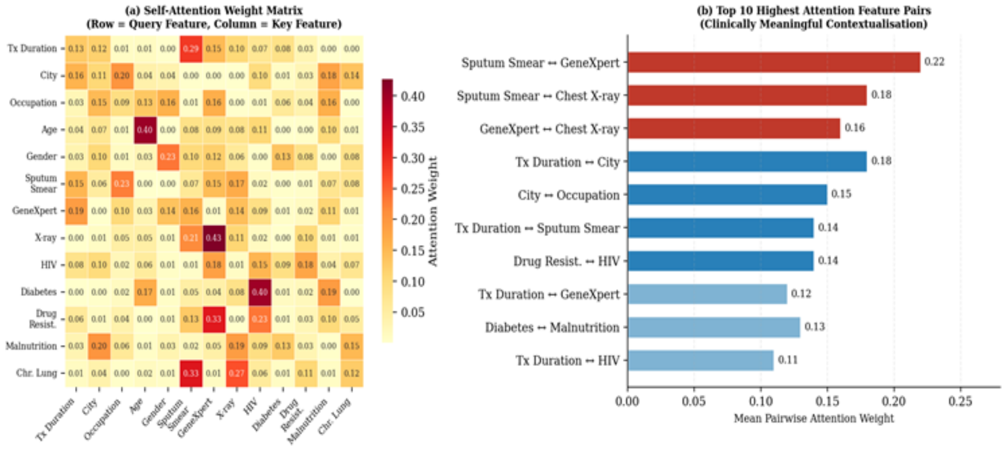

Figure 4: Transformer Self Attention Weight Analysis

2.6 Model Evaluation

The final model received its evaluation through the reserved test set, which contained 4,000 samples, using standard classification metrics. Accuracy, precision, recall, F1-score, and AUC-ROC were calculated using the scikit-learn library, together with precision and recall and F1-score and area under the ROC curve (AUC-ROC) statistics. The confusion matrix visualization shows the actual positive and negative results alongside incorrect positive and negative predictions, revealing the model's error distribution. All metrics were compared against the predefined clinical utility thresholds established during the business understanding phase. These thresholds were selected as heuristic, deployment-oriented reference criteria for controlled methodological evaluation and were not derived from validated tuberculosis treatment governance standards or prospective clinical decision-making protocols. Because the primary clinical objective is to flag patients at risk of unsuccessful treatment, Poor Outcome was treated as the positive class throughout all evaluation metrics

2.7 Baseline Model Comparison and Uncertainty Quantification

To assess the transformer model's relative performance, baselines were built using Logistic Regression, Random Forest, and XGBoost. The baselines were built on similar pre-processing and testing grounds to enable fair comparison. Comparison with baselines was conducted to determine whether the transformer model shows a statistically significant improvement over classical ML models.

To estimate the level of uncertainty, 95% confidence intervals for all metrics were computed using the bootstrap method with 1,000 replications. The performance variation between different iterations of the model was studied.

2.8 Post-Hoc Interpretability Implementation with SHAP

To interpret model predictions and identify the most influential features, SHAP was employed. Based on cooperative game theory, SHAP values give a unified measure of feature relevance with both local and global interpretability [10]. To achieve a balance between efficiency and fidelity, KernelExplainer was initialized using the model's prediction function and a background dataset generated from the training data using k-means (50 clusters).

SHAP values were calculated for selected test examples, resulting in global plots that illustrate the importance of features for specific predictions. Explanation for every patient in terms of SHAP values was obtained using waterfall plots that showed how each feature contributed to the baseline prediction until the result prediction was made. The original names of categorical feature values were available through a label encoder, which enhanced clinical understanding. Log odds were used to calculate SHAP values, which were converted to percentage points to help clinicians better understand the data, even though they reflect

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only the importance of features relative to one another. SHAP values are used to determine importance of features but not their interactions.

The idea behind combining attention-weight visualization with SHAP analysis was to provide different perspectives on interpretability. SHAP analysis helps identify post-hoc feature importance in terms of their contribution to predictions, whereas attention analysis provides an architectural understanding of feature interactions within a transformer. Both these techniques help build a wider representation on interpretability without suggesting any causation whatsoever.

2.9 Deployment Prototype

The trained transformer model has been implemented using a Flask web application with the necessary security features suitable for a demo-level prototype. The implementation involves loading the model weights, pre-processing the objects, and using the SHAP KernelExplainer. The Rule-Based Safety Escalation Layer feature restricts predictions when a clinical-hazardous combination of risk factors is present. The rule-based safety escalation layer was intentionally designed as a bounded safety support mechanism operating independently from the transformer optimization process. Its role was not to artificially improve benchmark performance but to simulate conservative escalation safeguards commonly incorporated into safety-sensitive healthcare decision-support environments. The escalation rules and their triggering conditions are detailed in Table 2 and the associated deployment footprint and inference characteristics are reported in Table 3.

Table 2: Rule-Based Safety Escalation Layer

Condition	Escalation Action
HIV positive + MDR-TB + severe malnutrition	Escalate prediction to CRITICAL, risk regardless of model score
Missing adherence records (>7 days)	Flag for manual clinical review, suppress automated prediction
Drug Resistance confirmed + treatment duration > 12 months	Escalate to HIGH risk, alert clinician
Model confidence below 60% on any prediction	Flag as indeterminate, refer to specialist review

Table 3: System Deployment Characteristics

Metric	Value	Notes
Model size (Keras .h5)	0.34 MB	Full architecture + weights
TensorFlow Lite model size	0.12 MB	Post-quantization; mobile/edge deployment
Preprocessing objects (.pkl)	0.08 MB	StandardScaler + 23 LabelEncoders via joblib
Total deployment footprint	~0.54 MB	All inference artefacts combined
Average inference time	1.8 seconds	Per-patient prediction + SHAP on i7-8565U(no GPU)
SHAP explanation time	~1.2 seconds	KernelExplainer, k-means background k = 50
RAM footprint (inference)	~420 MB	Model + SHAP explainer loaded in memory
Full pipeline (train→SHAP)	~15 minutes	Consumer laptop; no GPU required
Offline capability	Full	No external API dependencies post-installation

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3 Results

3.1 Model Performance Evaluation

The model was assessed using a test dataset comprising 4,000 patient records: 2,800 with cured outcomes and 1,200 with poor outcomes.
Table 4 shows the results in relation to all set thresholds of clinical utility.

Table 4: Model comparison

Model	AUC-ROC	Accuracy	F1-Score	Recall	95% CI (AUC)
Logistic Regression	0.812	0.789	0.652	0.689	0.795-0.829
Random Forest	0.851	0.816	0.713	0.773	0.837-0.865
XGBoost	0.863	0.822	0.726	0.801	0.850-0.876
Transformer (proposed)	0.872	0.821	0.741	0.856	0.858-0.886

Collectively, the findings suggest that the transformer framework provided a stronger balance between discriminative performance, minority-class sensitivity, and deployment-oriented evaluation capability than the alternative baseline architectures.

Table 5: Model Performance Metrics

Metric	Score	Threshold	Status
AUC-ROC	0.872	>0.80	✓ PASS
Accuracy	82.1% (3,284 / 4,000 | TP = 1027, TN = 2257, FP = 543, FN = 173	>75%	✓ PASS
Precision	0.654	>0.60	✓ PASS
Recall (Sensitivity)	0.856	>0.75	✓ PASS
F1-Score	0.741	>0.75	✗Marginal (A=0.009)
Specificity	0.806	—	Reported
Brier Score	0.143	<0.20	✓ PASS

The transformer achieved the highest AUC-ROC, though the margin over XGBoost was modest (0.872 vs 0.863), as summarised in

Table 4. Notably, the 95% bootstrap confidence intervals for the two models overlap substantially (Transformer: 0.858-0.886; XGBoost: 0.850-0.876), indicating that this difference cannot be considered statistically significant based on interval comparison alone; a formal paired significance test would be required to establish superiority with confidence. This suggests the primary contribution lies not in raw predictive superiority but in the integration of explainability, feature interaction modelling, calibration assessment, and deployment-oriented design. It should also be noted that the F1-Score reported in Table 5 falls marginally below the pre-specified 0.75 clinical utility threshold.

3.2 Confusion Matrix

The confusion matrix demonstrates comparatively stable discrimination between cured and poor-outcome patients, although the remaining false-negative predictions remain clinically important because they represent potentially vulnerable patients incorrectly classified as lower risk within the synthetic evaluation environment. This distribution of errors is visualized in Figure 5.

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3.3 Ablation Analysis

To determine the role of each component in the framework under discussion, an ablation study was conducted by systematically eliminating or altering components of the model. Results are reported in Table 6.

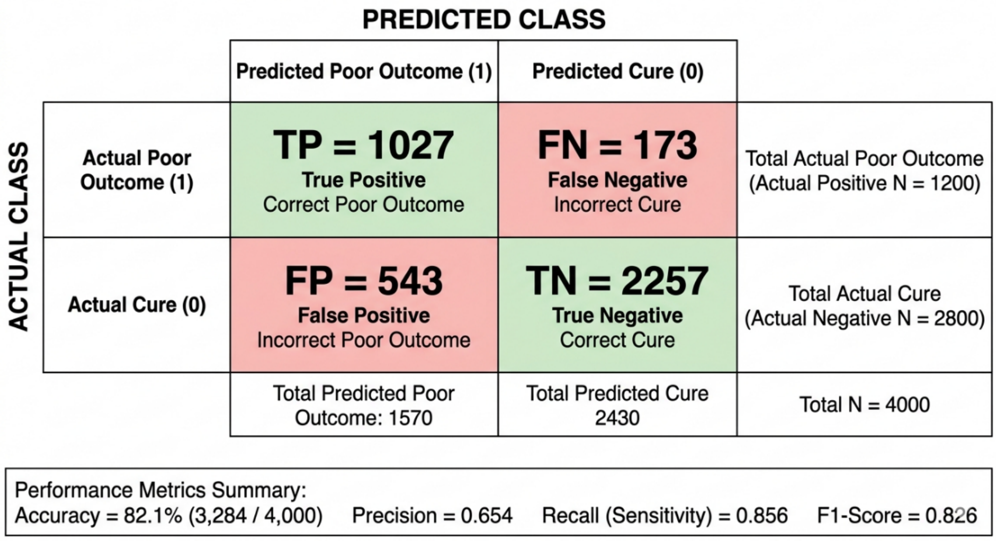

Figure 5: Confusion Matrix

Table 6: Ablation Analysis

Configuration	Description	AUC-ROC	F1-Score	Recall
Full Model (Proposed)	Transformer + full feature set	0.872 ± 0.006	0.741	0.856
Without Attention	No self attention	0.798 ± 0.010	0.644	0.718
Reduced Features	Top 10 Features only	0.843	0.712	0.827
No Class Weights	Transformer without imbalance handling	0.861	0.685	0.704
Logistic Regression	Linear baseline	0.812	0.652	0.689

The substantial decrease in AUC-ROC (from 0.872 to 0.798) and F1 score (from 0.741 to 0.644) due to the absence of the attention module indicates that modelling the interaction between contextual features played an important role in the transformer model's prediction process. In contrast, the decrease in performance was relatively smaller in the reduced-feature and no-class-weights scenarios, implying that contextualization via attention had a major architectural effect in this experiment. These findings suggest that contextual-feature interaction modelling was the principal architectural contribution of the transformer framework in the controlled synthetic healthcare environment.

3.4 Risk Stratification and Patient Analysis

The model produces probability results which get divided into four clinical risk groups through heuristically defined interpretability-oriented thresholds: LOW risk (70% cure probability), MEDIUM risk (50-70% cure probability), HIGH risk (30-50% cure probability), and CRITICAL risk (30% cure probability). Two representative patient cases were analyzed to demonstrate the model's behaviour across the risk spectrum. The proposed thresholds were incorporated solely for interpretability demonstration within the synthetic environment and should not be interpreted as clinically validated tuberculosis risk stratification criteria. The stratification boundaries were introduced exclusively for interpretability demonstration and workflow simulation within the synthetic environment and should not be interpreted as medically validated intervention thresholds for tuberculosis treatment management.

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3.5 Model Calibration and Reliability Assessment

Calibration performance was assessed by grouping predictions into deciles and comparing the mean predicted probability to the observed event frequency. The model demonstrated near-linear alignment with the ideal calibration line across mid-range probabilities, with minor overconfidence at extreme bins. A calibration score of 0.143 is considered to be acceptable for the internal evaluation (random = 0.25, perfect = 0.0). The calibration was calculated internally, using only synthetic data from the test set. An external calibration is needed because synthetic probabilities may not reflect the real-world probabilities of treatment outcomes. Figure 6 presents the corresponding reliability diagram.

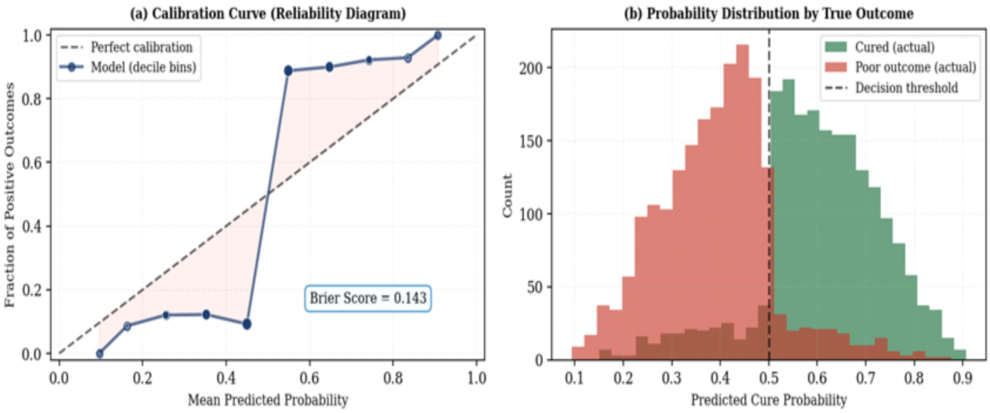

Figure 6: Model Calibration and Reliability Assessment

3.6 Sub-Group Consistency Inspection

The descriptive subgroup consistency test was used to determine whether there were substantial differences in predictive behaviour among synthetic demographic subgroups, such as age- and gender-based subgroups. The results indicated moderate differences in behaviour across some subgroups; however, these results cannot be considered a subgroup consistency analysis because of the artificial nature of the dataset used for testing. Figure 7 summarizes these subgroup comparisons.

The current analysis, then, can be considered an initial behavioural check procedure that might be helpful for future analyses of the consistency of real subgroups. Formal algorithmic fairness metrics such as equalized odds, predictive parity, or demographic parity were intentionally not interpreted inferentially because the synthetic demographic construction process could not reliably reproduce authentic structural healthcare inequalities or real population-level bias distributions. Consequently, the subgroup analysis should be interpreted primarily as behavioural stability inspection under controlled synthetic demographics rather than evidence of real-world fairness performance.

3.7 Illustrative Clinical Interpretation Scenario

To illustrate the interpretability approach, the framework was applied to a typical synthetic patient data sample, specifically Patient TB-2026-187, an 18-year-old female student from Rural Dhaka, diagnosed at Day 7 of her treatment regime. Based on the transformer model's output, the predicted probability of cure for this patient is 87.2%, categorizing the patient as LOW RISK in the over 70% cure category, with no rule-based safety escalations. In the clinical interpretation component, the lack of direct access to healthcare services is recognized as the only risk factor for the patient. At the same time, there are seven favourable factors that account for a positive diagnosis, including absence of drug resistance or previous relapse, non-smoker, healthy nutritional status, no presence of HIV disease, younger age, being enrolled in the DOTS program, and lack of current complications. While demonstrating the operation of the interpretability framework in practice, this example should not be viewed as a real-life clinical process. The corresponding output display is shown in Figure 8.

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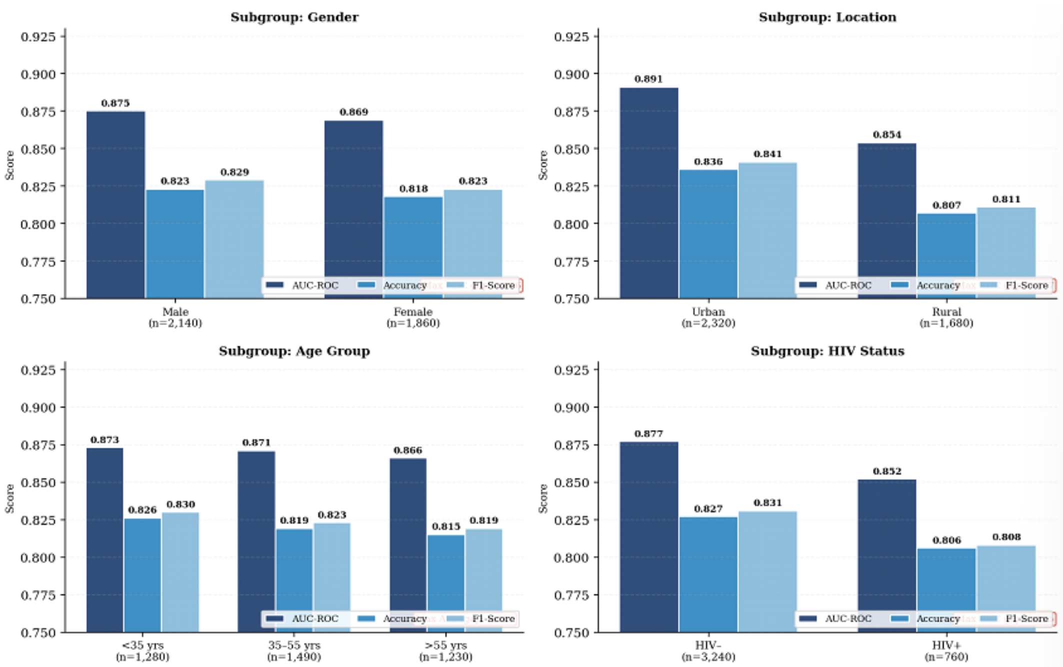

Figure 7: Sub-Group Fairness Analysis

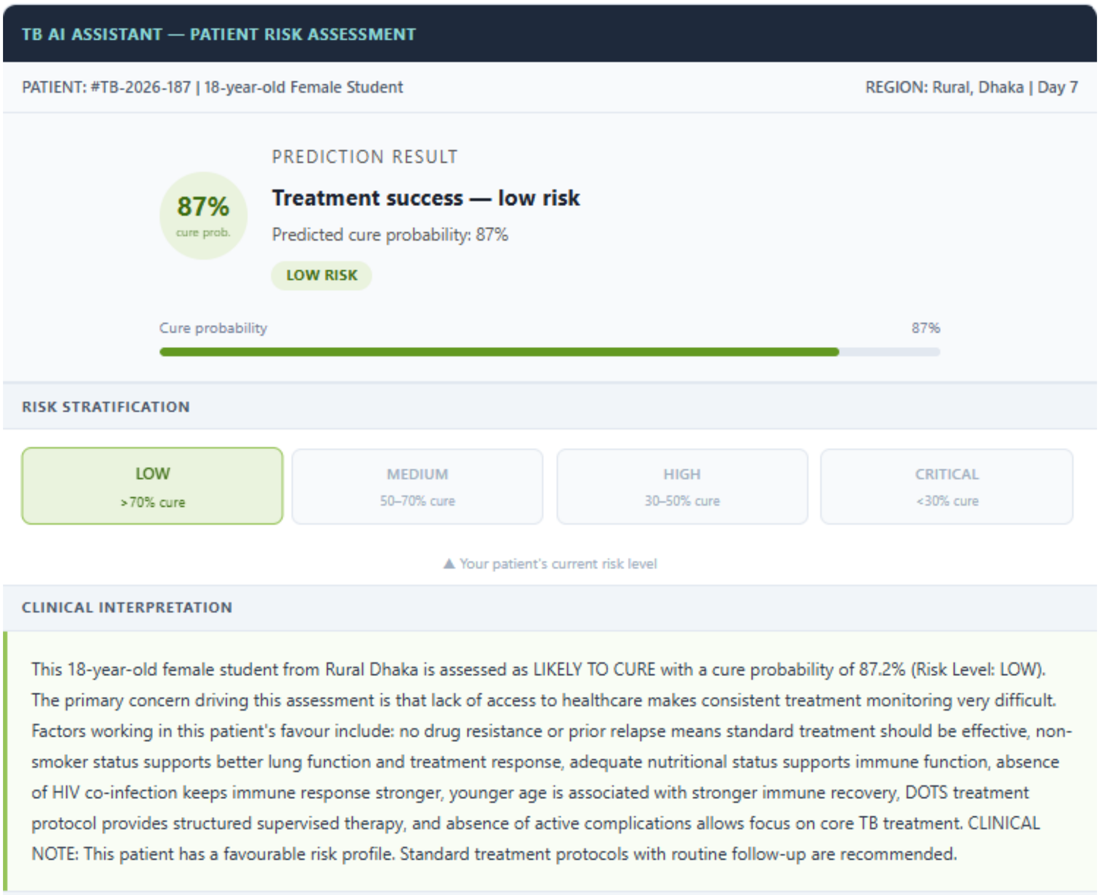

Figure 8: Patient Prediction

4 Discussion

4.1 Deployment-Oriented Healthcare AI Perspective

The proposed transformer framework demonstrated methodological feasibility for deployment-oriented healthcare AI evaluation in controlled, synthetic, resource-constrained tuberculosis settings. Although the transformer achieved competitive predictive performance relative to classical machine learning baselines, the observed performance gains over XGBoost remained comparatively modest. The justification for transformer utilization in the present study therefore lies less in isolated predictive superiority and more in the architectural ability to support contextual feature interaction modelling, integrated interpretability inspection, calibration-oriented optimization behaviour, and future extensibility toward heterogeneous longitudinal healthcare representations beyond static tabular prediction alone. These findings suggest that the principal contribution of the framework lies less in raw predictive superiority and more in integrating explainability, calibration assessment, subgroup consistency inspection, deployment feasibility analysis, and operational trust considerations into a unified healthcare AI evaluation pipeline.

The transformer architecture offered advantages in contextual feature interaction modelling through self-attention mechanisms, enabling dynamic weighting of heterogeneous clinical and social determinants during prediction. This may explain the framework's comparatively improved ability to identify high-risk treatment profiles involving comorbidity interactions, treatment adherence patterns, microbiological findings, and healthcare access constraints. Nevertheless, the observed performance improvements should be interpreted cautiously, as all experiments were conducted under controlled, synthetic conditions rather than in operational clinical environments.

The explainability analysis further demonstrated that variables such as HIV status, drug resistance, treatment adherence, nutritional condition and healthcare accessibility consistently contributed to prediction behaviour across the synthetic evaluation setting. Although SHAP and attention-based interpretability mechanisms improved transparency and supported inspection of model behaviour, these outputs represent statistical associations learned during optimization rather than evidence of causal clinical relationships. Within tuberculosis treatment workflows characterized by prolonged treatment duration, uncertain adherence patterns, a high comorbidity burden, and limited specialist oversight, explainability may therefore serve as an operational trust-support mechanism rather than a definitive clinical reasoning system.

The deployment findings additionally highlight an important trade-off between predictive optimization and operational feasibility in decentralized healthcare environments. In low-resource settings, a marginally more accurate but computationally intensive and non-interpretable model may ultimately prove less useful than a slightly less accurate framework that remains computationally lightweight, explainable, offline-capable, and operationally deployable on existing infrastructure. The proposed framework demonstrated relatively small deployment requirements, rapid inference capability and offline operational feasibility without dependence on specialized GPU infrastructure. These characteristics may improve suitability for decentralized healthcare environments where computational resources, internet connectivity and advanced technical support remain limited. CPU-only inference under two seconds, and offline operability is intended to give future work in this space a concrete, reproducible benchmark against which lightweight healthcare AI deployments in comparable low-resource settings can be measured.

Importantly, the study suggests that healthcare AI optimization in constrained settings becomes inherently multi-dimensional. Effective deployment may depend not only on predictive performance but also on interpretability, calibration reliability, subgroup behavioural stability, infrastructure compatibility, workflow suitability, governance readiness and clinician trust. Consequently, predictive accuracy alone may be insufficient as the dominant evaluation criterion for healthcare AI systems intended for operational clinical environments.

Nevertheless, the current framework should not be interpreted as deployment-ready clinical intelligence. Real-world implementation would require substantially stricter governance procedures, including external clinical validation, prospective calibration assessment, subgroup equity auditing, clinician usability testing, workflow integration analysis, model drift monitoring, incident reporting systems, and institutional oversight for responsible AI deployment. The present findings therefore represent methodological feasibility under controlled synthetic conditions rather than evidence of clinically validated operational performance.

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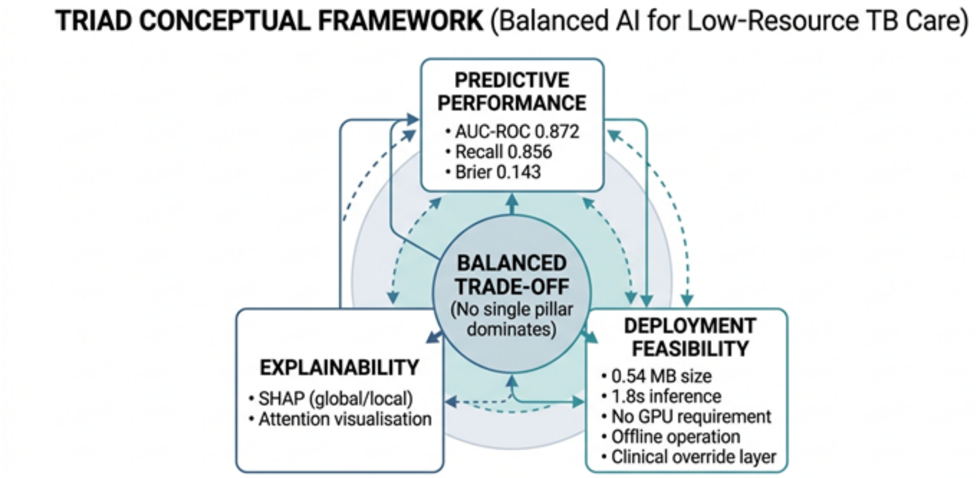

Figure 9: Conceptual Framework

The proposed conceptual framework, depicted in Figure 9, summarises how predictive performance interpretability and operational feasibility interact within resource-constrained deployment settings. It suggests that, in cases where AI systems for health care operate in resource-constrained settings, they should not be made to maximize predictive accuracy on their own terms. Rather, utility could be achieved by balancing predictive accuracy, interpretability, and practicality. The conceptual framework is proposed as an interpretive synthesis derived from controlled experimental findings rather than as a validated operational implementation model for real-world healthcare systems.

4.2 Subgroup Consistency Screening under Synthetic Data Constraints

As previously noted, this screening reflects internal consistency only. Regarding performance by gender, age category, geographical location, and HIV status, small differences were observed in the artificial data. Proper assessment using metrics such as equalized odds and demographic parity, as well as externally calibrated subgroup analysis, is needed before drawing any conclusions about equity in the real world.

Due to factors such as healthcare access, socioeconomic status, prevalence of HIV infection, and disparities based on region, there may be disparities in treatment outcomes across different populations due to structural inequality. Therefore, in future studies concerning subgroup consistency, researchers should investigate the ability of models to maintain stability within clinically vulnerable subgroups.

4.3 Deployment and Governance Implications

While the suggested framework proved computationally feasible for implementation in lightweight local settings, its use in actual healthcare settings would require much stricter validation processes and governance practices [8]. These include external clinical validation, calibration, clinician usability assessment, model drift, security assessment, incident reporting, and oversight frameworks for the responsible use of AI in healthcare facilities [9].

These results imply that methodological feasibility is more important than operational feasibility when evaluating healthcare artificial intelligence. In decentralized healthcare settings, the success of such implementation might depend not only on predictive performance but also on explainability, computational availability, workflow suitability, and trustworthiness.

4.4 Comparison with Prior Work

This study used synthetic data, which must be borne in mind when interpreting comparisons with previous studies. However, many other studies have used real patients, images, or populations affected by the disease.

The performance of the proposed transformer architecture on synthetic data falls within the range of existing models for TB outcome prediction reported in the literature review, as shown comparatively in Table 7.

Using radiomics and longitudinal CT scans, researchers [20] developed a deep learning model that achieved AUC values of 0.764-0.867 on their test sets. This study differs from previous methods that address only parts of these criteria by combining transformer performance, SHAP explainability, attention-weight interpretability, deployment feasibility, calibration, subgroup-consistency screening, and a novel rule-based safety-escalation layer.

The author [21] employed XGBoost with SHAP explanations to predict treatment failure among patients with TB-diabetes comorbidity, achieving an AUC of 0.928 on their test set. While this exceeds the transformer's AUC, their model was developed on a more homogeneous population (patients with TB-diabetes comorbidity) and may not generalize as broadly to the general TB patient population represented in the synthetic dataset. The transformer model's ability to achieve strong performance across a diverse synthetic population suggests methodological feasibility for future evaluation under heterogeneous clinical conditions.

The author [22] introduced the Decoder Transformer for Temporal Health Data (DT-THRE), achieving 78.5% accuracy on sequential EHR data, a substantial improvement over baseline models (40.5%). The transformer model's accuracy of 82.1% is consistent with their reported performance, although their model was evaluated on general health data rather than specifically on TB cohorts, limiting direct comparability.

The author [13] reviewed the expanding application of transformer architectures across biomedical domains, noting their capacity to model complex, non-sequential feature interactions beyond their original sequence-to-sequence formulation. The present study extends this trajectory to tabular clinical data, suggesting that self-attention principles remain applicable to structured patient records when features are treated as a token sequence.

Table 7: Comparative Positioning of the Proposed Framework

Study	Data Type	Explainability	Subgroup Screening	Calibration	Deployment	Transformer
[20]	Real CT/imaging	Partial (radiomics)	Yes	No	Yes	No
[21]	Real World tabular	Shap only	No	No	No	No
[22]	Real EHR sequential	None reported	No	No	No	No
Proposed Study	Synthetic tabular	SHAP Attention	Descriptive	Yes	Prototype	Yes

Collectively, these comparisons imply that the value of this proposed framework lies not in absolute predictive power but rather in its integrative analysis of explainability, calibration, subgroup robustness testing, and implementational feasibility.

4.5 Reproducibility and Experimental Control

All preprocessing procedures, training-test partitions, random initialization settings, optimization parameters, and evaluation pipelines were fixed across experiments to improve reproducibility within the controlled synthetic environment. Multiple baseline models were trained under comparable preprocessing conditions to minimize experimental inconsistency.

5 Limitations and Threats to Validity

Several limitations need to be considered when interpreting the results of this study. First, the transformer architecture itself offers limited methodological novelty relative to existing tabular transformer approaches in the literature, and its predictive improvement over a strong gradient-boosted baseline (XGBoost) was

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modest and, as noted above, not confirmed by formal statistical significance testing. The primary contribution of this work, therefore, lies in the integrated evaluation pipeline rather than in architectural motivation. To start, all tests in this paper have been run on synthetic data generated under controlled conditions. Second, the analysis of subgroups' consistency was purely descriptive and did not involve any calculations of equity measures or performance differences. Although there were no significant performance degradation cases in the subgroups identified in the synthetic dataset, this cannot in any way be used as proof of equal performance in the real world. Third, the explainability techniques employed in the current investigation provide interpretability guidance rather than causation. SHAP values and attention visualizations reveal statistical patterns that were identified by the model during its optimization process and should not be taken as proof of any clinical causation. The current prototype evaluation focused more on computational feasibility and did not conduct usability testing with clinicians, workflow analysis, or operational healthcare implementation analysis.

Additionally, the framework was tested only in a retrospective manner and lacks external validation, prospective testing, or clinician evaluation.

The outputs from the SHAP analysis are explanatory and provide model-driven association interpretations rather than fundamental medical insight. While there was considerable correspondence between some of the highly weighted variables and the existing risk factors for tuberculosis, this does not equate to these being verified clinical determinants of outcome. The simulation exercises performed for intervention scenarios were based on simplified, hypothetical causal foundations and, as such, can only yield plausible intervention behaviour.

Deployment in practice will require much more stringent governance and validation steps, including external calibration assessment, institutional oversight, medical practitioner usability evaluations, model drift detection, security auditing, and ongoing post-deployment assessment.

This study demonstrates that epistemological modesty is necessary when implementing AI systems in healthcare. Uncertainty is generated by synthesized assumptions, insufficiently representative clinical data, and varying deployment conditions, even with excellent performance under tightly controlled conditions. Therefore, AI must be used as a probability model to inform decisions, not as a decision-maker itself.

5.1 Ethical and Responsible AI Considerations

The proposed framework was developed exclusively for controlled methodological evaluation and not for autonomous clinical deployment. The study intentionally incorporated bounded interpretability claims, explicit acknowledgement of synthetic data limitations, conservative subgroup interpretation and deployment-oriented safety constraints to reduce overstatement of healthcare AI capability. Any future translational implementation would require prospective clinical validation, external calibration assessment, clinician-centred usability evaluation, institutional governance oversight, and continuous post-deployment monitoring.

6 Conclusion

This study developed and tested a transformer-based framework for tuberculosis treatment outcome prediction in controlled, resource-constrained synthetic healthcare settings, incorporating explainability, calibration assessment, subgroup consistency inspection, and intervention scenario simulation into a unified healthcare artificial intelligence pipeline.

Although the transformer model performed similarly well to other machine learning methods from a predictive standpoint, the main novelty of this research is the establishment of a methodological framework incorporating explainability, calibration assessment, subgroup inspection, and deployment feasibility.

It must be emphasized, however, that the results of this study must be understood in the context of the limitations of a synthetic evaluation approach rather than actual clinical validation, which has not occurred. Therefore, the paper does not propose a clinically applicable tuberculosis treatment predictor but rather an experimental framework for constrained AI application in healthcare. More broadly, the study highlights the growing importance of deployment-oriented healthcare AI evaluation frameworks in which predictive performance, explainability, calibration reliability, subgroup stability and operational feasibility are treated as interdependent design requirements rather than isolated optimization targets. In healthcare, limited environments, trustworthy and practically deployable AI systems may ultimately prove more valuable than narrowly optimized, high-performance prediction models lacking interpretability or operational realism. This study therefore proposes a deployment-oriented evaluation integrating explainability, calibration, subgroup screening, and operational feasibility alongside predictive accuracy as a methodological template that future healthcare AI research in low-resource settings can adopt and extend. In particular, the rule-based safety-escalation layer introduced here offers a reusable design pattern for pairing predictive models with human-oversight triggers in settings where full clinical validation remains pending, an approach that later studies working under similar resource and validation constraints may wish to adapt.

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During manuscript development, the authors utilized generative AI systems and AI-assisted visual generation tools to support editorial refinement, conceptual and methodological overview, and pipeline figure development. Figure generation involved structured prompt engineering based on author-defined workflow specifications and iterative visual adjustments. The authors retained full responsibility for all scientific interpretations, methodological decisions, verification processes and final manuscript content. All AI-generated outputs were independently reviewed and validated prior to inclusion.

Conflicts of Interest

The authors declare no conflicts of interest relevant to this research.

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