Journal of Health Informatics in Africa

Volume 12 (2025) Issue 1

Eds: Nicky Mostert, Ulrich Kemloh

Published by Koegni-eHealth Innovation for Development
ISSN: 2197-6902
DOI: 10.12856/JHIA-2025-v12-i1

Published in the Journal of Health Informatics in Africa
Volume 12 (2025) Issue 1

ISSN: 2197-6902
ISSN/NLM abbreviation: J Health Inform Afr
DOI: http://dx.doi.org/10.12856/JHIA-2025-v12-i1

Publisher
Koegni eHealth, Innovation for Development e.V. Germany
Postfach 652166
D-22372 Hamburg, Germany
www.koegni-ehealth.org
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Editorial to JHIA Vol. 12 (2025) Issue 1

Nicky Mostert

Nelson Mandela University, Port Elizabeth, South Africa

The Journal of Health Informatics in Africa (JHIA) is dedicated to publishing innovative, high-quality research that explores the use of information and communication technologies (ICTs) to address healthcare challenges in Africa.

To maintain the journal's integrity and commitment to originality, all submissions undergo a meticulous screening process. As part of this process, a Turnitin report is generated for each manuscript before it is assigned to reviewers. Only submissions with a Turnitin similarity index below 15% are considered for review. Manuscripts exceeding this threshold are promptly rejected. We urge authors to ensure their work is both original and unpublished prior to submission.

Once a manuscript qualifies for review, it is subjected to a rigorous double-blind peer review process. This review determines whether the submission will be accepted, revised, or rejected. For manuscripts that are accepted, a second round of peer review is often required. Authors must carefully address the reviewers' feedback and resubmit their revised manuscript for further evaluation. Final acceptance is granted only when both the reviewers and the editorial team are fully satisfied with the revisions, ensuring the publication of work that meets the highest scholarly standards.

This issue features six insightful papers:

- Chumba, Waema, and Ochieng conducted a scoping review of 29 studies on Health Information Technology governance, highlighting its mechanisms, applications in hospital and national healthcare systems, and identifying gaps in community-level governance and alignment practices.
- Ssegujja, Msanjila, and Shao conducted a systematic literature review to evaluate frameworks for maternal e-service delivery in resource-constrained settings, highlighting limitations in current approaches, such as reliance on traditional methods, and proposing a conceptual framework to enhance maternal healthcare through technology-driven solutions.
- Ogundare demonstrated that tree-based machine learning models, particularly random forest and bagging classifiers, outperform non-tree-based algorithms in accurately subtyping renal cell carcinoma using RNA-seq gene expression data, highlighting their potential for improving personalized cancer treatment.
- Mwesigwa, Nakibuuka, Wanyana, Waiswa, Serubugo, and Tumwesigye evaluated the usability of a DHIS2-based cancer reporting system at Mbarara Regional Referral Hospital, finding it improved access to comprehensive cancer data with a high usability score, and recommending its scale-up to other regional hospitals.
- Gokula Chandar, Shanmugam, Vijayakumar, Sugumaran, Senthil, and Srinivasulu and Lakshmi developed a Smart Medical System using LoRaWAN and ESP32 microcontrollers to securely monitor and transmit encrypted health data in real-time, enabling remote access and efficient alerts for caregivers and doctors.
- Boateng, Agyapong, Dorson, Avuglah, and Nigre utilized a Random Forest model to predict malaria outbreaks in Ghanaian children under five, achieving strong accuracy while identifying regional disparities and emphasizing the potential of machine learning for targeted public health interventions.

I extend my heartfelt thanks to the editorial team, authors, and peer reviewers for their unwavering dedication and efforts in bringing this issue to fruition. I also invite health informatics researchers to connect with me regarding opportunities to join JHIA's esteemed panel of reviewers. Your expertise and insights are vital in upholding the rigorous standards and excellence that define the research published in our journal.

Thank you for your continued support of JHIA.

Nicky Mostert
June 2025

Journal of Health Informatics in Africa

Health Information Technology Governance: A Scoping Review of Literature

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Purpose: The scope of this review is aimed at mapping the existing literature on Health Information Technology (HIT) Governance and pointing out the existing knowledge gap(s).
Design/methodology/approach: The investigation was conducted using a scoping review methodology. Existing literature on this area of study charts the nature and content by summarising existing evidence on HIT governance. Searches were conducted in four databases: PubMed, ScienceDirect, ACM Digital Library, and IEEE Xplore databases for literature published between 1st January 2000 and 31st December 2023.
Findings: A total of twenty-five (29) articles met the search criteria and were included in this review. The findings indicated that HIT governance is operationalised through governance mechanisms and their context-specific practices. In addition, HIT governance is mainly applied in systems that are functional at the hospital and national levels of healthcare, as well as those that facilitate health information exchange, data governance, and health information governance. Governance of HIT systems that are functional at the community healthcare level have received little research attention. Furthermore, the alignment aspect has not been addressed in the reviewed literature, yet it is an essential aspect of HIT governance.
Research limitations: A significant constraint of this review is the limited scope of literature searches conducted exclusively in four databases.
Practical implications: This study contributes to the theoretical understanding of HIT governance in HIT implementation and use.
Originality/value: This study covers the governance of HIT integrations and applications by investigating how it is achieved. This is done to shape further research agenda.

Keywords: Health Information Technology, Health Information Systems, Governance

1 Introduction

In most developing countries, the healthcare sector is organised in levels such as the national, sub-national and community levels. Kenya is one of the developing countries where the healthcare sector is divided into distinctive levels namely: national referral hospitals, county and sub-county hospitals, primary healthcare facilities and the community healthcare levels. The overall leadership and governance of health lies with the Ministry of Health (MoH). At the sub-national levels, governance of healthcare lies with the County Health Management Team (CHMT), the Sub-County Health Management Team (S-CHMT), and the Facility Health Management Team (FHMT). Community Health Committees (CHCs) act as the leadership and governance body at the community level. The responsibility of each of these bodies is to facilitate the strengthening of health systems. Information Technology (IT) integration plays a crucial role in this endeavour.

Information Technology has become a crucial enabler in every sector of the economy [1]. It facilitates efficient and effective service delivery in different industries. Among them is the healthcare sector, which has also experienced a significant increase in the adoption and use of Health Information Technology (HIT) across the globe [2] [3]. Different Health IT integrations have been rolled out in different levels of healthcare to support and facilitate health service delivery. HIT encompasses various technologies and applications such as computer and electronic communication systems that collect, analyse, manage, store, and exchange health-related information. Examples of HITs include Electronic Health Records (EHRs), Electronic Medical Records (EMRs), Health Information Exchange (HIE), Telemedicine and Telehealth, Mobile Health (mHealth), Healthcare Analytics, Health Information Systems (HIS),

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Health Information Management Systems (HIMS), Healthcare Interoperability, Clinical Decision Support Systems (CDSS), Patient Portals, among others [4] [5] [6] [7] [8] [3] [9] [10].

Several opportunities and benefits are associated with the adoption and use of HIT in developing countries. These benefits include improving patient care, reducing medical errors, enhancing care coordination, increasing the efficiency of healthcare processes, better management of patient data, improving communication among care teams, improving service quality, operational efficiency, and patient satisfaction, among others [11] [12]. Whereas the different governance bodies are required to strengthen health service delivery, governance of the different HIT integrations is also necessary to facilitate HIT performance and to improve health outcomes.

1.1 Rationale of the study

Despite literature on Information Systems (IS) revealing the benefits as well as the associated opportunities in HIT integrations, especially in developing countries, there is limited performance and sub-optimal value derivation seen from HIT investments [13] [14] [15] [16] [17] [18] [19]. Existing literature reveals that over 50% of EHR systems (an example of HITs) either fail or are inadequately utilised [20]. Similarly, [21] postulated that HIT activities exhibit a failure rate of up to 70%, leading to negative and unintended consequences. According to [21], project delay, cost overrun, failure to meet the intended goal, and complete project abandonment are some of the noted failures.

To avoid these failures and get an optimum performance and value derived from HITs, several interventions, including HIT governance, need to be addressed [22] [23] [2] [24] [25] [26]. Effective HIT governance is essential for ensuring successful HIT integrations and the smooth functioning of HIT systems [27] [26]. Furthermore, HIT governance facilitates positive health outcomes [22] [23] [2] [26], and consequently, a proper functioning of the health system [28] [29] [30] [2] [26].

The primary objectives of this review are (1) to examine how Health Information Technology governance is discussed in the existing literature and (2) to identify Health Information Technology governance knowledge gap(s) that exist in the literature.

Two research questions guided the review:

RQ1. Which Health Information Technology governance mechanisms and associated practices operationalise HIT governance in the existing literature?

RQ2. What are the Health Information Technology governance knowledge gaps in the literature?

While acknowledging that HIT governance and associated practices are context-specific and what may apply to one healthcare level and organisation may not be generalised in other healthcare levels and organisations. This review presents a theoretical understanding of how HIT governance has been addressed in the existing Information Systems (IS) literature in order to benefit academia. In addition, this review seeks to benefit IS practitioners by providing clarity on HIT governance mechanisms and practices that can be designed and implemented for different HIT integrations and applications. Furthermore, the results of this review may have policy implications that can inform the development of HIT governance policy.

1.2 Health Information Technology (HIT) Governance

IT Governance has been defined differently by many authors. As laid out by the IT Governance Institute (ITGI), IT Governance is a set of governance approaches rooted in organisational structures, leadership, processes, and relational mechanisms. According to [31], IT governance is the capacity of the board, executive, and information technology management to effectively guide the development and execution of IT strategy, thus assuring the integration of business and IT. [32] defined IT governance as establishing a framework that determines decision-making authority and accountability to promote desired behaviour in the utilisation of IT.

Three fundamental principles of IT governance arise from these definitions. These principles are executive-level participation, integrating business and IT plans to achieve optimal performance, and implementing risk mitigation techniques concerning the chosen IT strategy. The fundamental concept is to enable organisations to establish IT alignment, allowing them to accomplish their strategic objectives. IT governance assesses the level of synchronization and benefits obtained from IT investments and resources. The more the organisation can effectively and efficiently utilise its IT resources, the better the level of organisational success in achieving its goals and objectives.

Like other sectors, IT in healthcare (digital health) has become pervasive and indispensable. Therefore, governance of such digital health solutions and applications is critical in determining how and when to harness digital health solutions. This is done to improve accessibility, quality, and affordability for the health system, and generally to improve health outcomes [33] [34] [27] [2] [35] [26]. Health IT governance refers to structures, processes, relational mechanisms, and associated practices that ensure health IT supports, extends and sustains the realisation of the healthcare mission, vision, objectives and goals. On this basis, the governance of health IT cannot be overlooked.

As stated earlier, health IT governance practices are contextual and cannot be generalised, and this fact should not be overlooked when implementing HIT. The lack of generalisability of such practices is more apparent in the healthcare sector, which is multi-level characterised by many stakeholders. For instance, some HITs are functional at the national healthcare level, at the sub-national levels, hospitals, and at the dispensaries, clinics, and community levels. As such, governance practices for all these HITs cannot be generalised. For example, governance practices for HITs functioning at the hospital level differ from those at the community level. [36] [37] posited that every organisation calls for context-specific IT governance mechanisms and associated practices. While affirming this argument, [38] argued that a high-level IT governance model cannot be applied across all sectors and produce similar results.

These arguments show that mapping the body of knowledge on HIT governance is necessary. The research studies included in our scoping review examined the governance of different Health Information Technologies (HITs), such as Electronic Health Records (EHRs), community-driven health information technology, Health Information Exchange (HIE), Personal Health Records (PHRs), MEGAHIT System, Computerized Provider Order Entry (CPOE), data warehouse, virtual data warehouse, among others. Nevertheless, of interest to this study was the extent to which HIT governance was discussed in the existing literature and how it is accomplished. Examining the level of discussion on HIT governance in the current literature was essential as IT professionals, academics, and policymakers need to understand how to regulate HIT applications and solutions in the healthcare industry. Our approach provides valuable insights for these professionals and informs policy interventions.

2 Materials and Methods

2.1 Selection of the scoping review method

The investigation was conducted using a scoping review methodology. This approach is driven by the overarching objective of the study, which is to systematically document the current understanding of HIT governance. Scoping reviews, as described by [39] [40], is a method of synthesizing information aimed at methodically discovering and categorising a wide variety of data on a specific topic, field, concept, or concern. It includes utilising primary research, reviews, and non-empirical evidence without regard to their source or the particular contexts in which they are found. The aim is to identify deficiencies in the research knowledge base, elucidate fundamental concepts, record and categorise the various relevant evidence forms and provide guidance for further research agenda [41]. [39] contended that the selection of the review is kind of contingent upon the inquiries posed by the researchers and the objectives of their review. Systematic reviews are well-suited for endeavours that attempt to assess the suitability or effectiveness of a given practice.

Similarly, scoping reviews are good for investigations that intend to identify specific concepts for mapping, reporting, or discussing them [42] [39]. A scoping review approach was chosen based on the study's objectives, which sought to examine how HIT has been addressed in the literature and point out the existing knowledge gaps. Before conducting the review, the study group formulated a protocol.

2.2 Information sources

A scoping review was conducted to map the existing body of literature from January 2000 to December 2023. The review focused on peer-reviewed articles from four databases: PubMed, ScienceDirect, ACM Digital Library and IEEE Xplore. The search was designed for “specificity” using "Health information technology" and "governance" search terms. The search was also limited to peer-reviewed articles published in English. Table 1 presents the four databases searched and the search terms utilised.

2.3 Eligibility criteria

The studies included in the review met the specified criteria for inclusion. The articles focused on three main aspects: (1) HIT governance, (2) publications from January 2000 to December 2023, and (3) addressing HIT governance mechanisms which are, in particular, structures, processes and relational mechanisms. Studies were excluded if they: (1) did not exist in full-text; (2) were not written in English; (3) they had missing information and abstracts and indexes; (4) were commentaries or editorials.

2.4 Extracting and charting the results

PubMed, ScienceDirect, ACM Digital Library and IEEE Xplore databases were searched simultaneously on 31st December 2023 using the advanced search interface using the terms indicated in Table 1.

Table 1. Databases and the search terms

S.No	Database	Search terms
1	**ScienceDirect**	"Health information technology" and "governance"
2	**PubMed**	
3	**ACM Digital Library**	
4	**IEEE *Xplore* databases**	

The following limits were applied: scholarly journals (peer-reviewed); publication date (1st January 2000 to 31st December 2023); language (English); and article type (review and research articles). The search terms used are “health information technology" and "governance". A total of 1,217 articles were retrieved and screened by title and abstract. Duplicate articles were excluded in the exclusion process. The study selection method also rejected articles that did not match the inclusion requirements. The excluded articles encompassed healthcare system governance, adopting Health Information Technologies (HITs), and applying governance of technologies like Artificial Intelligence (AI) and blockchain in healthcare. We carefully reviewed a total of 46 articles, out of which 29 were selected for our scoping review. These articles are included in Figure 1, which depicts the PRISMA flow chart.

The main reason for exclusion was articles that generally focused on the governance of general health systems but did not focus on HIT governance. In addition, 17 articles were omitted from the review for the reasons that they focused on general health governance and big data governance [43] [44] [45], those focusing on AI governance [46] [47]. Other excluded a study that examined Ambidextrous governance of IT-enabled services [48], Governance of Blockchain Technology [49], E-Governance [50] and Governance's role in local health departments' information system and technology usage [51].

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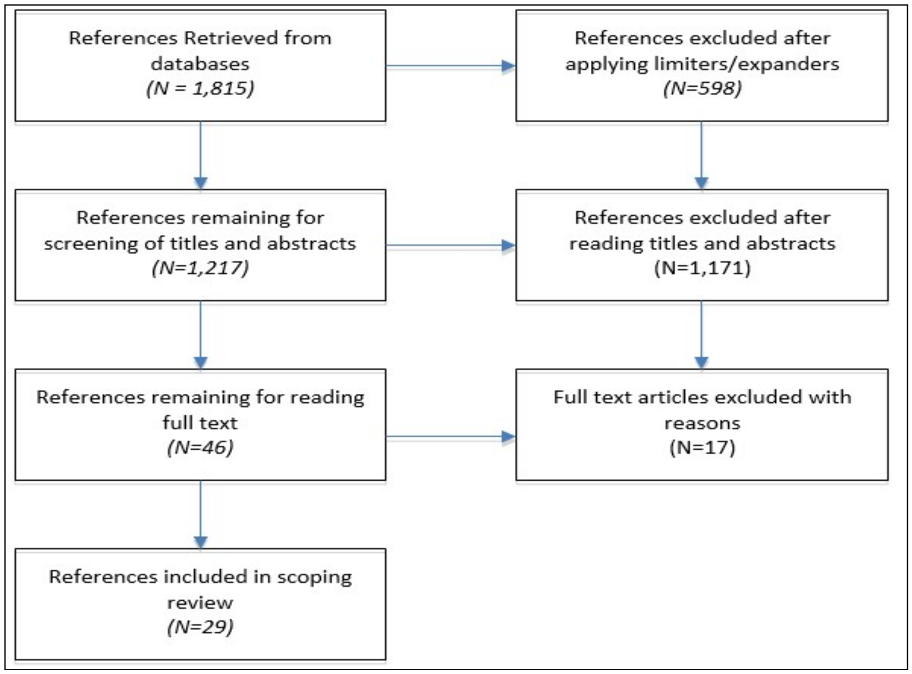

Figure 1. PRISMA flow chart of study selection as described by [52]

2.5 Data charting process and analysis

Consistent with scoping studies by [52], we gathered the data from the articles included in the research and organised it into a table before analysing and summarising the results. Table 2 summarises the article's title, author, year, aim/purpose, method, findings regarding HIT governance mechanisms and practices, and recommendations/research gaps. The data were analysed following the three manual stages of theme analysis as described by [53]. The stages are data reduction, data display and data conclusion. Data reduction involves selection, simplification and transformation of the data. Data display entails organising and compressing data with the guidance of research questions/objectives. The third stage entails concluding after having displayed data in a variety of ways.

3 Results and Findings

This scoping review yielded 29 articles. Of these, 14 were from the PubMed database, 11 were from the ScienceDirect database, and the remaining 4 were from the IEEE Xplore database. None of the articles from the ACM database met the inclusion criteria. Out of the 29 articles that met the inclusion criteria, 24 (representing 82.8%) presented primary collected and analysed data. The remaining 5 (representing 17.2%) articles were a review of literature articles. Table 2 summarises the articles, capturing the title, author, year, aim/purpose, method, findings (HIT governance mechanisms and practices), HIT governance mechanism category, and recommendations/research gaps.

Table 2. Summary Table of the articles that met the inclusion criteria

S.No	Title, Author and Year	Aim/Purpose	Method	Findings (HIT governance mechanisms and associated practices)	HIT Governance Mechanism Category	Recommendations/Research gaps
1	Data governance and data sharing agreements (DSA) for community-wide health information exchange: lessons from the beacon communities Allen *et al.* [54]	Address data governance challenges and create Data Sharing Agreements (DSAs) to promote the interchange of health information across the community.	A collaborative effort that included holding Conference calls	Organisations engaged in electronic data sharing must resolve governance matters and establish Data Sharing Agreements (DSA). DSAs are essential for addressing legal and market-related considerations.	HIT governance Processes Mechanism	Lessons learned and approaches to developing DSA include engaging stakeholders, identifying and communicating the value proposition, starting small, and expanding. It also includes Implementing a cost-effective strategy, tackling market-related issues, modifying and expanding current agreements and partnerships, and forecasting the necessary time and financial resources.
2	Long-term care and health information technology: opportunities and responsibilities for long-term and post-acute care providers (LTPAC). MacTaggart and Thorpe [55]	To examine HIT issues, the providers of LTPAC need to comprehend for successful implementation	Qualitative study	The challenges associated with transitioning to HIT encompass technical and financial aspects as well as legal and legislative considerations, technical and commercial operations, and, most importantly, governance.	HIT governance Processes Mechanism	The study stops at acknowledging the need for governance of HIT initiatives.
3	The Southeastern Minnesota Beacon Project for community-driven health information technology: origins, achievements, and legacy Chute *et al.* [56]	Documenting the origin, achievements, and legacy of the organisation and infrastructure of the Southeastern Minnesota Beacon Project	Qualitative study	The Beacon project encourages the adoption of health information technology (HIT) within a particular geographical area. A community-chartered governance structure, which all members supported, facilitated the development and management of health information technology based on the community's needs. The governance body established a governing council with representatives from each entity involved.	HIT governance Structural Mechanism	Collaboration, cooperation, and shared governance are essential for successfully implementing HITs across a population that includes many providers and non-traditional healthcare organisations.
4	Digital health transformation in Saudi Arabia: A cross-sectional analysis using Healthcare	The study evaluates the readiness for digital health transformation in	Questionnaires	For digital health transformation to succeed, it is crucial to have four fundamental components: individual-empowered healthcare, predictive analytics, effective governance and workforce, and seamless interoperability.	HIT governance Processes Mechanism	The study recommends the proper implementation of different healthcare aspects. Among these, healthcare digital transformation requires governance and workforce dimensions.

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	Information and Management Systems Society's digital health indicators Al-Kahtani *et al.* [28]	numerous health facilities in the Eastern Province of Saudi Arabia.				
5	Health information exchange implementtation: lessons learned and critical success factors from a case study Feldman *et al.* [57]	To understand the technological, organisational, and governance elements necessary for implementing a health system into a statewide Health Information Exchange (HIE).	Qualitative methods	Implementing a health system across the states to facilitate Health Information Exchange (HIE) requires three crucial aspects: technological, organisational, and governance. The Inova onboarding project aims to implement a health system into a statewide Health Information Exchange. It identifies leadership and project champions with decision-making power, communication, onboarding guidelines and project resources as essential success factors.	HIT governance structural, processes and relational mechanisms	Future research should evaluate the economic and clinical elements linked to the value of HIE and expand the investigation to include social factors and public value. To comprehensively comprehend the issue, it is imperative to utilise mixed-method case studies that incorporate surveys and encompass extensive geographical locations.
6	Smart Health Community: The Hidden Value of Health Information Exchange Ciriello and Kulatilaka [42]	Examine how to create more value than efficiencies from HIT investments through the innovative health community.	Qualitative study	Comprehensive governance of the Health Information Exchange (HIE) is necessary to achieve the coevolution of healthcare markets and business models and generate additional value beyond efficiencies from investments in Health Information Technology (HIT). Nevertheless, the process of coevolution is characterised by a slow pace, primarily due to the lack of motivating factors for existing delivery systems and limitations imposed by the dominant patient-healthcare paradigm.	HIT governance structural, processes and relational mechanisms	The study suggests that developing healthcare markets and business models simultaneously requires implementing novel governance processes, structures, and partnerships.
7	A Mid-South Chronic Disease Registry and Practice-Based Research Network to Address Disparities Surbhi *et al.* [25]	To elucidate a cutting-edge health information technology (HIT) framework to facilitate community-wide health enhancement.	Case study	HIT data structure and governance practices include the DWPC registry data governance board, DWPC steering committee, and DWPC registry data management committee. The study indicates that the Health Information Technology (HIT) Governance framework facilitates the enhancement of overall community health.	HIT governance structural mechanism	The study suggests that implementing regional HIT initiatives, such as registries and practice-based research networks (PBRNs), can contribute to a more efficient healthcare delivery system.
8	Data warehouse governance programs in healthcare settings: A literature review and a call to action Elliott *et al*. [58]	The review examines what is known about data warehouse governance to	A literature review	A data warehouse governance (DWG) primarily concerns strategic decision-making and oversight, carried out by DWG's committees The secondary objectives are to prioritise the distribution of resources, the assessment of investment worth, the	HIT governance structural and processes mechanisms	Further investigation is required to tackle the issue of data warehouse governance policies. The limited research on this topic shows a significant lack of explicit governance policies for data warehouses in healthcare settings.

		assess its current status.		establishment of policies and processes related to privacy and security, compliance, and the reduction of risks. Additional governance processes encompass accountability, authority, roles, rules of engagement, management of multifunctional conflicts, decision-making and entitlements, leadership, change management, issue resolution, legislation creation and implementation, cost and complexity management, value creation, user training and support, and technical operations.		
9	Building and Strengthening Infrastructure for Data Exchange: Lessons from the Beacon Communities Torres *et al.* [59]	Investigates the strategies and encounters of the Beacon Communities in constructing and enhancing Health Information Technology infrastructure.	Qualitative research that utilised interviews, observations and document analysis	The study indicates that technical progress, stakeholder engagement and governance are three crosscutting priority areas for strengthening HIT infrastructure. According to the study, governance is critical to fostering trust and stakeholder confidence through neutral conveners and transparent governance structures, especially in competitive markets.	HIT governance structural and relational mechanisms	The study recommends measures which include promoting technological advancements and innovations, engaging essential stakeholders, and setting up accountable leadership and governance of the infrastructure with unbiased facilitators to improve data-sharing infrastructures.
10	Driving digital health transformation in hospitals: a formative qualitative evaluation of the English Global Digital Exemplar (GDE) programme Krasuska *et al.* [27]	The study aims to analyse how the GDE program facilitates digital transformation in the provider organisations involved.	Qualitative study	Providing dedicated funds, adherence to governance criteria, and acquiring a positive reputation as a centre of digital excellence expedites the digital transformation in organisations participating in the GDE project. Some of the practices associated with governance include the GDE programme board and the chief clinical information officer (CCIO).	HIT governance structural and processes mechanisms	The study recommends implementing measures that include protected funding and governance mechanisms and exploiting reputational benefits, which are crucial for driving local progress necessary for large-scale digital transformation programs in healthcare.
11	Lessons learned from the implementation of computerised provider order entry in 5 community hospitals: a qualitative study Simon *et al.* [24]	The study describes the experiences of hospitals that have effectively used Computerized Provider Order Entry (CPOE) systems.	Qualitative approach (observations and semi-structured interviews)	Implementing CPOE involves five domains: governance, planning, assistance, opinions, and implications. Governance matters focus on implementing a well-defined organisational decision-making process and involving clinicians. Governance issues include preparation, planning, support, managing perceptions, and assessing the effects.	HIT governance structural and processes mechanisms	The study suggests that for CPOE adoption to be effective in community hospitals, it is essential to consider concepts such as governance, preparation, support, perceptions, and repercussions during the project design phase.
12	The HMO research network (HMORN) virtual data warehouse (VDW): a public data	The study addresses the HMORN VDW data model,	Qualitative study	HMORN established a governance framework consisting of the VDW operations committee, the VDW implementation group (VIG), the asset stewardship committee, and the HMORN governing board.	HIT governance structural and processes mechanisms	The study proposes that healthcare and health insurance systems not affiliated with the HMORN can adopt the VDW data framework to create a decentralised and

 J Health Inform Afr. 2025;12(1):1-19. DOI: 10.12856/JHIA-2025-v12-i1-509

	model to support collaboration Ross *et al.* [60]	governance principles, data content, and quality assurance techniques.		The report emphasises the structured procedures for modifying VDW specifications, introducing new VDW tables, and establishing new workgroups.		compatible healthcare data system or collaborate with the HMORN through partnerships.
13	Identifying Organisational Capacities and incentives for clinical data-sharing: the case of a regional perinatal information system Korst *et al.* [61]	To investigate the progress of regional data exchange among healthcare institutions	A case study using standard qualitative methods	The study demonstrates that effective data sharing among healthcare organisations necessitates the following: 1) An evaluation of preparedness, 2) a recognised authority, 3) a formal governance structure, and 4) an external IT provider.	HIT governance structural mechanism	The study suggests that it is advisable to establish a governance structure before developing a data-sharing system.
14	Developing a Model for National Health Information Governance (IG) Program in Iran Rouzbahani *et al.* [62]	The study aims to create a framework for Iran's national health information governance initiative.	Applied, cross-sectional descriptive study	The national IG program comprises 11 components, 12 principles, and natural and judicial authorities. These authorities are responsible for implementing the health IG program and have specific job descriptions.	HIT governance structural mechanism	The report suggests the creation of a health Information Governance (IG) council and a steering group for health IG inside the Ministry of Health and Medical Education. Additionally, it suggests the creation of a board of directors tasked with supporting the national health IG program.
15	Health Information Technology and Value Middleton and Cheung [18]	Examine the obstacles and factors that contribute to the successful utilisation of Health Information Technology (HIT) and explore specific value of HIT.	Literature review	The primary impediments to HIT implementation include the intricate nature of healthcare, subpar system usability, user dissatisfaction, and challenges relating to the organisation, such as leadership issues.	HIT governance structural mechanism	The study recommends various strategies to enhance the value of Health Information Technologies (HITs). These aspects encompass engaging experts, offering incentives, prioritising activities, improving usability and workflow assistance, promoting interoperability and adhering to standards.
16	Governance for Personal Health Records (PHR) Reti *et al.* [63]	The study aims to explore effective organisational-level personal health records (PHR) governance structures.	Used semi-structured interviews within specifically chosen organisations in the United States.	Governance structures vary in all healthcare organisations/settings. They include the Steering Committee, Senior Management, eHealth Product Team, Connecting Portfolio Oversight Group, Advisory Group, and Advisory Board. The current governance of the Personal Health Record (PHR) system involves indirectly representing patients through doctors or Consultative assistance networks. The study argues that such indirect representation is insufficient and patients must “be at the table.”	HIT governance structural mechanism	Personal health records serve as communication tools for professionals and patients. Therefore, the study suggests that the governance of Personal Health Records (PHR) should include the participation of patients to enhance patient-centered treatment and the development of policies.

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17	Governance structures impact on eHealth Kierkegaard [64]	Investigated Denmark's success in moving into an eHealth-focused healthcare system	A case study approach and literature search	The efforts to implement national eHealth initiatives must move beyond technological considerations and examine enablers and barriers such as governance structures and policies.	HIT governance structural and processes mechanisms	Successful national eHealth implementation requires consideration of the dynamic nature of governance. Also, it is essential to balance centralisation and decentralisation models of governance.
18	Collaboration in electronic medical evidence development: A case study of the Social Security Administration's MEGAHIT System Feldman and Horan [29]	To investigate the individual contributions of technological, organisational, and governance aspects to the effectiveness of collaborative endeavours in generating value from the MEGAHIT system.	A case study that involved conducting interviews with 43 participants	The MEGAHIT application facilitates the authorised exchange of patient health information by sending requests for and receipts. The success of information sharing through MEGAHIT requires the establishment and strengthening of end-to-end governance structures, addressing privacy, security, data use and reciprocal support agreements (DURSA), certificate authority (CA), and Service Level Agreements.	HIT governance structural and processes mechanisms	The study suggests enhancing collaboration to effectively exchange information via a safe and accessible system.
19	Social Franchising: Scale and Spread of Innovation in Canada Maciejewski *et al.* [30]	Examined how Canada leverages social franchising (governance model) in healthcare contexts and innovations.	A literature review	Catalysing HIT innovations and use requires a governance model and approach incorporating different teams and committees to oversee the rollout and use of health IT. According to the study, the National BASE™ Governance model comprises networks, a national BASE™ committee, a corporate subcommittee, an Information Technology subcommittee, and action teams.	HIT governance structural mechanism	The study suggests implementing a National BASE™ model that utilises social franchising to expand and disseminate effective HIT initiatives.
20	Building resilient hospital information technology services through organisational learning: Lessons in CIO leadership during an international systemic crisis in the United States and Abu Dhabi, United Arab Emirates. Cousins *et al.* [33]	To document the most effective strategies employed by Chief Information Officers (CIOs) to recover from challenges	A qualitative study	Four essential practices required to establish robust hospital information technology services include ambidextrous leadership, governance (including committee structures, strategic planning processes, project approvals, strategic partnerships, regulatory flexibility, financial support Health Information Technology (HIT) activities, investment in IT infrastructure, and enhancement of innovation and learning capacities are required.	HIT governance structural and processes mechanisms	The article proposes a conceptual framework to direct the creation of healthcare IT resilience and emphasises the significance of organisational learning as a fundamental aspect of HIT resiliency.
21	Breaking the Healthcare Interoperability Barrier by Empowering and	The study examined essential elements required to break the	An evaluation of related work	The study introduces a framework characterising the essential elements of interoperable healthcare systems.	HIT governance structural and processes mechanisms	The study suggests that three essential components are necessary for the successful integration of healthcare: an

	Engaging Actors in the Healthcare System Azarm *et al.* [65]	healthcare interoperability barrier in Canada.		The management and legal enforcement of the framework should be entrusted to the governing body overseeing the healthcare system.		adequate dataset, interoperable technology solutions, and a governing authority.
22	Transforming healthcare with information technology in Japan: A review of policy, people, and progress Abraham *et al.* [66]	Investigated the adoption of Health Information Technology (HIT) in the medical community of the Kyoto Yamashina area. Impact of historical and current Japanese governmental policies that promote the use of HIT.	A case study utilising interviews as well as document analysis	An IT leadership with strong IT knowledge is necessary for transformation in healthcare IT. Equally significant are the Chief Information Officer (CIO), governmental factions, and consortiums that guide the IT Policy Office. It is crucial to train healthcare organisational staff on the fundamental aspects of IT management and the responsibilities of a Chief Information Officer (CIO) to foster strong leadership within organisations that will implement Health Information Technology (HIT). Furthermore, it is crucial to comply with policies and standards and prioritise security, privacy, and confidentiality considerations. Functionality related to meeting security and data encryption.	HIT governance structural and processes mechanisms	The study suggests that it is necessary to establish a comprehensive governance framework to achieve widespread implementation of Health Information Technology (HIT).
23	Successfully implementing a National Electronic Health Record (EHR): a rapid umbrella review. Fennelly *et al.* [34]	It analyses crucial elements that influence the effectiveness of an Electronic Health Record (EHR) deployment in various healthcare settings.	A rapid umbrella review	Critical determinants of Electronic Health Record (EHR) success encompass essential elements such as effective governance, strong leadership and organisational culture, active participation of end-users, comprehensive training programs, robust support systems, adequate allocation of resources, and optimised workflows. Additional considerations encompass usability, interoperability, adaptability, infrastructure, regulations, standards, and testing.	HIT governance structural and processes mechanisms	The study recommends contextual healthcare considerations for issues affecting EHR initiatives.
24	Computerised Provider Order Entry (CPOE): Important Non-technical Issues and Considerations Harrington *et al.* [67]	The study sought to explore critical non-technical issues required in CPOE implementation and use	Qualitative study	CPOE implementation requires technological and non-technical considerations. Some of the governance structures for CPOE success include a safety committee, a governance group, a committee or a council. Processes include workflows and personnel training and engagement.	HIT governance structural and processes mechanisms	The study emphasises the importance of careful planning to minimise disturbance. It also highlights the need for active involvement and guidance from all clinicians using CPOE in the clinical setting.
25	A literature review for large-scale Health Information System project planning, implementation and Evaluation Sligo *et al.* [35]	Important factors necessary for HIS implementation	A literature review	The efficient execution of Health Information Systems necessitates meticulous administration, governance, and task-orientated structures. Equally important is the need for low staff turnover, strong staff capabilities, practical timetables, well-organised logistical procedures about the innovation, and recognition that the implementation process is continuous. HIS implementation involves legal, administrative, communication, human factors and support.	HIT governance structural, processes and relational mechanisms	The study recommends a more rigorous evaluation of the implemented HISs in healthcare settings. The current body of literature is insufficient and hindered by oversimplified and varied methodologies, making it challenging to draw general conclusions from the findings.

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26	Health Data Governance Issues in Healthcare Facilities: Perspective of Hospital Management Oktaviana *et al.* [68]	Analyse the issues in healthcare facilities related to health data governance	A qualitative study	Identified five major health data governance issues in healthcare facilities. These are IT resources and responsibility, data quality, data security, data standards, and policies	HIT governance processes mechanism	There is a need to explore both internal and external challenges facing health data governance to improve the benefits of the technology
27	e-Health should be governed as other assets in healthcare organizations Juiz *et al.* [69]	Sought to develop a common IT governance framework model for healthcare institutions based on the ISO/IEC 38500 standard.	A qualitative study in four different hospitals	The Standardization of IT governance in healthcare institutions is in the following categories: Structures - IT governance steering committee and the IT governance advisory/technical committee Alignment processes: IT services adjustment, the IT project portfolio selection and the IT investment prioritization. Communication: Exchange of documents and reports and the publication of the results of IT activities	HIT governance structural, processes and relational mechanisms	The proposed model provides how to deploy particular IT governance frameworks including the usual governance components: structures, alignment processes and communications. Need to examine the effectiveness of the proposed governance framework.
28	Establishing ICT Governance for Regional Information Infrastructures in Healthcare Ulriksen *et al.* [70]	Sought to develop an ICT governance organization	qualitative interpretive methods - meetings	Governing Information Infrastructure requires structures, processes and relational mechanisms but more importantly, a focus on the process for handling diverging political interests and managing tensions and complex interdependences. Governing the Information Infrastructure requires local, regional and technical perspectives to be able to serve all the needs of all the stakeholders.	HIT governance structural, processes and relational mechanisms	Need to develop an ICT governance organization to govern Information infrastructure to facilitate information sharing, standardization and interoperability of healthcare IT integrations.
29	IT Governance Design for Hospital Management Information System Case Study: X Hospital Shalannanda *et al.* [71]	Sought to develop an effective IT Governance mechanism for X Hospital.	A Single Case Study	IT Governance design process follows the structure, processes and relational mechanisms The findings indicate the need to tailor-make IT Governance practices for X Hospital.	HIT governance structural, processes and relational mechanisms	Recommends the integration of COBIT 5 and ITIL v3

4 Discussion of research findings

The section below presents findings as per the review objectives.

4.1 Objective 1: How Health Information Technology (HIT) governance is discussed in the literature

This study showed that Health Information Technology (HIT) Governance is essential and cannot be overlooked. It supports studies [28] [29] [30] who argue that HIT Governance enables the well-functioning of digital health solutions and also acts as a prerequisite for health system functioning. This argument is a departure from the usual ideology where HITs have majorly focused on the technological components and less on the broader social issues. In support of this proposition, [33] [67] [64] [27] argued that the implementation of HITs needs to consider both the technical as well as social issues, such as leadership and governance, which also include structures and policies. According to [55] [72] [34] [60], non-technical issues of HITs include funding, legal and policy concerns, business operations, HIT governance, among others.

However, the mere mention of the need for HIT governance is not enough, it needs to be operationalised and contextualised. Studies [56] [42] [58] [57] [69] [63] [60] [71] [25] [70] provided a more detailed examination of the HIT governance and suggested its three categories commonly referred to as governance mechanisms. These are the HIT governance structures, processes and relational mechanisms.

4.1.1 HIT Governance Structural Mechanism

The HIT governance structure pertains to the power distribution that decides across the health information technology ecosystem. As defined by the IT Governance Institute, an IT governance structural mechanism is a formal device and mechanism that promotes horizontal communication and collaboration between business and IT management roles in decision-making. Examples include the HIT steering committee, HIT council, and project management office, among others. Such bodies/teams are responsible for making HIT decisions. Of the 26 articles reviewed, 17 (65.4%) explicitly mentioned the need to design and implement appropriate HIT governance structures. Studies [42] [58] [29] [34] [64] postulated the existence of a HIT governance structural mechanism operationalised through various governance practices.

According to [30], specific eHealth governance teams and committees have been established to supervise the implementation and utilisation of HIT innovations. These include the Networks Committee, National BASE™ Committee, Corporate Subcommittee, Information Technology Subcommittee, Action Teams, and the Secretariat. [27] investigated the success of the GDE program. The authors observed the establishment of project management structures and the rise of various leaders in clinical health informatics, including the Chief Clinical Information Officer, Chief Nursing Information Officer, Chief Medical Information Officer, and Deputy Chief Clinical Information Officer, who possess a blend of clinical and digital transformation knowledge. The success of health information exchange functionality and networking infrastructures at Kyoto Yamashina in Japan relied on different enablers, including the creation and inclusion of the office of the CIO [66]. [67] also noted that the success of the Computerized Provider Order Entry (CPOE) system relied on establishing governance practices such as committees or councils instead of workgroups and the safety committee. [35] echoed the need for sustainable structures as opposed to temporary workgroups, transparent management and governance structures, and task-orientated structures as opposed to output-oriented structures, which play a crucial role in HIS project planning, implementation and evaluation. [62] reiterated that the information governance (IG) council and the steering committee form essential governance practices.

[56] reiterated for the need of HIT governance structures. They argued for the establishment of HIT governance teams, including a governing council. In addition, a project champion with decision-making power is also essential [57]. [25] pointed out other governance structures, including the Diabetes Wellness and Prevention Coalition (DWPC) Registry Data Governance Board, the DWPC Steering Committee, and the DWPC Registry Data Management Committee. A study by [60] on virtual data warehouses pointed out that some of the HMO Research Network (HMORN) Virtual Data Warehouse governance structures included Virtual Data Warehouse (VDW) Operations Committee (VOC), VDW Implementation Group

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(VIG), Asset Stewardship Committee (ASC) as well as the HMORN Governing Board. Furthermore, [63] pointed out some Personal Health Records (PHR) governance structure practices including a steering committee, senior management, eHealth product team, connecting portfolio, oversight group, advisory group, and advisory board with patient representatives.

4.1.2 HIT Governance Processes Mechanism

HIT governance processes form the second category of HIT governance. It refers to the different actions or activities implemented to achieve health outcomes. These processes include workflows, allocation of resources, standard operating practices, policies and procedures. Studies [66] [29] [34] [67] argued for the need to implement HIT governance processes.

The reviewed literature pointed out various practices associated with HIT governance processes. For example, conducting training, end-user involvement, resourcing, system implementation support, developing HIT standards, providing incentives, clear legislation regarding accountability, change management, as well as addressing security, privacy and confidentiality are some of the governance practices aimed at transforming healthcare with information technology [66] [34] [68]. In addition, establishing Data Use and Reciprocal Support Agreements (DURSA), Certificate Authority (CA), and Service Level Agreements (SLA), policies, procedures, privacy, security, risk assessment and compliance, and risk mitigation as well as data sharing agreements (DSAs), are also essential practices [54] [58] [29] [68] [25].

[67] [60] reiterated the importance of governance processes issues, such as establishing workflows and engaging personnel. They also advocated for organisations to address emerging CPOE implementation issues such as content changes, the functionality of the CPOE system for updates and enhancement, review and evaluation, adherence to the regulatory standards and provisions, as well as approved content changes, including appropriate policies and procedures. In their reviewed literature on large-scale health information system (HIS) projects, [35] emphasized on the significance of governance practices including but not limited to low staff turnover, competent staff with adequate capabilities, appropriate staffing levels, realistic timelines, well-organised logistical procedures for innovation, and recognition that implementation is an ongoing process. Other studies [57] opined that on boarding guides and project resources are some of the HIT project governance issues that should also be addressed.

4.1.3 HIT Governance Relational Mechanism

The third category is the relational mechanism of HIT governance. It refers to the communication and relationships between stakeholders in HIT governance. It is as essential as HIT governance decisions and processes [42] [58] [35] [25]. HIT governance relational mechanism involves active engagement and cooperative interactions among healthcare stakeholders. It comprises stakeholders' identification and the communication approaches adopted to disseminate HIT decisions and actions. According to [57], the relational mechanisms of HIT governance are essential and of utmost importance for achieving and maintaining alignment, even when the necessary structures and processes are established. Examples of relational mechanisms in healthcare include executive-level enterprise-wide communication and the establishment or inclusion of the CIO's office, among others. [57] observed that communication through sending and receiving timely and accurate emails and promptly communicating plays a vital role in HIE and health systems implementation. [58] [25] reiterated on the role of communication practice and posited that the processes, decisions and activities that ensure data warehouse user engagement, organisational leadership and executive support, and value to the data warehouse greatly rely on effective and efficient communication.

In light of these propositions, this study concluded that there exist three broad categorisations of HIT governance mechanisms (HIT governance structures, HIT governance processes and the HIT governance relational mechanism). Furthermore, the findings from the study revealed that context-specific governance practices further operationalise each mechanism. This proposition is in tandem with other studies in healthcare contexts [11] [2] **Error! Reference source not found.** that postulated the three categorisations of HIT governance. Similarly, studies [38] [32] posit that every organisational asset requires mechanisms and associated practices necessary for alignment.

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4.2 Objective 2: To identify the Health Information Technology governance knowledge gap(s) that exists in the literature

The 29 articles reviewed focused on the governance of HITs, such as those facilitating health data sharing, health information exchange, systems functional at the hospital level organisations, and national HITs. Other studies [54] [56] [42] [59] also examined community-level HITs which were the community-wide health information exchange, Smart Health Community and community-driven health information technology. The governance practices associated with the identified community-level HITs included the use of neutral conveners as a transparent governance structure [59], the use of a governing council [56], and the use of Data Sharing Agreements (DSA) [54].

Despite these attempts, none of the reviewed studies comprehensively examined the practices associated with Community-level HIT governance, yet HIT governance is contextual and should not be generalised. The governance of hospital-level HITs and their practices cannot be the same as that of community-level HITs. Such a proposition is even more apparent in healthcare organisations characterised by multiple functional systems at different levels of healthcare. In support of this argument, [12] postulated that the governance of health IT has been majorly for systems functional at hospital levels and higher levels of healthcare with little emphasis on governance of community-based health IT. [36] [37] posited that every organisation calls for context-specific IT governance mechanisms and associated practices. This argument reflects that of [38], who argued that a high-level IT governance model cannot be applied across all sectors and produce similar results.

Further, although the search strings did not contain the term alignment, none of the 29 articles reviewed mentions or even related alignment (healthcare – HIT alignment) to HIT governance, yet alignment is an essential aspect in information systems governance, particularly in HIT governance. This presented another knowledge gap. [1] conceptualised the linkage between IT governance and strategic alignment. They concluded that a mix of mature IT governance practices leads to higher IT alignment and value derivation.

5 Limitations

Our scoping review had some limitations. A major constraint of this scoping review was its reliance on only four databases, ScienceDirect, PubMed, ACM Digital Library and IEEE Xplore, to conduct literature searches. In addition, evidence from the four databases was used. A broader scoping exercise may have resulted in a more comprehensive dataset. Furthermore, this scoping review was an enormous undertaking, and the results only captured literature up to the 31st of December 2023. Finally, some studies that did not explicitly use HIT were not included due to the choice of the search strategy used in the study.

6 Conclusion

To begin with, governance for HIT integrations and systems functional at the hospital levels, national healthcare organisations, and information and data governance, including those supporting health information exchange (HIE), were addressed. Little knowledge was available in terms of community-level HIT governance, and although healthcare-HIT alignment is an essential component of HIT governance, none of the reviewed literature addressed it.

Therefore, this review unravelled the need to comprehensively examine the governance of community-level HITs, including Community-Based Health Information Systems (CBHIS). Furthermore, studies should examine healthcare-HIT alignment as an essential aspect of HIT governance. Finally, there is a need to explore the three constructs (HIT governance, alignment and health outcomes) more holistically by incorporating a mix of research methodologies (qualitative and quantitative methods). Such a holistic view will establish the downstream effect of HIT governance on health outcomes. The findings of this review form the basis for subsequent research that focuses on CBHIS governance.

Acknowledgements

The authors acknowledge the support of the academic staff of the Department of Computing and Informatics, University of Nairobi.

Statement of conflict of interest

The authors declare the nonexistence of any conflict of interest.

Research funding

This study received no funding.

Ethical approval

This study reviewed the existing literature and did not require ethical approval.

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 J Health Inform Afr. 2025;12(1):1-19. DOI: 10.12856/JHIA-2025-v12-i1-509

Journal of Health Informatics in Africa
JHIA online.org

Maternal Healthcare Access and Maternal Electronic Service Delivery in Resource-Constrained Environments: A Systematic Literature Review on Frameworks, Approaches, and Insights

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Background and Purpose: Ensuring the well-being of mothers and newborns is contingent upon guaranteeing access to maternal health services. However, marginalized communities in Developing Countries (DCs) often face obstacles in accessing these critical services, primarily due to limitations in the strategies and methods used to deliver maternal healthcare. These barriers encompass various challenges, such as geographical remoteness, inadequate infrastructure, and socio-economic disparities. Additionally, the limited availability of trained healthcare professionals and insufficient medical facilities exacerbate the situation. Overcoming these challenges necessitates a comprehensive review of the existing literature to find the best practices for integrating sensitive interventions, community engagement, and innovative technological solutions for the subject under investigation. This study was motivated by the imperative to investigate the integration of maternal healthcare services with e-services and assess the effectiveness and efficiency of existing approaches for accessing maternal e-services. This was driven by a sustained objective of enhancing maternal health service delivery using technologically supported platforms.
Methods: This study sought to answer the research question: “What are the strengths and weaknesses of existing frameworks for delivering and supporting maternal e-services?” A systematic literature review was conducted to address this, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) model. This rigorous approach ensured inclusive coverage and transparency in selecting and analyzing relevant studies. The methodology involved systematically searching multiple online databases using a keyword-based search technique to identify studies focused on maternal healthcare services and delivering maternal e-services.
Results: The study highlighted numerous potential e-services for improving maternal healthcare, yet their implementation appears uncertain due to the limited effectiveness of existing approaches, which predominantly rely on traditional methods. While several e-service frameworks exist to guide maternal healthcare delivery, they predominantly focus on textual and voice-based maternal education, with limited attention to multimedia capabilities. The study developed a conceptual framework delineating the current state of maternal e-service delivery, emphasizing key domains as services supported by existing maternal e-service delivery frameworks and weighing a desired future state that integrates potential e-services to improve maternal healthcare and women’s health.
Conclusion: The study emphasizes the urgency of exploring how technology-driven frameworks, especially those centered on mobile platforms, can integrate potential e-services to enhance maternal healthcare delivery. Bridging this gap holds the promise of revolutionizing maternal healthcare through effective maternal e-service delivery, making it more accessible and effective for women in need worldwide.

Keywords: Maternal e-services, maternal healthcare, health informatics, mobile health.

1 Introduction

Maternal health encompasses the well-being and healthcare of women and infants, which can be broadly categorized into three stages. The first stage is during pregnancy, commonly known as antenatal care (ANC)

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 J Health Inform Afr. 2025;12(1):20-38. DOI: 10.12856/JHIA-2025-v12-i1-523

[1], [2]. During this stage, healthcare services are provided to monitor the pregnant woman's health and ensure the well-being of the developing fetus. The second stage is childbirth, often referred to as birth care [3]. This stage focuses on providing appropriate medical support and assistance during pregnancy, labor, and birth to ensure a safe and healthy birth. The final stage is the postnatal or postpartum care (PNC) period, which involves healthcare services and support for the mother and newborns in the weeks following childbirth [4]–[6]. This stage aims to address any potential complications, provide guidance on breastfeeding, and promote the physical and emotional recovery of the mother while ensuring the optimal health and development of the newborns [7]–[9].

Maternal health presents a vital component of population health that encompasses various dimensions of healthcare, including family planning, preconception care, prenatal care, and postnatal care, all of which are essential for the well-being of mothers and babies [10], [11]. It is closely linked to other aspects of women's health, such as reproductive health and general well-being, underscoring its importance in comprehensive healthcare [10], [11]. Therefore, it is essential to prioritize women's health and provide adequate maternal healthcare services to safeguard the lives of both mothers and newborns to support sustainable and unhindered population growth [12]–[14]. Maternal health services are essential for mothers' and infants' overall health and well-being [15]–[17]. The proper utilization of mainstream maternal health services plays a vital role in reducing mortality and morbidity [18]. This is possible through early detection of danger signs and management of potential complications associated with pregnancy and childbirth, as discussed earlier [19]. Several studies have indicated that if proper maternal care services are provided to mothers, fewer complications during pregnancy are anticipated with safe and successful delivery [20], [21].

Despite the discussed benefits of maternal care services, the actual utilization of these services remains low in many communities [22]. This is especially evident in low-resource settings, such as various Sub-Saharan African countries, including Uganda, Kenya, Tanzania, Nigeria, and Ethiopia, where healthcare delivery systems face numerous challenges [23], [24]. Key obstacles include a shortage of healthcare providers, long distances to healthcare facilities, financial limitations, limited awareness of the importance of maternal care, and compromised or substandard quality of care [25]. These challenges are compounded by traditional approaches to accessing maternal healthcare, primarily through antenatal care visits at health facilities and home visits by trained healthcare workers [26], [27]. Studies have underscored the importance of adequate maternal healthcare provision, revealing a multitude of risks that may compromise the well-being of both mothers and newborns if not addressed. These risks span a range of complications associated with pregnancy and childbirth, including preterm birth, low birth weight, and elevated maternal mortality rates, each carrying significant health impacts [28]–[30]. Maternal mortality compromises the population and lives of pregnant women and their newborns [31]. Statistics show that the global maternal mortality rate declined from 2000 to 2017 by 38%, derived from 342 to 211 deaths per 100,000 live births respective of the year range, giving the average annual reduction rate at 2.9%. Following the UN Sustainable Development Goal 3 - "Good Health and Well-being" projections show that by 2030, an annual rate of 6.4 % %is needed to achieve the global goal of 70 maternal deaths per 100,000 live births [8], [32], [41], [33]–[40]. Further studies showed that of the approximately 295,000 global maternal deaths, 94% occurred in countries with low resource settings, such as developing countries, especially in sub-Saharan Africa and Southern Asia [42], [43].

Despite the existing challenges in the delivery of maternal health services, it is a fact that many maternal care services can be enhanced and facilitated through technological innovations [27], [44], [45]. Therefore, it is crucial to embrace emerging technological trends and incorporate tech-related innovations in the provision and support of maternal care services. These innovative approaches, often referred to as maternal e-services, have the potential to overcome barriers and limitations in delivering adequate maternal healthcare [18]. By leveraging technology, such as mobile applications, telemedicine, and digital platforms, access to maternal care services can be improved, addressing the constraints and challenges that exist in traditional service delivery models. The paper is structured as follows: Section 2 outlines the methodology adopted in the study, followed by the presentation of results in Section 3. Section 4 provides a discussion of the findings, while Section 5 highlights the study's limitations. Finally, the conclusion is presented in Section 6.

2 Materials and methods

The study utilized the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement (Figure 1) to conduct a review of the literature concerning maternal healthcare and the provision of maternal e-services. This process began with the development of the research questions to direct the study's focus: "**What are the strengths and weaknesses of existing frameworks for delivering and supporting maternal e-services?**" In line with this question, the study contributes to knowledge in two key aspects. Firstly, it assesses the status of maternal e-service delivery by uncovering the current available maternal e-services and suggesting ways to enhance access to maternal healthcare through their expansion. Secondly, it synthesizes academic literature to analyze existing approaches in the delivery of maternal e-services, with a particular focus on how technology-based frameworks have facilitated and influenced the provision and support of these services. The PRISMA (Figure 1), an established model in literature reviews, facilitated the sourcing of numerous studies from scientifically recognized electronic databases. This model serves as a comprehensive guideline for conducting literature reviews, ensuring transparency and rigor in the review process. Subsequently, the review activity unfolded sequentially as follows:

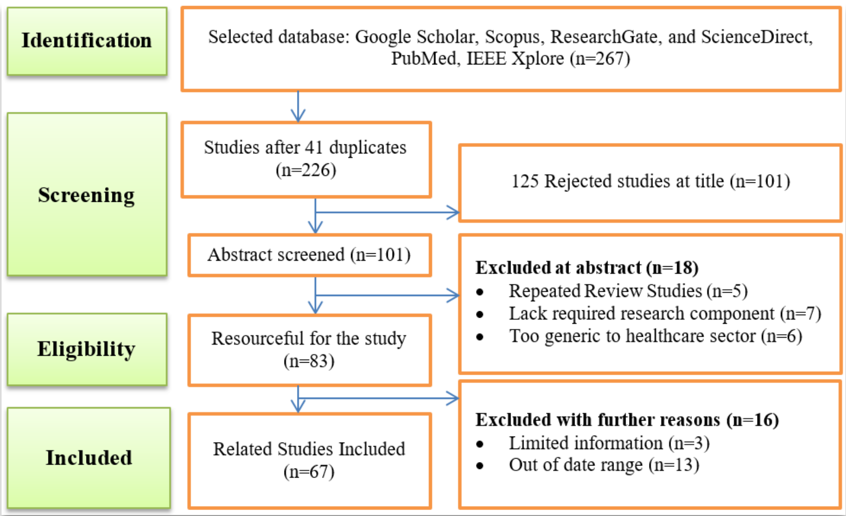

Figure 1. Flow diagram for the selection of related studies. **Source:** Author's synthesis(s) (2024)

The process of identifying and identifying relevant publications for the study involved the following steps:

- **Identification**: Studies were retrieved from scholarly databases, including Google Scholar, Scopus, ResearchGate, PubMed, IEEE Xplore, and ScienceDirect, following a systematic keyword search technique. The keywords used included but were not limited to maternal health AND maternal electronic health OR maternal electronic services, mobile health services AND mobile health, pregnancy OR prenatal care AND postnatal care, childbirth AND electronic intervention, electronic delivery AND digital intervention, AND digital health. In some instances, these keywords were used in combination to ensure a comprehensive search and retrieval of closely related studies. This strategy ensured that a broad spectrum of studies related to maternal e-services and maternal healthcare access at large was considered. As a result of this thorough search, a total of 267 articles were initially identified. However, upon closer examination, it was found that 41 of these articles were duplicates, which were subsequently removed from the pool, leaving a refined selection of unique studies for further review and analysis.
- **Publication screening**: The screening phase involved reviewing the titles and abstracts of the identified studies to assess their relevance to the research topic. Studies that are deemed irrelevant or do not meet the inclusion criteria are excluded at this stage. Out of the 226 studies after removing duplicates, 125 were excluded at the title screening stage (n=101), and 18 were excluded based on the abstract screening (n=83). Reasons for exclusion at the abstract screening phase include repeated review studies (n=5), lack of required research component, i.e., not focused on maternal healthcare

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access (n=7), and being too generic to the healthcare sector (n=6). The screening of the relevant details about the publications was accomplished by using advanced features of Microsoft Excel 2019, such as sorting and filtering, if and if else function, among others.

- **Eligibility of the publication**: Studies that passed the screening phase were further assessed for eligibility based on predefined criteria. A total of 83 studies were considered resourceful for the study after the screening phase. Out of these 83 studies, 16 were excluded for reasons including limited information as required by the researchers (n=3) and being out of date range (n=13) because the study focused on research published from 2015 onwards to ensure the inclusion of the most current and relevant data.
- **Publication inclusion**: Studies that meet all the inclusion criteria were considered relevant for the review and are included in the final review. In this case, 67 studies were included for further analysis

2.1 Some Common attributes of the selected publications

2.1.1 The exclusion and inclusion criteria

Numerous inclusion and exclusion criteria have been used because the publication selection procedure is important for adding scientific value to the literature reviews. Therefore, we decided to concentrate on research on maternal healthcare access and maternal electronic service delivery, particularly focusing on potential electronic services to maternal healthcare, potential insights on maternal electronic services to maternal healthcare, electronic service frameworks for maternal healthcare, and related works to maternal healthcare and developing solutions to the same. The modified inclusion and exclusion criteria are displayed in Table 1. The publications that were not published in the English language or ones that were still in publication at the time of selection were disqualified. The goal of our work was to examine maternal healthcare access and maternal electronic service delivery: strategies in resource-constrained environments; hence, we also incorporated quantitative, qualitative, and case study analyses. Additionally, a variety of epistemological stances were also adopted to emphasize the topic's multidisciplinary aspect.

Table 1. Inclusion and exclusion criteria of publications

Inclusion criteria	Exclusion criteria
Books, empirical studies, editorials, fields of social science, information science, economic science, humanities, English language articles, articles in academic journals, case studies, quantitative and qualitative analyses, and epistemological approaches	Summaries of conferences, convention lawsuits, book reviews, field of agriculture science, interviews, technical as well as health science, summaries of meetings, editorial letters; non-academic texts, and non-English papers, papers that were still in publication

Source: Synthesized by the Author(s) (2024)

2.1.2 Inclusion and exclusion criteria of frameworks for maternal e-services

The study emphasized analyzing existing frameworks for maternal e-services, adopting a different approach to identify, include, and exclude frameworks that have been studied to support access to these services. While some frameworks were identified based on the criteria outlined in Figure 1, others were not found. To source relevant frameworks, a comprehensive keyword search was conducted across online scholarly databases, as illustrated in Figure 1. The search specifically targeted practical electronic frameworks for maternal e-services rather than purely conceptual models. Key search terms included "maternal e-services frameworks," "approaches to maternal healthcare access," "digital frameworks for maternal health," "e-health interventions in maternal care," "mHealth solutions for maternal services," "electronic systems for maternal healthcare," and "maternal health digital access models."

Table 2. Inclusion and exclusion criteria of frameworks for maternal e-services

Inclusion Criteria	Exclusion Criteria
Practical Implementation: Frameworks that have been practically implemented and tested in real-	Conceptual Frameworks/Models: Frameworks that are purely theoretical or conceptual without practical implementation or testing.

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world settings, as opposed to purely theoretical or conceptual models.	
Relevance to Maternal Health: Frameworks specifically designed to address maternal healthcare, focusing on improving access, quality of care, and health outcomes for mothers.	Non-Specific to Maternal Health: Frameworks addressing general healthcare or other areas not specifically focused on maternal health
Digital Solutions: Frameworks incorporating digital or electronic solutions, including mobile health (mHealth) applications, electronic health (eHealth) systems, and other technological interventions	Non-Digital Solutions: Frameworks that do not incorporate digital or electronic components.
Evidence-Based: Frameworks supported by empirical evidence demonstrating their effectiveness and impact on maternal health outcomes.	Lack of Empirical Evidence: Frameworks without supporting evidence or data on their effectiveness and impact.

Source: Synthesized by the Author(s) (2024)

2.1.3 Distribution of articles by publication year

The only publications released between 2015 and 2024 were chosen. To benefit from a period in which the associated theme, in addition to a viable dynamic, has found considerable resonance, publications on the topic should be as current as feasible. The review concentrated on reports written for maternal healthcare access and maternal electronic service delivery. Amongst the reviewed papers, 8 were published in 2019, 16 in 2020, 15 in 2021, 8 in 2022, and 10 in 2023; the years with the fewest publications were 2015, 2016,2017,2018, and 2024. Indicating the present interest in this area of study, the majority of the papers were published between 2018 and 2023 (Figure 2).

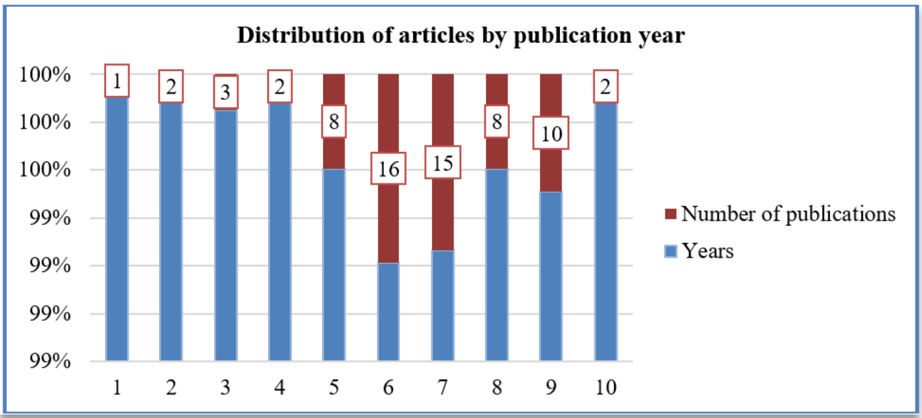

Figure 2. Distribution of articles by publication year.
Source: Synthesized by the Author(s) (2024)

2.1.4 Distribution of articles by database

Figure 3 shows the distribution of publications across various databases, with a focus on those related to the topic being studied. PubMed has the highest number of publications, with a total of 19, followed by Google Scholar and Scopus, with 17. ResearchGate and IEEE Xplore are also a significant source, contributing 6 publications, while Science Direct has the fewest in this selection, with 2 publications. Although other databases exist, such as CINAHL, Web of Science, and Embase, their publications were already included in the counts from the considered sources. In line with this study, the distribution indicates that PubMed is the most prominent source for publications relevant to the topic of this study, followed by Google Scholar and Scopus, suggesting these databases are particularly valuable for researchers in terms of maternal healthcare access.

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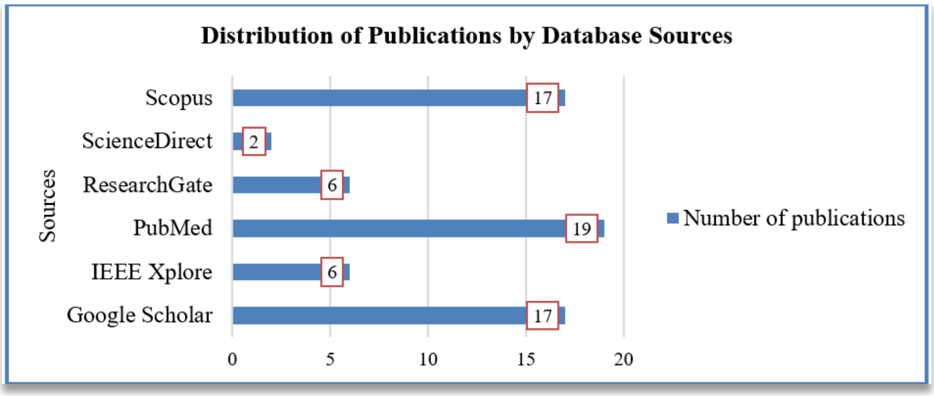

Figure 3: Distribution of publications by database Sources
Source: Synthesized by the Author(s) (2024)

3 Results

The results of this review study are presented in four sections: (3.1) the nature of maternal e-services, which discusses the state-of-the-art maternal electronic services identified in the literature review, followed by potential electronic services that could enhance access to maternal healthcare access and improve women's health; (3.2) traditional approaches to accessing maternal healthcare, which provides state-of-the-art insights into both maternal electronic services and traditional access methods found in the literature; (3.3) frameworks for maternal e-services, which details the state-of-the-art frameworks for electronic maternal healthcare services found in the literature review; and (3.4) related studies, presenting the state-of-the-art insights, challenges, and barriers toward accessing maternal healthcare as found in the literature review.

3.1 The nature of maternal e-services and potential maternal e-services

The nature of maternal e-services centers on the involvement of electronic technologies, such as the Internet and mobile phones, to deliver maternal healthcare services. These services can include online resources for pregnancy and childbirth education, telemedicine consultations with healthcare providers, and access to remote monitoring and support from healthcare professionals [46], [47]. The goal of maternal e-services is to improve access to healthcare and support for pregnant women and new mothers, particularly in areas where access to in-person healthcare may be limited, as well as in emergency-based situations [30], [48]. These services can be particularly useful for women who live in rural or remote areas or who have mobility issues that make it difficult to access in-person care [49]. The study identified the following as the potential e-services that can be considered to improve access to maternal healthcare.

a) **Maternal health education:** At each phase of maternal health, mothers are entitled to access information required for the management of conditions and complications specific to that particular stage [50], [51]. The necessity lies in obtaining this information from credible, accredited, and qualified healthcare professionals. This clarifies the reason behind the advice for mothers to regularly seek antenatal care from authorized healthcare service providers such as hospitals. This activity is termed the Antenatal Care Visits (ACV) [52], [53]. Moreover, after giving birth, new mothers are supposed to purposely acquire information to ensure the healthy living of both the mother and newborn baby. It is worth noting that the information provided after childbirth varies based on the mode of delivery, that is, vaginal delivery or cesarean section (c-section) [54]–[56]. Electronic delivery of information often prioritizes text-based formats like SMS and voice notes. However, it's crucial to acknowledge the potential of multimedia composition and delivery for digital content. This includes infographics, images, videos, animations, and text-based formats [57], [58]. Multimedia content delivery enhances comprehension and retention by leveraging visual elements, which are known to facilitate better recognition and understanding,

b) **Emergence support services**: Maternal life is fraught with various levels of risk, posing challenges and potential dangers to both mothers and infants [59], [60]. Complications can arise at any time, putting the lives of mothers and infants at risk [61], [62]. This imperative extends to new mothers, especially those

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who undergo cesarean section deliveries, as they face a myriad of medical risks and complications that can adversely impact both their health and the well-being of their newborns [63], [64]. Following this situation, it's pivotal for research studies to investigate the potential of technology-based solutions to facilitate responses to emergencies linked with maternal health, thereby ensuring the protection of lives for both mothers and infants,

c) **Expert consultation services**: Pregnant and new mothers must consult health providers to seek health assistance in uncontrollable situations [65], [66]. Traditionally, maternal consultations have required mothers to visit healthcare facilities. However, various challenges, such as geographical distance, financial limitations, and a shortage of healthcare providers, often result in missed consultation appointments [67]. Missing dialogues with experts create potential vulnerability, which could lead to an escalation in maternal risks and complications. This situation places the lives of both mothers and infants in a state of uncertainty and heightened danger [68], [69]. Therefore, it is essential to establish a framework that outlines the integration of technology to assist in remote consultations for better maternal health care and

d) **Medical prescriptions and investigations services**: Similar to other aspects of healthcare, maternal well-being involves the administration of prescribed medications and necessary medical tests/investigations [70]. These interventions are designed to promote health outcomes for both mothers and infants. Urgency intensifies, particularly for mothers who undergo cesarean section, owing to their heightened susceptibility to various health complications and risks [71], [72]. Nevertheless, there are instances where the dosages of these drugs and medications are overlooked, leading to terrible situations in which lives are put at risk [73], [74]. Despite the critical nature of this aspect, the existing frameworks for maternal e-services lack specific guidelines for addressing the management of medications and medical procedures through technological interventions. This emphasizes the necessity for research to investigate how e-service frameworks can guide the management of medical prescriptions to enhance adherence during maternal life.

3.2 Traditional approaches for maternal healthcare access

Scholarly literature highlights a range of e-services that have the potential to enhance access to maternal healthcare. However, their implementation remains limited by the absence of well-established frameworks and approaches, particularly within the digital ecosystem. As a result, traditional methods continue to dominate the delivery and support of maternal healthcare services in resource-constrained countries. While these conventional approaches have facilitated access to some extent, they face several challenges that undermine their effectiveness, as outlined below.

a)In-person visits to health facilities: In-person visits to health facilities, commonly known as antenatal care (ANC) visits, are crucial to accessing maternal services [26]. During these visits, healthcare professionals engage in direct dialogues with pregnant mothers to assess their health, provide specialized care, conduct check-ups, offer health education, and address concerns [46], [75]. ANC visits also allow for necessary medical procedures, immunizations, and mental health monitoring However, there are limitations to ANC visits, including distance and transport costs for mothers and long waiting times due to a limited number of healthcare practitioners [62], [76].

b) Home Visits by healthcare workers: Home visits by trained health workers are a valuable method of accessing maternal services, especially for expectant and new mothers who face barriers to attending ANC visits [77], [78] Health professionals provide personalized care, including health advice, prenatal check-ups, and assessing the mother's living conditions [27]. However, challenges such as long distances and limited healthcare workers restrict the widespread implementation of this method [79]–[81]. Additionally, it may not be suitable during situations where physical meetings are prohibited, such as pandemic and endemic situations.

c) Use of Phone calls for consultation purposes: Mothers commonly use phone calls to access maternal services, allowing them to seek medical advice and receive health education remotely [65], [82]. This method offers convenience and eliminates barriers associated with in-person visits, making it particularly useful during situations like pandemics [25], [66]. However, the effectiveness of this method is limited as it provides fewer services compared to in-person visits and lacks a reference source for shared information. This highlights the need for better approaches that support the diverse sharing of maternal information with attention to multimedia integration.

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3.3 Analysis of frameworks for maternal electronic services access

With the advent of technological advancements, the healthcare sector has witnessed transformative interventions aimed at enhancing service access and improving care quality. Within the realm of maternal health, numerous studies have highlighted the emergence of potential solutions leveraging technology to facilitate the provision of maternal healthcare services, particularly by aiding mothers in accessing critical resources through technology-based platforms. As mobile devices, such as smartphones and tablets, become increasingly integrated into communities, mobile technologies are recognized for their potential to enable access to maternal e-services. This study delved into the examination of existing frameworks guiding the design and development of technology-based applications for maternal e-service access, elucidating prevalent approaches and practices in this domain. Table 2 summarizes these frameworks, reflecting the name of the framework, Strengths/Services Supported, and areas that require Improvement (weakness/loopholes).

a) The mobile health communication framework for postnatal care

Employing a multi-method research approach, as illustrated in the works by Mbuthia et al. [83], [84] yielded the development of a theory-driven framework designed to improve postnatal care in rural Kenya through mobile health communication. This innovative framework was constructed by amalgamating the most robust available evidence on mobile health communication, along with valuable insights gleaned from both users and policymakers. Consequently, Mbuthia's framework sheds light on the pivotal role of mobile communication, particularly through the exchange of mobile messages (SMS), as a critical strategy for fostering the adoption of postnatal care practices in rural Kenya. However, it is crucial to acknowledge that the scope of Mbuthia's framework is circumscribed solely to the domain of postnatal services. While it excels in addressing postnatal care uptake, it leaves out other critical stages of maternal care and overlooks the vast potential of various other maternal e-services.

b) The mHealth Messaging Service Framework (MomConnect)

MomConnect, originating in South Africa, is a noteworthy mobile health framework designed with the primary objective of delivering essential maternal education and information to mothers, with the ultimate aim of enhancing maternal and child health outcomes [85]. This framework guides leveraging Short Message Service (SMS) technology to offer information and support to expectant and new mothers. The practical implementation of this framework materialized through the development of the MomConnect application, which has demonstrated its effort to reach a diverse number of women, including those residing in underserved regions [86]–[88]. MomConnect's personalized approach, which allows mothers to filter and receive messages tailored to their needs, has notably increased the utilization of maternal health services [14], [88]–[90].

c) The Mobile Alliance for Maternal Action Framework

The Mobile Alliance for Maternal Action (MAMA) framework is a remarkable product of a collaborative effort between the public and private sectors [91], [92]. This initiative centers on the integration of mobile technologies as a means to disseminate critical healthcare information to mothers residing in resource-limited settings, with the ultimate goal of enhancing their health and overall well-being. MAMA was introduced to engage healthcare experts in the practice of mobile health messaging, directing its efforts towards subscribed mothers and imparting essential knowledge on a wide range of topics, including pregnancy, infant care, HIV prevention, infant feeding, and post-partum family planning. The achievements of MAMA are truly commendable, having made a significant impact by reaching approximately 600,000 mothers and their families across nearly 60 countries, fostered through partnerships with over 235 organizations. This has addressed the challenge of providing maternal health education to economically disadvantaged mothers, who often encounter barriers in accessing crucial healthcare information [93].

d) AI Pregnancy companion chatbot framework

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The AI-enabled framework known as the PCC (Pregnancy Care Companion) represents a notable innovation in the realm of maternal education [94], [95]. This framework harnesses modern technology, leveraging Amazon Web Services and Alexa, Amazon's AI-powered virtual assistant, to deliver maternal education through text- and voice-based interaction. PCC addresses the limitations commonly observed in text-based frameworks, such as MomConnect and MAMA Technology, by offering voice-based interactions, enabling pregnant mothers to receive real-time AI-generated responses to their health inquiries [96]. The accuracy and reliability of PCC's implementation have been robustly established through rigorous testing on Amazon Echo Dot devices. PCC's distinguishing feature lies in its interactive voice-based approach, which surpasses traditional text-based platforms in addressing maternal health concerns [97]–[99].

e) AI framework for fetal health status prediction

The Fetal Health Status Prediction Framework (FHSP) is an e-health framework specifically designed to aid in the prediction of fetal health status by harnessing the capabilities of machine learning algorithms [100]. FHSP is distinguished by its utilization of algorithms trained on maternal clinical history data, enabling accurate health predictions. These algorithms include a diverse array of models, such as averaged perceptron, boosted decision tree, Bayes point machine, decision forest, decision jungle, locally deep support vector machine, logistic regression, neural network, and support vector machine. FHSP collects health and clinical history information from pregnant mothers through an assessment form, utilizing these data to generate predictions encompassing medical recommendations, potential risks, and mitigation criteria [101]. As an AI-driven tool, FHSP is a valuable resource for maternal health screening.

f) KIA e-health framework for maternal and child health services

Hayati et al. [102] explain the development of an Android-based application, KIA, designed to modernize the delivery and accessibility of maternal and child health services in Indonesia. This approach was underpinned by the implementation of the KIA E-Health Theoretical Framework, which placed maternal health information provision at its core, encompassing various facets of maternal health, including prenatal and postnatal care and family planning. The framework organized the information domain into user-friendly services, which included immunization information, health-related content, pregnancy calculators, weight tracking for pregnant women, a fertility calculator, and a survey tool. The KIA Framework received favorable acceptance and usability feedback following rigorous testing of the KIA Application. However, it's important to note that while KIA demonstrated strong features and promise in the realm of maternal information delivery, it falls short of being a better framework for maternal services. Its primary focus on the information domain leaves the other vital domains unaddressed.

Table 3. Summary of existing frameworks for maternal e-services

Name of the Framework	Strengths/Services Supported	Weakness / Suggested Areas of improvement
The Mobile Health Communication Framework for Postnatal Care in Rural Kenya (mHCFPC)	Maternal Health Education through Voice based interactions	Lacks Multimedia Capabilities. Only focus on Maternal education leaving other services
The Mobile Health Messaging Service and Helpdesk Framework for South African Mothers (MomConnect)	Maternal Health Education through text-based SMS	Lacks Multimedia Capabilities. Only focus on Maternal education leaving other services
The Mobile Alliance for Maternal Action (MAMA) framework	Maternal Health Education through text-based SMS	Lacks Multimedia Capabilities. Only focus on maternal education leaving other services No filtration of what should be received.

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AI Pregnancy Companion Chatbot (PCC) Framework	Maternal Health education and support through both text and voice-based interactions	Still limited to multimedia capabilities and also the coverage of maternal services is only on maternal education
AI Framework for FHSP	Automated assessment with smart recommendations and maternal education support	Lacks multimedia capabilities and coverage of maternal services is low
KIA E-Health Framework Maternal and Child Health Services in Indonesia	Maternal Health Education through text and Voice-based communications	Lacks Multimedia Capabilities. Only focus on Maternal education leaving other services

Source: Synthesized by the author(s) (2024)

3.4 Studies on insights, challenges towards maternal healthcare access

Pant et al. [25] conducted a study to assess the impact of the emerging COVID-19 pandemic on the provision and accessibility of maternal health services. Employing a narrative review approach, their study sheds light on the myriad challenges introduced by the pandemic that significantly hindered women's ability to access essential healthcare facilities for maternal health needs. These obstacles encompassed a range of factors, including pandemic-related restrictions, transportation difficulties, and heightened concerns about potential exposure to the coronavirus. A critical finding of this study was that a substantial number of women opted to seek hospital-based services, including essential antenatal care visits. The decision is largely driven by the fear of contracting the virus or transmitting it to unborn children. Even for those who managed to reach healthcare facilities, timely care was not consistently provided. This alarming trend has contributed to a significant increase in global maternal mortality rates during the pandemic.

Abejirinde et al. [103] conducted a realistic review to explore the capacity of mobile health technology to enhance the usefulness of maternal healthcare practitioners in low and middle-income nations. The primary motivation behind their research was to uncover the untapped potential of mHealth in improving maternal healthcare provision through healthcare workers. Findings revealed the considerable impact of implementing mobile health solutions on enhancing the proficiency of healthcare workers involved in maternal health.

Indira & Srihari [104] developed a conceptual framework for investigating the efficacy of text messages in the context of maternal healthcare. This study highlights the growing prevalence and user-friendliness of mobile communication, which has paved the way for the adoption of mobile applications to manage diseases and promote healthy behaviors. Beyond the advantages of facilitating health education among patients and reducing waiting times and healthcare expenses, mHealth has emerged as a potent tool for enhancing patient support. It offers a robust platform for swift emergency response and continuous monitoring of patient health status. Consequently, this study illuminates a conceptual framework that elucidates the vast potential of mobile phones in delivering health messages, particularly in providing critical support to mothers throughout their maternal journeys.

The study conducted by Bekyieriya et al. [82] sheds light on the significant potential of mobile health technologies in delivering maternal health services, particularly to expectant mothers in rural areas. The primary objective of their research was to assess the level of awareness among women about Mobile Health (mHealth) technology and identify the challenges faced by these women when attempting to utilize mHealth technology to improve maternal health outcomes in rural areas within the Upper West Region (UWR) of Ghana. To achieve their research goals, the team employed an exploratory design complemented by quantitative data collection tools, most notably semi-structured interviews. Through this approach, they were able to discern that many mothers in remote areas were aware that mHealth is a crucial source of health education information. Information is typically provided by healthcare providers to assist mothers in various aspects of pregnancy activities. However, their study revealed slow adoption of these technologies, primarily attributed to factors such as low female literacy rates within households, financial hardships, deeply ingrained cultural beliefs, network connectivity issues, and other related challenges.

A qualitative study by Mwase et al. [105] explored the implementation and use of toll-free telephone lines (TFL) in four health facilities. These TFLS were established by Save The Mother (STM), aiming to connect vulnerable mothers to healthcare providers, thereby granting them access to maternal and newborn healthcare services, particularly essential information. The findings of this study indicated that the TFL

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network played a crucial role in facilitating the delivery of health information to mothers and nurturing relationships between community members and healthcare experts. This was achieved by ensuring prompt responses to inquiries and facilitating timely referrals when necessary. This marked the value of the TFL approach in bridging the gap between healthcare providers and mothers, thereby enhancing maternal and newborn healthcare services.

The study conducted by Bilal et al. [106] , which focused on Africa, aimed to investigate the potential of telemedicine and digital health in improving access to maternal healthcare. Their findings underline the significant challenges faced by women in Africa when it comes to accessing maternal healthcare. As previously discussed, this study reinforced the notion that the delivery of maternal healthcare services remains a critical and fundamental approach to mitigating maternal mortality and morbidity along with their associated devastating consequences. Bilal et al. firmly asserted that the utilization of telemedicine and digital health holds great promise as an alternative means to enhance access to maternal healthcare. This potential lies in the ability of telemedicine and digital health to provide long-distance, real-time services, thereby mitigating various hardships related to geography and economic constraints, including issues such as transport costs, long distances to healthcare facilities, and financial challenges. Bilal et al. believe that with the adoption of these technologies, there is a strong possibility of achieving improved maternal health outcomes in the low-resource settings of African countries.

[108] piloted a quasi-experimental study in various regions of Ghana, with the primary objective of assessing the impact of technological interventions on maternal and child health. Their study involved the recruitment of both mothers and healthcare experts with an interest in T4MCH (Technology for Maternal and Child Health) interventions. The researchers and innovators of this study introduced the concept of T4MCH, which is designed to improve access to maternal healthcare services for expectant mothers and healthcare facilities. This was achieved through the implementation of a mobile-based application called SGS Collect. The application collected personal information from pregnant mothers during their antenatal care (ANC) visits and subsequently delivered SMS and voice-based messages to these mothers within a week. These messages were provided in both English and local languages using a multilingual feature. The key takeaway from this study, which is relevant to the current research, is the demonstration of technology's potential to support the delivery of maternal education. This serves as a reminder that many existing interventions predominantly focus on maternal health education as their core domain. This study highlights the need for a framework that extends beyond education to encompass a wider range of maternal services, ultimately aiming to improve access to and delivery of maternal healthcare services. Table 4 summarizes this related work by reflecting on the source/citation, results of the work, and contribution.

Table 4. Related Studies on Maternal Healthcare and Maternal Electronic Services

Citation/ Method	Results/Key Findings	Contribution/Relevance
Narrative Literature Review [25]	Women opted to forgo hospital-based services, including essential antenatal care visits due to COVID-19	It broadened perspectives on the feasibility of leveraging technology to deliver maternal services in pandemic situations
Realist review study [103]	Revealed the impact of implementing mobile health solutions on enhancing the proficiency of healthcare workers involved in maternal health	Highlights how the conceptualized health framework can improve access to maternal services through the involvement of health workers.
A pilot study at Coimbatore (India) [104]	Pinned the growing prevalence and user-friendliness of mobile communication through mobile apps to promote healthy behaviours	Yields vital insights into the transformative potential of mobile technologies in rendering maternal and health services.
Quantitative data using semi-structured interviews [107]	Many mothers in remote areas are aware of mHealth as a crucial source of health education information with a slow adoption of these technologies' due challenges like financial hardships etc.	Reinforcing the notion that existing health interventions often focus predominantly on maternal health education while side-lining other potential essential services

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Qualitative study [105]	Indicated that the TFL network played a crucial role in facilitating the delivery of health information to mothers and nurturing relationships between community members and healthcare experts	Emphasizes the need for innovative solutions to address and alleviate the limitations of the TFL approach
Literature Review [106]	Emphasized that utilization of telemedicine and digital health holds great promise as an alternative means to enhance access to maternal healthcare	Highlights the relevance and potential of telemedicine in the context of maternal health
Quasi-experimental study [108]	There was improved access to maternal healthcare services for expectant mothers and healthcare facilities through access to antenatal care voice and text messages powered by SGS Collect.	It served as a reminder that many existing interventions predominantly focus on maternal health education as their core domain for maternal e-service delivery

Source: Synthesized by the Author(s) (2024)

Literature has indicated the existence of several e-services that have the potential to alleviate the state of maternal healthcare access in developing communities. This is accompanied by several frameworks that have demonstrated the ability of technology to support maternal health through mHealth innovations and interventions. Numerous studies have concentrated on the potential of mHealth to support maternal education access via mobile messages, which are typically disseminated from healthcare providers to mothers, covering various topics. While there have been some attempts to explore voice interactions, such as in the PCC Framework, these initiatives remain in the minority. Despite their merits, current frameworks exhibit limitations in their concentration on maternal health education using text and voice communication methods. This underlines the necessity for a framework that expands the scope of covered maternal e-services, harnessing multimedia capabilities for content delivery and holistically addressing the needs of maternal care.

4 Discussion

Traditional maternal healthcare approaches, including antenatal care (ANC) visits, home visits, and phone consultations, offer valuable services but face significant limitations. ANC visits provide comprehensive medical care but are constrained by distance, costs, and limited healthcare personnel. Home visits address access barriers with personalized care but are resource-intensive and impractical during crises. Phone consultations offer convenience but lack the depth and scope of in-person interactions. These limitations highlight the emergence of several e-service frameworks that leverage digital technologies to integrate and enhance these approaches, providing better solutions to improve maternal healthcare delivery. Realizing the critical importance of maternal healthcare and women's health, several scholars have studied this area, highlighting the insights, challenges, and barriers to accessing this care. Extended studies developed frameworks that have potentially supported access to this crucial care. The findings of this study underscore the role of existing frameworks in enhancing maternal healthcare through digital means, particularly by providing accessible educational content to mothers. Frameworks like MAMA and MomConnect primarily rely on SMS messaging, which has proven effective in reaching mothers in various circumstances but faces limitations in message size and accessibility. To address these challenges, improved frameworks such as the KIA E-Health Framework and the AI Pregnancy Companion Chatbot (PCC) have introduced voice-based delivery, which is especially beneficial for visually impaired mothers and offers a more intuitive user experience.

However, this study identified a notable gap in current frameworks: the limited use of multimedia elements, such as images, animations, and infographics, which could significantly improve the comprehension and the impact of maternal healthcare information. Moreover, existing frameworks mainly focus on educational services, whereas a broader range of e-services like emergency support, telemedicine,

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and medication tracking could provide a more holistic approach to maternal and women care. As illustrated in Figure 4, this study developed a conceptual framework that serves as a structured model to provide a summative and graphical understanding of the insights, challenges, and barriers identified in maternal healthcare. The conceptualization's independent variables are the features and services provided by the frameworks, with existing ones primarily focusing on maternal education but often lacking support for interactive multimedia content. The dependent variables, which are the outcomes of these services, include improved access to healthcare and the quality of care for expectant and new mothers, ultimately leading to reduced maternal mortality rates. This illustrates how improving the independent variables can positively impact the dependent variables.

The conceptualized framework presents the following domains rooted in the potential services for maternal healthcare: **a) Maternal health education with multimedia support**: The domain goes beyond basic text-based information to incorporate engaging multimedia elements like videos, infographics, and interactive modules. This approach enhances comprehension, knowledge retention, and user engagement. **b) Emergency support: emergency support**: This concerns integrating emergency support services to assist mothers in urgent situations. This can be through real-time response to emergent situations, especially for pregnant mothers and C-section mothers. **c) Medications and Investigations Tracking**: This domain focuses on providing mothers with a secure and convenient platform to track their prescribed medications and test results electronically. This promotes medication adherence and facilitates informed communication with healthcare providers. **d) Remote consultations and appointment management**: This should focus on functionalities for scheduling appointments and conducting consultations with healthcare providers remotely via telemedicine. This purpose is to reduce geographical barriers and improve access to specialist care.

Determinants of the conceptualized framework refer to the expected outcomes of the potential e-services for maternal health that are put in place under a comprehensive framework, typically mobile health-driven, to guide how these services can be implemented and realized in the realm of maternal health. This presents the long-term goals resulting from improved access to maternal healthcare. They include the following: reduced maternal complications and health challenges: improved access to comprehensive health education, emergency support, and remote consultations can empower mothers to make informed decisions and address health concerns effectively, potentially leading to fewer complications and improved overall health. Lower risks of maternal mortality: Timely access to emergency support and improved monitoring of medication adherence can contribute to earlier detection and management of risks, potentially reducing maternal mortality rates. Enhanced care for mothers: E-services offer additional touch points for mothers to receive care and support throughout pregnancy and motherhood. This fosters a more comprehensive and patient-centered approach to healthcare delivery and Improved Emergency Response. The inclusion of a dedicated emergency support system allows for timely intervention in critical situations, potentially saving lives.

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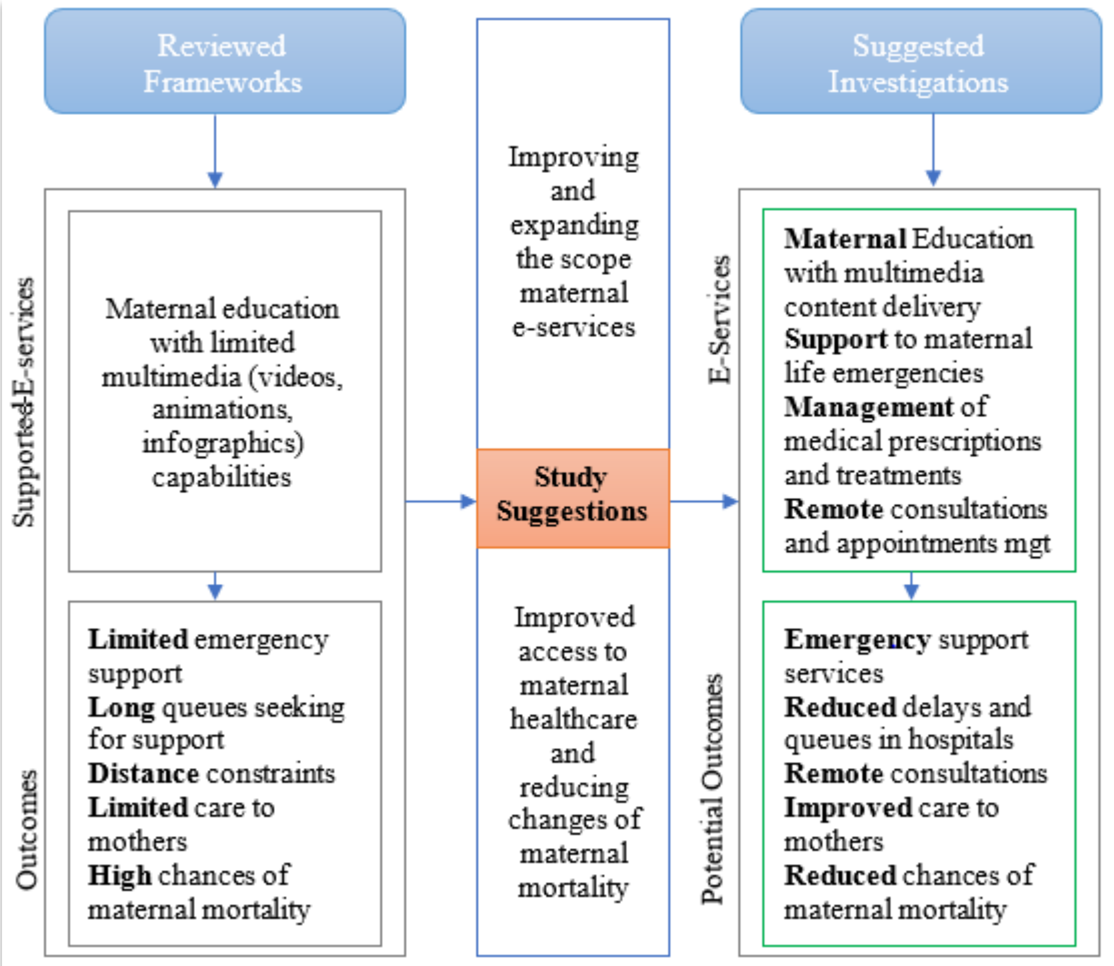

Figure 4. The conceptual framework.
Source: Synthesized by the Author(s) (2024)

5 Limitations

Firstly, the review relied heavily on studies from selected scholarly databases, which may have excluded relevant frameworks or insights not indexed in these sources. The review also did not conduct empirical assessments of the frameworks' effectiveness, relying instead on theoretical analyses of their components and published benefits. Lastly, the study was limited by a lack of region-specific analyses, which could have offered deeper insights into the unique challenges and needs within particular resource-constrained settings, especially in rural and low-literacy populations. These limitations highlight the need for further research that includes a broader range of sources, emerging technology assessments, and empirical validation of framework effectiveness across diverse geographical and demographic contexts.

6 Conclusion and Future Work

This paper highlights the urgent need to utilize technology-based approaches to enhance access to maternal services. The identified challenges in existing approaches, including limited healthcare providers, geographical barriers, financial constraints, lack of awareness, and restricted services, contribute to suboptimal utilization and negative impacts on maternal and infant health outcomes. Integrating technology can address these limitations and improve the quality of healthcare systems in developing countries. Therefore, further studies should prioritize investigating the necessary prerequisites for integrating

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technology platforms in the delivery of maternal services, with a particular focus on addressing the specific needs and limitations faced by marginalized communities with a realization of the identified potential e-services for maternal healthcare improvement. The exploration aims to mitigate the constraints associated with current approaches and enhance the accessibility and effectiveness of maternal healthcare. Future work can also look at including more studies while using other literature review approaches to minimize the potential bias in the selected individual studies.

Acknowledgements

None

Statement on conflicts of interest

No Conflict of Interest

Statement on Funding & Registration

The review was neither funded nor registered.

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Journal of Health Informatics in Africa

A Tree-based Machine Learning Approach for Precise Renal Cell Carcinoma Subtyping using RNA-seq Gene Expression Data

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Background and Purpose: Renal cell carcinoma (RCC) is a malignant neoplasm of the kidneys, characterized by distinct molecular and histological subtypes. Accurate subtyping is crucial for personalized treatment and improved patient outcomes. High-throughput sequencing has enabled precise gene expression profiling for cancer classification. This study compares tree-based and non-tree-based machine learning algorithms for differentiating between gene expression profiles of chromophobe, clear cell, and papillary RCCs.
Methods: RNA-seq data from a diverse cohort of patients diagnosed with these three cancer subtypes was used. Data preprocessing and normalization were performed, followed by feature selection using Analysis of Variance (ANOVA). Tree-based and non-tree-based algorithms were trained on the preprocessed data. The tree-based algorithms included decision tree, random forest, extra trees classifier, and bagging classifier. The non-tree-based algorithms included logistic regression, support vector machine, and naive bayes. Each algorithm was evaluated using sensitivity, specificity, F1 score, and AUC.
Results: Tree-based algorithms demonstrated superior performance across all evaluation metrics compared to non-tree-based algorithms. Specifically, the random forest classifier achieved the highest specificity and F1 score, the decision tree classifier achieved the highest sensitivity, while the bagging classifier achieved the highest AUC score. In contrast, non-tree-based algorithms showed comparatively lower performance in distinguishing between the cancer subtypes.
Conclusions: This study demonstrates the potential of machine learning, particularly tree-based models, for precise RCC subtyping. By leveraging tree-based models, we can effectively capture the complex, non-linear patterns in gene expression datasets. Future studies should aim to validate these findings across larger and more diverse datasets of RCC subtypes.

Keywords: Machine Learning, Renal Cancer, Gene Expression, Oncology.

1 Introduction

Kidney cancer is the seventh most common cause of cancer globally, and its prevalence is on the rise [1]. Renal cell carcinoma (RCC) accounts for more than 90% of all renal malignancies and is the most frequent malignant tumor of the kidney [2]. According to the International Agency for Research on Cancer, over 400,000 new cases of RCC are diagnosed each year, with more than 170,000 deaths globally [3]. The three most frequent histological subtypes of RCC are clear cell, papillary, and chromophobe, which account for more than 90% of all RCCs [4]. Accurate subtyping of RCC is crucial, as these subtypes greatly influence treatment and prognosis of these tumors [4] [5].

In recent years, RNA-seq gene expression platforms [6] [7] have emerged as the preferred method for simultaneous gene expression quantification when compared to DNA microarrays [8] [9]. Gene expression data from RNA-seq provide useful information on the differential activation of genes involved in cancer development [10]. Because cancer is a complex disease with several genetic changes, analysing gene expression data from tumor samples allows for the study of the molecular factors influencing disease

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progression and patient outcomes [11]. By effectively extracting information from RNA-seq data, physicians can gain a more comprehensive molecular view of a patient's condition, potentially leading to more precise diagnostic and prognosis procedures [12].

While RNA-seq gene expression data has significantly improved cancer classification, it does have limitations, particularly due to its typically small sample size [13]. Moreover, these samples often include numerous genes that are uninformative, which can negatively impact the performance of classification algorithms [13] [14]. To tackle the challenge of high dimensionality, it is essential to perform gene selection by eliminating redundant and uninformative genes [15]. One strategy to address this is to first apply filtration and feature selection techniques before proceeding with model development [14] [16].

Researchers have employed various machine learning methods, including supervised and unsupervised learning, and deep learning, to classify cancers using gene expression profiles. In a study by Mohammed et al. [14], a novel deep learning architecture was developed by stacking the outputs of five one-dimensional convolutional neural networks (1D-CNNs) to a feedforward neural network. This model was used to classify five of the most commonly diagnosed cancers in women. The results of this study suggested that this model could potentially enhance early cancer detection and diagnosis in women, as well as inform the design of early treatment strategies to improve survival.

Divate et al. [17] used transcriptomic data from 37 different cancer types sourced from The Cancer Genome Atlas (TCGA) to develop a deep neural network for identifying cancer-specific gene expression signatures based on tissue of origin. Their model successfully identified 976 genes capable of classifying various cancer types with >97% accuracy. In a different study, Abdelwahab et al. [18] employed a hybrid approach combining mutual information and recursive feature elimination methods with a support vector classifier model. They also incorporated a random forest model as an embedded feature selection technique. This strategy led to the identification of 12 candidate biomarkers strongly associated with different lung cancer types, especially lung adenocarcinoma.

Marostica et al. [19] used whole-slide histopathology images and demographic, genomic, and clinical data from multiple sources to develop convolutional neural networks for diagnosing renal cancers and linking quantitative pathology patterns with genomic profiles and prognoses of patients. Their deep learning models successfully detected histological subtypes of RCC, predicted survival outcomes for stage I clear cell RCC patients, and identified patterns in histopathology images indicative of copy-number alterations and tumor mutation burden. Their findings demonstrated that machine learning and deep learning techniques can effectively extract clinically relevant signals from histologic and genomic data, potentially aiding in patient diagnosis, prognosis, and identification of important genomic variations.

In this study, we demonstrate that tree-based models comparatively outperform non-tree-based models in differentiating between the gene expression profiles of chromophobe, clear cell, and papillary RCCs. Findings from this study could inform future research aimed at the early detection and accurate classification of these cancer subtypes.

2 Materials and methods

For this study, RNA-seq gene expression data from Pan-Cancer Atlas (https://portal.gdc.cancer.gov/) was used [20]. The data was retrieved using R statistical software version 4.3.1 via the TCGAbiolinks package accessible on Bioconductor [21] [22]. The data consisted of 897 samples representing chromophobe, clear cell, and papillary RCCs. Subsequently, seven machine learning algorithms were trained to discriminate between these cancer subtypes based on their unique molecular signatures. The data download was performed using R software [21], while the machine learning methods were implemented using Python [23] and scikit-learn [24].

2.1 Datasets

We downloaded the dataset from the Pan-Cancer Atlas using the GDCquery function in the TCGAbiolinks package, available on Bioconductor [22]. The dataset included samples of chromophobe, clear cell, and papillary RCCs, with benign tumor cases excluded. The GDCquery function was configured with specific parameters to retrieve the desired data. We used the project codes TCGA-KICH, TCGA-KIRC, and TCGA-KIRP to obtain data for the three RCC subtypes. Data filtering was done by setting the data.category to

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"Transcriptome Profiling" and the data.type to "Gene Expression Quantification." We restricted our query to The Cancer Genome Atlas files by using the barcode "TCGA*." Additionally, we specified "STAR – Counts" for the workflow.type and "Primary Tumor" for the sample.type. The resulting dataset was structured as a matrix, with samples represented in columns and genes in rows. In total, we obtained 897 samples and 60,660 genes. To address the issue of high dimensionality, we filtered out non-informative genes and performed feature selection to identify the most relevant genes for enhancing the performance of our machine learning models. Table 1 below shows a summary of the downloaded dataset, including the training and testing fractions for each tumor class.

Table 1. Number of samples across each cancer subtype

Cancer subtype	Number of samples	Training set (≈80%)	Test set (≈20%)
Chromophobe	66	53	13
Clear cell	541	427	114
Papillary	290	237	53
Total	897	717	180

2.2 Data Pre-processing

For the data preprocessing phase of our study, we employed the TCGAanalyze_Preprocessing function from the TCGAbiolinks package [22]. This function implements an array-array intensity correlation (AAIC) method to construct an N × N square symmetric matrix, where N represents the number of samples. Each element of this matrix corresponds to the Pearson correlation coefficient between a pair of samples. As illustrated in Figure 1, AAIC identifies samples with low correlation that could potentially be removed as outliers. In our analysis, no outliers were detected, suggesting a high degree of consistency across our dataset.

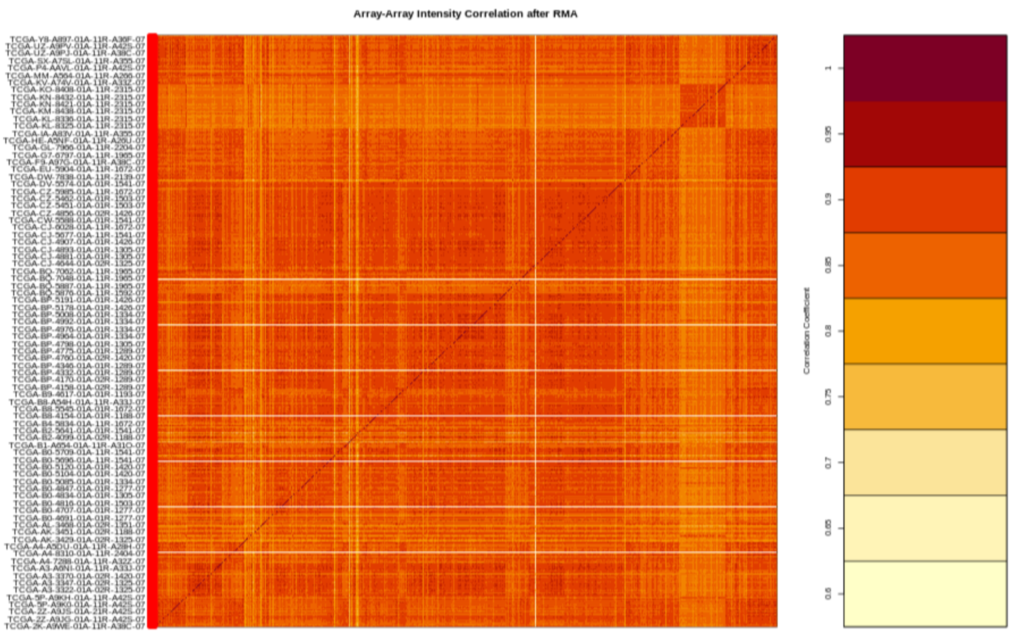

Figure 1. Array-array intensity correlation (AAIC) matrix defining the Pearson correlation coefficients among the samples.

Following this step, we conducted filtration of the expression matrix. Genes with a transcripts-per-million (TPM) value greater than 2000 were excluded from the matrix, as they were considered to be overly expressed and possibly indicative of housekeeping genes. Likewise, genes with a TPM value less than 100

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were also removed from the matrix as they were regarded as underexpressed. The resulting matrix comprised 8,540 genes, indicating that a total of 52,120 genes were filtered out.

2.3 Feature Selection

ANOVA was further employed to reduce the number of genes. ANOVA evaluates the relationship between gene expression levels and cancer subtypes by comparing group means and calculating F-statistics. Genes with higher F-statistics are considered more relevant for distinguishing between the cancer subtypes, helping to identify the most informative genes in the expression dataset.

2.4 Data Splitting

The dataset was divided into an 80% training set and a 20% test set. We performed a 10-fold stratified cross-validation on the training set, where each fold served as a validation set while the remaining nine folds were used for training. This process was repeated ten times, with a different fold acting as the validation set in each iteration. The optimal hyperparameters for the models were determined based on this cross-validation. The test set was then used for the independent evaluation of the machine learning algorithms.

2.5 Machine Learning Algorithms

Seven machine learning algorithms were used: logistic regression, naive bayes, support vector machine, decision tree, random forest, extra trees classifier, and bagging classifier.

2.5.1 Logistic Regression.

Logistic regression is a statistical model used for binary classification tasks, where the goal is to predict one of two possible outcomes based on input features [25]. In our case, we want to classify samples into three categories: chromophobe, clear cell, and papillary RCCs. To adapt logistic regression for multi-class classification, we can use the "one-vs-all" (also known as "one-vs-rest") approach.

Let's denote the following:

- X as the input feature matrix with n samples (rows) and m genes (columns).
- Y as the output variable representing the class labels. In this case, Y will have three categories: chromophobe ($Y = 1$), clear cell ($Y = 2$), and papillary ($Y = 3$).

The probability that a sample belongs to a particular class is modeled using the sigmoid function ($\sigma(z)$):

$$\sigma(\mathrm{z}) = \frac{1}{1+e^{-\mathrm{Z}}} \tag{i}$$

Where Z is the linear combination of the input features and model parameters (θ):

$$\mathrm{Z} = \theta_0 + \theta_1 \cdot X_1 + \theta_2 \cdot X_2 + \cdots + \theta_m \cdot X_m \tag{ii}$$

And where, $X_1, X_2, \ldots, X_m$ are the gene expression values for a particular sample, and $\theta_0, \theta_1, \theta_2, \ldots, \theta_m$ are the model parameters to be learned from the data.

For the three-class classification, three separate logistic regression models are created, one for each class. The models are trained as follows:

Chromophobe RCC ($Y = 1$):

- Set Y^i to 1 if the sample is chromophobe RCC, and 0 otherwise.
- Train a logistic regression model with the sigmoid function using the above formulas.

Clear Cell RCC ($Y = 2$):

- Set Y^i to 1 if the sample is clear cell RCC, and 0 otherwise.
- Train a logistic regression model with the sigmoid function using the above formulas.

Papillary RCC ($Y = 3$):

- Set $Y^i$to 1 if the sample is papillary RCC, and 0 otherwise.
- Train a logistic regression model with the sigmoid function using the above formulas.

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Once the models have been trained, prediction is made for a new sample by computing the probability for each class using the trained models:

$$P(Chromophobe \mid X) = \sigma\left(\theta_0^{(1)} + \theta_1^{(1)} \cdot X_1 + \theta_2^{(1)} \cdot X_2 + \cdots + \theta_m^{(1)} \cdot X_m\right) \tag{iii}$$

$$P(Clear\ Cell \mid X) = \sigma\left(\theta_0^{(2)} + \theta_1^{(2)} \cdot X_1 + \theta_2^{(2)} \cdot X_2 + \cdots + \theta_m^{(2)} \cdot X_m\right) \tag{iv}$$

$$P(Papillary \mid X) = \sigma\left(\theta_0^{(3)} + \theta_1^{(3)} \cdot X_1 + \theta_2^{(3)} \cdot X_2 + \cdots + \theta_m^{(3)} \cdot X_m\right) \tag{v}$$

Where $\theta^{(1)}, \theta^{(2)}, \theta^{(3)}$ are the learned model parameters for each class.

Finally, the predicted class for the new sample is the class with the highest probability:

$$\hat{Y} = \arg\max_{Y} P\left(Y \mid X\right) \tag{vi}$$

So, $\hat{Y}$ will be one of the three classes: chromophobe, clear cell, or papillary RCC, based on the highest computed probability.

2.5.2 Naive Bayes.

The naive bayes algorithm makes predictions using Bayes' theorem [26]. It assumes that the features of a given dataset are conditionally independent given the class. It begins by calculating the prior probabilities of each class (chromophobe RCC, clear cell RCC, and papillary RCCs) based on the frequency of each class in the dataset. This is done using the following formula:

$$P\left(C_k\right) = \frac{Number\ of\ samples\ in\ class\ C_k}{Total\ number\ of\ samples} \tag{vii}$$

For each class, it estimates the likelihood of observing the gene expressions for that class. This step can vary depending on the type of naive bayes algorithm (e.g., Gaussian, Multinomial, or Bernoulli), but it essentially computes the probability distribution of the features, that is, genes within each class. Naive bayes then assumes that the features are conditionally independent given the class. This simplifying assumption makes the calculations tractable and is expressed as:

$$P\left(X_1 = x_1, X_2 = x_2, \ldots, X_n = x_n \mid C_k\right) = P\left(X_1 = x_1 \mid C_k\right) * P\left(X_2 = x_2 \mid C_k\right) * \cdots * P\left(X_n = x_n \mid C_k\right)$$

(viii)

To predict a new sample, that is, a new set of gene expressions, naive bayes computes the posterior probability for each class by using Bayes' theorem:

$$P\left(C_k \mid X\right) = \frac{P\left(X \mid C_k\right) * P\left(C_k\right)}{P(X)} \tag{ix}$$

Where $P(X|C_k)$ is the likelihood of observing the gene expressions for class C_k, $P(C_k)$ is the prior probability of class C_k, and $P(X)$ is a normalization constant. Naive bayes then predicts the class that maximizes the posterior probability:

$$\text{Predicted Class} = \arg\max_{C_k} P\left(C_k \mid X\right) \tag{x}$$

2.5.3 Support Vector Machines (SVMs).

SVMs are a type of supervised machine learning algorithm used for both classification and regression tasks [27]. When applied to a dataset with three distinct classes, the SVM algorithm seeks to determine the best hyperplane that separates the classes while maximizing the distance between the closest points from different classes. It does this by solving the following optimization problem:

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$$\min_{w,b} \frac{1}{2}||w||^2 + C\sum_{i=1}^{n} \max\left(0,\ 1 - y_i\left(w * x_i - b\right)\right) \quad \text{(xi)}$$

Where *w* represents the weights, *b* is the bias term, *C* is a hyperparameter controlling the penalty for misclassification, x_i are the input features, and y_i is the target class label (1 for the positive class, -1 for the negative class). The decision boundary is determined by the hyperplane that separates the data points of different classes with the largest margin. New data points are classified based on which side of the hyperplane they fall on.

2.5.4 Decision Tree.

Decision tree is a machine learning algorithm whose output is determined by recursively partitioning data based on the values of different features, with the goal of maximizing the information gain or Gini impurity reduction at each step. This is achieved through a series of if-else conditions leading to leaf nodes, which represent the final class predictions [28].

2.5.5 Random Forest.

Random forest is a machine learning algorithm based on ensemble learning that builds multiple decision trees using bootstrapped samples of data, with the final output determined by aggregating the predictions of individual trees, often through a majority vote. The output can be represented as an average or a weighted sum of the individual decision tree predictions [29].

2.5.6 Extra Trees Classifier.

Extra trees classifier also constructs multiple randomized decision trees. However, it differs from random forest in that it splits nodes using randomly selected features and thresholds, rather than searching for the best split. The final prediction is determined by aggregating the outputs of individual trees, typically through majority voting [30].

2.5.7 Bagging Classifier.

Bagging classifier creates multiple subsets of the original dataset through bootstrap sampling, trains a separate classifier (like decision trees) on each subset, and combines their predictions. The final output is determined by aggregating individual classifier predictions through majority voting [31].

2.6 Class Imbalance

To address the class imbalance, class weighting was implemented based on the frequency of each class in the dataset. The weighting was inversely proportional to the class frequencies, such that the class with the least frequency was assigned the highest weight, and the class with the most frequency was assigned the lowest weight.

2.7 Performance Evaluation

Four statistical metrics, namely sensitivity, specificity, F1 score, and AUC, were selected for assessing and comparing the performance of the various models in this study.

Sensitivity, also known as recall or true positive rate, assesses how well the model captures all the actual cancer cases. It measures the ratio of true positives to the total number of actual cancer cases.

$$Sensitivity = \frac{True\ \ positives}{True\ \ positives\ +\ False\ \ negatives} \quad \text{(xii)}$$

Specificity, otherwise known as true negative rate, evaluates how well the model correctly identifies non-cancer cases among the cases it predicted as negative. It measures the ratio of true negatives to the total number of actual non-cancer cases.

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$$Specificity = \frac{True\ negatives}{True\ negatives + False\ positives} \tag{xiii}$$

F1 score is the harmonic mean of precision and recall, providing a balance between the two metrics.

$$F1\ score = 2 * \frac{Precision \times Recall}{Precision + Recall} \tag{xiv}$$

AUC assesses the ability of the model to discriminate between cancer and non-cancer cases at different classification thresholds. It represents the area under the receiver operating characteristic curve, which is a graphical representation of the true positive rate against the false positive rate at various threshold settings.

3 Results

We evaluated the performance of the machine learning algorithms using a hold-out test set comprising 180 samples. Table 2 shows the overall performance of each of the algorithms.

Table 2. Overall performance of each of the algorithms.

Model	Sensitivity	Specificity	F1 Score	AUC
Logistic Regression	82.53	94.63	86.58	97.78
Naive Bayes	90.27	95.89	88.83	98.06
Support Vector Machine	85.63	96.69	89.64	98.23
Decision Tree	93.21	96.44	89.51	96.82
Random Forest	93.12	98.09	91.42	99.14
Extra Trees Classifier	92.20	97.38	89.84	98.49
Bagging Classifier	84.42	95.72	87.43	99.16

Overall, the tree-based ensemble models, particularly random forest, demonstrated superior performance across all metrics. Random forest achieved the highest specificity (98.09%) and F1 score (91.42%), indicating its robust ability to correctly identify negative cases and maintain a strong balance between precision and recall. Decision tree achieved the highest sensitivity (93.21%), suggesting its effectiveness in identifying positive cases.

Bagging classifier, despite not leading in sensitivity, specificity, or F1 score, achieved the highest AUC score (99.16%). Extra trees classifier also showed competitive performance, achieving high scores across all metrics.

In contrast, non-tree-based algorithms, including logistic regression and SVM, showed comparatively lower performance in distinguishing between cancer subtypes.

Table 3 shows the performance of each of the algorithms across the three cancer subtypes.

Table 3. Performance of each of the algorithms across the three cancer subtypes.

Classifier	Performance Metrics								
	Sensitivity			Specificity			F1 Score		
	KICH	KIRC	KIRP	KICH	KIRC	KIRP	KICH	KIRC	KIRP
Logistic Regression	61.54	97.37	88.68	100.00	89.39	94.49	76.19	95.69	87.85
Naive Bayes	84.62	95.61	90.57	97.60	92.42	97.64	78.57	95.61	92.31
Support Vector Machine	61.54	99.12	96.23	100.00	92.42	97.64	76.19	97.41	95.33

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Decision Tree	92.31	92.98	94.34	97.01	95.45	96.85	80.00	95.07	93.46
Random Forest	84.62	97.74	100.00	98.20	100.00	96.06	81.48	97.30	95.50
Extra Trees Classifier	84.62	93.86	98.11	97.60	98.48	96.06	78.57	96.40	94.55
Bagging Classifier	61.54	97.37	94.34	99.40	90.91	96.85	72.73	96.10	93.46

KICH, Chromophobe; KIRC, Clear Cell; KIRP, Papillary.

The confusion matrices for the tree-based models are shown in Figure 2, Figure 3, Figure 4, and Figure 5.

Figure 2. Confusion matrix for decision tree. *KICH, Chromophobe; KIRC, Clear cell; KIRP, Papillary.*

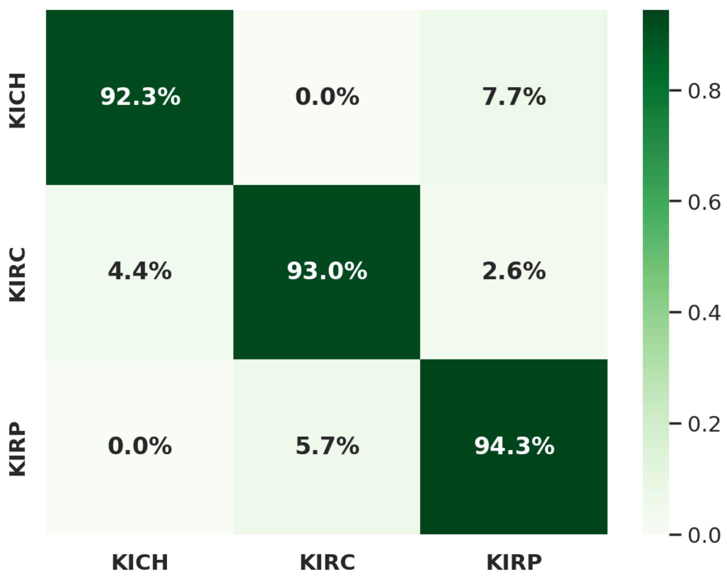

Figure 3. Confusion matrix for random forest. *KICH, Chromophobe; KIRC, Clear cell; KIRP, Papillary.*

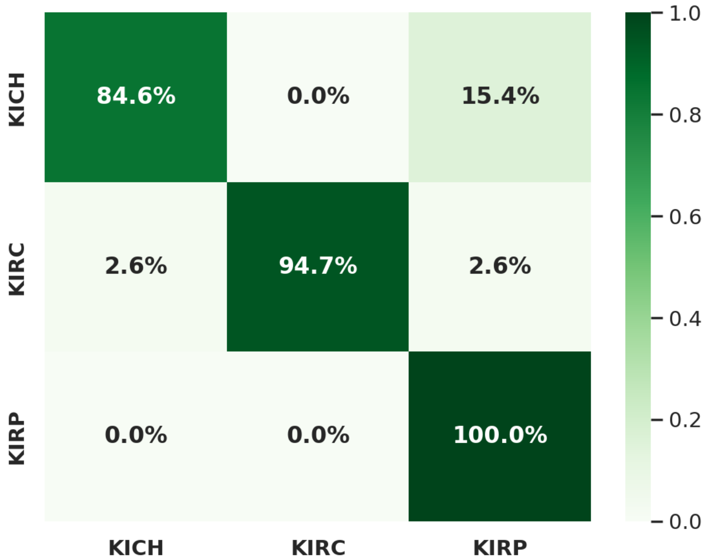

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Figure 4. Confusion matrix for extra trees classifier. *KICH, Chromophobe; KIRC, Clear cell; KIRP, Papillary.*

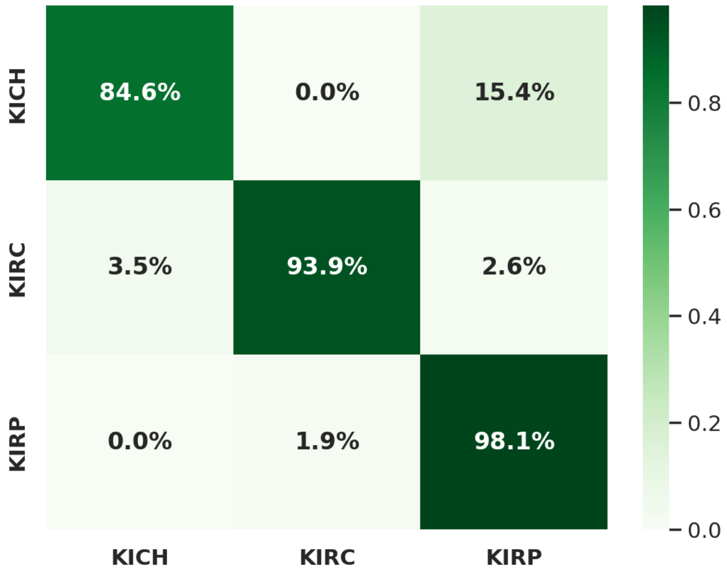
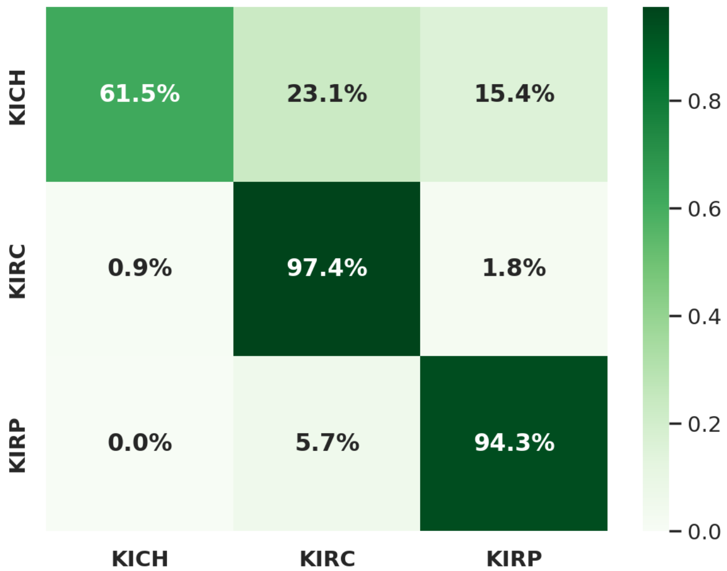


Figure 5. Confusion matrix for bagging classifier. *KICH, Chromophobe; KIRC, Clear cell; KIRP, Papillary.*



The receiver operating characteristic (ROC) curves for the tree-based models are shown in Figure 6, Figure 7, Figure 8, and Figure 9.

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Figure 6. Multi-class ROC curves for decision tree. *KICH, Chromophobe; KIRC, Clear cell; KIRP, Papillary.*

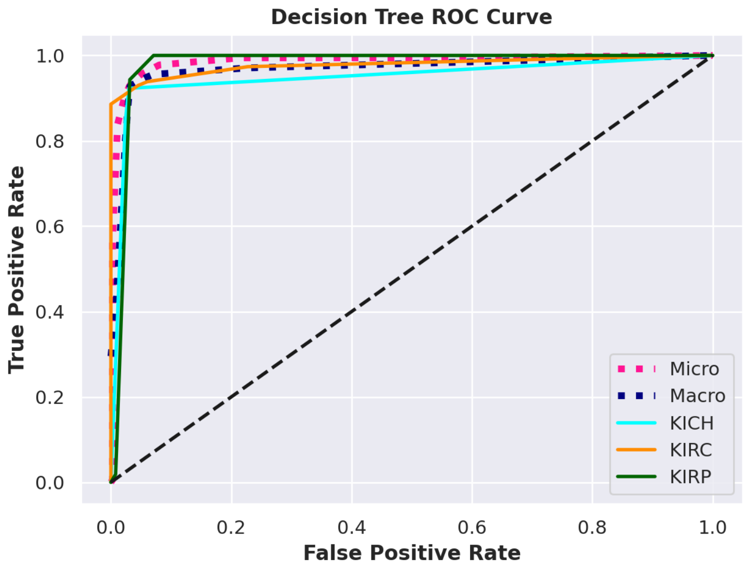


Figure 7. Multi-class ROC curves for random forest. *KICH, Chromophobe; KIRC, Clear cell; KIRP, Papillary.*

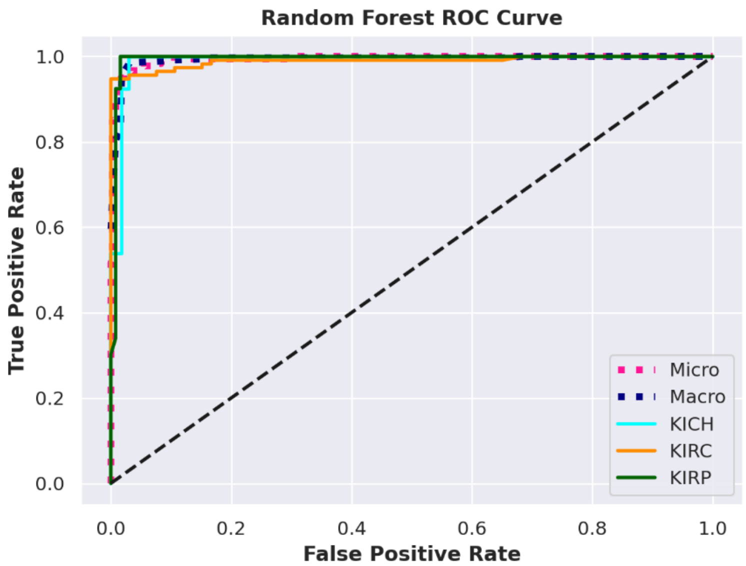


Figure 8. Multi-class ROC curves for extra trees classifier. *KICH, Chromophobe; KIRC, Clear cell; KIRP, Papillary.*

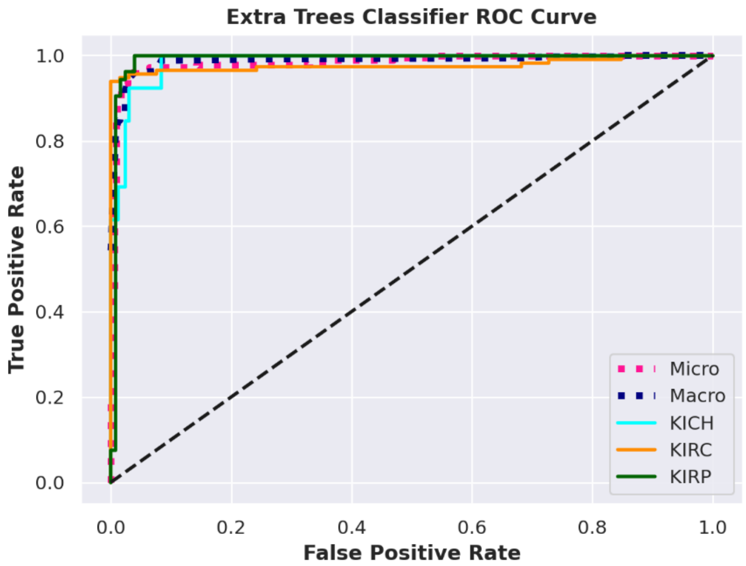
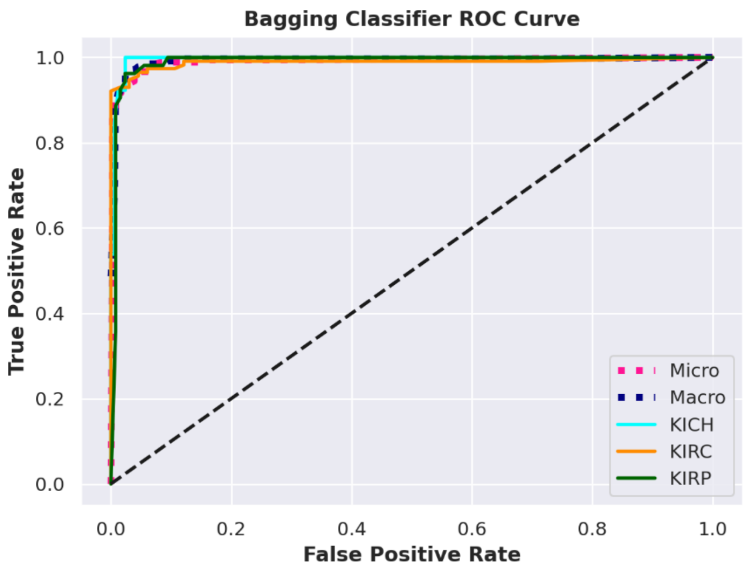


Figure 9. Multi-class ROC curves for bagging classifier. *KICH, Chromophobe; KIRC, Clear cell; KIRP, Papillary.*



4 Discussion

This work extends previous efforts in cancer genomics, such as TCGA project, which has provided comprehensive molecular characterization of various cancer types, including renal cell carcinoma [32]. Our approach builds upon previous work in cancer subtyping using gene expression data, such as the study by Ramaswamy et al. [33], which utilized SVMs for tumor classification. However, our research demonstrates that tree-based algorithms outperform non-tree-based algorithms in this context. Our tree-based method offers the advantage of handling complex, non-linear relationships in high-dimensional gene expression data.

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The superior performance of tree-based models, particularly random forest, can be attributed to their ability to capture complex, non-linear relationships in gene expression datasets [34] [35]. Cancer subtype classification often involves complex interactions between multiple genes [11] [36], which may not be adequately captured by models such as logistic regression or SVM [37]. The ensemble nature of random forest, combining multiple decision trees, allows it to model these complex relationships more effectively, resulting in its high specificity and F1 scores.

The high sensitivity achieved by the decision tree model suggests that simpler tree-based structures can effectively identify positive cases [38]. However, the slightly lower specificity compared to random forest indicates a trade-off between sensitivity and specificity. In clinical settings, the choice between these models may depend on whether it is more important to minimize false positives or false negatives for the particular cancer subtype being studied.

The high AUC score of the bagging classifier suggests its ability to discriminate between cancer subtypes across various classification thresholds [39]. This further supports the effectiveness of tree-based models in RCC subtyping.

The relatively lower performance of non-tree-based algorithms like logistic regression and SVM underscores the importance of model selection in genomic studies. While these models are often favored for their interpretability and efficiency [40], our results suggest that they may not adequately capture the complexity of gene expression data in cancer subtype classification [11] [36].

These findings hold significant implications for both research and clinical practice. In research settings, our results emphasize the importance of considering tree-based and ensemble methods when analyzing gene expression data, particularly for cancer subtype classification. Clinically, the high performance of these models suggests potential for improving diagnostic accuracy and treatment planning in RCC.

However, it is important to note that model selection should not be based solely on performance metrics. Factors such as interpretability, computational efficiency, and the specific requirements of the clinical application should also be considered. For instance, while random forest showed the best overall performance, its “black box” nature [41] may make it challenging to interpret in clinical settings where understanding the decision-making process is important [42].

Our study was limited by the small sample size and the significant class imbalance in the RCC samples, particularly with chromophobe RCC compared to the other cancer subtypes. These limitations could potentially affect the reliability of our findings. Also, the study focused solely on RNA-seq gene expression profiles and did not incorporate other data types, such as histological images, mutation profiles, or copy number alterations, which could have impacted the outcome.

Future research should focus on validating these findings across larger and more diverse datasets of RCC subtypes and taking further steps to incorporate additional genomic and clinical data to enhance the clinical utility of machine learning-based RCC subtyping models.

5 Conclusion

In conclusion, we demonstrated the superiority of tree-based models in differentiating between the gene expression profiles of RCC subtypes, namely chromophobe, clear cell, and papillary RCCs. Future research should explore the integration of other data types to improve clinical utility of these models.

Acknowledgements

The author received no specific funding or support for this research.

Statement on conflicts of interest

The author has no competing interests to declare.

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 J Health Inform Afr. 2025;12(1):39-53. DOI: 10.12856/JHIA-2025-v12-i1-533

Journal of Health Informatics in Africa

Improving cancer data availability within routine reporting systems in a low-income setting; The Case of Mbarara Regional Referral Hospital, Uganda

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Background and purpose: Worldwide, an estimated 19.3 million new cancer cases and almost 10.0 million cancer deaths occurred in 2020. In the same year, 801,392 new cancer cases and 520,158 cancer deaths occurred in sub-Saharan Africa where cancer survival is even disproportionately lower. In Uganda, there is limited knowledge about the usability levels of national electronic reporting systems with patient-level cancer data. Such data guide operational planning, track progress and performance over time, evaluate and understand cancer risk factors, study phenomena, explore relationships, test hypotheses, or draw meaningful conclusions. This study intended to fix the knowledge gap on the usability level of a routine electronic reporting system using standard tools.
Objective: To determine the usability of the developed reporting system at a cancer unit in a low-resource setting.
Methods: This observational study used a design science approach, configuring the Maintenance application and Tracker domains in DHIS2 version 2.40.3. Sixteen users participated in the study. The usability of the built cancer registry was determined using the system usability scale (SUS).
Results: 16 out of 21 staff achieved a mean SUS score of 72.34 (SD 11.23), a 76.19% response rate. Most respondents were male (12 out of 16, 75%) and had a mean age of 30.81 (SD 7.4).
Conclusions: A web-based DHIS2 instance improved access to comprehensive cancer data, demonstrating high usability. This system needs to be scaled to the remaining 15 regional hospitals, utilize prospective data in future studies, and conduct pre-training to enhance user engagement.

Keywords: Cancer, system usability scale (SUS), retrospective studies, Internet, prospective studies, electronic reporting systems.

1 Introduction

Cancer – a disease characterized by uncontrolled division of cells in a body part – is an increasing public health burden [1], [2], [3]. Worldwide, an estimated 19.3 million new cancer cases and almost 10.0 million cancer deaths occurred in 2020 [4], [5]. In that year, lung cancer was the leading cause of death before the age of 70 years in 112 of 185 countries while female breast cancer was the most commonly diagnosed cancer among new cases in a further 23 countries [4]. In that year alone, 801,392 new cancer cases and 520,158 cancer deaths were estimated to have occurred in sub-Saharan Africa [4]. Worryingly, cancer survival was disproportionately lower in sub-Saharan Africa than in the rest of the world regions [6]. In Uganda, cervical cancer was the leading cause of high cancer rates per year among women at 47.5 per 100,000 in 2020, likely due to the high prevalence of human papillomavirus, low screening rates mostly in urban areas, changes in population dynamics, lifestyles, etc [7], [8]. This is far from the 2030 global targets of reducing mortality from non-communicable diseases by a third and reduction of illnesses and death from hazardous chemicals and pollution [9]. However, cancer is neither a reportable nor notifiable disease in Uganda despite a rising burden [7], [10].

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 J Health Inform Afr. 2025;12(1):53-64. DOI: 10.12856/JHIA-2025-v12-i1-546

In an ideal scenario, patient-level data should be integrated into a routine reporting system [11], [12], [13]. The data generated guide operational planning, track progress and performance over time, and strengthen accountability for better results [14], [15]. Such data are also used to evaluate and understand cancer risk factors, study phenomena, explore relationships, test hypotheses, and draw meaningful conclusions [16]. However, in Uganda, there is limited knowledge about the usability levels of the nationally approved electronic reporting system for comprehensive cancer data [17], [18]. In this study, usability is defined as how usable DHIS2 (District Health Information Software version 2) software is towards the intended purpose of making cancer data available in a routine reporting system [19], [20], [21]. Whereas there is no electronic system (DHIS2) at the Mbarara Regional Referral (RRH) System for reporting cancer, only 4% of the data is available nationally in aggregate form within the running DHIS2 platform, covering merely eight cancer types out of the over 200 types that exist globally [22], [23]. Consequently, it is challenging to determine patient care indicators for cancer at various levels of the healthcare system, assess potential risk factors, and formulate national cancer policies [8]. This study used software very similar to the nationally approved DHIS2 software, facilitating feasible integration and sharing of the cancer data [24], [25].

Meanwhile, other electronic systems such as health management information systems (HMIS), CANREG, etc have supported patients in cancer treatment in some countries but not Uganda [20], [26], [27]. The barriers to the limited use of these systems in Uganda include lack of local ownership and accountability, lack of health worker competence in e-health, poor interlinkages among existing systems, reliance on donor funding which is volatile, lack of proper implementation frameworks, poor health worker attitudes, lack of intuitive user interfaces, etc [14]. This study's cancer registry system built aimed at improving patient-level cancer data available. It also solves the issue of interoperability with the existing national information system since both have DHIS2 as the core software. Therefore, it is easier to work across both systems seamlessly such as the exchange of data or reports from one system to the other. The system improves health worker competence through the use of open-source software with an intuitive user interface. Whereas the usability of a medical system or device is vital and mandatory [28], there is limited knowledge on the usability level of routine information systems with patient-level cancer data in a low-resource setting such as Uganda [11]. Multiple studies have focused on data quality within DHIS2 with few or no studies on the usability of that system in low-income settings [29], [30], [31], [32]. Even for the few implemented systems in low-income countries like Uganda, there are reports of usability challenges hence different usability is expected [19]. Therefore, this study determined the usability level of DHIS2 in a regional public health facility without an electronic information system.

2 Materials and methods

2.1 Study location:

This study was conducted in Uganda, a low-income, landlocked country in sub-Saharan Africa. It is located between 1° N and 4° N latitude, and 30° E and 35° E longitude, sharing borders with South Sudan, Kenya, Tanzania, Rwanda, and the Democratic Republic of Congo. As of July 2023, Uganda had 146 districts and 10 cities, with Kampala as the capital. The districts operate under a decentralized governance system across four regions: Northern, Eastern, Central, and Western, where Mbarara Regional Referral Hospital is situated [33].

2.2 Characteristics of Study Site:

Mbarara Regional Referral Hospital (RRH) was the study site because there was a functional cancer unit that lacked an open-source cancer electronic reporting system. The RRH is in Mbarara City, Ankole sub-region, and is located within the central business district of the city [34]. This is approximately 268 kilometres (167 mi), by road, southwest of Mulago National Referral Hospital, in Kampala, the capital city of Uganda. It is the referral hospital for that region serving but not limited to the districts of Bushenyi, Ibanda, Isingiro, Kiruhura, Mbarara, and Ntungamo. The hospital serves as the teaching hospital for Mbarara University of Science and Technology [35]. The implementation was carried out at the Uganda Cancer Institute (UCI) Mbarara unit located within the hospital. It is supervised by UCI

 J Health Inform Afr. 2025;12(1):53-64. DOI: 10.12856/JHIA-2025-v12-i1-546

Kampala and the Ministry of Health (MOH) [36]. It is divided into two sections: children (pediatric oncology) and adults (adult oncology).

2.3 Study design:

This was an observational study with a design science approach [37] carried out from 1st May – 31st July 2024. The setup of the cancer registry included downloading and installing open-source health information software (DHIS2 version 2.40.3) [38]. It was hosted virtually on the Google Cloud servers [39] despite the drawbacks of cloud storage [40] and was available at https://robertm.codezoneug.com/rob/

While using the Maintenance application and Tracker domain in the DHIS2 platform, design changes were made in the configuration layer to develop a data entry form similar to what has been used in most African cancer registries to capture cancer data [31], [41], [42], [43]. The cancer notification form [43] provided the use-case from which the tracked entity attributes (data elements or variables), option sets, and options were identified and associated with the program under design. The metadata setup of the DHIS2 instance was composed of the option sets, data elements, and data element groups, which were added to the created program. From this stage, a Tracker program entry form was created according to the format of the use-case. Meanwhile, a standard coding reference book for oncology (ICD-O-3) was selected and uploaded to provide the disease coding options for data elements morphology and primary site of tumor [44]. The use-case used in this study was adapted from the form being used at the Kampala cancer registry and it contains forty-six (46) variables [7], [43]. These variables were organized into five frames, which are patient, tumor, treatment, source of information, and follow-up. The patient frame or stage had 19 variables and these are ID number, given name, surname, date of birth, age, sex, usual residence address (with variables zone, village, parish, sub-county, county, and district), patient or next-of-kin telephone number, LC1 leader name/telephone number, religion, ethnic group, occupation, education, and marital status. The tumor frame or stage had seven (7) variables, which were date of incidence, basis of diagnosis, primary site of tumor, morphology, and stage. The treatment frame had four (4) variables that included surgery, radiotherapy, chemotherapy/hormone therapy, and others while the source of information stage had institution/ward, case number, laboratory, and lab number as variables. The fifth frame (follow-up) had nine (9) variables which included date of last contact, status at last contact, cause of death, form filled by, data entered by, date, and signature. To maintain consistency, options sets were allocated their respective variables and such variables included sex, the basis of diagnosis, treatment, status at last contact, and cause of death. Some of their options included 1 = male, 2 = female, 9 = not known, 0 = death certificate only, 1 = clinical only, etc. The enrolment date and cancer registry number preceded the frames on the final data collection form. The metadata was assigned respective sections on the data collection form after which they were registered into the program stages. Thereafter, the program was assigned to specific organization units, i.e. Uganda Cancer Unit (UCI) Centre Mbarara Regional Referral Hospital, UCI Kampala, and Mulago Specialized National Referral Hospital. Sharing settings were then applied to the users and user roles created previously. User access was limited through password controls to maintain confidentiality and privacy [45]. A pilot run of the instance was conducted at UCI Mulago.

The instance was installed on a computer in the data room at UCI Mbarara from where cancer records were entered and validated [46]. Since the paper records have very sensitive and personal information, the clinic management purposively selected and provided access to only those paper records of 104 cancer patients enrolled in FY 2023/2024. Data from these records was entered in the instance by the clinic staff. This sample size provided was within the range of 100 – 400 records as used in survey studies involving information studies [47]. A larger sample size like this one improves the credibility and validity of the findings unlike previous usability studies involving DHIS2 which had varying and less sample sizes [19], [48]. Analysis and visualization of entered data was conducted by the researcher concurrently with the clinic staff using the Data Visualizer app within DHIS2 and the dashboard. The data visualizer app was used to create, edit, manipulate, share, and/or download the entered comprehensive cancer data according to period and organization units [49]. Examples of data visualizations included line charts, pivot tables, column charts, bar charts, scatter diagrams, pie charts, etc. This demonstrated the practical usability of a system that met the key aspects of cancer care and data availability, including reviews and downloads of entered data at UCI Mbarara [41]. The author and each of the 16 staff rated and reviewed the 104 records of the new cancer cases in the system. A questionnaire was digitized using KoboCollect software and

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administered to smartphones of 16 consenting users at the center to determine the system usability score (SUS) [50].

In this study, usability is defined as the extent to which the DHIS2 instance could be used by the clinic staff to attain the availability and accessibility of patient-level cancer data with effectiveness, efficiency, and satisfaction at UCI Mbarara [51]. The author used the system usability score (SUS) to measure the extent of the instance's usability since it has been used in previous usability studies within Uganda [19], [20], [21], [52]. The SUS is a simple and effective tool that measures the perceived usability of a system in real-time. It is a 5-point Likert questionnaire with 10 questions. Each question scores a maximum of 10 points when normalized by a factor of 2.5 [19]. The SUS total scores range from 0 to 100, they are not percentages nor percentiles, and high scores indicate better usability of a system. SUS scores above 80.3 are graded A and considered excellent while scores in the range 68 – 80.3 are good and graded B. SUS score 68 is considered okay and graded as a C, scores in the range 51 – 68 are poor while scores below 51 are worse and graded F. Software systems with scores below 68 are considered unusable [53]. The study aimed to have at least a mean SUS score ≥ 68 for an optimal system to be considered usable for a sample size of at least 15 participants [54]. Some of the other benefits of SUS include providing a quantitative measurement, enhancing user-centered evaluation, promoting consistency, offering speed and simplicity, ensuring user feedback, and aiding resource allocation [54].

The dataset obtained was downloaded as a CSV file from which the SUS was calculated using the formula stipulated by [54]. In it, SUS was calculated as stated; Y was 25 minus the sum of all points for even-numbered questions while X was the sum of all points for odd-numbered questions minus 5. The sums of all points for even-numbered questions and odd-numbered questions were calculated for each respondent and thereafter used to calculate Y and X. Therefore, SUS is the product of $(X + Y) * 2.5$ from which product the mean SUS, standard deviation, and 95% confidence interval are calculated from all the respondents [52].

2.4 Ethical Considerations:

The study was approved by the Research and Ethics Committee of Makerere University School of Public Health (MakSPH-REC) under protocol number 347 on 27th March 2024 and even provided an introduction letter valid for one year. The letter delineated the study purpose and was thereafter presented to the Uganda Cancer Institute and Mbarara Hospital administration, which granted permission to conduct the study and access to the patient's records. Consent was provided by the clinic management to utilize some patient records for the study as per the current national data protection and privacy regulations [45]. Also, informed consent of patients was not sought much as the law covers for collection of de-identified and limited personal data for research purposes. However, informed verbal consent was sought from the study participants (staff at UCI Mbarara) before carrying out the study with nobody withdrawing at any stage thereafter.

3 Results

3.1 Characteristics of Study Participants and Site:

The study participants were staff at the UCI Mbarara in the pediatric and adult oncology units. Out of the total staff (21) available then and interacting with cancer data, 11 staff were nurses, and nine of them were in the pediatric section. All the 21 staff interact with cancer data daily, and these were purposively selected to participate in the study. The center is supported occasionally by postgraduate student doctors, nurses, and interns from Mbarara University who rotate in the unit. On average, the new cancer cases were 15-20 monthly among children and about 100 among adults. The cancer deaths were about 5 -7 deaths per month among children and about 25 – 30 deaths monthly among adults [55]. This unit had a paper-based record system, with records being kept in two secured data rooms. With consideration for confidentiality and privacy, the unit management purposively selected and granted access to 104 records of new cancer cases for entry and validation into the instance [47]. The inclusion criteria included records of new cancer cases registered for the period 1st April – 30th June 2023, active for the financial year (FY) 2023/24, included all age categories, and had been filled. The exclusion included records not entered, such as those declined

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access, inactive, dead, lost-to-follow-up, incompletely filled, and files of other months that were in circulation during clinic visits of the patients at the time of research.

3.2 Performance of the developed DHIS2 instance:

The instance configured and labeled as Mbarara Cancer eRegistry produced data visualizations as dashboards consisting of several chart types such as pie charts, pivot tables, graphs, line lists, etc. Each chart could be modified using the internal Data Visualizer app. The built system or cancer registry showed an ability to enter and validate more cancer records, though the study was limited to just >100 but less than 400. This sample size was in line with the survey findings of sample sizes of studies conducted for information systems. The minimum threshold was 100 entries while the maximum threshold was not exceeding 400 entries to produce valid results [47]. However, some usability studies involving DHIS2 have used smaller and varying sample sizes [19], [48] unlike this study which had a larger sample size. This study entered 104 records of new cancer cases in the inclusion period. Data entered could be shared or extracted in three formats, either as Graphics (in the form of images as .png files and/or PDF format) as plain data sources (in the form of JSON, XML, Microsoft Excel, CSV), or as advanced (as data value sets, JRXML, raw data SQL) [31]. Since this was sensitive and personal information, data captured was secured at different levels using user names and passwords to control and secure access [45].

3.3 System Usability Score (SUS) of the developed instance:

Sixteen (16) out of 21 answered the SUS digital questionnaire and produced a 76.19% response rate. The majority of the respondents (75% i.e. 12 out of 16 respondents) were male, with a mean age of 30.81 and a standard deviation of 7.4 [56], [57]. Due to technological difficulties in answering a digitalized questionnaire, five staff declined to respond and these were not included in the analysis of the responses.

Following the formulae stipulated in section 2.3 above, the instance scored an average SUS of 72.34 which is higher than the target mean score of 68 for a system to be usable [28], [47], [54]. The standard deviation was 11.23, and the 95% confidence interval was 72.34 ± 5.51 (±7.61%) (Maple Tech 2024a). This means the developed instance had a moderate usability level above the target threshold. With an overlap between the confidence interval and mean score obtained, the results had no statistical significance.

4 Discussion

A web-based DHIS2 version 2.40.3 was configured and customized to a patient-level cancer instance. It was able to capture and validate cancer records. The instance produced a mean system usability score (SUS) of 72.34 at a 76.19% response rate and various visualizations. The standard deviation was 11.23 and a 95% confidence interval of 72.34 ± 5.51 (±7.61%). The instance performed beyond expectations as evidenced by the high usability score obtained for that new system, as compared to a minimum expected target of 68 for a usable system.

These results are consistent with similar research carried out in Iran by Jamshidi et al. in the year 2022 and a 2021 Guinea study by Eggers et al [46], [58]. In both situations, DHIS2 instances were developed and utilized successfully for bone cancer and Ebola surveillance respectively. In a multi-country study published in 2022 by Kinkade et al, DHIS2 was extended and strengthened for successful surveillance of COVID-19 in Uganda, Sri Lanka, and Sierra Leone [59]. As stated by WHO, visualization dashboards supported with easier access to COVID-19 vaccination data [60], thus they were utilized to improve data accessibility and availability, to make timely decisions, and to inform public health policy. This shows that DHIS2 is user-friendly, highly intuitive, attractive, and acceptable as an open-source health information system in a low-income setting. It performed better than similar software such as CANREG in terms of data visualization, analysis, data security, etc [61], [62], [63], [64]. In a few cases, though, there has been low usability of DHIS2, poor performance, and no improvement in health information systems among health workers, for example among nurses in emergency hospitals in Iran [65].

This study is the first of its kind to provide findings on usability scores of open-source health information systems in cancer care in Uganda [19], [20], [21], [52]. Though many studies have been done on DHIS2, most of them have concentrated on the evaluation of data quality in low-income countries [30], [31], [32].

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Few or no studies have been conducted on the usability of DHIS2 within a similar context, unlike this study [48], [66], [67], [68], [69]. Secondly, the mean SUS score of the cancer instance obtained in this study competes favorably with some long-established software applications. For example, in a 2022 study, the mean SUS score of Microsoft Word was 74.7 at a 95% confidence interval [70]. This further strengthens the applicability and acceptance of DHIS2 in global healthcare. Thirdly, the use of a built DHIS2 cancer registry in this study provided a software system similar to the nationally approved routine reporting system in Uganda [71], [72]. This cancer registry relates to the national system by both being built from DHIS2 open-source software, thus they share similar core properties and source codes. This would also improve the inter-linkage and interoperability among both systems according to the interoperability prerequisites [73], thus enabling easier reporting, assessment of cancer indicators, and improvement of cancer data available in a routine reporting system. The problem of silos among software developers would also be reduced [74], [75].

A detailed analysis of the SUS results showed general agreement (mean obtained 4) in questions 1, 3, 5, 7, and 9. These correspond to the system's frequency of use, ease of use, system functions well integrated into context, ease of learning, and confidence in system use. There was a neutral response (mean obtained 3) to questions 4 and 10, which cover technical support and learning of new things. If addressed in future research, these areas can also lead to higher usability obtained with the cancer system [29]. However, questions 2, 6, and 8 received a mean of 2. These indicated disagreement with the unnecessary complexity of the system, inconsistency, and cumbersomeness of the system. This further indicates the persistent challenges encountered in digitalizing some areas in the health sector [58], [76]

Despite these strengths of the study, there were key limitations to the study. Firstly, data in our study was based on programmatic information retrospectively abstracted from a portion of records for new cancer patients of FY 2023/24 provided by the hospital management. This led to selection bias and some misclassification of some cancer types or potential risk factors. This offered an opportunity for more research on instances with prospective cancer records. Secondly, the web server costs for hosting the instance were unsustainable since this study had no external funding. This was overcome by setting up idle modes of the instance when not in active use, hence reducing the costs of full-time access to the instance even when not in active use.

The study faced the challenge of limited user engagement in responding to the study questionnaires. One of the reasons cited included the heavy workloads faced by the staff at the cancer, affecting the responses to the questionnaires. The other reason was the limited technological competencies to answer digital questionnaires,, it led to a suboptimal response rate. This underscores the urgent need to conduct pre-training of software or system users before deployment in future studies.

Despite these limitations, this study provides important evidence supporting the use of routine reporting systems to enhance the availability of patient-level cancer data in low-income settings. Future research should focus on exploring the use of prospective data to validate these findings further and the online sustainability of such systems amid funding considerations. Additionally, similar implementations in different settings could provide a broader understanding of the system's effectiveness and adaptability.

In conclusion, a web-based DHIS2 instance made cancer data easily available despite an unsustainable online presence. The usable instance led to increased access to cancer information as per the 2030 targets of the Sustainable Development Goals and consequently improved quality measurements and patient safety [9], [77]. The programmatic implication for UCI Mbarara is to seek international support and/or development assistance for infrastructure through enhanced financial, technological, and technical support to African countries. As for UCI Kampala and MOH, there is a need to scale the instance to the remaining 15 regional hospitals out of 17 [36]. To improve the usability of DHIS2 further at UCI Mbarara, the following are recommended: (1) Conducting system training regularly (2) Motivating system users with incentives (3) Upgrading existing infrastructure to be compatible with DHIS2 (4) Regularly upgrading system modules (5) Providing appropriate user access rights and access levels to UCI Mbarara staff and (6) Providing adequate ICT support and assistance to UCI Mbarara [19]. The author also recommends the following to the Research agencies: (1) Use of prospective programmatic data in future studies (2) Conduct system pre-training to improve user engagement (3) Utilize open-source systems to achieve universal health coverage through increased access to cancer information and quality healthcare [9], [78].

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Acknowledgments

The author thanks the Almighty God, the School of Public Health, the Department of Epidemiology and Biostatistics, and my family for supporting me while doing this work. I thank Uganda Cancer Institute Mbarara, the management of Mbarara Regional Referral Hospital, and the Ministry of Health for accepting the study.

Statement on conflicts of interest

There was no conflict of interest by the authors.

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Appendices

Appendix 1: System Usability Questionnaire

IMPROVING CANCER DATA USABILITY WITHIN ROUTINE REPORTING SYSTEMS IN A LOW-INCOME SETTING; A CASE OF MBARARA REGIONAL REFERRAL HOSPITAL, UGANDA.

The below is a standard tool modified for measuring the usability of an electronic application or system. Please select the answer (using **X** or ✓) that best describes how you feel after using the cancer instance today.

Table 3: System usability scale

SYSTEM USABILITY SCALE	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1. I think I would like to use this instance frequently.					
2. I found the instance unnecessarily complex.					
3. I thought the instance was easy to use.					
4. I think that I would need the support of a technical person to be able to use this system.					
5. I found the various functions in this instance were well integrated.					
6. I thought there was too much inconsistency in this instance.					
7. I would imagine that most people would learn to use this instance very quickly.					
8. I found the instance very cumbersome to use.					
9. I felt very confident using the instance.					
10. I needed to learn a lot of things before I could get going with this instance.					

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Appendix 2: Dashboards for the instance (Cancer eRegistry Mbarara)

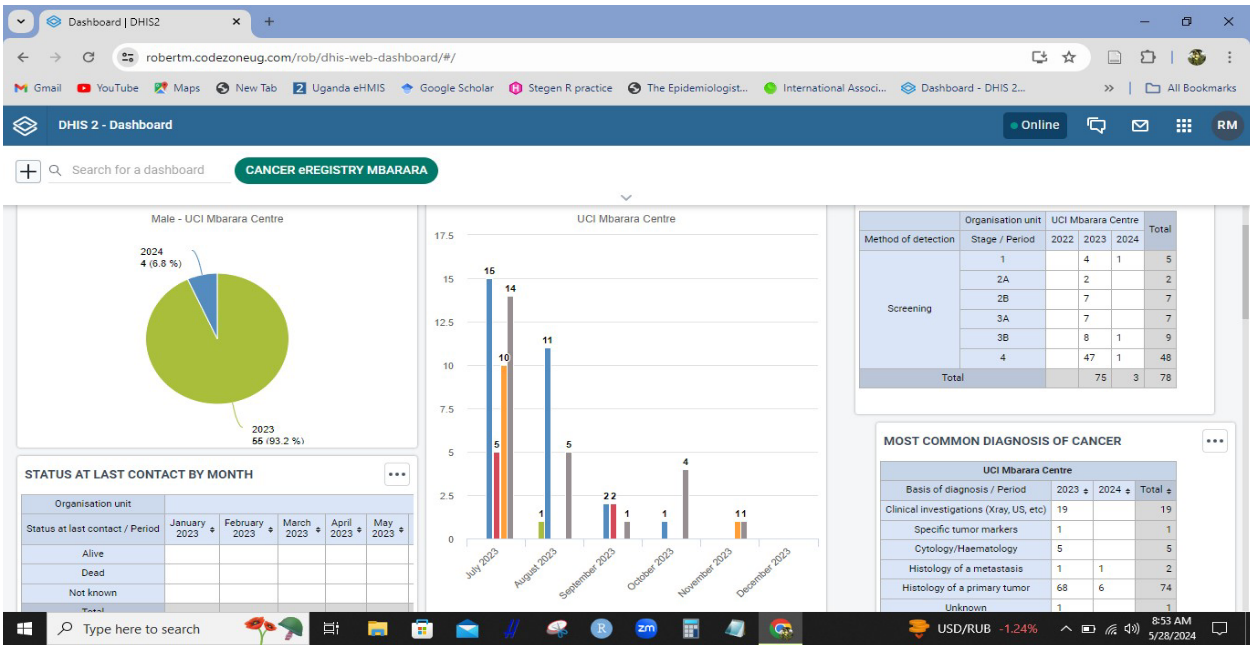

Figure 1: Screenshot 1 of the dashboard in the configured cancer instance

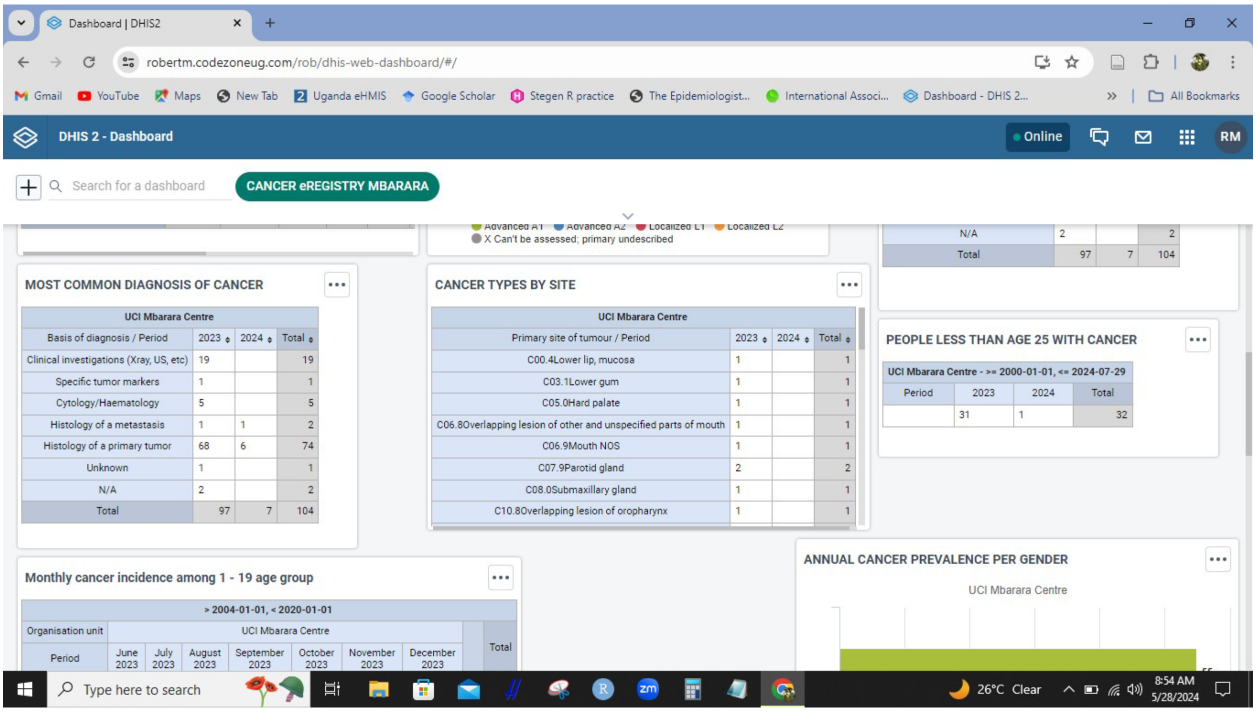

Figure 2: Screenshot 2 of the dashboard in the configured instance

Journal of Health Informatics in Africa

Smart Medical System for Trusted Lorawan Server

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Background and Purpose: Leading tech of LoRaWAN in Smart Medical System (SMS) measures the human health parameters with no laboratory diagnosis.
Methods: The system uses an ESP32 microcontroller and bio-sensors to examine the human physiological conditions based on environmental factors using low power components but provides a seamless experience with long-range communication modules (LoRa). Monitored data is centralized in a server that can be accessed securely from remote place.
Results: The main goal of this paper is to implement the patient's health records maintenance with end-to-end encrypted data using consensus algorithms. An Authorized person only accesses encrypted data with the private key through decentralization.
Conclusions: Simultaneously, the proposed system introduces an efficient method to get alert messages from the patient that enables sharing the predicted data in real-time to the caretaker and hospital doctor.

Keywords: Consensus Algorithm, Decentralized, Encrypted, LoRaWAN, SMS.

1 Introduction

In the past decade, various communication technologies have been exhausted and widely used in the universe. This paper introduces IoT with block-chain technology for confidential LoRaWAN servers in hospitals. The Internet of Things (IoT) is an emerging technology, which consists of numerous connections to communicate with each other. It ensures human life more comfortably and is widespread with various paradigms for numerous purposes. IoT facilitates many standard methods to adopt rejuvenation, and it serves many valid tenacities to keep it worth. Hence IoT is the main parameter in the healthcare system's advancement from face-to-face consultation to telemedicine and maintaining health records through Peer to Peer encrypted data. The IoT environment monitors the real-time basic health signs of patients, as present in the room condition. ESP32 Lora Sensor Nodes are used to examine real-time sensor readings wirelessly. A wearable device has various biomedical sensors such as temperature sensors, pulse rate sensors, and glucose-sensor to monitor body temperature, pulse rate, and blood sugar level. Moreover, this system predicts the local temperature and humidity level of the location in real-time to ensure the patient's situation concerning the room condition. The final data comes with digital and graphic visualization, is allowed to be accessed anywhere, from any device, including P.C. and smartphones. It restricts the menacing attacks from IoT and ensures a safe connection between the connected devices start from the beginning.

An analysis system provides excellent insight to bring patient self-assessment in a remote place. The proposed smart medical system circuit and authenticate patient health record function, mainly focused on monitoring the patient's health condition and process of the medical report in an efficient method. Secure transaction of health records to authenticate a person is cost-effective and improves the quality of healthcare or hospital sector. The rest of the paper is discussed as follows: Section 2 discusses this paper's related works. Section 3 presents proposed system design and workflow of the trusted LoRaWAN network using

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block-chain. Section 4 has the results. Section 5 has the discussion about measurements of the data transaction performance. Finally, conclusion in Section 6.

2 Related Works

One of the rapidly developing assertive communication of the Internet of Things (IoT) connects several objects such as mobile or electronic devices, vehicles, and home appliances connected to the internet. It shares the stored data with the user in a remote place [1]. Evolving a wireless sensor to observe basic health parameters in real-time rate with an alarm indication for the abnormal patient [2], and that support remote healthcare monitoring system [3]. The estimation of blood glucose level is essential for a diabetic patient to avoid the critical stage [4]. A wearable body area network (WBAN) monitors the human body and surface conditions around the people, including temperature and humidity [5]. Recently, LoRa technology used in broad areas like research and industrial interests. It connects several wireless devices with low-cost power and long-range communication [6]. For encryption and data security, the LoRaWAN use three different security keys and transfer the data through wireless sensor [7]. A remote Healthcare Monitoring system is portable that detects the patient's current condition, conveys it to the medical staff or guardians in real-time with safe and secure [8] & [9]. To improve the healthcare sector, electronic health record system involves in secure data storage and transaction using block-chain technology [10], [11] & [12]. This method has a decentralized, data transparency and confidential features for data exchange verification at a particular time in network [13], [14], [15], [16] & [17].

3 Materials and Methods

The proposed system construct with the bio-medical sensor to detect the physiological human health and the LoRaWAN network server integrated with block-chain for privacy and more security data transaction.

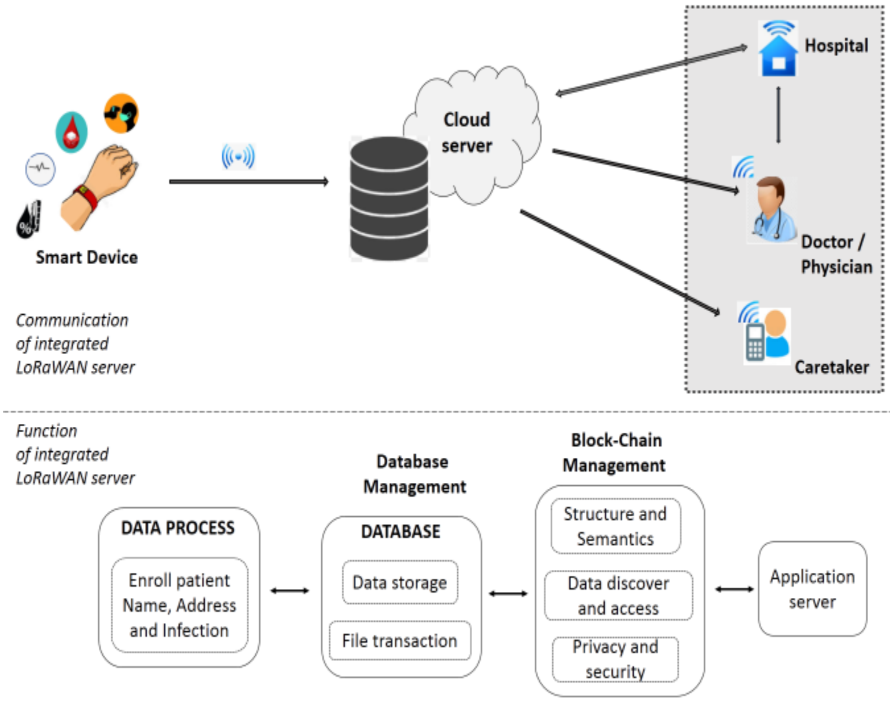

Figure 1. System architecture

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3.1 User - Server Communication Interface

The user interface system module could be patient, caretaker, doctor, physician, nurse, hospital, etc. The smart medical device consists with bio-sensor equipment to monitor the human health condition which depend upon the environment parameter. In an emergency period, the smart device helps to determine the patient body health before undertaking treatment. ESP32 encloses a pulse and temperature sensor to examine the human condition body level and send it to the webserver through the Wi-Fi /internet /Bluetooth. MAX30100 Pulse Oximeter sensor is integrated pulse oximetry and heart-rate monitor sensor kit. The sensor emits the infra-red light used to measure oxygen levels in the blood. As a result of having more blood, the oxygenated blood increases when the heart pumps the blood, whereas the heart relaxes, the volume of oxygenated blood decreases. The time interval between the increase and decrease of oxygenated blood or the counts were taken to move to another phase determines the pulse rate. In general, oxygenated blood absorbs more I.R. rays and passes red light, while deoxygenated blood absorbs red light and passes more I.R. rays. The variation of sugar level in blood signifies as diabetic and that monitor using the analyzing system. In wireless communication, the data are sent to the internet and served in the IoT cloud server to reach the user. Receiving sensor information infer the environment that can affect the actuators to move accordingly. The actuators control the receiving signal into physical system. The data stored in a buffer can read via I2C. DHT11 is a low-cost digital temperature and humidity sensor that uses a capacitive humidity monitor and thermistor, respectively. It detects the environment contamination level, and that illustrate in Fig.3. It is relatively easy to integrate and predicts results more accurately. Monitor the room temperature and humidity level in a continuous manner. These sensors are integrated with a single PCB board to achieve examination, similar to the laboratory workings easily.

In the transmitting node, hold an accelerometer and gyroscope that measure the static acceleration. Whenever the patients need any help, fingers' movement works as an input to the microcontroller and different processes. The microcontroller maps the 0 – 5 voltage into 0 – 1023 analog values and is more sensitive. Even a slight movement can change the values, and thus the sensitivity is reduced. Receiving data information and alerts are stored in data storage such as name, address, and patient health information. These messages maintained and delivered to the user for corresponding request. The data table ensures the statistics of human health and corresponding alert messages to the health senses level. A health monitoring system evaluates and tracks from remote area in real-time approach.

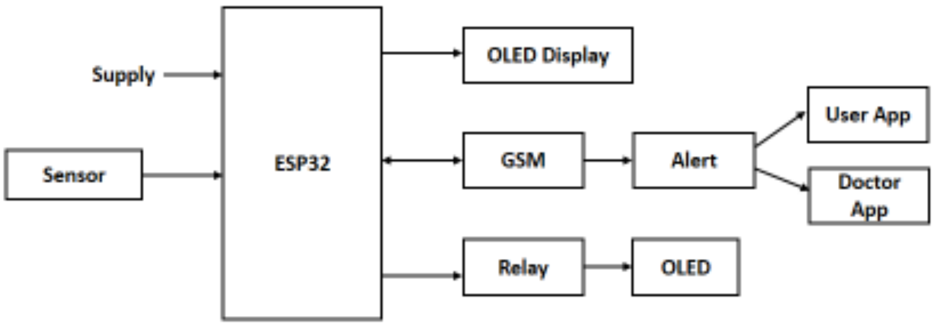

Figure 2. Server sends an alert to mobile app

LoRa Radio sends a signal through a server or mobile application designed dedicatedly to such an application. As an alternative, for immediate output response, OLED is connected and can be viewed quickly. The I.P. address display on the OLED and the data can be monitor after accessing it in the browser. The advantage of using LoRaWAN is that the system cannot be broken or interrupted by any external agency unless the battery goes down, thus providing a stable connection between the transmitter and receiver. The alarm is set in the device to alert their time of treatment and consume food and medicine. Sudden changes in the human body increase the illness; in that situation, this analyzing system examines the temperature and body condition to proceed for the next stage of treatment. Furthermore, this device sends a message with no delay and operates in a remote place with full security.

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Table 1. – Data variation's an alert's

No.	Sensor Name	Monitoring Rate	Data Range	Alert Message
1	MAX30100 Pulse oximetry	Pulse rate	>100 beats	Take rest to reduce your stress.
2	MAX30100 temperature sensor	Body temperature	>36 ℃	Remind to drink more water and take a rest
3	DHT11	Temperature and humidity	>50 and above 70%	Avoid working and take rest

Table 1 shows a variation of collected information and the alert message for corresponding data. The human health rate fluctuations notify the user in the form of an alert message. The message variation guides the user to treat the patient properly and the regular analyzing indicates improvement of health. An alert transfer to mobile app (caretaker, physician and Doctor) and access the medical data from storage.

3.2 Trusted LoRaWAN Network Server Function

The smart medical system is another potential application to collect the patient health records. In medical environment, the LoRaWAN server provides secure transaction in private organization network. In this paper, the LoRaWAN technology integrated with block-chain method to improve more secure transaction. It is open, trusted, decentralized and tamper-proof network. To reduce the communication traffic, the consensus algorithm implemented to encrypt the data information before updating the block-chain ledger which stores hash data. Each block-chain has transaction function of packaging, hashing, verifying, block creation and storing block-chain, etc. The following transaction Functions are given below to ensure the privacy and data authentication. Such as,

- Hashing – A unique ID to identify the block.
- Asymmetric cryptography – public/ private key establishment and secure data transaction
- Digital signature – the digital signature of the generating a node
- End to End encryption – the data transaction between Smart device to users without hacking at a specific time.

The PoA algorithm implement to ensure privacy and authenticate data transaction. The PoA is a combination of proof of work and proof of stake algorithm which provides more secure transaction against hackers or attack types.

Algorithm for Security

Input: m smart devices and n number of users participating in the network

Output: block chain- data for m smart devices

For SD_x, U_y,CS_r MN_ido

Register all assigned values {SD_x, U_y,CS_r}

Generate the secret key

Prepare block BLK_p from SD_x receiveddata

Call mining method for block addition using the algorithm with MN_q

If other MN_q performs adding of BLK_p then

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Add BLK_p in block-chain

Else

Abort addition of BLK_p in block-chain

End if Prepare block BLK_p from SD_x receiveddata then

Call mining method for block addition using the algorithm with MN_q

If other MN_q performs adding of BLK_p then

Add BLK_p in block-chain

Else

Abort addition of BLK_p in block-chain

End if

End for

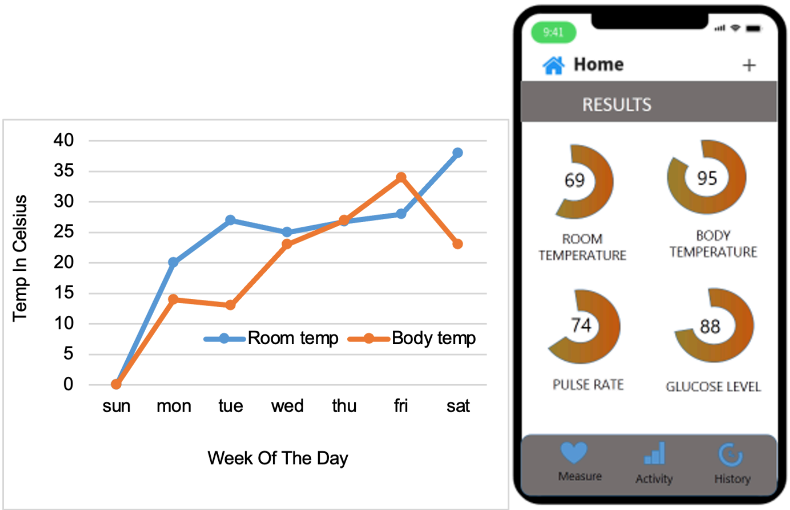
Table 2. Abbreviation used in proposed algorithm

Abbreviation	Meaning
SD_x	x^{th} position of Smart Device
U_y,	y^{th} User
BLK_p	p^{th}Block in block-chain
MN_q	q^{th}Miner Node
CS_r	r^{th} Cloud Server

The algorithm explains the function of authenticate transaction in network. The proposed algorithm possesses patient medical records (Name, address, disease, etc.) that are to define the functions to insert, update and delete accounts. Consider the m number of smart device and n number of users are participating in the proposed network. Register the assign the values (SDx, Uy, CSr) for smart devices, user and cloud server. Performing a mutual authentication and generating a secret key among the register values. After a key generation the block is prepared to store a secure information from the smart devices. Request the mining procedure to add block using the proof of Activity (PoA) protocol with other miner nodes. The other miner node sends a request to add block, and it verifies the block signature successfully to perform the block-addition function. Nevertheless, it performs to abort the block in block-chain and it repeats the function.

4 Results

The system makes it more reliable to the users, guardians, or physicians. The smart device monitors the temperature level, blood glucose, and pulse rate measures and represented in a graphical view with quick access to digital text. It is ultimately showing accurate results tested and transfer the medical report to authenticate user through trusted network.



(a) (b)

Figure 3. (a) Monitoring the room temperature and human body temperature, (b) Health Monitoring Dashboard.

Fig.3 (a) & (b) illustrates the graphical representation of the room temperature and the human body temperature. A significant factor, health condition depends upon the environment climate. The output of the temperature plot in Celsius displays its temperature level of the human body and its surrounding environment. The room temperature and relative humidity change the body temperature, affecting the pulse level and other health parameters. The variation of the glucose level also monitored for an average person and diabetics. The glucose level in the blood is always high for diabetics than the typical person. The pulse rate and glucose level are sequential high for the people with diabetes; they test and verify their body condition using this system. The monitoring system is helpful for the person to maintain their health condition.

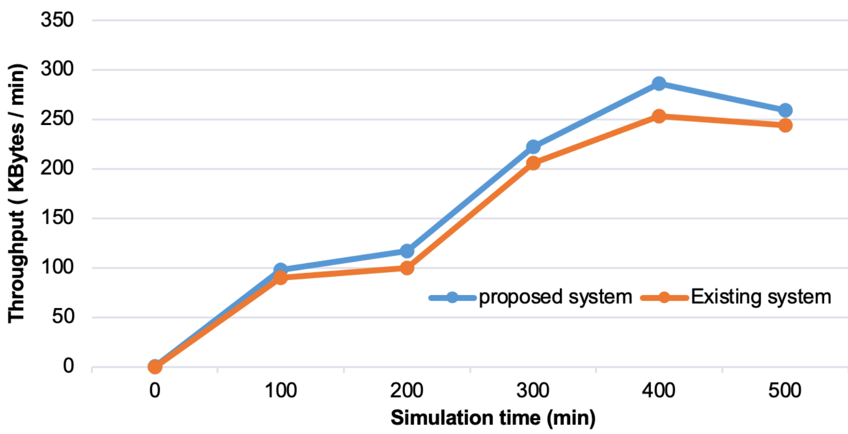


Figure 4. Throughput Vs Simulation time

The Fig.4 graph represents the throughput performance for proposed and existing system. The throughput has been measured, and it denotes as KB/min unit. The medical report delivers to authenticate user from the smart device which used to monitor the physical condition. Increasing throughput value indicates the improvement of secure transaction with low traffic rate.

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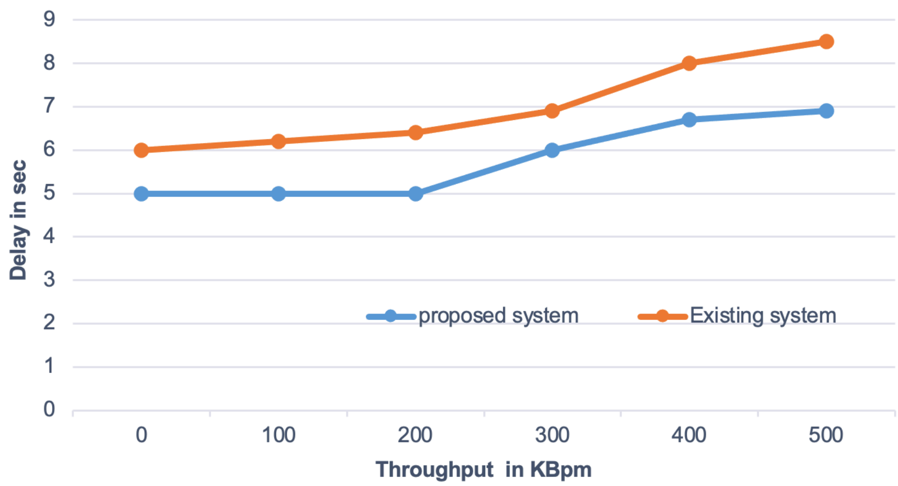

Figure 5. Transaction Delay for comparison work

The Fig.5 graph represents the delay that states the difference between two actions. The minimum delay improves the data transaction speed in a specific time. Hence, compute the transaction size before the calculation of throughput and delay parameters.

5 Discussions

The smart medical system delivers a data through the network at a particular time without delay. The network gathers the information from smart device and validates the cryptographic mechanism. The hash performs to create the unique ID to validate the secret key and provide secure transaction. The stored data in database (block) can be view, verify, add and delete records. The calculation of data collection has major parameters they are follows,

5.1 Transaction size and time

The transaction time refer as time duration between the two operations (appending and deleting) in the block-chain network. The calculation for the transaction time is given below,

$$\text{Time} = \text{Max}\ (t_x) - \text{Min}\ (t_y)$$

The ratio of blocks size to transaction per block provides the size of a transaction. The transaction size of each block can be calculated as follows,

Transaction per block = No. of transaction per min / No. of blocks per min

Transaction size = blocks size / transaction per block

Transaction per block is obtained by dividing number of transactions per minute with number of blocks per minute. The measurement of transaction size is 0.18KB approximately for better performance.

5.2 Throughput performance and delay

The amount of data transfers from one block to another block in a block-chain network within a particular time is known as throughput. Increasing of the throughput value improves the performance level in the network. Delay refers as the transaction time between the deployment and completion time in a block. The low value of delay increases the transaction speed in the network.

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6 Conclusion

This paper introduces the smart medical system to monitor the human health and describes the secure data transaction in the integrated LoRaWAN network. The LoRa gateway communicate the data between user and server. The health report can be view, update by authenticate user in real-time using the consensus algorithm. This system is more trusted using emerging block-chain technology through generating a secret key. The health report includes the patient details, and it helps to identify the patient ID for consultation at a time. The transaction size is also evaluated to improve the throughput performance and reduce the transaction delay in a block-chain network. The proposed system also helps us in pandemic season like COVID-19 for under treatment. Moreover, the medical report transfers in a concurrent session for consultation and treatment. The database ensure privacy than the existing system to provide quality transaction performance. It improves the highly efficient data transaction with low traffic in a real-time manner.

Acknowledgment

No acknowledgment.

Statement on Conflicts of Interest

The author(s) have not declared any conflict of interest.

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Predicting Malaria Outbreaks in Children Under Five: Insights from Ghana

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Background and Purpose: Malaria, a persistent public health challenge in sub-Saharan Africa, disproportionately affects children under five, with socio-economic disparities and environmental factors exacerbating its burden.
Methods: This study employs the Random Forest algorithm to predict malaria outbreaks using historical incidence data from Ghana (2011–2021). By incorporating lagged variables and analysing spatial and temporal dynamics, the model captures seasonality, including peaks during rainy seasons, and regional disparities in malaria cases.
Results: The model achieved a robust R-squared value of 0.8193, reflecting strong predictive accuracy, with additional performance metrics including RMSE of 150.54, MAE of 96.46, and a correlation coefficient of 0.91 between predicted and actual values. Regional hotspots such as Ashanti and Western exhibited higher case numbers than Greater Accra, emphasizing the need for localized interventions.
Conclusions: This study demonstrates the potential of Random Forest as a scalable tool for malaria prediction in resource-constrained settings, enabling data-driven decision-making and optimizing public health resources. Key limitations include potential biases from underreporting in rural areas, variations in healthcare-seeking behaviours affecting data quality, and uncertain generalizability beyond Ghana's ecological context. These findings align with global malaria reduction goals, emphasizing the integration of machine learning into public health strategies to reduce morbidity and mortality in vulnerable populations.

Keywords: Machine learning, random forest, decision-making, malaria, public health, morbidity.

1 Introduction

Malaria, an infectious disease transmitted to humans through the bite of female Anopheles mosquitoes, remains a significant global health issue and an obstacle to socio-economic development, particularly in sub-Saharan countries. Children under the age of five are the most vulnerable to malaria and its complications due to their developing immune systems [1]. In Ghana, malaria is one of the leading causes of disease, especially in children under five years of age, imposing a substantial burden on families and the public health system [2]. Despite various social and health interventions such as the free distribution of treated mosquito nets, free malaria treatment under the National Health Insurance Scheme (NHIS) and public education on malaria, its causes and effects, the prevalence of malaria continues to persist in the 16 regions of the country, claiming thousands of lives each year. Malaria disproportionately affects children under five, contributing to over 80% of malaria deaths in Sub-Saharan Africa [3].

Accurate prediction of malaria outbreaks, particularly in children under five, is crucial for optimizing public health resources. By allowing for the timely distribution of interventions such as medications and preventive tools, health officials can direct supplies to high-risk areas well in advance [4]. Although many predictive models integrate climate, socioeconomic, and environmental data, such data is often complex to obtain in rural and resource-limited regions like Ghana. Consequently, relying on historical malaria

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 J Health Inform Afr. 2025;12(1):74-86. DOI: 10.12856/JHIA-2025-v12-i1-550

incidence data from national health surveillance records offers a practical and effective alternative to predict malaria trends in such settings [5].

This study's significance is underscored by its alignment with Ghana's National Malaria Control Strategic plan (2021 – 2025), which emphasizes technological innovation and evidence-based decision making as essential components for reducing malaria burden [6]. The research is particularly timely as health systems face resource constraints due to recent global health challenges, making the efficient allocation of malaria control resources increasingly critical [7]. The recent improvements in Ghana's health information systems provide an unprecedented opportunity to leverage historical data for predictive modelling to inform targeted interventions.

Despite advances in malaria predictions, significant research gaps persist. Previous models have often failed to account for the unique epidemiological patterns of malaria in children under five, who exhibit different clinical manifestations compared to adults [8]. Additionally, existing models frequently overlook local healthcare-seeking behaviors and socioeconomic factors specific to Ghana that significantly influence malaria transmission patterns [9][10]. Many sophisticated prediction systems require extensive data infrastructure and continuous monitoring of multiple parameters, making them impractical for resource-constrained settings like rural Ghana [11]. This study addresses these limitations by developing a prediction model tailored to the Ghanaian context, focusing on children under five, and utilizing readily available historical health surveillance data.

Although this project is focused on the Ghanaian context, its implications extend beyond national borders to other malaria-endemic regions worldwide that face similar challenges. Sub-Saharan Africa, for example, accounts for more than 90% of global malaria cases and deaths, with socioeconomic disparities, inadequate healthcare infrastructure, and environmental factors that worsen the burden of the disease [12]. Predictive models, tailored to specific local contexts but informed by global best practices, are critical tools for malaria control. These models help optimize resource allocation and guide interventions, offering indispensable support in malaria eradication efforts in resource-constrained settings [4][13]. The success of such models is contingent on integrating innovative technologies and methodologies. Advances in artificial intelligence, machine learning, and geographic information systems (GIS) have demonstrated significant potential to improve the accuracy and scalability of malaria prediction models. These technologies enable synthesizing diverse data types, climatic variables, demographic trends, and real-time health surveillance data, thus improving the precision of outbreak predictions [14][15]. Furthermore, incorporating insights from global initiatives such as the Malaria Atlas Project, which has successfully mapped malaria incidence worldwide, can improve the model's ability to address the unique challenges of resource-limited settings [16][17].

This project aligns with the World Health Organization's Global Technical Strategy for Malaria 2016 to 2030, emphasizing data-driven decision-making, community engagement, and resource optimization as central components of malaria control efforts [18]. Through better planning and more efficient intervention strategies, this project has the potential to contribute significantly to global malaria reduction. The insights generated could also lay the groundwork for further research, ensuring that the benefits extend beyond Ghana and address the needs of vulnerable populations worldwide [4][19].

The use of Random Forest for malaria prediction is particularly suited due to its ability to handle complex, non-linear relationships and large datasets. As an ensemble learning technique, Random Forest aggregates multiple decision trees, improving predictive accuracy and reducing overfitting. This is especially valuable in malaria prediction, where data is often noisy and non-linear [20][21]. Random Forest has been successfully applied in epidemiology, utilizing historical data, environmental factors, and climate variables such as rainfall and temperature to predict malaria outbreaks [4][22]. In malaria prediction models, Random Forest can integrate various data types, including climatic and socio-economic variables, crucial for understanding disease transmission patterns. Models incorporating factors such as land use, vegetation, and temperature have demonstrated strong predictive capabilities in malaria hotspots [4].

While other machine learning approaches, such as neural networks and support vector machines, have been applied to disease modelling, Random Forest offers distinct advantages. It demonstrates superior performance with limited training data compared to deep learning methods [23], provides higher interpretability than "black box" models [24], and shows remarkable robustness to missing data and outliers, which are common challenges in health surveillance datasets from resource-limited settings [25]. Comparative studies have demonstrated Random Forest's superior performance in malaria prediction compared to logistic regression and artificial neural networks when applied to contexts with comparable data limitations [22][26]

Furthermore, Random Forest's ability to handle missing data is invaluable in resource-constrained settings, where health surveillance data may be incomplete or inconsistent [4].

The interpretability of Random Forest models also allows public health officials to identify key variables associated with malaria outbreaks, facilitating better resource allocation and more targeted interventions [19]. Given its proven effectiveness in malaria prediction, Random Forest is an ideal tool for this project, which aims to predict malaria outbreaks among children under five in Ghana. By analysing historical case data, the model will identify patterns that serve as early indicators of potential outbreaks, thus enhancing the country’s ability to allocate resources efficiently and improve early warning systems. The methodological framework developed here can be adapted to similar resource-constrained settings, providing a template for malaria prediction that balances accuracy with feasibility, potentially transforming how predictive analytics supports public health decision-making across malaria-endemic regions.

2 Materials and methods

2.1 Data collection and Pre-processing

The dataset used in this study provides malaria incidence across 16 regions and their districts in Ghana, spanning the years 2011 to 2021. Each sheet corresponds to a specific year and contains four primary columns: Region, District, Period, and Total Sum. The Region and District columns identify the geographic location, while the Period specifies the time in months and years. The Total Sum column captures the number of malaria cases or related statistics for each period, specifically targeting children under five. Prior to analysis, the dataset underwent thorough data cleaning and preprocessing. Missing values in the dataset were addressed using mean substitution, where missing data points were replaced with the mean value of the available data within the same region and month across different years, preserving the seasonal patterns. This study aggregates the data by month and year, then visualizes the trends in malaria cases using a line plot to identify any patterns or seasonal trends in the data. The malaria data is also pre-processed to filter any noise or outliers. Instead of just predicting based on categorical variables (Month, Year, etc.), the study will leverage historical malaria cases. Adding lagged variables (e.g., cases in the previous month or previous year for the same month) can significantly improve the model. Figure 1 shows Ghana's total number of malaria cases per month from 2011 to 2022. Figure 1 illustrates a clear downward trend in the total number of malaria cases over the years, particularly after 2014. This could suggest improved control measures, public health interventions, or environmental factors influencing malaria incidence. There is a visible decline in malaria cases in the latter part of the timeline, with lower peak values than earlier years, decreasing from peaks of approximately 300,000 cases in 2014 to around 200,000 cases by 2021. Figure 1 demonstrates pronounced cyclical patterns throughout the dataset, revealing strong seasonality in malaria transmission. These regular fluctuations in cases yearly are consistently linked to specific months associated with Ghana's rainy and dry seasons. Peaks in malaria cases typically occur during or shortly after the rainy season (May-October) when mosquito breeding conditions are most favourable, with the highest incidence often observed in June-August. These seasonal peaks in tropical regions like Ghana reflect heightened transmission during increased rainfall and humidity. Conversely, troughs in malaria cases are observed during the dry season, corresponding to months like December to February and October to December, when mosquito populations decline significantly due to reduced breeding sites. The cyclical pattern remains consistent across all years in the dataset. However, the amplitude of these seasonal fluctuations appears to decrease in later years, suggesting potentially improved year-round malaria control measures. The most significant anomaly in the seasonal pattern appears around mid-2020, where cases dropped to nearly 100,000, possibly coinciding with COVID-19 pandemic measures that may have affected either malaria transmission or reporting patterns.

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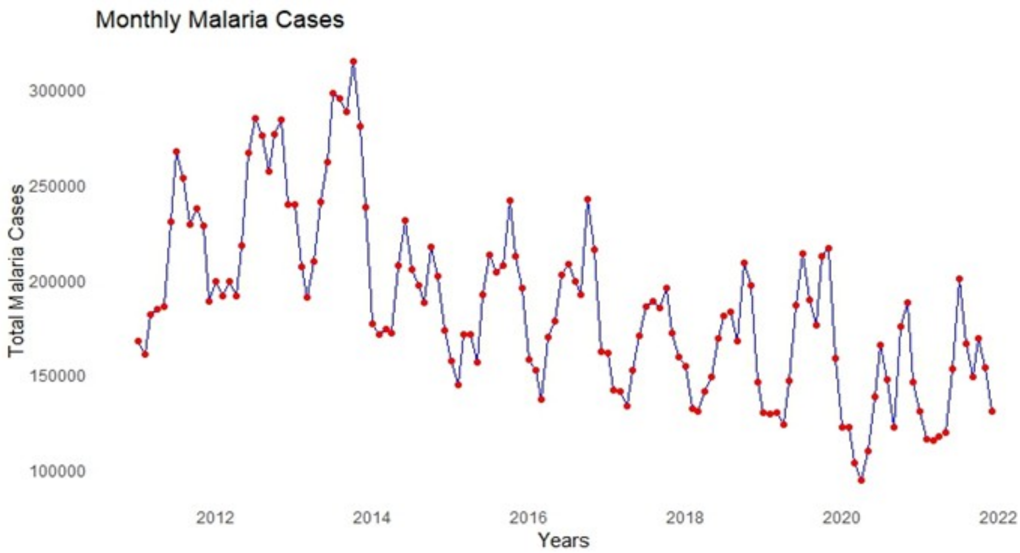

Figure 2. Total number of malaria cases per month from 2011 to 2022

2.2 Random Forest Algorithm

Random Forest (RF) is an ensemble machine learning algorithm known for its robustness, accuracy, and ability to handle complex datasets, making it an excellent choice for predicting malaria outbreaks in children under five. It operates by constructing multiple decision trees during training and aggregating their predictions, thereby reducing overfitting and enhancing model generalization. RF is particularly well-suited for datasets with non-linear relationships and numerous predictors, such as rainfall, temperature, and humidity, critical factors in malaria transmission. Additionally, it provides insights into variable importance, enabling researchers to identify key environmental drivers of malaria outbreaks. Several studies underscore the effectiveness of RF in malaria prediction. Ayele and colleagues [27] demonstrated its superior performance in Ethiopia, where RF outperformed logistic regression and support vector machines in predicting malaria cases using climate and environmental data. Similarly, Ngom and colleagues [28] applied RF in Senegal, highlighting its robustness in managing noisy data and its ability to capture complex interactions between variables. In Kenya, Anyona and colleagues [29] found RF highly effective in analysing the influence of rainfall and temperature on malaria prevalence, emphasizing its interpretability in identifying significant environmental factors. Further, studies by Mburu and colleagues [30] and Kamau and colleagues [31] also endorsed RF for its accuracy and practical utility in predicting malaria incidence across sub-Saharan Africa. Mburu and colleagues [30] utilized RF to predict malaria hotspots with high spatial precision, recommending it as a reliable tool for malaria intervention strategies. Kamau and colleagues [31] highlighted RF's versatility in combining epidemiological and climatic data for accurate forecasting. Moreover, Boateng and colleagues [32] validated RF's performance in malaria prediction in Ghana, advocating for its integration into public health decision-making processes. While we implemented Random Forest directly without comparing multiple algorithms in this study, the choice was informed by an extensive literature review consistently demonstrating RF's advantages for disease prediction. RF offers several benefits that make it particularly suitable for malaria prediction: Unlike linear models such as logistic regression, RF effectively captures the complex nonlinear relationships inherent in malaria transmission dynamics. As Ayele and colleagues [27] demonstrated, RF consistently outperformed logistic regression in similar malaria prediction contexts. RF provides feature importance scores that are particularly valuable for public health applications where understanding key drivers is essential for intervention planning. This interpretability advantage over "black box" models like neural networks is crucial for translating findings into actionable public health measures. Health surveillance data from resource-constrained settings often contains noise and inconsistencies. RF's ensemble approach, which averages predictions across multiple trees, provides robustness against such noise as demonstrated by Ngom and colleagues [28]. RF has shown strong performance for regions with limited historical data compared to more data-hungry approaches like deep learning [33]. Given the proven advantages of RF, including its

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adaptability to complex datasets, high predictive accuracy, and capacity to identify critical drivers of malaria, it is an ideal choice for this study. Its application in similar contexts provides a strong scientific foundation for predicting malaria outbreaks in Ghana, particularly in vulnerable populations such as children under five.

2.3 Model Development and Performance Evaluation

Machine learning models such as Random Forest perform predictive modelling of malaria cases. The model was developed with parameter initialization by starting with a set of initial parameters for the Random Forest, including the number of trees, the depth of trees, and the criteria for splitting. The model's performance on the test dataset is evaluated using R-squared (to determine the proportion of variance explained by the model). The respective machine-learning approaches of R code are also incorporated in this study.

2.3.1 Importing Libraries

The R programming language was used for the data analysis and machine learning. These libraries, readxl, dplyr, ggplot2, and randomForest, were used for data pre-processing, analysis, and potentially machine learning tasks.

```
library(readxl)
library(dplyr)
library(ggplot2)
library(randomForest)
```

2.3.2 Importing Data

Readxl was used to read the files and store them in the data.

```
file_path <- "E:/Malaria_Outbreak/Malaria_Incidence.xlsx"
sheet_names <- excel_sheets(file_path)
all_data <- lapply(sheet_names, function(sheet) {
data <- read_excel(file_path, sheet = sheet)
data <- data %>%
mutate(Period = as.Date(paste0(Period, "-01"), format = "%B %Y-%d")) %>%
na.omit()   # Remove rows with missing values in 'Period'
return(data)})
all_data <- bind_rows(all_data)
```

Adding new columns, Years and Month, while adding lagged variables (e.g., cases in the previous month or previous year for the same month) can significantly improve your model. Below is another R code snippet for data transformation and feature creation:

```
all_data <- all_data %>%
mutate(
Month = format(Period, "%B"),      # Extract month name
Year = as.numeric(format(Period, "%Y")),      # Extract year
Total_Sum = ifelse(is.na(Total_Sum), 0, Total_Sum)  # Handle missing values in 'Total_Sum' )

# Create lagged features for previous months
all_data <- all_data %>%
arrange(Period) %>%
group_by(Region, District) %>%
(
Lag_1 = lag(Total_Sum, 1),
Lag_2 = lag(Total_Sum, 2),
Lag_3 = lag(Total_Sum, 3),
```

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```
Lag_12 = lag(Total_Sum, 12) # Previous year's same month
) %>%
ungroup() %>
na.omit() # Remove rows with missing lagged values
```

3 Results

3.1 Model Building

The dataset was split into training and testing sets based on the year: Training Set: Data prior to 2021. Testing Set: Data for the year 2021. To prepare the data for the Random Forest model, categorical variables were one-hot encoded using the model. Matrix function. This ensures the model can correctly interpret the categorical predictors, especially for regions and districts.

```
# Split data into training and testing sets
train_data <- all_data %>% filter(Year < 2021)
test_data <- all_data %>% filter(Year == 2021)

# One-hot encoding of categorical variables
    X_train_encoded <- model.matrix(~ . - 1, data = train_data %>% select(-Total_Sum, -Period))
    X_test_encoded <- model.matrix(~ . - 1, data = test_data %>% select(-Total_Sum, -Period))

    # Define target variable (Total_Sum) for training and testing
    y_train <- train_data$Total_Sum
    y_test <- test_data$Total_Sum

    # Train the Random Forest model
    set.seed(42)  # Set seed for reproducibility
    rf_model <- randomForest(x = X_train_encoded, y = y_train, ntree = 10, importance = TRUE)

    # Make predictions on the test set
y_pred <- predict(rf_model, X_test_encoded)
```

3.2 Random Forest Implementation Details

In our Random Forest implementation for malaria prediction, each decision tree in the ensemble starts with a root node containing all training data points and recursively partitions data based on features that best separate malaria incidence levels. We implemented the model with 10 trees (ntree = 10), with each tree trained on a bootstrap sample of the original data. At each node, potential splits were evaluated based on reduction in mean squared error (MSE), framing this as a regression problem predicting the exact number of cases (Total_Sum), while considering temporal features (lag variables Lag_1, Lag_2, Lag_3, and Lag_12), geographical information (Region and District), and seasonal patterns (Month).

The model heavily relied on lagged variables, with previous months' incidence rates emerging as top predictors in feature importance analysis, aligning with malaria's seasonal and cyclical transmission patterns. Each decision tree's terminal nodes (leaves) contained predicted numerical values for malaria incidence, and unlike classification trees that output class labels, our regression trees produced continuous numerical predictions of malaria cases. The final prediction was determined by averaging predictions from all 10 trees, providing a robust estimate of expected malaria cases.

3.3 Model Evaluation

When evaluating the performance of a model, it is crucial to select appropriate metrics based on the nature of the problem. One standard metric is R-squared, which measures the proportion of the variance in the

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target variable that the model's predictors can explain. A higher R-squared value indicates a better fit for the developed model.

```
r2 <- 1 - sum((y_test - y_pred)^2) / sum((y_test - mean(y_test))^2)
```

The R-squared value of 0.8193 indicates that the model explains approximately 81.93% of the dependent variable (target) based on the independent variables (predictors) included. This relatively high R-squared value suggests that the model fits the data well and has strong predictive power. However, it is essential to note that while a high R-squared indicates a good fit, it does not guarantee that the model is free from overfitting or other issues, such as bias in predictions.

To provide a more comprehensive evaluation of our model's performance, we calculated additional metrics:

```
# Calculate RMSE (Root Mean Square Error)
rmse <- sqrt(mean((y_test - y_pred)^2))

# Calculate MAE (Mean Absolute Error)
mae <- mean(abs(y_test - y_pred))
# Calculate MAPE (Mean Absolute Percentage Error)
mape <- mean(abs((y_test - y_pred)/y_test)) * 100
# Calculate R-squared
r_squared <- 1 - sum((y_test - y_pred)^2) / sum((y_test - mean(y_test))^2)

# Calculate correlation
correlation <- cor(y_pred, y_test)

# Create performance summary
performance_summary <- data.frame(
 Metric = c("RMSE", "MAE","R-squared", "Correlation"),
Value = c(rmse, mae, r_squared, correlation)
)
print("Summary of Model Performance:")
print(performance_summary)
```

The RMSE value of 150.54 represents the standard deviation of the prediction errors, while the MAE of 96.46 indicates the average magnitude of errors in the predictions. The correlation coefficient 0.91 further supports the strong relationship between the predicted and actual values. Together, these metrics confirm that our model performs well, with the R-squared showing that approximately 82% of the variance in the target variable is explained by our model.

Monthly, the predicted cases are plotted against the actual cases for the entire nation.

```
# Filter test_data to include only rows corresponding to y_test
filtered_test_data <- test_data %>% filter(Year == 2021)

# Ensure lengths match
stopifnot(nrow(filtered_test_data) == length(y_test))

# Combine Actual (y_test) and Predicted (y_pred) with Month and Year
plot_data_monthly <- data.frame(
Actual = y_test,
Predicted = y_pred,
Month = filtered_test_data$Month,
Year = filtered_test_data$Year
) %>%
 group_by(Year, Month) %>%
summarise(
 Actual = sum(Actual, na.rm = TRUE),
Predicted = sum(Predicted, na.rm = TRUE),
 .groups = "drop"
) %>%
```

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```
mutate(
 Date = as.Date(paste(Year, match(Month, month.name), "01", sep = "-"))
 )

# Plot the aggregated data
ggplot(plot_data_monthly, aes(x = Date)) +
geom_line(aes(y = Actual, color = "Actual"), size = 1) +
geom_point(aes(y = Actual, color = "Actual"), size = 2) +
geom_line(aes(y = Predicted, color = "Predicted"), size = 1, linetype = "dashed") +
geom_point(aes(y = Predicted, color = "Predicted"), size = 2) +
labs(
title = "Monthly Predicted vs Actual Malaria Cases",
x = "Date",
y = "Malaria Cases",
color = "Legend"
 ) +
scale_color_manual(values = c("Actual" = "blue", "Predicted" = "red")) +
theme_minimal() +
theme(
panel.grid.major = element_blank(),  # Remove major grid lines
panel.grid.minor = element_blank()   # Remove minor grid lines
)
```

Figure 2 compares actual and predicted monthly malaria cases for 2021, highlighting the model's ability to capture seasonal trends. Both actual and predicted cases exhibit a sharp increase, peaking around mid-year (July), followed by a decline. While the model aligns well with the general pattern, it slightly underestimates the magnitude of the peak and overestimates in some months during the decline. These discrepancies suggest that while the model effectively captures seasonal variability, its precision in predicting extreme values could be improved.

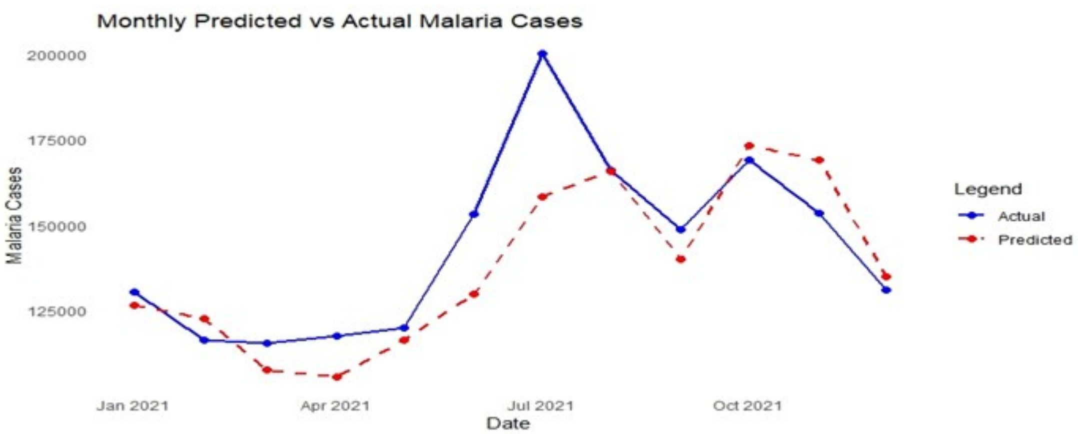

Figure 2. Actual and predicted monthly malaria cases for 2021

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Plotting the predicted cases against the actual cases for each region in the country.

```
# Prepare the data for plotting by region, year, and month
plot_data_monthly <- data.frame(
Actual = y_test,
 Predicted = y_pred,
Month = filtered_test_data$Month,
Year = filtered_test_data$Year,
 Region = filtered_test_data$Region
) %>%
group_by(Region, Year, Month) %>%
summarise(
Actual = sum(Actual, na.rm = TRUE),
Predicted = sum(Predicted, na.rm = TRUE),
.groups = "drop"
) %>%
mutate(
Date = as.Date(paste(Year, match(Month, month.name), "01", sep = "-"))
 )
# Plot the data
ggplot(plot_data_monthly, aes(x = Date)) +
 geom_line(aes(y = Actual, color = "Actual"), size = 1) +
  geom_point(aes(y = Actual, color = "Actual"), size = 2) +
 geom_line(aes(y = Predicted, color = "Predicted"), size = 1) +
 geom_point(aes(y = Predicted, color = "Predicted"), size = 2) +
labs(
title = "Monthly Predicted vs Actual Malaria Cases by Region",
x = "Date",
y = "Malaria Cases",
color = "Legend"
) +
 scale_color_manual(values = c("Actual" = "blue", "Predicted" = "red")) +
 theme_minimal() +
theme(
panel.grid.major = element_blank(), # Remove major grid lines
panel.grid.minor = element_blank()  # Remove minor grid lines
 ) +
 facet_wrap(~Region, scales = "free_y") # Facet by Region with independent y-scales
```

Figure 3 compares monthly predicted malaria cases and actual cases across regions from 2020 to 2021, highlighting spatial and temporal variations. Each region exhibits a clear seasonal pattern, with annual peaks that align with expected environmental conditions, such as rainy seasons. Ashanti, Central, and Western regions report higher malaria cases, indicating a significant disease burden. Meanwhile, Greater Accra and North East areas show relatively lower cases but maintain consistent seasonal peaks. The model demonstrates strong predictive accuracy, as the predicted values closely follow the actual trends in most regions, capturing both seasonality and magnitude effectively. However, minor deviations are observed in regions like Bono East and Northern, where the model occasionally overestimates or underestimates case magnitudes. Overall, this analysis underscores the importance of considering regional disparities and seasonal dynamics in malaria transmission to enhance intervention strategies and allocate resources efficiently.

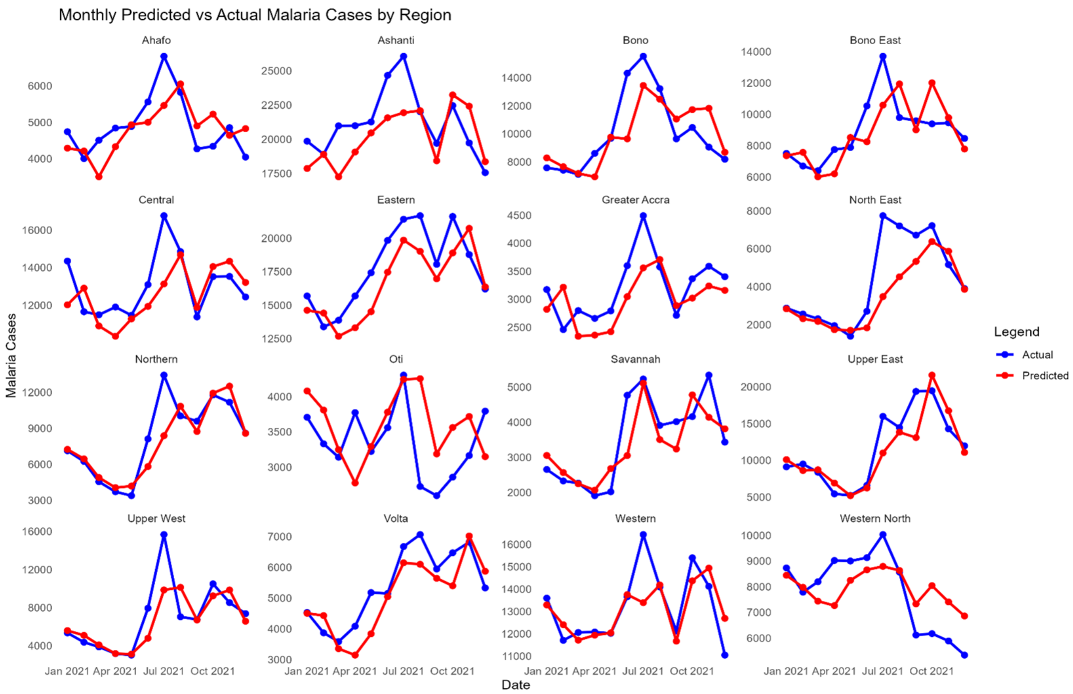

Figure 3. Monthly predicted malaria cases and actual cases across regions from 2020 to 2021

4 Discussion

This study validates the Random Forest algorithm as a reliable and effective tool for predicting malaria outbreaks among children under five in Ghana. Achieving an R-squared value of 0.8193, the model demonstrates strong predictive accuracy, capturing seasonal trends that align with the well-documented rainy seasons, a finding consistent with studies by Ngom and colleagues [28] in Senegal and Anyona and colleagues [29] in Kenya. This research corroborates prior work by Boateng and colleagues [32], who validated the application of Random Forest in Ghana for malaria prediction, further substantiating its utility in public health frameworks tailored to resource-constrained environments.

Identifying high-burden regions, such as Ashanti, Central, and Western, aligns with Mburu and colleagues (2020), who employed machine learning to pinpoint malaria hotspots across sub-Saharan Africa. Similarly, Boateng and colleagues [32] highlighted regional variations within Ghana, emphasizing the need for localized interventions informed by robust predictive models. The study further supports findings by

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Kamau and colleagues [31], which demonstrated that integrating epidemiological and climatic data enhances the spatial precision of malaria forecasts.

This study's reliance on historical incidence data highlights its relevance in data-limited settings, a methodological choice previously validated by Adams and Smith [5]. By incorporating lagged variables, the model captures temporal dependencies crucial for improving predictive accuracy, echoing the findings of Mwandama and colleagues [19]. The approach also complements global observations by Ayele and colleagues [27] and Basu and colleagues [4], who found Random Forest highly adaptable, particularly in handling incomplete and noisy datasets.

Within Ghana, the study builds on local evidence provided by Boateng and colleagues [32], whose work emphasized Random Forest's ability to guide the strategic allocation of malaria control resources. The model's capacity to accurately predict temporal and regional variations is critical for optimizing interventions such as insecticide-treated nets and antimalarial distribution, aligning with the World Health Organization's Global Technical Strategy for Malaria (2016–2030).

Based on these findings, we recommend several policy actions: (1) Implementing regionalized intervention strategies that allocate resources proportionally to the predicted disease burden, with particular attention to high-transmission regions identified by the model. (2) Timing prevention campaigns to precede predicted seasonal peaks, particularly in the months leading up to July. (3) Surveillance systems in underreported areas should be enhanced to address data quality concerns. (4) Establishing formal partnerships between the Ghana Health Service, the Meteorological Agency, and environmental monitoring institutions to facilitate data sharing. (5) Developing protocols for communicating predictive insights to communities through culturally appropriate channels that promote preventive actions.

Despite the model's strong performance, several limitations warrant consideration. First, potential biases exist in the dataset, particularly regarding underreporting of malaria cases in rural and resource-constrained areas. Health facilities with limited diagnostic capabilities may record symptomatic cases without laboratory confirmation, affecting data quality. Additionally, seasonal variations in healthcare-seeking behavior could skew temporal patterns in the recorded data. The generalizability of this model beyond Ghana remains uncertain, as malaria transmission dynamics vary significantly across different ecological zones in sub-Saharan Africa. While the methodological framework could be transferred to other contexts, model parameters would require recalibration to account for regional differences in climate patterns, vector species distribution, and intervention coverage.

In conclusion, the findings validate the use of Random Forest in malaria modelling, particularly in Ghana, where regional disparities and seasonal dynamics present unique public health challenges. By bridging predictive analytics with actionable insights, this study advances the application of machine learning in malaria control efforts, providing a scalable framework for other malaria-endemic regions globally.

5 Recommendation

Integrating predictive modelling into national public health frameworks to enhance malaria control efforts is critical. Governments and stakeholders should prioritize adopting machine learning tools like Random Forest for early detection of high-risk periods and regions, enabling the timely allocation of resources such as insecticide-treated nets and antimalarial medications. To maximize effectiveness, these models should be implemented as decision-support tools within existing health information systems like Ghana's DHIMS, complementing rather than replacing traditional surveillance methods. Integrating automated data pipelines would enable continuous model updating with real-time information, significantly enhancing predictive capabilities. Investments in data infrastructure are also essential to improve data availability and quality, particularly in rural settings where climatic and socioeconomic variables are often inaccessible. Furthermore, targeted public health campaigns should address regional disparities, focusing on high-burden areas like Ashanti and Western, while maintaining surveillance in lower-incidence regions. Implementation success depends on developing technical infrastructure, creating clear response protocols, and providing targeted training for health officials on interpreting and applying model outputs. Looking ahead, future research should expand this work by testing additional variables such as satellite-derived environmental data on rainfall and vegetation indices, applying the methodology to different regions or diseases, and exploring alternative AI techniques like deep learning and ensemble methods. Establishing partnerships

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between health departments and meteorological agencies could facilitate the incorporation of mobile health reporting platforms to provide early signals of increasing malaria incidence. Collaborations with global health organizations can support capacity building and technology transfer to scale such models across other malaria-endemic regions. We call upon health ministries in endemic countries to initiate pilot programs incorporating these predictive frameworks into their decision-making processes, as their deployment in real-world healthcare settings could revolutionize resource allocation efficiency and ultimately accelerate progress toward malaria eradication.

Statement on conflicts of interest

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria, educational grants, participation in speakers' bureaus, membership, employment, consultancies, stock ownership, or other equity interest, and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

Data Availability Statement

Data is available upon request from the corresponding author.

Funding Statement

This study did not receive funding from any source.

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 J Health Inform Afr. 2025;12(1):74-86. DOI: 10.12856/JHIA-2025-v12-i1-550

Journal of Health Informatics in Africa

ISSN: 2197-6902
DOI: http://dx.doi.org/10.12856/JHIA-2025-v12-i1

Publisher
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