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Journal of Health Informatics in Africa

Editorial to JHIA Vol. 12 (2025) Issue 2

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The Journal of Health Informatics in Africa (JHIA) continues to provide a scholarly platform for research that advances the design, implementation, governance, and evaluation of health information systems within African and comparable low- and middle-income country contexts. Volume 12, Issue 2 reflects the journal's sustained focus on digital health adoption, health information system governance, data quality, and evidence-based decision-making, with contributions spanning empirical studies, methodological validation, governance frameworks, and systematic reviews.

Collectively, the papers in this issue highlight both the transformative potential of digital health technologies and the structural, social, and data-quality challenges that continue to shape their impact. Several contributions underscore the importance of moving beyond technical implementation toward user engagement, trust, governance, and data integrity as foundational elements of sustainable digital health systems.

Research by *Kanny and Adebesin* explores user engagement with mobile health applications for diabetes self-management within a South African context. Using a quantitative design, the study applies principal component analysis to validate the User Engagement Scale (UES) in a local mHealth setting. The findings confirm the multidimensional nature of user engagement, encompassing factors such as focused attention, perceived usability, and aesthetic appeal. The paper contributes methodologically by demonstrating the contextual applicability of an established engagement scale and substantively by reinforcing the role of user-centred design in promoting sustained mHealth use for chronic disease management.

Focusing on governance at the community level, *Chumba et al*. examine structural mechanisms within a community-based health information system (CBHIS) using a mixed-methods approach. The study explores how governance practices influence data use, accountability, and service delivery, highlighting the importance of clearly defined roles, stakeholder participation, and coordination structures. By foregrounding community-based systems, the paper extends health informatics governance scholarship to an area that is critical for primary healthcare delivery but often underrepresented in the literature.

A broader perspective on digital service delivery is provided by *Alton Mabina*, who present a systematic literature review on trust and access in telemedicine. Synthesising findings from 32 peer-reviewed studies published between 2018 and 2025, the review shows that telemedicine initiatives frequently improve access to care, particularly in rural and underserved settings. However, sustained adoption is constrained by trust-related concerns, including privacy, data security, cultural alignment, and provider–patient relationships. The paper highlights the interdependence of access and trust and emphasises the importance of participatory, user-centred approaches in telemedicine design and implementation.

Extending the discussion to a continental scale, *Oladosu* et al. offer a systematic review of digital health innovations across Africa, drawing on evidence from 68 studies published between 2014 and 2025. The review maps the prevalence of mHealth, telemedicine, electronic health records, and emerging artificial intelligence applications, with a strong concentration in maternal and child health, infectious disease management, and chronic care. While improvements in efficiency and service delivery are reported, persistent challenges related to infrastructure, digital literacy, financing, and regulation are identified. This paper provides a macro-level context that complements the more focused empirical studies in the issue.

Issues of data integrity and health system decision-making are addressed by *Tungbani* and *Nhlapo*, who assess the quality of cause-of-death data in Ghana's District Health Information Management System II (DHIMS II) using 2023 institutional mortality records coded with ICD-11. Applying the WHO's ANACOD3 tool, the study reveals that non-communicable diseases account for the majority of recorded deaths, reflecting Ghana's epidemiological transition. At the same time, substantial data quality limitations are identified, with over 30% of records classified as ill-defined or unusable "garbage codes." The paper demonstrates how systematic quality assessment tools can identify structural weaknesses in mortality reporting and support more reliable, evidence-based health planning.

In addition to the scholarly contributions presented in this issue, JHIA is pleased to announce an important change to its publication model. From January 2026, the journal will adopt a continuous publication approach, whereby articles will be published as soon as they are accepted and finalised, rather than being held for biannual issues. Historically, JHIA published two issues per year, released at six-month intervals. The move to continuous publication is intended to reduce time to publication, improve the timeliness of research dissemination, and better serve authors, readers, and the broader health informatics community.

Accepted articles will continue to be organised within annual volumes, but publication will no longer be constrained by fixed issue schedules. This change aligns JHIA with evolving scholarly publishing practices and supports more responsive engagement with rapidly developing digital health and health information system research.

Volume 12, Issue 2 reflects the growing maturity and diversity of health informatics research in Africa. The papers collectively emphasise that technological innovation must be accompanied by strong governance, user engagement, trust, and high-quality data to realise meaningful and sustainable health system improvements. We thank the authors, reviewers, and editorial team for their continued contributions to the journal and look forward to advancing timely, impactful scholarship through JHIA's new continuous publication model.

Nicky Mostert
December 2025

Journal of Health Informatics in Africa

Community-Based Health Information System Governance Structural Mechanism: Role in Attaining the Alignment and Improvement of Community Health Outcomes

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Background and purpose - Health Information System (HIS) governance is necessary for the effective functioning of HIS to improve health outcomes. However, practices associated with the Community-Based Health Information System (CBHIS) governance structural mechanism remain unclear. In addition, there is a paucity of knowledge on the nature of the interrelationships between the CBHIS governance structural mechanism, community health-CBHIS alignment and community health outcomes. The study sought to establish the practices associated with the CBHIS governance structural mechanism and its interrelationships with community health-CBHIS alignment and community health outcomes.
Methodology - This study employed a mixed-method research approach, utilising a convergent parallel research design. Two study sites were purposefully chosen from a total of 47 counties. A sample size of 179 respondents participated in the study. The study used Partial Least Squares (PLS) Structural Equation Modelling (SEM) to analyse quantitative research data. Qualitative data were thematically analysed using ATLAS.ti V24.1.0.30612.
Findings – The study established and validated eight practices associated with the CBHIS governance structural mechanism, which form part of the CBHIS governance practices necessary for community health-CBHIS alignment to occur. Additionally, the study identified six indicators that measure the community health outcomes construct. Furthermore, the study findings revealed a positive and significant relationship between the CBHIS governance structural mechanism and community health outcomes. In addition, the exogenous construct positively affected the endogenous construct; thus, the study concluded that the model had an overall predictive relevance.
Practical implications – The study findings revealed the practices associated with the CBHIS governance structural mechanism necessary for community health-CBHIS alignment to occur. Through the findings, it is suggested that designing and implementing such practices can significantly improve community health outcomes. Health informatics practitioners and policymakers should consider adopting these governance practices to improve health outcomes at the community level.

Keywords: Alignment, CBHIS Governance Structural Mechanism, Community Health Outcomes, Health Information Systems.

1 Introduction

Health Information Systems (HIS) integrations (also called digital health) are on the rise in different levels of healthcare, including the community healthcare level. Examples of community-level HIS integrations include Integrated Community Health Information System (iCHIS), Electronic Community Health Information System (eCHIS), Mobile-Jamii Afya Link (MJali), Smart Health application, Kobo Collect, DHIS2 Tracker, Totohealth, mDharura, Community-wide Health Information Exchange, among others [1]-[10]. They facilitate community health data collection, analysis and reporting and are generally referred to as Community-Based Health Information Systems (CBHIS).

Effective Health Information System (HIS) governance is essential for ensuring successful integrations and the smooth functioning of HIS systems [11], [12]. HIS governance also improves health outcomes [13],

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[14], [12] and consequently, leads to a properly and fully functioning health system [15], [16], [14]. Studies have shown that companies with a well-functioning IT governance program earn at least 20% more than companies without one, especially if they are pursuing the same strategy [17].

HIS Governance is operationalised via structures, processes, and relational mechanisms, as well as their associated practices [18], [14]. These practices are contextual [19], [20] and are necessary for the health-HIS alignment to occur [21]. Similarly, CBHIS governance is operationalised via the three mechanisms, namely, CBHIS structures, processes and relational mechanisms. Practices associated with these governance mechanisms are necessary for community health-CBHIS alignment, referred to as the alignment, to occur. In addition, CBHIS governance mechanisms determine the realisation of community health outcomes. The focus of this study was on the CBHIS governance structural mechanism and its associated practices.

Existing literature has highlighted certain practices linked to community-level digital health integrations; however, no study to date has comprehensively examined the practices associated with the CBHIS governance structural mechanism. Moreover, the nature of the interrelationship between the CBHIS governance structural mechanism and community health outcomes remains insufficiently understood. While prior research acknowledges the importance of Health Information System (HIS) governance structural mechanisms, it offers a limited in-depth exploration of their operationalisation and impact [22], [23], [12]. Several studies [24], [18], [25] have emphasised the need to investigate both the nature and the how underpinning the interrelationships between community-level HIS governance mechanisms and health outcomes. Addressing this knowledge gap, the present study first sought to identify and validate the practices associated with CBHIS governance structural mechanism, and subsequently to examine the relationships between this mechanism and community health outcomes.

To achieve these objectives, the study employed the HIS governance theory and the Strategic Alignment Model (SAM), focusing on: (1) to identify the practices associated with the CBHIS governance structural mechanism that facilitate community health-CBHIS alignment to occur; and (2) to analyse the interrelationships between the CBHIS governance structural mechanism, alignment, and community health outcomes.

2 Literature Review

The healthcare sector in most developing countries is categorised into the national, sub-national and community levels. In Kenya, 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, the County Health Management Team (CHMT), the Sub-County Health Management Team (S-CHMT), and the Facility Health Management Team (FHMT) act as the health governance bodies. Community Health Committees (CHCs) act as the leadership and governance body at the community level. The responsibility of each of these bodies is to strengthen health systems. Health Information Systems integration plays a crucial role in this endeavour.

2.1 Health Information System (HIS) Governance

IT governance concerns setting up practices associated with structures, processes and relational mechanisms that ensure that the organisation's Information Technology supports and is supported to sustain and extend the organisation's vision, mission, strategies, objectives and goals [26]. In the healthcare sector, governance of HIS ensures health performance and improved health outcomes [13], [27], [28], [11], [14], [29], [12]. It is operationalised through HIS governance structures, processes and relational mechanisms [18]. The next section analyses existing literature on the practices associated with the community-level HIS governance structural mechanism, the HIS outcomes, and the interrelationships between HIS Governance, alignment and health outcomes are discussed.

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2.2 Practices Associated with the Community-Level Health Information System Governance Structural Mechanism

The community-level health information system's governance structural mechanism is one of the elements operationalising community-level HIS governance. According to [14], the HIS structural mechanism encompasses committees, teams and bodies whose roles and responsibilities are to make HIS decisions and provide directions. Different digital health integrations in different levels of healthcare have context-specific practices associated with the HIS governance structural mechanism. Practices associated with the hospital-level HIS governance structural mechanism differ from those of community-level HIS. Different studies have examined particular practices associated with the community-level HIS governance structural mechanism.

Notably, a study by [24] observed that Work Improvement Teams (WITs) governance practice improves the quality of services and propels the performance of community health units. According to the study, the outcome of leveraging WITs in the structures of the community health units is improved health of the community members. Similarly, [30] argued that the Quality Improvement Team (QIT), which is a governance body, improved the outcomes of the implemented community health interventions in Benin. The study reported that QITs improved the quality of healthcare as well as increased the performance of CHWs and the utilisation of maternal and child health (MCH) services. Others include the Community-Based Information System (CBIS) steering committee, which is responsible for making timely and well-aligned decisions and ensuring that the CBIS agenda is presented at meetings where policy, programming, and financing decisions are made, both at the national and local government levels [23]. Similarly, community information champions form another governance practice which ensures that community data guides high-level discussions [23]. [25] reiterated the importance of using champions as a health IT governance practice. Feldman et al. argued that the success of the implementation of a health information exchange system in a state-wide relied on the establishment of a project champion with decision-making power. [31] further reiterated that community champions are needed to ensure that policies and plans developed at the national and county levels are implemented with accountability and transparency to achieve the objectives of programs.

Other governance practices for the community-level HIS include the use of Community Health Committees (CHCs). CHC is a community-level body that provides leadership and oversight functions as outlined in the Strategy for Community Health 2014–2019 [32]. Furthermore, the eHealth Technical Working Group [33], the Community Health Digital Team/implementation technical team [33], and the Community Stakeholders Team [33], [34] are also some of the community-level HIS governance practices. Others include the use of neutral conveners as a transparent governance structure [10] and the use of a governing council [2].

It is evident from the existing literature that Work Improvement Teams, Quality Improvement Teams, Community Information Champions, Community Health Committees, eHealth Technical Working Group, Community Health Digital Teams and Community Stakeholders form the practices associated with the different community-level HIS governance structural mechanisms. However, none of the existing studies comprehensively examined these practices in the context of Community-Based Health Information Systems governance. In light of this gap, a pre-study was conducted between January 2024 and March 2024, with the objective of contextualising, testing and refining the design methods and instruments. Table 1 presents practices associated with the community-level HIS governance structural mechanism, as gathered from the literature and the pre-study. The table also presents the sources of these practices.

Table 1: CBHIS Governance Practices (measurement items) and their sources

S.No.	CBHIS Governance Practice	Source
1	Community Health Committees (CHCs)	[32]
2	eHealth Technical Working Group (TWGs)	[6], [33]
3	Work/Quality Improvement Teams (WITs)	[24],[30]
4	eHealth, Technology Support and Information Office	[36], [35], [33]
5	Community Health Data Review Boards	This study's pre-study. Conducted between January 2024 and March 2024
6	Community Health Digital Team	[33]

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7	Community information champions	[23], [31], [25]
8	Community Stakeholders Team	[33], [34], [4]

2.3 Outcomes of Health Information Systems

HIS integration and use have several healthcare benefits. To begin with, CBHIS improves community healthcare coordination. Studies such as [23] opined that improvement in care coordination is one of the HIS benefits. The utilisation of CBHIS facilitates care coordination and management in healthcare cases like Tuberculosis (TB), facilitates ease of tracing drug defaulters such as Comprehensive Care Centre (CCC) patients, provides information on antenatal care (ANC), and provides immunisation coverage data of under-fives [4]. In tandem with these sentiments, [37] observed that the integration of Health IT systems strengthens coordination among all levels of healthcare. Implementation of eCHIS can be observed, for example, in Northwest Ethiopia, where women in the eCHIS intervention group had a higher chance of completing the maternal continuum of care than women in the comparator group [33].

Similarly, CBHISs improve community health data and information quality and make it available. [33] argued that the use of digital devices such as tablets for data processing reduced the number of errors as CHWs conduct their house-to-house registration, thus improving health data quality. The study further reiterated that eCHIS enhanced the quality of community health data. Similarly, [38] reiterated that by introducing HIT in healthcare organisations, the quality of health data and healthcare service delivery improved.

In addition, CBHISs reduce community health operational costs. In support of this argument, [38] pointed out that HITs reduced operational costs and presented an opportunity for further cost savings. Similarly, [36] opined that the use of health IT in beta and alpha healthcare organisations resulted in reduced healthcare organisation costs. However, the reduced costs are more often on the operational expenditure (OPEX) since the capital expenditure CAPEX is usually high [39].

Another outcome of CBHIS implementation and use is an increased efficiency and effectiveness in delivering community health services. Existing studies [38], [40] highlighted that HIT integrations bring benefits such as increased efficiency, improved safety, and patient satisfaction. Similarly, [4], [34] argued that through the utilisation of community health IT interventions, improvements in indicators such as an increase in hospital deliveries, advances in immunisation coverage, efficient distribution of drugs (pain killers, dewormers, multi-vitamins), and distribution of treated bed-nets are some of the reported cases.

Furthermore, the use of CBHISs results in an improvement in community engagement in health. [4] argued that CBHIS provides an avenue where community members engage and deliberate on issues affecting them. According to studies such as [38], [41], [14], [23] health outcomes resulting from HIT initiatives include increased community engagement in health. On the same breadth, a study by [33] on eCHIS implementation in northwest Ethiopia found that eCHIS promotes community engagement in health. Hailemariam et al. [33] observed that through eCHIS, Health Extension Workers (HEWs) promote health information by linking women to health centres and accessing health services.

Moreover, CBHIS promotes accountability and performance management. In support of this finding, [4] opined that Community-Based Information Systems (CBIS) provide information that helps to hold service providers accountable. On the same breadth, a study by [42] pointed out that the Nutritional Information System (NIS) implemented in community health units facilitated accountability. Similarly, [23] opined that HISs help in ensuring accountability in service delivery. According to studies such as [38], [41], [14], [23], HIS initiatives promote accountability. It is evident from the above arguments that several health outcomes result from HIS integrations as indicated in Table 2.

Table 2: HIS Outcomes (measurement items) and their sources

S.No.	Indicator	Source
1	Improved community healthcare coordination	[23], [4], [37], [33]
2	Improved community health data and information quality and availability.	[33], [38]
3	Reduced community health operational costs	[38], [36]
4	Increase in efficiency and effectiveness in delivering community health services	[38], [4], [40], [34]

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5	Improvement in community health engagement in health	[4], [38], [41], [14], [23], [33]
6	Improved accountability and performance management	[4], [42], [23]

2.4 Interrelationships between Health Information System Governance, Alignment and Health Outcomes

A mix of practices associated with IT governance mechanisms is necessary for alignment between business and IT to occur [43]. In the healthcare context, studies such as [36], [44], [38], [35] examined the link between health IT governance and health–IT alignment. Practices associated with the HIS governance mechanisms (structures, processes and relational mechanisms) determine the level of alignment between health and IT. According to [36], the HIS governance structural dimension is apparent in trying to attain IT alignment. In support of this proposition, [45] argued that the involvement of executive teams in IT Governance positively affects alignment. In light of these arguments, this study argues that practices associated with the CBHIS governance structural mechanism form part of the governance practices necessary for the alignment to occur.

Similarly, HIS governance through its mechanisms and associated practices determines the achievement of healthcare goals and objectives [13], [46], [14], [47], [12]. Alignment between health and HIS plays a crucial role in this linkage. [26] argued that alignment is necessary for improved organisational performance. A similar argument can be seen in the healthcare sector, where studies such as [41] have examined the linkage between health-IT alignment and health outcomes. The higher the level of alignment between health and IT, the more benefits it brings to the health sector. Therefore, appropriate governance practices are required to enable alignment to take place. It is evident from the literature that HIS governance practices are necessary for alignment and consequently the realisation of health outcomes. Although the CBHIS governance practices necessary for improving health outcomes are categorised into three governance mechanisms, the focus of this study was the CBHIS governance structural mechanism. The study hypothesised that the CBHIS governance structural mechanism (exogenous construct) is essential for improving community health outcomes (endogenous construct) (Link a), as depicted in the conceptual model in Figure 1. The IT governance theory and the Strategic Alignment Model (SAM) were jointly applied, given that neither framework alone could adequately address the research problem.

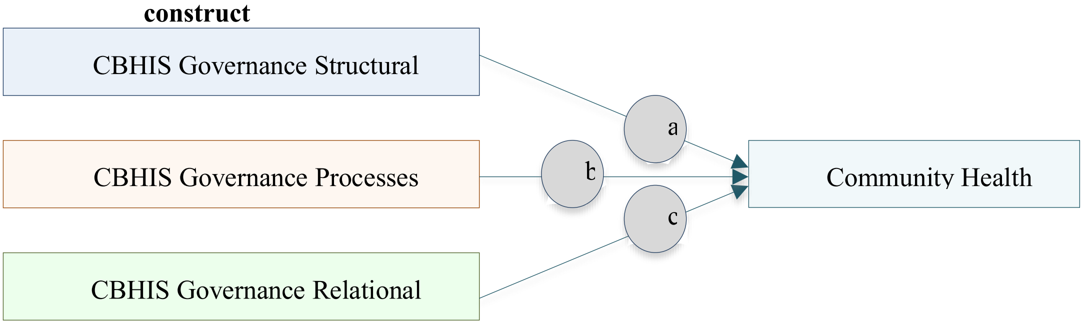

Figure 1: Conceptual model

3 Research Methodology

3.1 Pre-study

Before this study's actual data collection, a pre-study was conducted in Kibra Sub-County in Nairobi County between January and March of 2024. The objective of the pre-study was to refine the questionnaire and identify the research ambiguities. A total of 28 respondents, which included the County Community Health Focal Person (CCHFP), County Health Records & Information Officers (CHRIOs), County Health

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IT officers, the Sub-County Community Health Focal Person (S-CCHFP), Sub-County Health Records & Information Officers (S-CHRIOs) and Community Health Assistants (CHAs), participated in the pre-study exercise.

3.2 Data Collection

Guided by a pragmatic worldview, this study employed a mixed-method research approach which utilised a convergent parallel research design. Kisumu City County and Makueni County were purposefully chosen from a total of 47 counties due to their experience in CBHIS implementation and use. The study population consisted of 321 officers drawn from different strata using the CBHISs. The study adopted Yamane's formula of 1967, with a 95% confidence interval and +/- 5% margin of error applied, giving a sample size of 179 respondents. Both probability and non-probability sampling were utilised to pick respondents from the different strata. The distribution of the research population, sampling techniques utilised, and sample sizes are presented in Table 3.

The study utilised a semi-structured questionnaire having the following structured sections. The first section introduced the study, its aim and objectives. The second section comprised consent to take part in the research. Section 3 covered the respondent's general information. Section four consisted of practices associated with the CBHIS governance structural mechanism. This section carried both closed-ended and open-ended questions. The closed-ended questions were presented on a Likert scale of 1 to 5, where 1 represented 'strongly disagree' and 5 represented 'strongly agree'. The open-ended sections presented an opportunity for the respondents to provide additional important information related to the study. Section five covered Community Health Outcomes, where respondents answered six questions presented on a Likert scale of 1 to 5, where 1 represented 'strongly disagree' and 5 represented 'strongly agree'. This section also carried an open-ended section, which allowed respondents an opportunity to provide any additional information about community health outcomes.

Before the data collection exercise, the researchers sought and were issued a research license from NACOSTI (Ref No: 929552). In addition, the researchers also sought clearances from the study sites and were issued with authorisation to conduct research from the two study sites. Ten research assistants (one drawn from each sub-county) were trained and issued with the printed data collection instruments. Data was collected between March and May 2024. Of the 179 administered semi-structured questionnaires, 164 were filled out and returned, representing a response rate of 91.6%.

Table 3: The distribution of the research population, sampling techniques and sample sizes

County	Stratum	Population	Sampling	Sample
Kisumu County	County Executive Committee Member - Health	1	Purposive	1
	County Executive Committee Member - IT	1	Purposive	1
	Chief Officer - Health	1	Purposive	1
	Chief Officer - IT	1	Purposive	1
	Directors of Health Services	3	Purposive	1
	IT Directors	3	Purposive	1
	County Health Records & Information Officers	1	Purposive	1
	Sub-County Health Records & Information Officers	7	Purposive	7
	County Community Health Focal Person	1	Purposive	1
	Sub-County Community Health Focal Persons	7	Purposive	7
	Community Health Assistants/Officers (CHAs/CHOs)	198	Random Sampling	101
	IT Officers	7	Purposive	7
Makueni County	County Executive Committee Member - Health	1	Purposive	1
	County Executive Committee Member - IT	1	Purposive	1
	Chief Officer - Health	1	Purposive	1
	Chief Officer - IT	1	Purposive	1
	Directors of Health	3	Purposive	1
	IT Directors	1	Purposive	1
	County Health Records & Information Officers	1	Purposive	1
	Sub-County Health Records & Information Officers	6	Purposive	3
	County Community Health Focal Person	1	Purposive	1
	Sub-County Community Health Focal Persons	6	Purposive	3

	Health IT officers	8	Purposive sampling	4
	Community Health Assistants/Officers (CHAs/CHOs)	60	Random sampling	30
	Total	**321**		**179**

3.3 Data Analysis

To enable analysis, indicators measuring the CBHIS governance structural mechanism were renamed ‘SM1’ to ‘SM8’, while those measuring the community health outcomes were renamed ‘CHO1’ to ‘CHO6’. Coding was done in MS Excel in MS Office Professional Plus 2016. The data was then uploaded to SMART-PLS V 4.1.0.6 for the model construction and assessment. This study employed Partial Least Squares (PLS) Structural Equation Modelling (SEM) to analyse and validate the practices associated with the CBHIS governance structural mechanism and the indicators that measure the community health outcomes. PLS-SEM is appropriate when the goal is to predict variables rather than theory confirmation, which utilises CB-SEM [48]. In addition, the structural equation modelling technique helps to examine the interrelationships between the research constructs. Although research data was collected from 164 respondents drawn from Kisumu and Makueni counties, a bootstrapping technique with 5,000 resamples was used to estimate the significance of the indicator weights. The researchers determined that the instrument was conceptually coherent and that construct validity was sufficient to proceed to the structural tests of the model. In this study, the CBHIS governance structural mechanism was modelled as the formative and the community health outcomes as the reflective model.

Besides the quantitative data collected and analysed, this research also collected qualitative data using open-ended questions. It allowed respondents to express other issues related to the study, but not captured in the quantitative section. It also allowed the respondents to expound on issues they deemed important and necessary for the research, yet not captured. As a result, qualitative data for the CBHIS governance structural mechanism and Community Health Outcomes were captured.

4 Research Findings

4.1 Identification and Validation of Construct Indicators

The study assessed the reliability and validity of the indicators and constructs following prior studies, as advocated by researchers [49]. To begin with, the loadings of the indicators were examined for their respective latent variable. The higher loadings imply the existence of more shared variance between the construct and its associated item/indicator than error variance. A total of five indicators (SM2, SM4, SM5, CHO1 and CHO5) had their indicator loadings below the threshold of 0.7000. However, these were retained as their low loading (less than 0.7) did not affect the convergent validities, since they were both above 0.5000 (AVE>0.5000). As shown in Table 4, all items loaded heavily and significantly (at $P<0.05$) on their respective constructs. In addition, the t-statistics for the respective indicator weights of both formative and reflective constructs were also positive and significant. The results were indicative of individual item reliability as seen in Table 4.

The researchers assessed the reliability of the scales used by applying Cronbach’s alpha and composite reliability (rho_c). Cronbach’s alpha is always considered the lower bound, while the composite reliability is considered the upper bound. As suggested by [48], the reliability of constructs falls between Cronbach’s alpha and composite reliabilities. As indicated in Table 4, the Cronbach alpha and composite reliability scores for the two constructs were excellent, as they exceeded the minimum threshold level of 0.70 [48], thus indicating the reliability of the indicators used in this study. In addition, the convergent validities for the two constructs were above the minimum threshold of 0.5000 (AVE>0.5000) as shown in Table 4.

Furthermore, the study assessed the discriminant validity of the research constructs using three techniques, namely the Fornell-Lacker Criterion, HTMT and cross-loadings. Research findings demonstrated that the research constructs met the discriminant validity under the Fornell-Lacker Criterion as the construct’s correlations were higher than the correlations underneath. Similarly, the use of the Heterotrait-Monotrait Ratio (HTMT) by [50] revealed that the research constructs met the discriminant validity based on the HTMT assessment technique, as its value was less than 0.85, which was within the

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acceptable threshold. Further, although the two techniques (Fornell-Lacker Criterion and HTMT) revealed the non-existence of discriminant validity issues, the researchers examined the cross-loadings table, which confirmed the non-existence of indicators loading significantly to other constructs.

Table 4: A summary table of indicator loadings, construct's reliability and convergent validity

Construct	Indica-tor	Indica tor loading	T statistic	P values	Cronba ch's alpha	Compos ite Reliabilit y	Average Variance Extracted (AVE)
CBHIS Structural Governan ce Mechanis m	SM1	0.720	11.738	0.000	0.891	0.913	0.571
	SM2	0.629	12.609	0.000			
	SM3	0.900	35.385	0.000			
	SM4	0.645	7.87	0.000			
	SM5	0.697	13.406	0.000			
	SM6	0.839	18.941	0.000			
	SM7	0.774	16.517	0.000			
	SM8	0.800	15.356	0.000			
Communi ty Health Outcomes	CHO1	0.652	9.285	0.000	0.829	0.876	0.541
	CHO2	0.712	8.562	0.000			
	CHO3	0.762	15.013	0.000			
	CHO4	0.787	11.791	0.000			
	CHO5	0.678	10.353	0.000			
	CHO6	0.811	16.836	0.000			

SM1 = Community Health Committees; SM2 = eHealth Technical Working Group; SM3 = Work/Quality Improvement Teams (WITs); SM4 = Community Health Digital Team; SM5 = Community Health Data Review Boards; SM6 = Community Stakeholders Team; SM7 = Community information champions/leadership; SM8 = eHealth and information support office; CHO1 = Improvement in community healthcare coordination; CHO2 = Improvement in community health data and information quality and availability; CHO3 = Reduction in community health operational costs; CHO4 = Efficiency and effectiveness in delivering community health services; CHO5 = Improvement in community engagement in health; CHO6 = Promotes accountability and performance management.

The above analyses revealed that all the construct indicators and the constructs themselves met the reliability and validity threshold. Therefore, establishing and validating the practices associated with the CBHIS governance structural mechanism. These practices included the Community Health Committees (CHCs), eHealth Technical Working Groups (TWGs), Quality/Work Improvement Teams (WITs), Community Health Data Review Boards, Community Stakeholders Teams, Community Health Digital Teams, Community Health Information Leadership, and an eHealth and information support office. On the other hand, the community health outcomes resulting from the use of CBHISs were improvement in community healthcare coordination, community health data and information quality and availability, reduction in community health operational costs, efficiency and effectiveness in delivering community health services, improvement in community engagement in health and CBHIS, which promotes accountability and performance management.

4.2 Results of testing the structural model

Testing the structural (inner) model was a multi-stage process. To begin with, multicollinearity for the inner model was assessed. The collinearity statistics result for the inner model was 1 (SM -> CHO = 1). This value was less than the threshold of 5, i.e. VIF<5, indicating the nonexistence of collinearity issues.

After establishing the multicollinearity of the inner model, research findings revealed that the beta coefficient (β) for the original sample (O) was 0.507, while that of the sample mean (M) was 0.521 (mean of 5,000 bootstrap samples). This indicated that for every one-unit increase in the CBHIS governance

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structural mechanism, the community health outcomes positively increased by 0.521 units, with the assumption that all other factors were held constant. In addition, the linkage between the CBHIS governance structural mechanism and community health outcomes had a T statistic (t) of 7.159***. The t-statistic showed that the beta coefficient was significantly different from zero, thus greater confidence in the beta coefficient and not due to random chance or random variation. In addition, the positive relationship was highly significant at a P-value (p) of 0.000. A p-value of 0.000 (or < 0.001) indicated a very low probability that the observed beta coefficient was due to random chance, meaning that the beta coefficient was statistically significant. These results suggested a positive and significant relationship between the CBHIS structural mechanism and community health outcomes. Table 5 presents the Path Coefficients for the original sample and the sample mean, Standard deviation (STDEV), T-statistics, and the p-values.

Table 5: Path Coefficients - Mean, STDEV, T Values, p values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
SM -> CHO	0.507	0.521	0.071	7.159	0.000

Besides establishing the relationship between the CBHIS governance structural mechanism and the community health outcomes using the beta coefficients, T statistics and P values, this study further utilised the coefficient of determination (R2) [51] and the predictive relevance (Q2) [52] to assess the predictability of the structural model. To begin with, the coefficient of determination (R2) measures the proportion of variance shown in the endogenous variable as a result of the impact of the exogenous variables. It measured the model's explanatory power [53]. The study findings showed that the variance of the endogenous variable (community health outcomes) was 0.257. This value meant that the CBHIS governance structural mechanism was 25.7% of the variance in community health outcomes. Furthermore, the study utilised predictive relevance (Q2) to establish the predictive relevance of the endogenous construct in the study. Study results revealed that the predictive relevance of the exogenous construct on the endogenous construct was 0.224 or 22.4%. This value was above 0; hence, the study concluded that the model had an overall predictive relevance. Table 6 presents a summary of the coefficient of determination (R2), adjusted R2 and predictive relevance (Q2).

Table 6: A summary table of all the techniques utilised to assess the structural model

Predictor(s)	Outcome	Beta values	T statistics	P values	R^2	Adjusted R^2	Q^2
SM	**CHO**	0.521	7.159***	0.000	25.7%	25.2%	22.4%

4.3 Qualitative data analysis

Besides the quantitative data, qualitative data were collected and analysed using ATLAS.ti software. These are presented in the following section.

4.3.1 Practices associated with the CBHIS Governance Structural Mechanism

Qualitative data analysis revealed the practices associated with the CBHIS governance structural mechanism. Table 7 presents the governance practices and the frequencies at which they occurred in the qualitative data collected and analysed.

Table 7: Practices associated with the CBHIS governance structural mechanism

S.No.	CBHIS Governance Practices associated with the Structural Mechanism	Frequency
1	Community Health Committees (CHC)	13
2	Data Quality Assurance Team	2
3	ICT support office	2
4	Technology support officers	2

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5	Work improvement teams	2
6	Data Analysts Team	2
7	Quality improvement teams	2
8	Data Review Committee	1
9	Data stakeholders' Office	1
10	Ward-based coordinators champions	1
11	Ward-level Data Review Committee	1
12	Village Data Review Committee	1

Analysis of qualitative data revealed that the data quality assurance team and data analyst team formed the additional governance practices associated with the CBHIS governance structural mechanism. Although qualitative data revealed that the Data Quality Assurance Team and the Data Analyst Team formed the additional practices associated with the CBHIS governance structural mechanism, this study argues that their responsibilities fall broadly within the roles of Quality Improvement Teams and Community Health Digital Teams.

4.3.2 Community Health Outcomes

Qualitative data analysis revealed several indicators explaining community health outcomes. Table 8 summarises the community health outcomes indicators. In addition, the table presents the frequencies at which they occurred in the qualitative data collected and analysed.

Table 8: Indicators of community health outcomes

S.No.	Community Health Outcomes Indicators	Frequency
1	Improved quality of information	10
2	Timely decision making	9
3	Accountability	7
4	Improved commodity management and supply	5

Analysis of qualitative data revealed the existence of a subtle difference between the qualitatively collected indicators measuring community health outcomes and those covered under the quantitative section.

5 Discussion

5.1 Practices associated with the CBHIS governance structural mechanism

This study established and validated the following eight practices associated with the CBHIS governance structural mechanism. These were the Community Health Committees (CHCs), eHealth Technical Working Groups (TWGs), Quality/Work Improvement Teams (WITs), Community Health Data Review Boards, Community Stakeholders Teams, Community Health Digital Teams, Community Health Information Leadership and eHealth and Information Support Office. All eight practices associated with the CBHIS governance structural mechanism loaded heavily and significantly on their construct. In addition, the t-statistics for the respective indicator weights were also positive and significant. The following section presents the practices that were associated with the CBHIS governance structural mechanism.

The first is the Community Health Committee (CHC), which served as a community health governance structure composed of 11 to 13 members. These included a Community Health Promoter (CHP), a link facility representative, a Community Health Assistant (CHA), and representatives from groups such as women's groups, the faith community, youth, and people with disabilities. The committee was responsible for various activities, including advocating for community health resources and identifying an annual list of activities. This finding aligns with the roles of CHCs as outlined in the Community Health Strategy 2014–2019 [54], which emphasises their leadership and oversight functions.

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The second governance practice identified was the eHealth Technical Working Group (TWG), which functioned as a collaborative and specialised body within the Community-Based Health Information System (CBHIS) governance framework. The group was responsible for addressing key technical aspects of CBHISs, including system development, implementation, interoperability, standards and protocols, data security and privacy, infrastructure and architecture, integration with broader healthcare systems, as well as providing technical support and consultation. This finding aligns with [6], which emphasised the role of eHealth TWGs in overseeing community health IT operations and facilitating informed decision-making. Similarly, a study by [33] on the implementation of electronic Community Health Information Systems (eCHIS) in northwest Ethiopia found that eCHIS technical working groups were instrumental in discussing and monitoring the progress of eCHIS initiatives.

The third governance practice was the Work/Quality Improvement Team (WIT), which served as a key component of CBHIS governance. The team was responsible for identifying, analysing, implementing, and refining improvements in the processes and workflows of Community Health IT systems. Supporting this finding, previous studies, for example, [24], noted that WITs played a significant role in enhancing the quality of healthcare delivered within both health facilities and surrounding communities. Similarly, [30] found that Quality Improvement Teams (QITs) contributed to improved performance among Community Health Workers (CHWs) and increased utilisation of maternal and child health (MCH) services, thereby strengthening overall community health outcomes.

The fourth governance practice was the Community Health Digital Team (CHDT), a specialised group focused on implementing community Health Information Technology (HIT) solutions and applications, synchronising databases, and aligning workflows to harness digital technologies for improved community health outcomes. This finding aligns with the study by [33], which highlighted the critical role of the eCHIS implementation technical team in supporting the deployment of electronic Community Health Information Systems (eCHIS). While Hailemariam et al. [33] referred to the group as the eCHIS implementation technical team, their responsibilities—encompassing system development, technical support, and implementation—closely mirrored those of the CHDT.

The fifth finding further revealed that the Community Health Data Review Boards (CHDRBs) constituted another key CBHIS governance practice. These boards were responsible for overseeing data collection and utilisation, validating data quality, conducting data analysis, and generating reports to inform decision-making at the community level.

The sixth observed CBHIS governance practice was the Community Health Stakeholders Team, comprising religious leaders, community opinion leaders, Community Health Committees (CHCs), development partners, and administrative representatives such as chiefs and assistant chiefs. This team was responsible for several key functions, including identifying community health needs, prioritising health issues, and advocating for resources. This finding aligns with previous studies, such as [34], [55], which emphasised the importance of political goodwill and support from local government leadership, opinion leaders, faith-based organisations, non-governmental organisations, health facilities, and local administrators in strengthening Community Health Worker (CHW) programs. Similarly, [33] highlighted that the successful implementation of electronic Community Health Information Systems (eCHIS) required the engagement of Kebele leaders, volunteers, women's development armies, and both community and religious leaders.

The seventh identified CBHIS governance practice was the use of Community Digital Health Information Champions or Leaders. These individuals or groups are responsible for promoting access to health information, enhancing digital literacy, and advocating for the use of technology to improve community health and well-being. Supporting this finding, previous studies such as [23] highlighted that community information champions play a critical role in ensuring that community-level data are integrated into high-level planning and decision-making processes.

The final CBHIS governance practice identified was the establishment of an eHealth and Information Support Office. This office provided technical assistance, troubleshooting, and ongoing support to Health Information Technology (HIT) end-users who relied on a range of digital tools and systems. Additionally, it served as a central hub for health information, offering stakeholders access to relevant and up-to-date CBHIS data. This finding is supported by [33], who noted that the presence of a help desk—whether through the Woreda office or the University of Gondar (UoG) support team—significantly facilitated the implementation of eCHIS in Northwest Ethiopia. Similarly, [8] emphasised the importance of localised IT support to address challenges such as equipment malfunction and system failures.

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5.2 Interrelationships between CBHIS Governance, alignment and the community health outcomes

Whereas digital health governance determines the realisation of health outcomes, it also dictates the realisation of health-IT alignment. These practices (CBHIS governance structural mechanism) form part of the CBHIS governance practices necessary for community health-CBHIS alignment to occur. In support of this proposition, prior studies such as [36], [38] argued that the HIT governance structural dimension is apparent in attaining IT alignment. Similarly, research by [45] argued that the involvement of governance practices such as executive teams in ITG, positively affects alignment. Therefore, this study concluded that the practices associated with the CBHIS governance structural mechanism form part of the governance practices necessary for community health-CBHIS alignment to occur.

Furthermore, whereas the practices associated with the CBHIS governance structural mechanism form part of the practices necessary for alignment to occur, they also improve community health outcomes. The study findings revealed that the CBHIS governance structural mechanism had a positive and significant relationship with community health outcomes. In addition, the CBHIS structural mechanism explained 0.257 or 25.7% of the variation (R^2) in community health outcomes. Similarly, the study findings revealed that the exogenous variable had a predictive relevance (Q2) of 22.4%, thus concluding that the model has predictive relevance.

These study findings are generally in tandem with prior studies such as [13], [14], [56], which suggested that appropriate HIT governance leads to performance and value derivation from HIT integrations. Although there was a scarcity of literature examining community-level HIS governance mechanisms and their effect on community health outcomes, the existing few had established a positive relationship. In particular, a study by [24] examined community work improvement teams in the Kasarani sub-county in Kenya and concluded that WITs propel the performance of community health units and, in particular, improve community-level health service quality. A separate study by [30] examined Benin's Quality Improvement Teams (QITs) and argued that the use of QITs in Benin increased the performance of CHWs and the utilisation of maternal and child health (MCH) services in the municipality of Savè. Furthermore, a study by [6] on East African community digital health and interoperability assessments opined that the eHealth Technical Working Group was responsible for community health IT operations and decision-making to improve community health. Similarly, a study by [33], on eCHIS implementation in Northwest Ethiopia, postulated that eCHIS technical working groups discuss and monitor eCHIS progress and hence improvement in community health.

There was a scarcity of literature that exhaustively examined how the practices associated with community-based HIS affect health outcomes. The few existing studies, such as [24], [33], [30] are supported by the study's findings in the following fronts: from a directional perspective, the nature of the relationships and how they affect health outcomes. Thus, filling the knowledge gap that existed in the literature by identifying the context-specific practices associated with the CBHIS structural mechanism and examining how they relate to community health outcomes.

5.3 Study limitations, implications and suggestions for future research

This study utilised data collected from two (2) counties out of forty-seven (47) counties in Kenya. Although this was resolved using the bootstrapping technique, future research may consider expanding the sample size. The following are the implications of this study: it has established context-specific practices associated with the CBHIS governance structural mechanism that may guide health informatics practitioners. Similarly, the result of this study has policy implications as it may inform the development of CBHIS governance policy. In addition, the study contributes to knowledge by filling the gap on the 'how' and the 'nature' of the relationships between the CBHIS governance structural mechanism and community health outcomes. Future studies should be done to examine the practices associated with the other CBHIS governance mechanisms (processes and relational mechanisms) to holistically and comprehensively examine how the CBHIS governance affects community health outcomes. Moreover, such studies can examine how a mix of mature CBHIS governance practices affects both alignment and variance in community health outcomes.

6 Conclusion

This study aimed to establish and validate the practices associated with the CBHIS governance structural mechanism, and consequently, examine how these practices relate to the community health-CBHIS alignment. In addition, the study sought to examine the interrelationships between the CBHIS governance structural mechanism and community health outcomes. The study used survey data gathered from 164 community health officers drawn from two counties in Kenya to establish and validate the practices associated with the CBHIS governance structural mechanism. In addition, the researchers used the data to establish the coefficient of determination and also the predictive relevance.

In summary, the study finding suggests that the practices associated with the CBHIS governance structural mechanism form part of the governance practices necessary for the alignment to occur. In addition, the CBHIS governance structural mechanism has a positive and significant relationship, as well as positively affecting community health outcomes. These findings provide credence to [14] assertion of 'good digital health governance as a prerequisite for realising health system goals, objectives, and outcomes', paving the way to more effective governance of CBHIS to support and improve community health outcomes. This notion is consistent with the arguments of [17], [57], who concluded that effective IT governance is the single most important predictor of IT-generated value.

Further, the results of this study offer several contributions to the HIS literature. This study offers context-specific practices associated with the CBHIS governance structural mechanism. In addition, the findings underscore the importance of practices associated with the CBHIS governance structural mechanism in attaining community health-CBHIS alignment. Furthermore, the contribution of this study is that it establishes the nature of the relationships between the constructs and how they affect each other, demonstrating the importance of CBHIS governance. This contributes to the sparse HIS governance literature and how it translates to health performance and value derivation. Future studies may examine the other CBHIS governance mechanisms (processes and relational mechanisms) and their contribution to improving community health outcomes.

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The authors declare the nonexistence of any conflict of interest.

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User Engagement with Mobile Health Applications for Self-management of Diabetes: A Principal Component Analysis Approach

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Background and Purpose: Diabetes is a non-communicable disease that can arise from a genetic predisposition or develop due to the unhealthy lifestyle of an individual. mHealth applications (apps) can potentially revolutionise diabetes management by empowering people diagnosed with diabetes to take better control of their condition, promoting effective self-management. User engagement and sustained usage are critical determinants of mHealth apps' success. The study reported in this paper investigated the extent to which the User Engagement Scale (UES) can be applied in evaluating user engagement with a mHealth app for self-management of diabetes.
Methods: A 30-item UES questionnaire was distributed through Diabetes South Africa (DSA), a non-governmental organisation that supports and advocates for people living with diabetes in South Africa. Participants, who are either diagnosed with Type 1 or Type 2 diabetes, rated their agreement with each statement in the UES using a 5-point Likert scale. Principal Component Analysis (PCA) was conducted on 55 responses to evaluate the UES's dimensionality.
Results: PCA suitability was confirmed by the Kaiser-Meyer-Olkin (KMO) measure of 0.650 and a significant Bartlett's test of sphericity, $\chi^2(435) = 1124.16$, $p < 0.001$. A new factor, Incentive, emerged by combining Aesthetic Appeal and Reward, which impacted user engagement. Additionally, Focused Attention and Perceived Usability were identified as significant predictors of user engagement. A revised 25-item scale was produced after five items were removed due to low factor loadings.
Conclusions: This study validated the UES in a mHealth app context among South African participants, suggesting that the three-factor, 25-item solution is effective in evaluating user engagement in mHealth applications for self-management of diabetes.

Keywords: Diabetes self-management, mHealth, User engagement, User engagement scale, UES.

1 Introduction and Background

Diabetes affects society both clinically and economically [1]. According to Kumar et al. [2], there are an estimated 537 million people diagnosed with diabetes globally, and this number is expected to increase to 783 million by 2045 [2]. Diabetes, including other non-communicable diseases, will cost more than an estimated $47 trillion (R864 trillion) to manage worldwide in the next 20 years [3].

The two prevalent classifications of diabetes are Type 1 and Type 2. Type 1 diabetes is the complete loss of insulin-producing cells, a hormone that controls a person's blood glucose level. Without proper regulation of glucose emanating from food consumption, the build-up of glucose in blood cells leads to the onset of diabetes and further conditions such as hyperglycaemia [4]. Patients will typically experience long-term symptoms that include fatigue, skin conditions such as psoriasis and pruritus, as well as weight loss. There are further risks of more serious conditions associated with Type 1 diabetes, such as ketoacidosis, which occurs when there is an excessive level of ketones in the body due to a lack of sufficient insulin for the uptake of blood sugar by cells for energy [5]. This is a condition which may lead to coma in a patient or even death.

Type 2 diabetes is a progressive loss of the cells that produce insulin and is the most prevalent form of the disease. The onset of this type of diabetes is typically gradual and often associated with insulin resistance, where the body's cells do not respond effectively to insulin. Over time, the pancreas is unable to produce enough insulin to compensate for this resistance, leading to elevated blood glucose levels. Some

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of the risk factors for Type 2 diabetes include obesity, a sedentary lifestyle, poor diet and genetic predisposition to the disease [6]. In addition, the symptoms of Type 2 diabetes can be less pronounced initially but may include frequent urination, excessive thirst and persistent hunger.

According to Sifunda et al. [7], it is estimated that nearly 4.6 million people were living with diabetes in South Africa in 2019. However, the prevalence of the disease has increased significantly from about 4.5% in 2010 to 12.7% in 2019, with more than half of the people living with the disease not diagnosed. Hence, the term 'silent killer' is often used to refer to Type 2 diabetes. According to the WHO [8], in 2021, diabetes was one of the top 10 causes of death in South Africa and occupied position number five. At the same time, many countries from sub-Saharan Africa, including South Africa, have very low population-to-healthcare worker ratios [9].

The risks associated with diabetes can be mitigated by adopting healthier lifestyle changes like increased physical activities to reduce the onset of the disease [10]. Regular physical activity enhances insulin sensitivity, which allows cells to utilise glucose more effectively, thereby reducing blood sugar levels [11]. In conjunction with the traditional methods of diabetes management, technological advancements offer new opportunities for patient care and disease management. Mobile health (mHealth) involves leveraging mobile technology to improve healthcare services [12]. The use of mHealth applications (apps) can be harnessed to enhance the quality of healthcare service delivery. This enhancement can include various aspects of value, including the speed and precision of diagnosis, tailoring treatment plans to individual needs, and providing guidance for behavioural changes [13].

mHealth delivered through mobile devices could facilitate the provision of healthcare services to areas without access to basic health services due to geographical or resource constraints. Healthcare services can also be achieved at a more rapid rate, depending on the rollout of network infrastructure. The added benefits of mHealth include immediate and around-the-clock healthcare access [14]. Given the increasing prevalence of smartphone ownership, mHealth is positioned to have a significant impact on involving patients in self-care [15]. As of January 2024, there were 5.61 billion unique mobile phone users worldwide, equating to 69.4% of the global population [16]. This figure highlights the widespread adoption and access to mobile technologies, reinforcing the potential impact of mHealth apps in health-related fields. There is significant potential for mHealth to greatly enhance access to specialised clinical diagnostics and treatment guidance [13]. The increase in the ownership of smart mobile devices has been accompanied by the proliferation of mHealth apps, with a combined 300,000 health-related apps existing and about 200 being released daily [17]. One such mHealth application is MySugr, a free mHealth app that allows users to log meal intake, track physical activity and integrate data sources such as glucometers and fitness trackers. The MySugr app provides analytics aimed at the long-term management of diabetes. The app also generates reports that indicate whether a user is within their target blood glucose range or if corrective action is required.

Although promising, mHealth is also unfortunately subjected to factors within the Information Technology (IT) discipline that could affect the success of mobile apps [18]. For example, these factors include the complexity of the IT project being implemented, potentially resulting in failure [19]. Other factors include having a high number of bugs, which could lead to users abandoning the app [20]. Due to the potential failure of healthcare-related projects, it is important to consider the factors that could have an impact on the success of mHealth apps [2021]. Despite the high growth rate and availability of mHealth apps, there remains little investigation of the factors that affect their success [21]. This view is supported by Oakley-Girvan et al. [22] and Santos-Vijande et al. [23], with these researchers emphasising that user engagement, an essential aspect, is often overlooked in the design and evaluation of mHealth apps. Given this consideration, among the factors that influence the success of mHealth apps, such as usability and adoption [18], an important determinant of success is users' engagement and sustained use of mHealth apps [24]. User engagement entails a user's involvement in personal meaning and vigour, dedication, and absorption [25]. Previous studies have indicated that the underlying constructs of user engagement include usability, aesthetics, focused attention, novelty, and felt involvement endurability [26]. These factors were later refined to usability, aesthetics, focused attention, and reward [27]. These constructs indicate that user engagement relates to a psychological state which is affective, cognitive, and behavioural, and includes emotional elements [28].

Although previous studies have evaluated and measured user engagement, detailed knowledge regarding how to guide the development of apps to ensure that they possess the basic requirements of engagement and support user commitment to the app is lacking [29]. According to O'Brien and Toms [30], the

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complexity and abstract nature of user engagement add to the reasons why there is a sparseness of studies that focus on measuring user engagement. Consequently, the objectives of this study are:

1. To investigate the factors that could influence user engagement with mHealth apps for the self-management of diabetes.
2. To determine which of the User Engagement Scale (UES) factors, developed by O'Brien and Toms [30], can predict user engagement with mHealth apps for the self-management of diabetes.

The UES has been used in previous studies to measure user engagement with different mobile apps. The scale defines the full range of theoretical elements required in a technology to influence user engagement with an app to realise the intended benefits and return on investment. The scale has been applied to over 40 studies using different applications, including information search, online news, and online videos [31, 32]. The UES offers a robust measurement method to evaluate engagement with digital environments. In the context of this study, MySugr, a mobile mHealth app available on both iOS and Android platforms, was utilized as the mHealth app of choice because it is widely used and endorsed by Diabetes South Africa (DSA). This non-governmental organization supports and advocates for people living with diabetes in South Africa. It should be noted that the goal of this study is not to evaluate or test any software or application. Rather, the aim was to determine the extent to which the UES can be used to evaluate user engagement with mHealth applications that support the self-management of diabetes. Any mHealth application that supports self-management of chronic disease could have been selected for this purpose. The choice of MySugr is primarily because it is an app that has been endorsed for use by diabetes patients by DSA. As stated earlier, South Africa has a high prevalence of diabetes and a limited number of healthcare workforce. mHealth applications like MySugr can address local challenges but require sustained user engagement to succeed. Although widely used, the User Engagement Scale (UES) was originally developed for Western audiences. Hence, there is a need to investigate its applicability to the South African context.

2 Theoretical Framework

The research model for this study is based on the integration of two theories, the flow theory [33] and the theory of experience [34]. This study adopted the definition that user engagement is a quality of user experience and is characterised by attributes of the system [30]. According to O'Brien and Toms [30], the definition of an attribute is a characteristic that influences user engagement. The adopted definition [30] is informed by the synthesis of the two theories in sections 2.1 and 2.2.

2.1 The flow theory

User engagement research is informed by the flow theory [30]. Flow theory postulates that certain activities, such as gaming and writing [35], could have a user so captivated to the extent that little else matters in the user's environment [33]. The activity can be viewed as highly pleasurable or an end in itself. Flow is critical in user engagement because it represents a state of immersion and focus, where users are fully absorbed in the activity they are performing. This psychological concept is relevant in the context of user engagement with digital applications, including mHealth apps for self-management of diabetes, as it could help in explaining why users are motivated to use an app. According to O'Brien and Toms [30], attributes like feedback, control, challenge, attention, motivation, goal-directed behaviour, and meaningfulness are present in flow experiences. These attributes are also intrinsic to user engagement. A brief explanation of the attributes related to flow theory is provided in the following paragraphs:

- *Feedback* can be defined as the response from the environment or the system that transmits the appropriateness of the action taken [30].
- *Control* refers to how a user perceives their ability to manage their interactions with an app, or the extent to which they feel they are in control of their interactions with an app or a system [30].
- *Challenge* refers to a cognitive or navigability task given to a user. A cognitive challenge refers to how much mental effort is expended by a user when performing tasks, while a navigability challenge refers to the effort needed by a user when navigating an interface [30].
- *Focused attention* refers to the concentration of mental activity during the engagement [30]. A user's attention is either maintained or lost through the ability to communicate a specific message effectively.

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- *Motivation* presents itself as the need to achieve a goal or have an experience with the interface. Flow experiences are intrinsically motivating. Meaning that pleasure is derived from the action itself, while in user engagement, this may not be the case.
- *Flow* requires a user to form specific goals during their experience. In contrast, user engagement does not specifically need the user to have a specific interaction goal.
- *User engagement* activities may offer a level of *meaningfulness*. This could be in the form of the experience being joyful or challenging [30]. This contrasts with flow, which stresses that the experience has meaning and the user is purposeful in the activity in which they are engaged with.

2.2 The theory of experience

The theory of experience by Dewey [34] was adapted for the field of education by McCarthy and Wright [36] to explain aspects of user experience with technology. Based on the philosophy of experience [33], the threads of experience decompose the user experience into sensual, emotional, compositional and spatiotemporal threads:

- The *sensual* threads address the visual feedback, the auditory cues, and the tactile sensations that users experience separately during their interaction with a system [33]. The sensual thread presents the information and graphical elements that promote engagement when it meets the customizable needs of the user [30].
- *Emotional thread* relates to a user's engagement with a product on an emotional level. It presents the affective experiences of users and how engagement is influenced. This thread is linked to the motivational and interest attributes that influence a user's engagement with a system.
- *The spatiotemporal* thread refers to the aspects of space and time during the experience. This includes the user's perception about being aware of their physical surroundings and links to focused attention and absorption (as explained in flow experiences).
- *Compositional thread* is woven around the sensual, emotional and spatiotemporal threads to articulate engagement as a process. The engagement process involves an initial engagement, followed by continued engagement, and eventually disengagement [30].

Building on the threads of experience, O'Brien and Toms [30] postulated that the theory of experience is relevant to user engagement and mapped the process of user engagement by aligning it with the threads of experience and identifying the attributes present at each stage of engagement. Therefore, this research aims to determine the applicability of the user engagement scale (UES) to predict users' engagement with the MySugr mHealth app, which is used for the self-management of diabetes.

2.3 Research hypothesis

The UES, developed by O'Brien and Toms [30], is informed by the flow and experience theories. Based on the results of a 2018 study, Santos-Vijande et al. [23] refined the UES from a six-factor to a four-factor, 30-item questionnaire [26]. The four factors, namely Focused Attention (FA), Perceived Usability (PU), Aesthetic Appeal (AE), and Reward (RW), formed the basis of the hypotheses that were tested in the research reported in the paper. The factors and applicable hypotheses for the study reported in this paper are:

- Focused attention (FA): Focused attention relates to how a user perceives time and the awareness of their physical environment while interacting with a digital system. O'Brien and Toms [26] indicated that a change in FA will influence user engagement. To evaluate the influence of FA on user engagement with a mHealth app that supports self-management of diabetes, the following hypothesis was developed:
  H1: Focused attention will have a positive effect on user engagement with the mHealth application that supports self-management of diabetes.
- Perceived usability (PU): Perceived usability deals with the subjective assessment of how easy a system is to use and how well it meets the user's needs [30]. The level of difficulty when using an app is also related to PU. For example, the ease with which a user can navigate a website to complete a task would influence the user's perceived usability. Control and how the user perceives this during their interaction is also related to PU. This construct measures the perceived effort, the ability to accomplish tasks and

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the emotions felt during the interaction, hence, the label 'perceived usability' [30]. To evaluate the influence of PU on user engagement with the mHealth app that supports self-management of diabetes, it is hypothesised that:

H2: Perceived usability will have a positive effect on user engagement with the mHealth application that supports self-management of diabetes.

- Aesthetic appeal (EA): Aesthetics is the visual appearance that relates to interface as it aligns to the design principles which are symmetry, balance, emphasis, harmony, proportion, rhythm and unity [30]. The construct relates to aspects that affect the interface, covering the screen design and the application's visual appeal [30]. This also includes the graphics that are presented to the user. EA is considered a stable indicator for predicting user engagement [27]. To determine the influence of EA on user engagement with the mHealth app that supports self-management of diabetes, it is hypothesised that:

  H3: Aesthetic appeal will have a positive effect on user engagement with the mHealth application that supports self-management of diabetes.
- Reward (RW): Reward refers to the hedonic features of experience and the overall success of the interaction. Reward originally consisted of three constructs, namely endurability, novelty and felt involvement [30]. These were later merged into the single construct of reward [27]. Endurability relates to the probability of a user endorsing a product to someone else, the perception of how successful the experience was and whether the user was able to complete tasks. Novelty relates to how much curiosity the platform generated. The app should at least present something new and unexpected for the user. Felt involvement relates to a user feeling 'caught up' in the experience of interacting with the app. There is also a relation to the fun experienced in the engagement. The reward construct measured well on reliability and is a robust predictor of engagement [27]. To determine the influence of reward on user engagement with a mHealth app that supports self-management of diabetes, the following hypothesis was developed:

  H4: Reward has a positive effect on user engagement with the mHealth application that supports self-management of diabetes.

The research model of the study regarding the factors affecting user engagement in mHealth applications that support diabetes self-management is illustrated in **Error! Reference source not found.**.

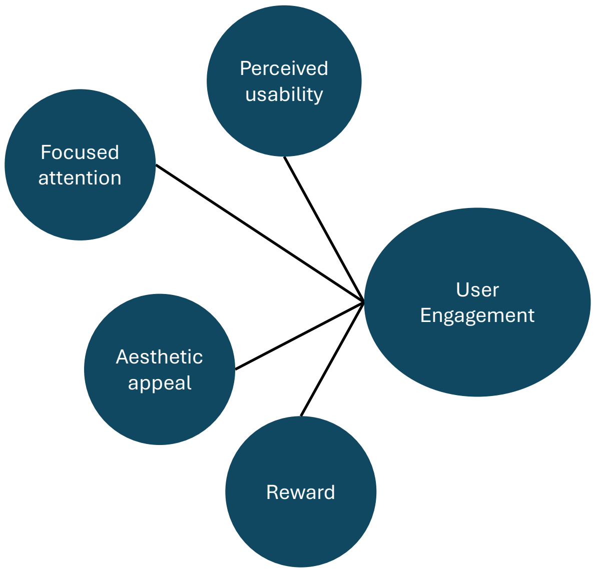

Figure 1. Research model

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3 Materials and Methods

3.1 Research design

The questionnaire and subscales adopted in this study were previously validated for their reliability by O'Brien [33]. The results of the reliability of each of the UES factors are shown in Table 9.

Table 9: UES Scale Reliability

Factor	ω MacDonald's Omega	Number of Items
Focused attention	0.92	7
Perceived usability	0.92	8
Aesthetic appeal	0.90	5
Reward	0.87	10

The research instrument was an online questionnaire through the survey strategy to collect the data from participants diagnosed with Type 1 or Type 2 diabetes who were using the MySugr app to manage their diabetes. Participants were recruited through the DSA, thus ensuring that only people who were living with diabetes completed the questionnaire. The questionnaire was distributed through DSA's social media channels with a link and QR code that participants could scan to complete the survey. A non-probability snowball sampling approach was used to ensure a good response rate. The data collection period lasted six weeks from July to mid-August 2023. The questionnaire was designed on the Qualtrics survey web platform. The questionnaire used a 5-point Likert scale, which participants used to indicate their agreement with each statement, with 5 being strongly agree and 1 being strongly disagree. All the questionnaire statements were set as mandatory in Qualtrics to ensure that there were no incomplete responses. However, to ensure that participation remains voluntary, study participants were asked to leave the survey by closing their browsers if they were no longer comfortable with continuing to participate in the study. A sample of the questionnaire is provided in Appendix A. Ethical clearance for the study was obtained from the Faculty of Economic and Management Sciences at the University of Pretoria.

3.2 Data analysis approach

Data from quantitative research can be analysed using descriptive or inferential methods. Both methods were adopted in this study through the normality of items with central tendency and the variability of the data with descriptive statistics, as well as correlation analysis and testing for inferential statistics. The survey responses were analyzed using the Statistical Package for the Social Sciences (SPSS) version 28. Before the analysis, the survey responses were prepared to ensure the accuracy of the research results. This preparation included converting the data into an interpretable format for input into the SPSS analysis tool, coding the data, checking for missing values and performing data transformation. Because each statement on the questionnaire was set as mandatory in Qualtrics, there were no missing values in participants' responses.

Some of the survey statements were negatively worded items, e.g., PU1: "I felt frustrated while using the MySugr mHealth application to manage diabetes" (see the survey instrument in Appendix A). Hence, these items were reverse coded during the data preparation stage, where a scale of 1 was changed to 5. Descriptive statistics include a measure of central tendency and a measure of variability (spread). Central tendency measures consist of the mean, median, and mode, while variability is assessed using standard deviation, variance, minimum and maximum values, kurtosis, and skewness [37]. The descriptive statistics indicated reasonable means, standard deviations, skewness and kurtosis, thus supporting the normality assumptions required for Principal Component Analysis (PCA) [38]. Based on the descriptive statistics provided in Table 10, the Kaiser–Meyer–Olkin (KMO) value of 0.650, and Bartlett's test of sphericity, which was significant at $\chi2(435) = 1124.16$, $p<0.001$, it was concluded that the research data were suitable for a PCA. The descriptive statistics indicate reasonable means, standard deviations, skewness, and kurtosis required for a PCA. The significant Bartlett's test [39] and acceptable KMO measure [40] further support the adequacy of the survey data for PCA.

Table 10: Descriptive statistics per questionnaire item

Item	Mean	Median	Std. Deviation	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis
FA1	3.09	3.00	1.043	-0.301	0.327	-0.544	0.644
FA2	3.07	3.00	0.988	-0.275	0.325	-0.640	0.639
FA3	3.05	3.00	0.951	-0.380	0.322	-0.648	0.634
FA4	2.84	3.00	0.977	0.341	0.322	-0.276	0.634
FA5	3.05	3.00	0.931	0.317	0.322	-0.334	0.634
FA6	3.25	3.00	0.907	-0.073	0.322	-0.320	0.634
FA7	2.91	3.00	0.928	0.042	0.322	-0.240	0.634
PU1	3.60	4.00	1.011	-0.674	0.322	0.146	0.634
PU2	3.60	4.00	1.029	-0.597	0.322	-0.010	0.634
PU3	3.67	4.00	1.019	-0.707	0.322	0.243	0.634
PU4	3.67	4.00	0.982	-0.505	0.322	-0.168	0.634
PU5	3.60	4.00	1.047	-0.627	0.322	-0.112	0.634
PU6	3.65	4.00	1.022	-0.652	0.322	0.155	0.634
PU7	3.49	4.00	0.940	-0.736	0.322	-0.229	0.634
PU8	3.25	3.00	0.927	-0.105	0.322	-0.483	0.634
AE1	3.58	4.00	0.875	-0.775	0.322	0.513	0.634
AE2	3.55	4.00	0.899	-0.538	0.322	0.172	0.634
AE3	3.64	4.00	0.930	-0.630	0.322	0.187	0.634
AE4	3.65	4.00	0.799	-0.643	0.322	0.083	0.634
AE5	3.53	4.00	0.959	-0.603	0.322	0.348	0.634
RW1	3.69	4.00	0.858	-0.807	0.322	0.987	0.634
RW2	3.55	4.00	0.959	-0.265	0.322	-0.846	0.634
RW3	3.36	3.00	0.950	-0.265	0.322	-0.492	0.634
RW4	3.62	4.00	0.757	-0.551	0.322	0.077	0.634
RW5	3.71	4.00	0.936	-0.499	0.322	0.131	0.634
RW6	3.56	4.00	0.877	-0.201	0.322	-0.577	0.634
RW7	3.71	4.00	0.832	-0.603	0.322	0.012	0.634
RW8	3.53	4.00	0.940	-0.706	0.322	0.526	0.634
RW9	3.56	4.00	0.834	-0.408	0.322	-0.361	0.634
RW10	3.75	4.00	0.821	-0.321	0.322	-0.257	0.634

FA = Focused Attention
PU = Perceived Usability
AE = Aesthetic Appeal
RW = Reward

As stated in Section 1, the aim of the research was to determine the applicability of the UES to predict user engagement with mHealth apps for the self-management of diabetes. The PCA method was used to analyze the research data. PCA is particularly suitable when the goal is to reduce data dimensionality and highlight its main features. Previous studies have used PCA to evaluate the UES [41, 42]. In this study, PCA was used to evaluate the responses related to the subscales of FA, PU, AE and RW.

Another consideration was the sample size. During the data collection period, 55 participants completed the questionnaire. According to Jenkins and Quintana-Ascencio [43], a sample size of 50 is sufficient to perform regression analysis in the context of PCA. Similarly, Latif et al. [44] indicated that a sample size of 50 participants is acceptable in studies that utilize PCA. Following these guidelines, the sample size of 55 collected in this study was deemed adequate and suitable for factor analysis. This lower sample size challenge is not uncommon in medical-related research, where the median is 20 respondents [43].

Principal axis factoring computations were carried out with direct Oblimin rotation on the dataset. The items underwent analysis to identify factor loadings that were either notably high or low. The correlation between the variable and the underlying factor is referred to as the factor loading. There is no agreement among researchers regarding the appropriate cut-off for factor loadings. Some studies, such as Stevens [45],

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suggest a cut-off of less than 0.3, while others, including Hair [46], recommend a cut-off greater than 0.4. This study adopted the recommendation by Comrey and Lee [47] and Tabachnick et al [48], who recommended values < 0.4 as this is seen as being more rigorous.

To determine the number of factors to retain for analysis, the three criteria used were (i) retaining factors with an Eigenvalue > 1 [49], (ii) examining the Scree plot and performing a Scree test and, (iii) performing a parallel analysis to compare the observed Eigenvalues with those from random data [50]. After the initial factor analysis, several items exhibited cross-loading, specifically the following items: Item 7 FA7 ('During this experience, I let myself go'), Item 14 PU7 ('I felt in control while using MySugr'), Item 15 PU8 ('I could not do some of the things I needed to do while using MySugr'), Item 23 RW3 ('The experience of using MySugr did not work out the way I had planned') and Item 26 RW6 ('I continued to use MySugr out of curiosity'). These items were subsequently removed from the analysis due to their weak loadings (i.e., below the threshold of 0.4). The analysis was then re-run without these items to establish a better factor structure.

4 Results

4.1 PCA results and reliability of the user engagement scale

The 30 items of the UES were subjected to a PCA to determine how many factors were to be extracted using the Kaiser criterion [48], which determines the number of factors to retain. The results of the PCA analysis initially suggested that nine factors could be extracted (Eigenvalues > 1), explaining 76.88% of the variance in the data. This was seen as an impractical solution. The first factor was particularly strong, explaining 30.38% of the variance. Horn's parallel analysis was conducted, with the results suggesting that five factors could be extracted [51]. However, theoretically, four factors were mostly cited in previous studies that are similar to the current one. For instance, O'Brien et al. [27] confirmed a four-factor UES structure. Similarly, Banhawi and Mohamad Ali [52] and Wiebe et al. [53] also supported this four-factor model. The result of the five-factor solution was also notably not well-defined. Three items exhibited cross-loadings, meaning they have substantial loadings on more than one factor. Further analysis revealed that a four-factor solution was also not well-defined. The fourth factor contained only two items (PU4 and RW3), which is insufficient for a well-defined factor [54]. Additionally, one of the items exhibited significant cross-loading on another factor, which diluted its unique contribution to factor four. This cross-loading indicates that the item does not exclusively belong to factor four and shares variance with other factors, further weakening the definition and interpretability of factor four.

The next step was to explore a three-factor solution. The rotated pattern matrix is presented in Table 11 with loadings < 0.4 suppressed. The first factor was a combination of the Aesthetic Appeal and Reward items. Item 13 (from Perceived Usability) also showed a loading on this factor, with a cross-loading on the third factor. This factor was termed Incentive. 'Incentive' is an appropriate term to describe both Aesthetic Appeal and Reward because it conveys the idea of providing motivation or inducement for certain behaviours or actions.

Aesthetic Appeal can serve as an incentive by motivating individuals to engage with an application or system due to its visual aesthetic [55]. Similarly, Reward can function as an incentive by motivating people to achieve a specific goal or complete a task to obtain that Reward. This motivational aspect is central to understanding why the term 'Incentive' effectively encompasses both Aesthetic Appeal and Reward. All items from the original Focused Attention factor were included in the second factor. The third factor mostly contained factors from Perceived Usability, with one item from Aesthetic Appeal loading and one from Reward also loading here. These two factors were therefore well-identified in the current data set.

Table 11: The proposed three-factor solution

Pattern Matrix			
Subscale Items	Factor		
	1	2	3
RW10: The experience of using the MySugr mHealth application to manage my diabetes was fun.	0.875		

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RW7: The content of the MySugr mHealth application for the management of diabetes incited my curiosity.	0.721		
AE1: The MySugr mHealth application for diabetes management is attractive.	0.710		
AE4: The MySugr mHealth application for the management of diabetes is appealing to the visual senses.	0.633		
RW2: I consider my experience of using the MySugr mHealth application to manage my diabetes a success.	0.620		
AE2: The MySugr mHealth application for diabetes management is aesthetically appealing.	0.609		
RW8: I was really drawn into the experience of using the MySugr mHealth application to manage my diabetes.	0.597		
RW4: My experience of using the MySugr mHealth application to manage my diabetes is rewarding.	0.558		
RW9: I felt involved in the experience of using the MySugr mHealth application to manage my diabetes.	0.525		
AE3: I liked the graphics and images of the MySugr mHealth application for the management of diabetes.	0.491		
RW1: Using the MySugr mHealth application to manage my diabetes is worthwhile.	0.479		
PU6: This experience of the MySugr mHealth application to manage my diabetes was demanding.	-0.419		0.403
RW6: I continued to use the MySugr mHealth application for the management of diabetes out of curiosity.			
FA2: I was so involved in the experience of using the MySugr mHealth application to manage my diabetes that I lost track of time.		0.845	
FA4: While using the MySugr mHealth application to manage diabetes, I lost track of the world around me.		0.764	
FA1: I lost myself in the experience of using the MySugr mHealth application to manage my diabetes condition.		0.637	
FA3: I blocked out things around me while using the MySugr mHealth application to manage my diabetes condition.		0.589	
FA5: The time I spent using the MySugr mHealth application to manage my diabetes just slipped away.		0.585	
FA6: I was so absorbed in the experience of using the MySugr mHealth application to manage my diabetes.		0.488	
FA7: During this experience of using the MySugr mHealth application, I let myself go.			
RW3: The experience of using the MySugr mHealth application to manage my diabetes did not work out the way I had planned.			
PU2: I found the MySugr mHealth application confusing to use.			-0.948
PU1: I felt frustrated while using the MySugr mHealth application to manage diabetes.			-0.784
PU3: I felt annoyed while using the MySugr mHealth application to manage diabetes.			0.647
PU5: Using the MySugr mHealth application to manage my diabetes was taxing.			0.532
RW5: I would recommend the MySugr mHealth application for the management of diabetes to my family and friends.			-0.519
AE5: The screen layout of the MySugr mHealth application for the management of diabetes is visually pleasing.	0.438		-0.518

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PU4: I felt discouraged while using the MySugr mHealth application to manage diabetes.			0.466
PU7: I felt in control while using the MySugr mHealth application to manage my diabetes.			
PU8: I could not do some of the things I needed to do while using the MySugr mHealth application to manage my diabetes.			
Extraction Method: Principal Axis Factoring. Rotation Method: Oblimin with Kaiser Normalisation. a. Rotation converged in 22 iterations. FA = Focused Attention; PU = Perceived Usability; AE = Aesthetic Appeal; RW = Reward			

Items 7 (FA7), 14 (PU7), 15 (PU8), 23 (RW3) and 26 (RW6) did not show substantial loadings (> 0.4) on any of the factors and were subsequently removed. The removal of items aligns with similar health-related studies, for instance, Holdener et al. [56]. The reliability estimates for all factors exceeded the acceptable threshold of 0.7, indicating ideal internal consistency. Specifically, the factors of the Incentive, FA and PU subscales of the UES demonstrated high reliabilities, with Cronbach alpha values of 0.902, 0.822 and 0.884, respectively.

4.2 Correlation between constructs

The Pearson correlation coefficient between Focused Attention and Incentive is -0.228 with a *p-value* of 0.095. This indicates a small, negative correlation that is not statistically significant at the 0.05 level. The Pearson correlation coefficient between FA and PU is -0.270 with a *p-value* of 0.046, indicating a small, negative correlation that is statistically significant at the 0.05 level. This finding is aligned with a previous study by O'Brien et al [27], where a negative Focused Attention and Perceived Usability were also noted, where the authors found a surprising negative link between the two in online shopping. Focused Attention, which involves being fully absorbed in an activity, usually connects well with usability factors such as control and challenge. However, the laboratory setting and assigned tasks in the study by O'Brien et al [27] might have made it difficult for participants to achieve deep focus, leading to lower Focused Attention scores. Despite the negative relationship, both Focused Attention and Perceived Usability are important for the overall user experience, as shown by the analysis, which revealed that removing either factor made the model weaker, as per the findings by O'Brien [57].

4.3 Hypothesis testing

The hypotheses stated in section 2.3 were tested using the results obtained from the research data to determine the relationships between Focused Attention (FA), Perceived Usability (PU), Aesthetic Appeal (AE) and Reward (RW) in user engagement with MySugr, a mHealth app for self-management of diabetes.

To reiterate, the initial four hypotheses formulated were:

- H1: Focused Attention will have a positive effect on user engagement.
- H2: Perceived Usability will have a positive effect on user engagement.
- H3: Aesthetic Appeal will have a positive effect on user engagement.
- H4: Reward will have a positive effect on user engagement.

The AE and RW factors combined to form a single factor termed Incentive. Given this overlap, Hypotheses 3 and 4 were combined into a single hypothesis, i.e., H3:

- H3: Incentive will have a positive effect on user engagement.

H1: Focused attention and user engagement: The hypothesis that FA (H1) would have a positive effect on user engagement was supported by analysis of the research data. The standardized path coefficient was -0.32 and was significant *($p < .019$)*. This aligns with previous studies by O'Brien and Toms [30] in which focused attention was a significant predictor of engagement in digital experiences. However, as in the webcast study by O'Brien and Toms [26], the current study found that the level of FA was less influential than expected, possibly due to the structured and task-oriented nature of the MySugr app.

H2: Perceived usability and user engagement: The hypothesis that PU (H2) would have a positive effect on user engagement was supported by analysis of the research data and is consistent with the findings of

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O'Brien and Toms [30]. The standardized path coefficient was 0.81 and was significant *($p < .001$)*. This result underscores the critical role that usability plays in the effectiveness of mHealth apps, particularly in ensuring that users can easily navigate and interact with the app, which is crucial for sustained engagement.

H3 (combined hypothesis): Incentive and user engagement: Incentive was found to have a strong positive effect on user engagement. The standardized path coefficient was 0.73 and was significant *($p < .001$)*.

The results validated the dataset's suitability for a PCA analysis and informed the merging of Aesthetic Appeal and Reward into the 'Incentive' factor. This adjustment enhances the research relevance by addressing the role of visual and motivational elements in improving engagement. The exclusion of low-loading items strengthened the scale's reliability. Findings, such as the negative correlation between Focused Attention and Perceived Usability underscore the need to balance immersion and ease of use. These insights emphasize the importance of combining intuitive, aesthetic, and context-sensitive features into mHealth apps to improve engagement.

5 Discussion

As stated in section 1, the objectives of the research reported in this paper are as follows:

1. To investigate the factors that could influence user engagement with mHealth apps for the self-management of diabetes.

Based on the results of the analysis, Focused Attention (FA), Perceived Usability (PU), and Incentive (which combines Aesthetic Appeal and Reward) have a significant influence on user engagement. FA and PU were found to be strong predictors of user engagement, underscoring the critical role of these two factors in the design of effective mHealth apps. Incentive had a moderate positive impact, suggesting that while important, it must be carefully balanced with other elements.

2. To determine which of the User Engagement Scale (UES) factors, developed by O'Brien and Toms [30], can predict user engagement with mHealth apps for the self-management of diabetes.

The UES was adapted for a mHealth app in the context of this study, with modifications that enhanced its relevance to the self-management of diabetes. This adaptation facilitated a more accurate measurement of user engagement, indicating the UES's robust applicability across different contexts. The analysis confirmed that specific UES factors, notably Focused Attention and Perceived Usability, are significant predictors of user engagement. This suggests that the UES is suitable for predicting and enhancing engagement with mHealth apps. The UES demonstrated good internal consistency, with Cronbach's alpha values exceeding the acceptable threshold of 0.70–0.79. This confirms that the UES is a dependable scale for assessing user engagement in this specialized context.

The findings from this research have practical and theoretical contributions concerning mHealth applications for self-management of diabetes, including the following:

- The research results provide evidence on the factors that influence user engagement, particularly Focused Attention, Perceived Usability, and Incentive. This contributes to the improved understanding of user engagement with mHealth applications for self-management of diabetes.
- The research adapted the original four-factor, 30-item questionnaire and validated the new three-factor, 25-item UES for a mHealth app for self-management of diabetes to demonstrate the applicability and reliability of the UES in a new context.
- The study also has practical implications for designers of mHealth applications for self-management of chronic disease in general and diabetes in particular. Designers must prioritize the optimization of usability since Perceived Usability is strongly linked to engagement. Hence, designers must focus on intuitive navigation and reducing cognitive load on users. Secondly, designers should integrate visually appealing interfaces and motivational elements like gamification or progress tracking to sustain user engagement.

6 Conclusion

This study investigated the factors that could influence user engagement with mHealth apps for the self-management of diabetes using the UES developed by O'Brien and Toms [30]. Data was collected from 55

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participants living with diabetes who were using the MySugr mHealth app at the time of data collection. The Principal Component Analysis (PCA) method was used to analyse the research data. The results showed that Focused Attention and Perceived Usability are significant predictors of user engagement. In addition, Incentive was shown to have a moderate positive impact on user engagement. The study provides an improved understanding of the factors that could influence user engagement with mHealth apps for self-management of diabetes.

6.1 Study limitations and recommendations for future research

While the findings of this research are significant, they are subject to limitations which include the following:

- Sample size concerns: The study was carried out with a relatively small sample size – 55 participants. This limitation could affect the generalizability of the results as the small sample may not adequately represent the broader population of mHealth app users. Future studies would benefit from a larger cohort to validate and extend these findings. Future studies should expand their investigations across diverse demographic and geographic populations to enhance the robustness and applicability of the new three-factor, 25-item UES.
- Cross-sectional design: The cross-sectional design of this study limits the ability to establish causal relationships from the data. While significant correlations were identified, determining whether one factor directly influences another, or vice versa, remains beyond the scope of this study. Longitudinal research designs in future studies could help establish causal relationships and track changes in user engagement over time and its impact on health outcomes.
- Reliance on self-reported data: The use of self-reported measures to assess user engagement introduces the potential for bias. Participants may overestimate or underestimate their level of engagement due to social desirability or memory recall biases. Objective measures of engagement, such as usage logs or behavioural tracking in mHealth apps, could be employed in future research.

Closing remarks

The study reported in this paper provides insights into the evaluation of mHealth apps, offering evidence on the factors that enhance user engagement. The adaptation and validation of the revised three-factor, 25-item UES in a new context underscore the scale's applicability and relevance, paving the way for further research and development in this vital area of healthcare. These findings not only contribute to academic research but also provide practical guidance for developers aiming to create more engaging and effective mHealth solutions for self-management of diabetes. The 3-factor solution is supported by other recent surveys [41], highlighting the need for further research on the UES. Similar studies that have adopted the UES provide evidence supporting the multidimensionality and variability of user engagement in mHealth apps [56, 58]. Concerning the factor structure, studies have shown that there is variation within different contexts; initial studies confirm a six-factor structure in an information-searching context [42] while other studies – also using PCA analysis – noted that Perceived Usability and Felt Involvement are the most significant indicators of user engagement [59]. This study, therefore, echoes the findings from previous studies and calls for more studies to investigate user engagement with mHealth apps for the self-management of chronic diseases in different contexts.

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Conflict of interest

None

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Trust And Access in Telemedicine - A Review

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Background and Purpose: Telemedicine has the potential to revolutionise healthcare delivery, especially in digitally marginalised populations; however, persistent challenges in access and trust limit its widespread adoption. Despite technological advancements, there remains a significant gap in understanding how these factors jointly influence telemedicine uptake in low- and middle-income contexts.
Methods: This study employed a systematic literature review guided by the PRISMA framework, analysing 32 peer-reviewed studies published between 2018 and 2025 that address access and trust in telemedicine.
Results: Telemedicine interventions yielded notable access gains in underserved settings, with rural reach improving by 40–75% across multiple studies. Trust outcomes, however, were less consistent, with confidence levels ranging from 44–71% and often constrained by privacy concerns, provider scepticism, and technological reliability
Conclusions: This research contributes a comprehensive synthesis of empirical evidence highlighting the critical interplay between access and trust, providing actionable insights for designing user-centred, secure telemedicine systems. By addressing this dual gap, the study offers a foundation for future technological innovation and policy development aimed at equitable healthcare delivery in underserved populations.

Keywords: Telemedicine, Digital health access, Trust in telehealth, Low-resource settings, healthcare Technology acceptance

1 Introduction

Telemedicine has emerged as a transformative tool in global healthcare, offering remote access to clinical services through digital platforms, particularly in contexts where traditional health infrastructure is limited. The body of knowledge has expanded to highlight the benefits of telemedicine, including cost efficiency, timely care delivery, and its pivotal role during public health emergencies such as the COVID-19 pandemic. Studies by [1], [2], [3], [4] consistently underscored the technological and clinical potential of telehealth systems, while also noting systemic barriers such as regulatory uncertainty, limited broadband access, and patient-provider communication gaps. Despite these contributions, much of the existing literature remains centred on technologically advanced regions, with limited empirical focus on digitally marginalised communities where adoption is hindered not only by infrastructure but also by digital trust deficits. This led to a persistent knowledge gap in understanding how perceptions of security, platform reliability, and structural readiness intersect to influence the practical use of telemedicine in under-resourced settings. As such, the current study situates itself within this discourse by critically examining the interplay between trust and access, aiming to generate evidence that responds directly to the lived realities of populations often excluded from digital health transformation.

Access is operationalised as a multidimensional construct encompassing (i) physical and infrastructural access :the availability of devices, connectivity, and affordability of digital services; (ii) organisational access: the presence and scheduling of telemedicine services within health systems; and (iii) digital literacy the capacity of users to effectively engage with telehealth platforms. Trust is delineated across critical dimensions including data security and privacy protection, perceived competence and reliability of

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providers, technological reliability and usability, and cultural congruence with local norms and expectations.

Understanding whether people can trust and access telemedicine is essential because it directly determines the success and sustainability of digital healthcare services, particularly in low-resource and digitally marginalised settings. Evidence from recent systematic reviews highlights that although mobile and internet-based solutions have improved healthcare accessibility by 40 to 75 per cent in some regions, persistent trust deficits arising from concerns over privacy, data security, and cultural relevance significantly hinder adoption. This interplay between trust and access explains why telemedicine often fails to achieve equitable healthcare outcomes, as technological readiness alone does not guarantee user engagement or continuity of care. Therefore, establishing secure, reliable, and culturally attuned telemedicine systems is a critical step towards achieving inclusive and effective digital health transformation, ensuring that vulnerable populations can confidently utilise these services to improve their health outcomes.

1.1 Research Gap

The proposed study primarily addresses a knowledge gap, as current literature lacks comprehensive understanding of how digital trust and infrastructural barriers jointly influence telemedicine adoption within digitally marginalised populations. Although telemedicine has been widely studied, most existing research focuses on clinical efficacy or technological advancement without sufficiently exploring the nuanced interplay between patient perceptions of security, system reliability, and access constraints, particularly in rural and low-resource settings. For instance, studies by [5] and [6] highlight broad challenges but do not deeply investigate how trust deficits and infrastructural inequality affect user engagement across diverse socioeconomic contexts. This insufficient theoretical and empirical exploration of user-centred trust dynamics creates a critical gap in knowledge, limiting the development of frameworks that can guide secure, equitable, and scalable telemedicine integration.

1.2 Research Objective

The main research objective of this study is to investigate how digital trust, and infrastructural limitations influence the adoption of telemedicine services in digitally marginalised communities. This objective directly aligns with the identified knowledge gap, as it seeks to generate a deeper understanding of the interrelationship between user confidence in digital platforms, perceived data security, and the structural accessibility of telehealth systems. Existing studies, such as those by [1], [2], [7] acknowledge trust and access as barriers but often treat them as isolated variables without examining their interactive effect on telemedicine adoption, especially in contexts where connectivity, digital literacy, and system reliability are limited. By focusing on these interdependencies, the research offers empirical and conceptual clarity that can inform policy and design frameworks for more inclusive telehealth services. Hence, the stated objective is both timely and necessary, addressing a foundational knowledge void critical for improving equitable healthcare delivery through digital innovation.

1.3 Research Questions

The research questions guiding this study are therefore centred on three interrelated themes: **(i)** how infrastructural limitations such as connectivity, device availability, and digital literacy constrain equitable access to telemedicine services in digitally marginalised communities; **(ii)** how dimensions of digital trust including data security, privacy, provider competence, and technological reliability shape user confidence and sustained adoption; and **(iii)** how the interaction between access and trust jointly influences uptake, extending beyond prior studies that examined these constructs in isolation. Together, these questions aim to generate empirical and conceptual clarity on the socio-technical factors underpinning telemedicine adoption, thereby informing policy and design frameworks for inclusive and sustainable digital health systems.

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1.4 Significance of the Study

The significance of this research lies in its timely and strategic contribution to bridging a knowledge gap in understanding how digital trust and infrastructural inequality jointly shape telemedicine adoption within digitally marginalised populations, particularly in low-resource settings. As global health systems increasingly shift toward digital care models, failure to address these underlying barriers risks deepening health disparities and rendering telemedicine solutions ineffective where they are most needed. This study offers a critical intervention by generating original, context-specific knowledge that goes beyond technical capabilities to interrogate user perceptions, access realities, and systemic readiness. Its findings can inform policymakers, system designers, and healthcare practitioners on how to craft trust-centred, inclusive telehealth frameworks that are both secure and functionally accessible. Moreover, the study contributes to the theoretical advancement of digital health by integrating socio-technical perspectives within the discourse on health equity. By filling this overlooked knowledge gap, the research positions itself as a foundational reference for both academic inquiry and practical implementation, especially in sub-Saharan Africa and other regions facing similar infrastructural and digital divides.

2 Materials and Methods

This study employed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to guide the literature review process, ensuring methodological rigour, transparency, and replicability in the identification, selection, and synthesis of relevant studies. The PRISMA approach structured the review across four phases: identification, screening, eligibility, and inclusion. The screening phase was involving the removal of duplicates and an initial review of titles and abstracts to assess relevance. Eligibility was determined through a full-text review guided by predefined inclusion criteria such as peer-reviewed status, publication within the last eight years, and relevance to the core variables of trust and access in telemedicine. The final inclusion phase yielded studies that meet the set criteria and systematically analysed to extract data related to themes, geographical contexts, methods, and key findings.

2.1 Search Strategy

The methodology adopted for this research followed a structured evidence synthesis approach, using the Preferred Reporting Items for PRISMA framework to ensure transparency and reproducibility. The search strategy involved querying major scholarly databases including PubMed, IEEE Xplore, ScienceDirect, and Google Scholar, focusing on peer-reviewed English-language studies published between 2018 and 2025 .This date range was selected to capture the most recent empirical evidence reflecting rapid advances in telemedicine technologies and the significant acceleration of adoption during the COVID-19 pandemic, which acted as a catalyst for digital health uptake, particularly in resource-limited contexts. Search strings included combinations of “telemedicine”, “trust”, “access”, “healthcare delivery”, “digital health”, and “low-resource settings”, with Boolean operators used to refine results. the Boolean strings used (“telemedicine” AND (“trust” OR “access”) AND (“LMIC” OR “developing countries”)), and by stating the number of records retrieved from each database. Both direct clinical telemedicine interventions and digital health applications such as mHealth reminders, SMS platforms, and app-based services were eligible, provided they involved patient provider interaction or measurable user engagement.

Inclusion criteria were restricted to empirical studies conducted in low- and middle-income countries or regions with recognised digital health disparities, reporting measurable outcomes related to user trust and accessibility of telemedicine services. Exclusion criteria eliminated opinion pieces, policy briefs, and grey literature. Articles were screened by title and abstract, followed by full-text reviews, resulting in the selection of 32 studies that directly aligned with the research objective. For multi-country or overlapping studies, data were extracted at the level of reported outcomes; where regional aggregates were presented, results were coded under the broader LMIC category to avoid duplication.

This comprehensive literature mapping enabled the construction of a comparative evidence table summarising country context, methodological orientation, conceptual frameworks, and statistically reported outcomes on access and trust. The method ensured that the final synthesis represented robust, peer-

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reviewed, and geographically diverse insights necessary for achieving the objective of identifying empirical trends and gaps in trust and accessibility in telemedicine uptake.

2.2 Study Selection

Initially, a total of 282 records were identified through database searches across PubMed, IEEE Xplore, ScienceDirect, and Google Scholar using tailored search strings centred on telemedicine, trust, access, and healthcare in underserved settings. Following the removal of duplicates, 976 articles remained for screening. Title and abstract screening excluded 783 studies that did not meet the predefined eligibility criteria, which required studies to be peer-reviewed, published between 2018 and 2025, and to report quantitative or qualitative data specifically addressing access or trust in telemedicine.

The remaining 193 full-text articles were assessed in detail, and 32 studies were finally included based on their methodological quality, relevance to the research objective, and their provision of measurable evidence on trust and access in digital health interventions. Each selected study provided either statistical outcomes or context-specific findings on access improvements or trust dynamics in telemedicine, across various socio-economic regions, thus reinforcing the empirical base required for a comparative synthesis. This rigorous selection phase ensured the reliability and contextual diversity of the studies used to fulfil the study's central research aim.

2.3 Critical Appraisal

The critical appraisal of the selected studies was undertaken using the Mixed Methods Appraisal Tool (MMAT), which provided a robust framework for evaluating methodological quality across diverse study designs including qualitative, quantitative, and mixed-methods research. A total of 32 studies were appraised, including systematic reviews, meta-analyses, surveys, case studies, field trials, and mixed-methods designs.Each of the 32 included studies was assessed on parameters such as clarity of research questions, appropriateness of data collection methods, validity of measurement tools, relevance of analytical techniques, and transparency in reporting results.

Applying a 0–100% scoring scheme ,studies scoring below 50% on the MMAT criteria were excluded to maintain high methodological integrity**.** Particular attention was paid to the degree of contextual sensitivity in addressing trust and access, ensuring that findings were not only statistically sound but also culturally and infrastructurally relevant. Studies that clearly demonstrated triangulated data sources, participant diversity, and robust ethical considerations were given greater interpretive weight in the synthesis. This process was essential to discern which studies provided not just surface-level insights, but deep, transferable knowledge that can meaningfully inform policy and design in telemedicine systems for digitally marginalised populations. Through this critical lens, the selected literature collectively presents a dependable foundation upon which this research's conclusions are based.

2.4 Data Extraction and Synthesis

Data extraction and synthesis were conducted systematically to ensure comprehensive capture and meaningful integration of findings related to telemedicine access and trust. Using a predefined extraction form, key data points including author details, study context, theoretical frameworks, research questions, methodology, sample characteristics, and quantitative measures of access and trust were collected from each study. This structured approach facilitated comparison across diverse study designs and geographic settings. The extracted data were then subjected to narrative synthesis, allowing for thematic integration of qualitative insights alongside quantitative outcomes such as percentage improvements in access and trust scores. Trust outcomes were coded using standardized survey scales for quantitative measures and qualitative coding frameworks for thematic analysis.

Where available, statistical results were tabulated to illustrate patterns and variations across regions and populations. This mixed synthesis approach enabled the identification of common barriers and facilitators to telemedicine adoption, as well as gaps in existing evidence. The process was iterative, with regular cross-validation between data sources and consultation of supplementary materials to ensure accuracy and completeness. The systematic extraction and synthesis of multi-dimensional data provided a rigorous

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empirical foundation to support robust conclusions on the interplay between digital access and trust in telemedicine implementation.

3 Results

Figure 1 shows that the literature search process yielded a total of 282 records, with 264 retrieved from databases such as PubMed, IEEE Xplore, ScienceDirect, and Google Scholar and an additional 18 identified from the Cochrane COVID Register. After the removal of 62 duplicate entries, 220 records proceeded to the screening stage. Of these, 110 were excluded due to irrelevance or lack of peer-review standards. Full-text reports were sought for the remaining 110 studies, of which 5 could not be retrieved due to access restrictions. The remaining 105 full-text reports were assessed for eligibility, and 75 were excluded for reasons such as, language barriers, lacking a focus on trust or access, absence of empirical data, or failure to meet the publication date criteria. 32 high-quality, peer-reviewed studies were included in the final review. This rigorous and transparent selection process ensured that only relevant and methodologically sound studies contributed to the synthesis of findings on the issues of trust and access in telemedicine, thereby strengthening the validity and reliability of the review's conclusions.

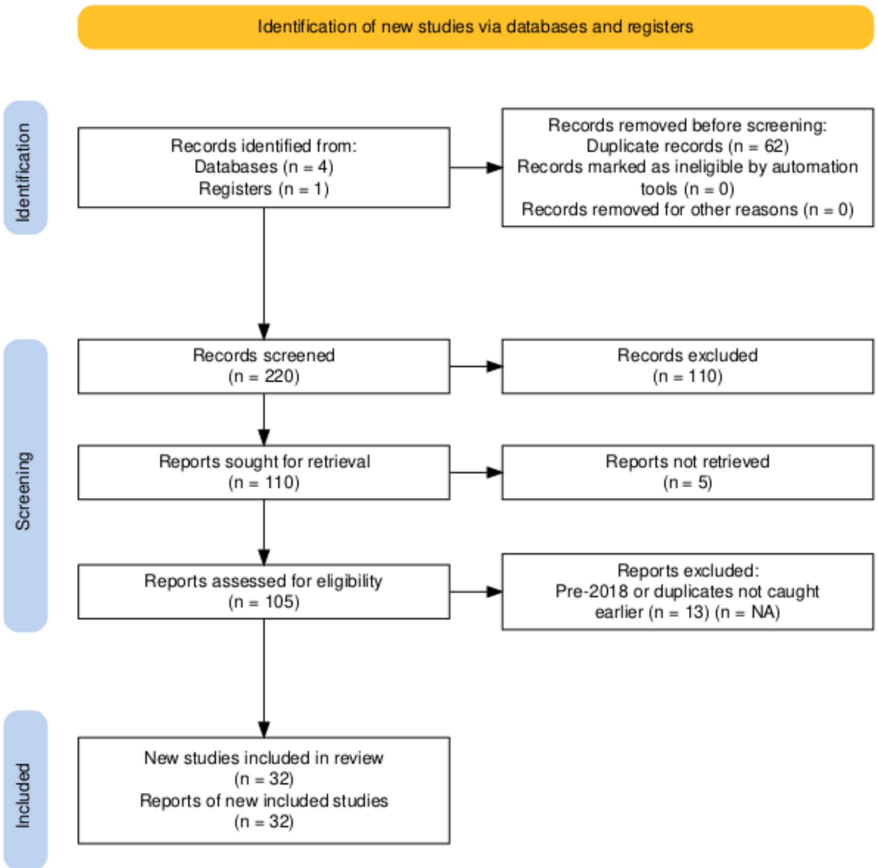

Figure 2:Prisma Flow Diagram Results

3.1 Interdependence of Access and Trust in Telemedicine Adoption

Table 1 presents 32 peer-reviewed studies that examine the dual dimensions of access and trust in telemedicine adoption, especially within low-resource and underserved settings. The table includes statistical indicators where available and outlines methodological approaches, findings, and conclusions, thus directly aligning with the research objective. Across the reviewed studies, notable regional and population-level variations emerge in both access and trust outcomes associated with telemedicine interventions. In Sub-Saharan Africa, systematic and case-based reviews consistently highlight substantial

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gains in rural access ranging from 40–75%, yet trust remains constrained by cultural, privacy, and literacy barriers, with provider scepticism persisting in multi-site implementations. Country-specific trials in Nigeria, Malawi, and Kenya demonstrate that co-design and ICT deployment can enhance reliability and usability, but privacy concerns and infrastructural limitations continue to impede adoption. In Asian contexts such as Taiwan and India, access improvements are strongly mediated by socioeconomic status and the broader technological environment, while trust deficits are most pronounced among older adults and in relation to perceived privacy risks. Global and LMIC-focused reviews underscore uneven progress in sensitive domains such as telemental health and HIV care, where sustainability, regulation, and relational trust issues are central. High-income settings, including the UK and US, reveal that while telehealth can improve quality of life and extend reach, technical difficulties, digital divides, and inadequate training undermine trust and equitable uptake. Collectively, these findings suggest that intervention type such as SMS, mobile apps, tele-visits interact with contextual factors such as infrastructure, literacy, regulation, and cultural norms to shape both access trajectories and trust dynamics, underscoring the need for tailored, system-level strategies.

Table 12: Telemedicine Access and Trust Outcomes (2018–2025)

Study (Author/ Year)	Region Country	Methodology	Access Findings	Trust Findings	Sample Size	Conclusion Summary
[7]	Sub-Saharan Africa	Systematic review	40 % improvement via tele-programs	45 % trust level; cultural/privacy issues	66 studies	Telemedicine uneven; access and trust barriers remain
[8]	LMICs	Review of 23 studies	50 % access gains	52 % trust score; privacy concerns	23 studies	Adoption limited by infrastructure and regulatory issues
[9]	Uganda/Botswana/Rwanda	Umbrella review	65 % diagnostic reach increase	63 % trust; system validation concerns	9 programs	Co-design bolstered confidence and access
[10]	Nigeria	ICT deployment trial	70 % uptime and reliability	71 % ease-of-use trust score	Field deployment	Tele-management supports engagement
[11]	Malawi	User-centred case study	60 % rural access increase	68 % trust via usability improvements	Case-based	Co-design increases both access and trust
[7]	SSA countries	Multi-site case studies	55 % reach via store-and-forward	50 % provider scepticism persists	53 studies	Quality assurance needed for provider trust
[12]	South Africa	SMS intervention	75 % access via	66 % trust hindered	400 participants	Mobile access

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			SMS platforms	by literacy gaps		effective with training
[13]	South Africa	Mixed methods questionnaire + interviews	58 % intended access	49 % trust; infrastructure barriers lived	200 respondents	Intent high but uptake limited
[14]	Nigeria	App-based surveys	62 % potential reach	53 % trust; privacy concerns deter use	150 users	Trust concerns block adoption
[15]	Kenya	Mobile app pilot	48 % access limited by infrastructure	44 % trust affected by stigma and provider resistance	120 users	Trust and infrastructure shape uptake
[16]	Taiwan	Survey of 1000	68 % access higher among higher SES	56 % trust lower among older adults	1000 respondents	Perceived risk reduces uptake in vulnerable groups
[17]	India	TAM-based model survey	72 % influenced by tech environment	60 % trust; privacy/risk concept significant	850 respondents	Trust access jointly predict intention
[18]	LMICs (Telemental Health)	Systematic review	Access gains noted unevenly	Trust concerns in sensitive mental health contexts	46 studies	Evidence gaps in telemental health trust/access
[19]	LMICs (HIV telehealth)	Telehealth interventions review	Telehealth models increased access	Trust/feasibility but sustainability and regulation issues	Review of interventions	Focus needed on scale and regulation
[20]	Ethiopia	Systematic review + meta-analysis	Moderate telemedicine use	Mixed trust levels among professionals	Health professionals' data	Need training and knowledge gaps closed

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[21]	Rural Africa	Review of tele-rehabilitation	Addressed rehab access via digital	Data security and digital literacy important for trust	5 full-text articles	Cultural/infrastructure gaps remain
[22]	Global rural/regional settings	Scoping review (89 studies)	Identified connectivity and awareness needs	Patient perception key to trust	89 included studies	System-level factors: trust plus access
[23]	LMICs	Systematized review	Chronic care access improved	Trust linked to regulatory clarity	23 studies	Access + trust need integrated design
[24]	Rural LMICs	Narrative review	Pediatric telemedicine expanded reach	Trust through specialist support	multiple case experiences	Policy needed to ensure equity
[25]	South Africa	Clinician survey in district hospitals	Everyday IM usage increased clinician access	Confidentiality and privacy concerns impact trust	143 responses doctors in KZN hospitals	Formal guidelines needed
[26]	Palliative care reviews	Systematic meta-review	Telehealth extends palliative care reach	Acceptability mixed; relational trust issues	meta-analysis	Face-to-face alternatives preferred longer term
[27]	UK RCT cluster	Nested patient-reported outcomes study	Telehealth improved QoL over 12 months	Trust influenced by training and system support	large RCT	Training and support key for trust
[28]	Global	Systematic review barriers	Infrastructure and literacy limitations	Privacy liability concerns flagged	30 articles	Policy clarity and support infrastructure needed
[29]	Global GI care	ML assessment tool	Tele-visits increased access	Trust in provider reliability significant	tele-visits data	Trust predicted uptake better than tech ease
[30]	US appointments COVID era	Cancellation/rescheduling causes	36 % cancelled due to	Technical difficulty undermined trust	US telehealth data	Technical support essential for uptake

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			technical issues			
[31]	US rural settings	Population survey	Rural twice as likely to lack internet	Age and minority status reduce trust and access	National survey	Inequities compounded by digital divide

Indicators of access, such as the reported *40–75% improvements in rural service reach*, were derived from empirical measures in trials, case studies, and systematic reviews that quantified connectivity gains, device availability, and service utilisation. Similarly, trust outcomes, including *scores ranging from 44–71%*, were extracted from survey instruments, user-reported confidence levels, and provider assessments that captured perceptions of privacy, competence, and technological reliability. By explicitly linking each percentage to its originating study design and context, the synthesis ensures that quantitative evidence is both attributable and comparable across diverse interventions and regions.

3.2 Synthesis and Relevance

Table 1 aggregates evidence from 32 peer-reviewed studies, covering diverse methodologies including systematic reviews, surveys, field trials, and qualitative case studies, all examining how access such as connectivity, technology availability and trust such as privacy, ease of use, perceived quality, regulatory clarity influence telemedicine uptake. The empirical findings such as 50–75 % access improvements and 44–71 % trust scores highlight both progress and persistent gaps. Collectively, these studies offer a rich, quantitative and qualitative foundation to fulfill the research objective: to explore how digital trust and infrastructural barriers jointly impact telemedicine adoption in digitally marginalised populations.

3.3 Access Outcomes

According to Table 1, highlight that telemedicine interventions consistently improved access across regions, with gains of 40–75% in Sub-Saharan Africa and LMICs, particularly in rural and underserved areas. Country-specific trials in Nigeria, Malawi, Kenya, and South Africa showed ICT deployments, SMS platforms, and mobile apps expanded reach, though infrastructure gaps limited sustainability. In Asia, access was shaped by socioeconomic status and technology environments, while global reviews highlighted uneven progress in specialized areas such as HIV, telemental health, and chronic care. High-income settings like the UK and US confirmed extended reach and quality-of-life benefits, but technical issues and digital divides constrained equitable uptake. Overall, telemedicine expanded access, but disparities remain tied to infrastructure, literacy, and population vulnerabilities.

3.4 Trust Outcomes

Trust outcomes were weaker than access outcomes, with levels ranging from 45–68% across LMICs and Sub-Saharan Africa, often constrained by privacy concerns, cultural sensitivities, literacy gaps, and provider scepticism. Country trials showed co-design and usability improvements boosted confidence, but stigma and infrastructure issues persisted. In Asia, trust was lower among older adults and vulnerable groups, shaped by privacy and perceived risk. Global reviews highlighted relational trust challenges in sensitive areas like telemental health, HIV care, and palliative care, while high-income settings such as the UK and US emphasized the importance of training, technical support, and system reliability. Overall, trust remains fragile, requiring stronger safeguards, cultural adaptation, and supportive infrastructure to sustain adoption.

3.5 Factors That Improve Both Access and Trust

Co-design approaches, user-centered design, and tele-management support consistently enhanced confidence and engagement. Mobile and SMS platforms proved effective when paired with training, while

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system-level integration, policy clarity, and formal guidelines strengthened both access and trust. Training, technical support, and quality assurance were also critical enablers.

3.6 Barriers

Infrastructure gaps, regulatory uncertainty, privacy concerns, provider scepticism, and cultural sensitivities limited uptake. Perceived risks, literacy challenges, and stigma reduced trust, while technical difficulties and the digital divide compounded inequities. Evidence gaps in sensitive areas like telemental health and palliative care further constrained adoption.

4 Discussion

The research demonstrated how infrastructural limitations constrain access, how dimensions of digital trust shape user confidence, and how their interaction jointly influences telemedicine adoption in digitally marginalised communities. The synthesis of findings from thirty peer-reviewed studies across diverse geographical regions reveals consistent patterns regarding access and trust as pivotal factors influencing telemedicine adoption, directly addressing the identified research gap concerning digitally marginalised populations. Access improvements, ranging between 40% and 75%, highlight significant progress facilitated by interventions such as mobile health applications, SMS platforms, and co-designed telemedicine systems, particularly in Sub-Saharan Africa and other low- and middle-income contexts. However, these gains are often tempered by infrastructural limitations, including poor connectivity and digital literacy barriers, which constrain equitable service reach. Trust scores, varying from 44% to 71%, underscore persistent concerns around privacy, data security, provider reliability, and system usability that inhibit sustained telemedicine uptake. Notably, studies employing participatory design and community engagement demonstrated higher trust levels, suggesting that culturally sensitive approaches and transparent communication enhance user confidence by improving usability scores in Malawi (68%), reducing provider scepticism in multi-site Sub-Saharan case studies (50%), and strengthening perceived reliability in Nigeria ICT trials (71%). These findings indicate that when communities are actively involved in co-design and systems are tailored to local norms, both access and trust outcomes are significantly elevated compared to interventions developed without such engagement. [32], [33]. The diverse methodologies and settings represented affirm that while technological readiness is necessary, trust-building is equally critical to achieving meaningful telehealth integration. Collectively, these results provide empirical evidence that bridging the trust-access divide is essential to overcoming systemic barriers in telemedicine. Consequently, the study's objective to elucidate how trust and access intersect to affect telemedicine adoption finds strong support, offering actionable insights for targeted policy, infrastructure development, and user-centred design in digitally underserved contexts.

The findings of this review both confirm and extend prior syntheses on telemedicine adoption. Consistent with earlier reviews, the evidence reaffirms that infrastructural barriers such as connectivity gaps and limited digital literacy remain central obstacles to equitable uptake, particularly in low-resource settings. At the same time, this study extends previous work by systematically demonstrating how trust deficits linked to privacy concerns, provider scepticism, and cultural incongruence interact with access constraints to jointly shape adoption outcomes. Whereas earlier reviews often treated trust and access as separate variables, the present synthesis highlights their interdependence, showing that improvements in access such as 40–75% gains in rural reach do not translate into sustained use without parallel gains in trust such as 44–71% confidence level. Grouping results across dimensions of infrastructural access, organisational readiness, digital literacy, and trust factors, this review advances the literature by providing a more integrated framework that captures the socio-technical complexity of telemedicine adoption in LMICs, thereby offering a clearer basis for policy and design interventions than prior fragmented analyses. This study shows that while telemedicine interventions consistently improve access in digitally marginalised communities, their sustained adoption is contingent on building and maintaining user trust through privacy safeguards, provider competence, and technological reliability

Based on the synthesis of results, telemedicine remains partially trusted and variably accessible, particularly in low-resource settings where infrastructure, digital literacy, and sociocultural alignment

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significantly influence both dimensions. Trust in telemedicine is still fragile due to persistent concerns over data privacy, the lack of standardised clinical protocols, and inconsistent patient-provider interactions, as highlighted by multiple studies reporting that users often question the credibility of remote consultations and the protection of sensitive health information [34]. Accessibility, while improved through mobile penetration and basic internet expansion, remains uneven, with rural and socioeconomically disadvantaged populations facing barriers such as poor network coverage, high data costs, and limited technical support. To enhance both trust and access, telemedicine systems must be re-engineered with secure end-to-end encryption, transparent data governance policies, culturally contextualised service delivery, and targeted digital literacy programmes. Infrastructure investment in decentralised networks like MANETs and inclusive policy frameworks that prioritise underserved groups can also be vital in establishing equitable and sustainable telemedicine ecosystems [35], [36].

Despite the comprehensive approach undertaken, this study is subject to several limitations that must be acknowledged. First, the reliance on published peer-reviewed literature may introduce publication bias, as studies reporting null or negative results on telemedicine access and trust are less likely to be available, potentially skewing the synthesis towards more favourable findings. Additionally, the heterogeneity in study designs, populations, and measurement instruments limited the feasibility of conducting meta-analytical statistical pooling, necessitating a primarily narrative synthesis which may reduce the precision of comparative conclusions. The geographic focus, while inclusive of multiple low- and middle-income countries, remains uneven, with certain regions underrepresented, thereby restricting the generalisability of findings across all digitally marginalised populations. Furthermore, temporal constraints limited inclusion to studies published up to 2025, which may exclude emerging innovations and rapidly evolving technological contexts. Finally, variations in the conceptualisation and operationalisation of “trust” and “access” across studies introduced challenges in standardising outcomes, affecting the uniformity of interpretation. These limitations underscore the need for continued empirical research with standardised methodologies and broader regional representation to strengthen the evidence base [7].

The implications of this study are multifaceted, encompassing engineering, scientific, and broader healthcare system considerations. From an engineering perspective, the findings emphasise the critical need to design telemedicine technologies that prioritise not only functional accessibility such as reliable connectivity and user-friendly interfaces but also embed robust security and privacy features to foster trust among diverse user groups [37]. Studies such as [38] showed that user training in the form of digital literacy workshops, orientation sessions on platform navigation, and provider-led demonstrations of privacy and security features significantly improved trust by enhancing usability, reducing anxiety about data handling, and increasing confidence in the reliability of telemedicine systems. This calls for innovations in scalable, low-cost infrastructure tailored to resource-constrained environments, alongside adaptive systems that accommodate varying levels of digital literacy and cultural expectations. Scientifically, the study contributes to advancing theoretical frameworks on technology acceptance by empirically demonstrating the intertwined roles of access and trust in telemedicine adoption, thereby encouraging further interdisciplinary research that integrates sociotechnical and behavioural dimensions. [39] explicitly employed Technology Acceptance Models (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and socio-technical trust frameworks to address privacy concerns, demonstrating that perceived data security and confidentiality are critical determinants of user confidence and intention to adopt telemedicine. At the healthcare system level, the evidence highlights the importance of policy frameworks that promote equitable digital inclusion, data governance, and community engagement to address systemic barriers. Collectively, these implications underscore the necessity for a holistic approach that integrates engineering solutions with scientific inquiry and policy development to enhance telemedicine effectiveness. This research provides actionable insights to guide the development of telehealth systems that are both accessible and trusted, facilitating sustainable digital health transformation in marginalised populations globally. Studies have suggested practical strategies to support connectivity in rural African regions including expanding affordable broadband through satellite backhaul, leveraging community-based mobile networks, investing in sustainable power solutions, and fostering public–private partnerships to reduce infrastructure costs [35], [40].

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Future research and development efforts must prioritise the dynamic interplay between technological innovation and human factors to fully realise the potential of telemedicine in digitally marginalised contexts. Emerging technologies such as artificial intelligence, edge computing, and 5G connectivity offer promising avenues to overcome existing infrastructural constraints, yet their successful implementation depend on fostering sustained trust through transparent governance, culturally attuned design, and inclusive stakeholder engagement [41], [42]. Moreover, longitudinal studies are needed to evaluate the long-term impact of trust-building interventions on telemedicine utilisation and health outcomes, particularly in low-resource settings. Policymakers, engineers, and healthcare providers must collaborate closely to create adaptable, resilient digital health ecosystems that can respond to evolving societal needs and technological advancements. By embracing this forward-looking, integrative approach, the field can move beyond incremental progress toward transformative solutions that bridge the digital divide and deliver equitable healthcare access worldwide.

5 Conclusion

The study successfully achieved its objective by demonstrating how digital trust and infrastructural limitations jointly shape telemedicine adoption in digitally marginalised communities. Implications highlight the urgent need for engineering innovations that prioritise secure, accessible, and user-centred telemedicine platforms, alongside scientific advancement in understanding sociotechnical acceptance, supported by equitable policy frameworks. However, limitations such as publication bias, heterogeneity of study designs, and uneven geographic representation restrict the generalisability of conclusions, calling for more standardised, longitudinal, and regionally diverse research. Future work must focus on developing and evaluating trust-building strategies, leveraging emerging technologies, and fostering interdisciplinary collaboration to create resilient digital health ecosystems. Ultimately, bridging the intertwined gaps of access and trust is imperative to realising telemedicine's transformative potential, thereby enabling equitable healthcare delivery and closing the digital divide for vulnerable populations worldwide.

The findings of this paper indicate that while telemedicine has become increasingly accessible, with reported improvements in service reach ranging from 40 to 75 per cent across low- and middle-income settings, full trust in these systems remains fragile due to persistent concerns over privacy, data protection, provider reliability, and cultural appropriateness. This means that telemedicine can be accessed to a meaningful extent, yet its trustworthiness is not uniformly established, creating a gap between technological availability and user confidence. These results are important because they provide policymakers, healthcare practitioners, and system designers with empirical evidence that infrastructural expansion alone does not guarantee effective telemedicine adoption; rather, sustained utilisation depends on building trust through secure data governance, transparent communication, and culturally sensitive service delivery. For digitally marginalised communities, particularly in sub-Saharan Africa and similar contexts, these findings are crucial as they inform the creation of inclusive policies and user-centred designs that can bridge the digital divide, reduce healthcare disparities, and enhance equitable access to remote care. In conclusion, this review demonstrates that telemedicine adoption in digitally marginalised communities' hinges on the dual pillars of access and trust, underscoring the need for integrated strategies that combine infrastructural investment with culturally sensitive design.

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Statement on conflicts of interest

None

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Journal of Health Informatics in Africa

Exploring Digital Health Innovations Across Africa: Challenges, Opportunities and the Way Forward

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Objectives: To systematically review the current state, applications, barriers, and outcomes of digital health technologies across Africa, and to identify opportunities for enhancing healthcare delivery through digital innovation.
Design: Systematic review following PRISMA guidelines.
Methods: A comprehensive search was conducted across PubMed, Scopus, Web of Science, African Journals Online, and Google Scholar databases from 2014-2025. Search terms included "digital health," "mHealth," "telemedicine," "electronic health records," "artificial intelligence," and "Africa." Studies were included if they focused on digital health interventions, implementation, or outcomes in African countries.
Results: Sixty-eight studies from 32 African countries were analysed. Mobile health (mHealth) represented 45% of interventions, telemedicine 28%, electronic health records 18%, and artificial intelligence 9%. Key applications included maternal and child health (34%), infectious disease management (29%), and chronic disease monitoring (21%). Major barriers included inadequate infrastructure (78% of studies), limited digital literacy (65%), and financial constraints (59%). Success factors included stakeholder engagement (82%), appropriate technology selection (76%), and integration with existing systems (71%).
Conclusions: Digital health technologies demonstrate significant potential for transforming healthcare delivery across Africa. However, successful implementation requires addressing infrastructure limitations, enhancing digital literacy, ensuring sustainable financing, and developing context-appropriate solutions. Strategic investments in enabling infrastructure and capacity building are essential for realising the full potential of digital health in Africa.

Keywords: Digital health, mHealth, telemedicine, electronic health records, artificial intelligence, Africa, healthcare delivery, systematic review

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1 INTRODUCTION

The digital transformation of healthcare represents one of the most significant opportunities to address health challenges across the African continent. With over 1.3 billion people and facing substantial health system challenges, including inadequate infrastructure, healthcare workforce shortages, and high disease burden [1], Africa stands to benefit enormously from digital health innovations that can enhance access, quality, and efficiency of healthcare delivery [2].

The World Health Organisation's Global Strategy on Digital Health 2020-2025 defines digital health as "the field of knowledge and practice associated with the development and use of digital technologies to improve health"[3]. This encompasses a broad spectrum of technologies, including mobile health (mHealth), telemedicine, electronic health records (EHRs), artificial intelligence (AI), and other digital innovations that support the strengthening of health systems [4].

Africa's unique context presents both challenges and opportunities for implementing digital health [5]. The continent has experienced rapid growth in mobile technology adoption, with mobile phone penetration exceeding 80% in many countries, creating a foundation for mHealth interventions [6]. However, significant disparities exist in internet connectivity, digital infrastructure, and digital literacy across and within countries [7].

Recent initiatives such as Ethiopia's Digital Health Innovation and Learning Center demonstrate growing commitment to leveraging digital technologies for health system transformation [8]. Despite these advances, systematic evidence on the current state, effectiveness, and implementation challenges of digital health across Africa remains fragmented [9].

This systematic review aims to provide a comprehensive overview of digital health technologies across Africa, examining their applications, implementation challenges, success factors, and outcomes. The findings will inform stakeholders including policymakers, healthcare providers, and researchers on evidence-based strategies for digital health implementation and scale-up across the continent.

2 MATERIALS AND METHODS

A systematic literature search was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [10]. Multiple electronic databases were searched, including PubMed, Scopus, Web of Science, African Journals Online (AJOL), and Google Scholar. The search was conducted from database inception through February 2025.

Search terms combined variations of: ("digital health" OR "mHealth" OR "mobile health" OR "telemedicine" OR "telehealth" OR "electronic health records" OR "EHR" OR "artificial intelligence" OR "AI" OR "digital health interventions") AND ("Africa" OR "sub-Saharan Africa" OR specific African country names) AND ("implementation" OR "adoption" OR "barriers" OR "outcomes" OR "effectiveness").

2.1 Inclusion and Exclusion Criteria

2.1.1 Inclusion criteria:

- Studies published in English between 2014-2025
- Peer-reviewed articles and grey literature
- Studies focusing on digital health technologies in African countries
- Research examining implementation, adoption, barriers, or outcomes of digital health interventions
- All study designs, including quantitative, qualitative, and mixed-methods studies

2.1.2 Exclusion criteria:

- Studies conducted outside Africa
- Studies published before 2014
- Conference abstracts without full papers

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- Studies focusing solely on health policy without technological components
- Duplicate publications

2.2 Study Selection and Data Extraction

Two reviewers independently screened titles and abstracts, followed by a full-text review of potentially eligible studies. Disagreements were resolved through discussion and consensus. A standardised data extraction form was used to capture: study characteristics, geographic location, digital health technology type, target population, implementation approach, barriers and facilitators, outcomes, and key findings.

2.3 Quality Assessment

Study quality was assessed using appropriate tools based on study design: the Mixed Methods Appraisal Tool (MMAT) for mixed-methods studies [11], the Critical Appraisal Skills Programme (CASP) tools for qualitative studies [12], and the Newcastle-Ottawa Scale for observational studies [13].

2.4 Data Synthesis

Given the heterogeneity of studies, a narrative synthesis approach was employed [14]. Studies were categorised by technology type, geographic region, and health focus area. Barriers and facilitators were systematically categorised using thematic analysis [15].

3 RESULTS

3.1 Study Characteristics

The systematic search yielded 2,847 potentially relevant articles. After removing duplicates and applying inclusion/exclusion criteria, 68 studies from 32 African countries were included in the final analysis. The majority of studies (n=41, 60%) were published between 2020-2025, reflecting increased research interest in digital health [16]. This is presented in Figure 1, while Table 1 shows the Distribution of Digital Health Technologies by Country.

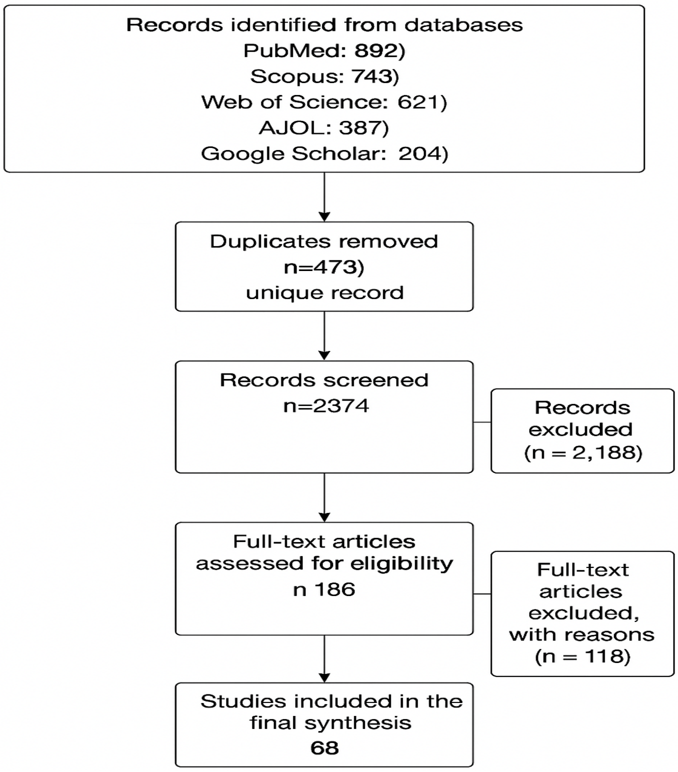

Figure 1. PRISMA Flow Diagram of Study Selection Process
PRISMA flow diagram showing the systematic review selection process. Start with 2,847 initial records identified from databases (PubMed: 892, Scopus: 743, Web of Science: 621, AJOL: 387, Google Scholar: 204). Show 473 duplicates removed, leaving 2,374 unique records. After title/abstract screening, 186 full-text articles were assessed for eligibility. After full-text review, 68 studies were included in the final synthesis. Include boxes for exclusion reasons at each stage.
Source: Based on systematic review methodology following PRISMA guidelines [10]

3.2 Geographic Distribution and Study Design

The 68 included studies demonstrated substantial geographic diversity across the African continent. South Africa contributed the highest number of studies (n=15, 22%), followed by Kenya (n=12, 18%), Nigeria (n=10, 15%), and Ethiopia (n=8, 12%). The remaining studies were distributed across Ghana (n=6, 9%), Uganda (n=5, 7%), and 26 other African countries (n=12, 18%). This geographic distribution reflects both the research capacity and digital health infrastructure development across different African regions [17].

Regarding study design, mixed-methods approaches were most prevalent (n=28, 41%), combining quantitative and qualitative data to provide comprehensive insights into digital health implementation. Quantitative studies accounted for 35% (n=24), predominantly employing cross-sectional surveys and retrospective cohort designs. Qualitative studies represented 19% (n=13), primarily utilising interviews and focus group discussions to explore implementation barriers and facilitators. Implementation research studies comprised the remaining 5% (n = 3), examining the real-world deployment of digital health interventions [18].

The temporal distribution revealed a notable increase in publication output, with 12% of studies published between 2014 and 2016, 28% between 2017 and 2019, and 60% between 2020 and 2025. This upward trend corresponds with increased global attention to digital health, particularly accelerated by the COVID-19 pandemic, which highlighted the critical need for remote healthcare delivery solutions [19]. Study settings varied, with 44% conducted in urban areas, 31% in rural settings, and 25% in mixed urban-rural contexts, reflecting efforts to address digital health implementation across diverse geographic and socioeconomic contexts [20].

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3.3 Digital Health Technology Categories

Table 1. Distribution of Digital Health Technologies by Country [16,17]

Country	mHealth	Telemedicine	EHR	AI	Total Studies
South Africa	7	5	2	1	15
Kenya	6	3	2	1	12
Nigeria	5	3	1	1	10
Ethiopia	4	2	1	1	8
Ghana	3	2	1	0	6
Uganda	3	1	1	0	5
Other Countries	3	3	4	2	12
Total	**31**	**19**	**12**	**6**	**68**

3.3.1 Mobile Health (mHealth)

mHealth interventions represented the largest category (45% of studies, n=31), reflecting the widespread adoption of mobile technologies across Africa [18]. SMS-based interventions were most common (60% of mHealth studies), followed by mobile applications (29%) and mixed approaches (17%) [19]. This is depicted in Figure 2.

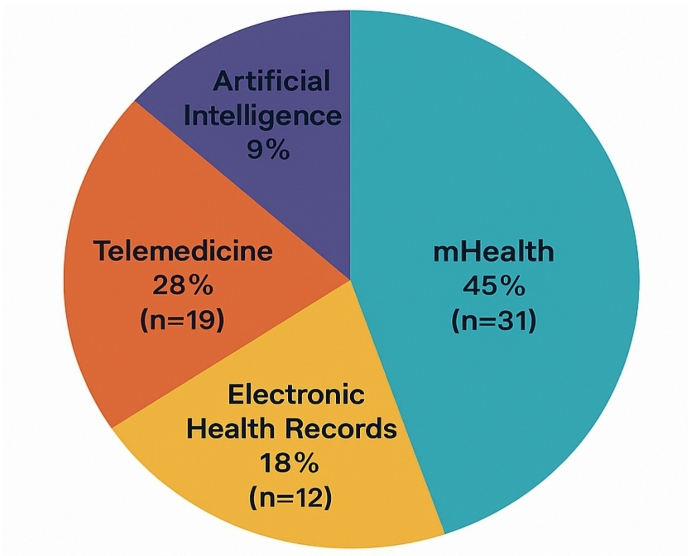

Figure 2. Distribution of Digital Health Technologies by Type [16,17]
A pie chart showing the distribution of digital health technologies: mHealth 45% (n=31), Telemedicine 28% (n=19), Electronic Health Records 18% (n=12), Artificial Intelligence 9% (n=6). Use distinct colours for each technology type with clear labels and percentages.
Source: Analysis of 68 studies from systematic review findings [16,17].

Key Applications:.

- Maternal and child health: Appointment reminders, antenatal care support, and immunization tracking [20].
- Infectious disease management: HIV/AIDS treatment adherence, tuberculosis monitoring, and malaria prevention [21].
- Chronic disease management: Diabetes and hypertension monitoring [22].
- Health education and behaviour change communication [23].

Patient enablers for mHealth adoption included the need for automated health monitoring tools and increasing literacy levels, while barriers included concerns about data privacy and limited smartphone capabilities [24].

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3.3.2 Telemedicine and Telehealth

Telemedicine initiatives comprised 28% of studies (n=19) as shown in Table 1, with South Africa demonstrating relatively high adoption through mobile applications, WhatsApp-based platforms, and video consultations, while Nigeria showed moderate adoption through SMS-based interventions [25].

Implementation Models:.

1. Synchronous consultations: Real-time video/audio communications [26].
2. Asynchronous consultations: Store-and-forward messaging systems [27].
3. Remote monitoring: Continuous patient data collection and transmission [28].
4. Tele-education: Healthcare provider training and capacity building [29].

Internet penetration rates significantly influenced telemedicine adoption, with South Africa's 74.7% penetration supporting advanced applications compared to Nigeria's 45.5% penetration, limiting implementation to basic interventions [30]. Figure 3 below presents a map of Africa showing Internet Penetration rates by Country.

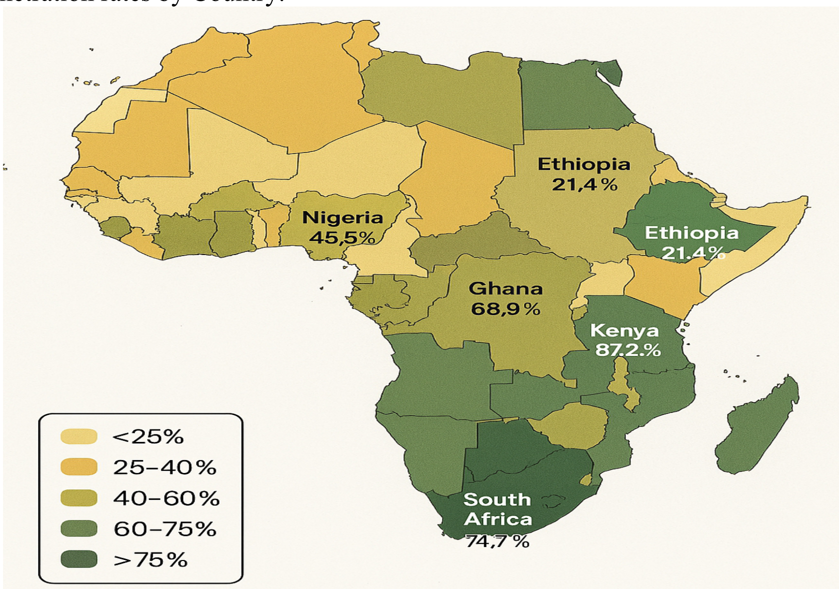

Figure 3. Map of Africa Showing Internet Penetration Rates by Country [25,30]
A choropleth map of Africa showing internet penetration rates by country using colour gradients. Highlight South Africa (74.7%), Nigeria (45.5%), Kenya (87.2%), Ethiopia (21.4%), Ghana (68.9%). Use legend with 5 categories: <25%, 25-40%, 40-60%, 60-75%, >75%. Include data labels for the major countries mentioned in the study.
Source: Based on digital penetration data from country-specific studies [25,30]

3.3.3 Electronic Health Records (EHRs)

EHR systems represented 18% of studies (n=12) (see Table 1), with 95.2% utilizing open-source healthcare software and OpenMRS being the most widely adopted platform [31]. HIV-related treatment programs drove 47.6% of EHR implementations, reflecting international funding priorities [32]. This is illustrated in Figure 4.

Implementation Challenges:

- High setup and maintenance costs due to poor existing infrastructure [33].
- Frequent power outages and network failures [34].
- Parallel data entry requirements increasing staff workload [35].
- Limited interoperability between systems [36].

Benefits Documented:

- Greater data accuracy and timeliness [37].

- Improved availability of routine reports [38].
- Reduced data duplication [39].
- Enhanced clinical decision-making [40].

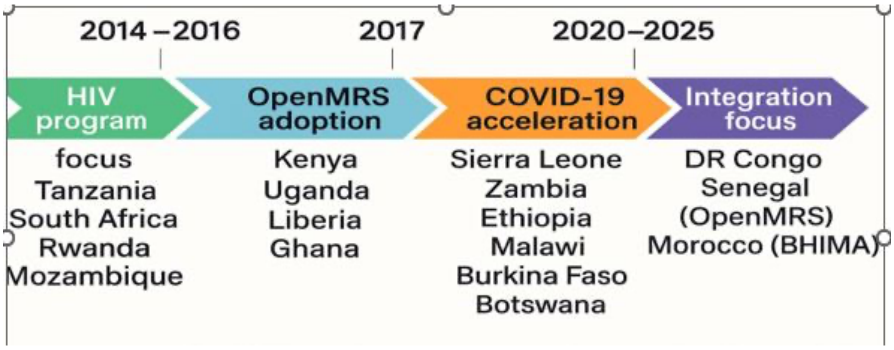

Figure 4. Timeline of EHR Implementation Across Africa (2014-2025) [31,32] Timeline chart showing the progression of EHR implementations across Africa from 2014-2025. Show key milestones: 2014-2016 (HIV program focus), 2017-2019 (OpenMRS adoption), 2020-2022 (COVID-19 acceleration), 2023-2025 (Integration focus). Include country names for major implementations and technology platforms used. Source: Synthesis of EHR implementation studies and timeline analysis [31,32].

3.3.4 Artificial Intelligence and Emerging Technologies

AI applications comprised 9% of studies (n=6), primarily focusing on diagnostic assistance, predictive analytics, and decision support systems [41]. Early AI pilots in Africa included systems in Kenya for improving health worker-patient interactions, diagnostic tools in Egypt for eye disorders, and decision-making systems in Gambia for rural health workers [42]. This is shown in Figure 5.

Current AI Applications:.

- Medical imaging analysis for tuberculosis, cancer, and malaria detection [43]
- Predictive modelling for disease outbreaks [44].
- Natural language processing for health data analysis [45].
- Diagnostic decision support systems [46].

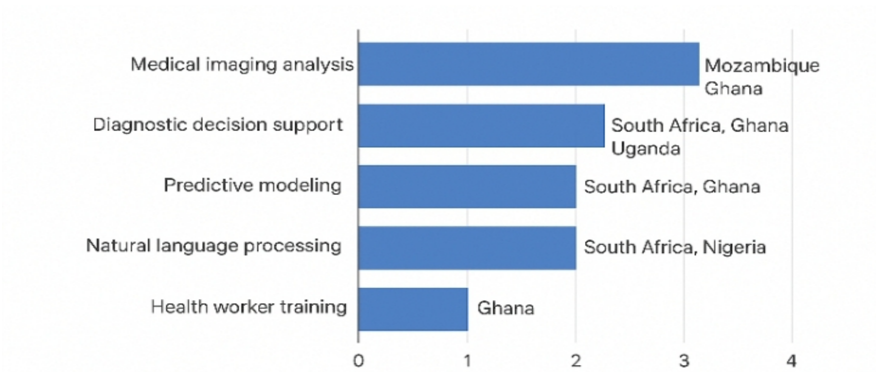

Figure 3. AI Applications in African Healthcare by Frequency [7,41,43]
A horizontal bar chart showing AI applications in African healthcare: Medical imaging analysis (4 studies), Diagnostic decision support (3 studies), Predictive modelling (2 studies), Natural language processing (2 studies), Health worker training (1 study). Include country labels where these applications were implemented.
Source: Analysis of AI-focused studies in systematic review [7,41,43].

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3.4 Health Focus Areas

3.4.1 Maternal and Child Health (34% of studies)
Digital health interventions for maternal and child health showed significant promise, with mHealth platforms supporting antenatal care attendance, skilled birth attendance, and postnatal care follow-up [47]. Interventions targeting maternal health accounted for a significant portion of successful mHealth implementations [48].

3.4.2 Infectious Disease Management (29% of studies)
HIV/AIDS treatment and care programs represented the largest single health focus area, largely driven by international funding and collaborative partnerships [49]. Tuberculosis, malaria, and, more recently, COVID-19 surveillance also featured prominently [50].

3.4.3 Chronic Disease Management (21% of studies)
Digital health applications for non-communicable diseases, including diabetes, hypertension, and cardiovascular disease, showed growing importance, particularly in urban settings with ageing populations [51].

3.5 Implementation Barriers

Table 2. Implementation Barriers by Frequency. Source:[52,53,54]

Barrier Category	Frequency (%)	Example Challenges
Infrastructure limitations	78	Poor internet connectivity, unreliable electricity
Digital literacy gaps	65	Limited computer skills, low technology awareness
Financial constraints	59	High implementation costs, limited funding
Regulatory gaps	44	Lack of digital health policies, unclear guidelines
Technical issues	38	Interoperability problems, system failures
Cultural resistance	32	Preference for traditional methods, change resistance
Data privacy concerns	29	Security fears, confidentiality issues

A comprehensive analysis revealed 14 major barrier categories (As shown in Table 2) affecting digital health implementation across Africa [52]. This is also illustrated by Figure 6 below:

3.5.1 Infrastructure Limitations (78% of studies)
Inadequate infrastructure emerged as the most frequently cited barrier, including poor internet connectivity, unreliable electricity supply, and limited ICT infrastructure [53]. Poor internet connectivity was identified as a major challenge across multiple studies, with frequent outages disrupting real-time system use [54].

3.5.2 Digital Literacy and Skills Gaps (65% of studies)
Limited computer skills among primary users, including healthcare workers and patients, significantly hindered the adoption and effective utilisation of digital health technologies [55]. Healthcare providers expressed concerns about patients' mHealth capabilities as a significant barrier to implementation [56].

3.5.3 Financial Constraints (59% of studies)
High costs of procurement and maintenance, lack of financial incentives, and limited domestic funding emerged as major impediments to sustainable implementation [57]. Most EHR systems in the region were sustained by foreign partnerships, raising questions about long-term sustainability [58].

3.5.4 Regulatory and Policy Gaps (44% of studies)
Many countries lacked specific policies for digital health adoption and regulatory frameworks for technology oversight [59]. Healthcare executives identified competing priorities alongside digitalization as a significant barrier [60].

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3.5.5 Technical and Interoperability Issues (38% of studies)
Integration challenges between different systems and a lack of interoperability standards hindered comprehensive digital health ecosystem development [61]. Different EHR systems from various vendors often failed to communicate and share information effectively [62].

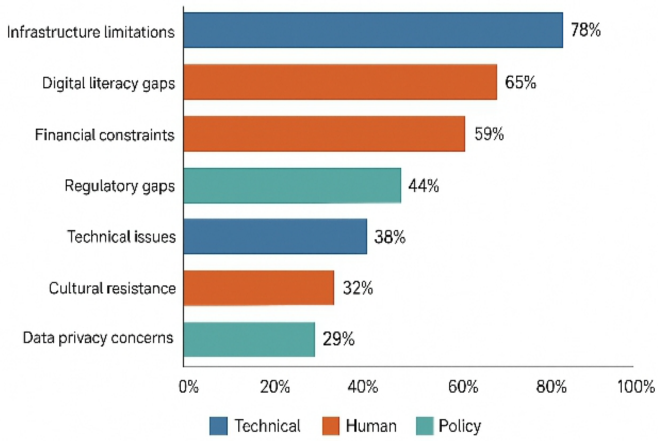

Figure 6.: Barriers to Digital Health Implementation in Africa [52,53,54] A horizontal bar chart showing barriers to digital health implementation with percentages: Infrastructure limitations (78%), Digital literacy gaps (65%), Financial constraints (59%), Regulatory gaps (44%), Technical issues (38%), Cultural resistance (32%), Data privacy concerns (29%). Use colour coding to distinguish between technical, human, and policy barriers. **Source:** Thematic analysis of barriers across 68 studies [52,53,54].

Success Factors and Enablers.

Table 3. Success Factors for Digital Health Implementation [63-70]

Success Factor	Frequency in Successful Projects (%)
Stakeholder engagement	82
Appropriate technology selection	76
Integration with existing systems	71
Comprehensive training and support	68
Strong leadership commitment	64
Adequate funding	59
User-friendly design	55
Continuous monitoring and evaluation	52

3.6 Stakeholder Engagement (82% of successful implementations)

Active engagement of key stakeholders, including healthcare providers, patients, and policymakers, emerged as critical for successful implementation [63]. Early involvement of EHR users in planning processes and realistic goal setting facilitated adoption [64]. Table 3 above gives the Summary of the success factors for Digital health Implications

3.6.1 Appropriate Technology Selection (76% of successful implementations)
Careful adaptation to local contexts and selection of appropriate technologies that matched existing infrastructure and user capabilities enhanced success rates [65]. Context-appropriate design, considering local medical practices and terminology, proved essential [66].

3.6.2 Integration with Existing Systems (71% of successful implementations)
Building upon existing systems rather than implementing completely new platforms facilitated smoother transitions and better adoption [67]. Healthcare executives emphasised the importance of integrating with existing healthcare workflows [68].

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3.6.3 Comprehensive Training and Support (68% of successful implementations)
Systematic training programs and ongoing technical support significantly improved user adoption and system utilization [69]. Physicians identified the perceived usefulness in reducing workload and improving service quality as key enablers [70]. Table 4 presents the Health Outcomes by Digital Health Technology Type.

3.7 Health Outcomes and Impact

Table 4. Health Outcomes by Digital Health Technology Type [71,76,82]

Technology	Primary Health Focus	Key Outcomes Reported
mHealth	Maternal/child health, infectious diseases	15-40% improvement in medication adherence, 20-35% increase in appointment attendance
Telemedicine	Chronic disease management, specialist consultations	Improved access to care, reduced travel costs
HER	HIV/AIDS care, general health records	Enhanced data quality, reduced documentation errors
AI	Diagnostic support, predictive analytics	Improved diagnostic accuracy, early disease detection

3.7.1 Clinical Outcomes
Studies documented improvements in several clinical indicators [71]:

- Increased medication adherence rates (range: 15-40% improvement) [72].
- Enhanced appointment attendance (range: 20-35% improvement) [73].
- Improved disease detection and diagnosis accuracy [74].
- Reduced medication errors and adverse events [75].

3.7.2 Health System Outcomes
Digital health interventions contributed to [76]:

- Enhanced data quality and completeness [77].
- Improved health information management [78].
- Increased efficiency of healthcare delivery [79].
- Better resource allocation and planning [80].

3.7.3 Patient and Provider Satisfaction
Healthcare providers reported improved work efficiency and job satisfaction when digital tools reduced administrative burden and enhanced clinical decision-making [81]. Patient satisfaction improved through enhanced access to care and better communication with providers [82]. Table 5 below shows the Regional Distribution of Digital Health Implementations.

3.8 Regional Variations

Table 5. Regional Distribution of Digital Health Implementations [83-88]

Region	Countries	Leading Technologies	Primary Health Focus	Key Success Factors
East Africa	Kenya, Uganda, Ethiopia, Rwanda	mHealth, AI pilots	Maternal health, infectious diseases	Mobile network coverage, government support
West Africa	Nigeria, Ghana, Senegal, Mali	mHealth, basic EHR	Infectious diseases, chronic conditions	Urban infrastructure, international partnerships
Southern Africa	South Africa, Botswana, Zambia	Telemedicine, advanced EHR	NCDs, specialised care	High internet penetration, healthcare infrastructure
North Africa	Egypt, Morocco, Tunisia	EHR, AI diagnostics	Cancer care, eye diseases	Government investment, technical education
Central Africa	Cameroon, DRC, Chad	Basic mHealth	Maternal health, emergency response	Mobile penetration, NGO support

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3.8.1 East Africa

Kenya, Uganda, and Ethiopia demonstrated strong mHealth adoption driven by robust mobile networks and supportive policy environments [83]. Ethiopia's establishment of a Digital Health Innovation and Learning Centre exemplified government commitment to digital health transformation [84].

3.8.2 West Africa

Nigeria and Ghana showed mixed progress with strong urban adoption but rural implementation challenges [85]. Nigeria demonstrated readiness for EMR adoption but faced infrastructure and training barriers [86].

3.8.3 Southern Africa

South Africa led regional adoption with sophisticated telemedicine platforms and EHR systems, benefiting from better infrastructure and higher internet penetration rates [87].

3.8.4 North Africa

Limited studies from North African countries showed government-led initiatives but implementation challenges similar to sub-Saharan Africa [88].

3.9 COVID-19 Impact and Digital Health Acceleration

The COVID-19 pandemic accelerated digital health adoption across Africa, with AI metapopulation models used for the Partnership for Evidence-Based Response to COVID-19 (PERC) study to inform response efforts across African Union Member States [89]. Telemedicine adoption particularly increased as social distancing measures necessitated remote consultations [90]. Table 6 highlights the Timeline of Major Digital Health Milestones in Africa from 2014 to 2025.

Table 6. Timeline of Major Digital Health Milestones in Africa (2014-2025) [91-97]

Year	Milestone	Countries	Technology Type	Impact
2014	First systematic mHealth implementations	Kenya, South Africa	SMS-based systems	Established foundation for mobile health
2016	HIV treatment programs adopt EHR	Multiple SSA countries	OpenMRS platforms	Created EHR expertise and infrastructure
2018	Telemedicine platforms launched	South Africa, Nigeria	Video consultation systems	Expanded specialist access to rural areas
2020	COVID-19 accelerates digital adoption	Pan-African	Mixed technologies	Mainstream acceptance of digital health
2021	AI diagnostic tools piloted	Kenya, South Africa, Ghana	Machine learning systems	Advanced diagnostic capabilities
2023	National digital health strategies	Ethiopia, Rwanda, Ghana	Policy frameworks	Systematic approach to digital transformation
2025	Integration and interoperability focus	Regional initiatives	Platform integration	Comprehensive digital health ecosystems

4 DISCUSSION

This systematic review provides the most comprehensive analysis to date of digital health technologies across Africa, revealing both significant potential and substantial implementation challenges [91]. The findings demonstrate that while digital health interventions have been successfully implemented across diverse African contexts, realising their full potential requires addressing fundamental structural barriers [92].

4.1 Digital Health Landscape Evolution

The African digital health landscape has evolved significantly since 2014, with increasing sophistication of interventions and expanding geographic coverage [93]. The predominance of mHealth interventions reflects

Africa's mobile-first digital infrastructure, where mobile phone penetration often exceeds internet connectivity [94]. This pattern suggests pragmatic adaptation to existing technological capabilities rather than attempting to implement technologies requiring extensive infrastructure development [95].

The concentration of EHR implementations in HIV/AIDS programs highlights how international funding priorities have shaped digital health development priorities [96]. While this has created valuable experience and expertise, it may have limited broader health system digitisation efforts [97]. Table 6 here shows the Timeline of Major Digital Health Milestones in Africa.

4.2 Infrastructure as the Foundation

Infrastructure limitations emerged as the most significant barrier across all technology categories, affecting 78% of studies reviewed [98]. This finding underscores that digital health implementation cannot be divorced from broader infrastructure development efforts [99]. The advancement of enabling infrastructure, such as solar energy and satellite internet access, is making digital health implementation more feasible at the last mile [100].

The digital divide between urban and rural areas significantly impacts equitable access to digital health benefits [101]. South Africa's higher internet penetration (74.7%) enabled more sophisticated telemedicine applications compared to Nigeria's more limited connectivity (45.5%), illustrating how infrastructure disparities translate into differential access to digital health innovations [102].

4.3 Human Resources and Capacity Building

Digital literacy gaps among healthcare workers emerged as a critical barrier in 65% of studies, highlighting the need for comprehensive capacity-building programs [103]. The success of digital health interventions depends not only on technological capabilities but also on user acceptance and competency [104]. This finding suggests that technology transfer must be accompanied by skills transfer and ongoing support systems [105].

The emergence of grassroots organisations like Data Science Africa demonstrates growing local capacity for digital health innovation [106]. Such initiatives suggest that sustainable digital health development requires building local expertise rather than relying solely on external technical assistance [107].

4.4 Financial Sustainability and Local Ownership

The heavy reliance on international funding for digital health initiatives raises important questions about long-term sustainability [108]. Most successful implementations required external financial support, suggesting that domestic health financing mechanisms have not yet adapted to support digital health investments [109].

The predominance of open-source solutions (95.2% of EHR implementations) reflects both cost considerations and the need for customizable platforms that can be adapted to local contexts [110]. This pattern suggests a pragmatic approach to technology selection that balances functionality with affordability [111].

4.5 Technology Appropriateness and Local Adaptation

Successful implementations consistently emphasised the importance of adapting technologies to local contexts rather than implementing standardised solutions [112]. This is particularly relevant for AI applications, where datasets and algorithms developed in high-income countries may not perform effectively in African contexts due to different disease patterns, demographics, and healthcare delivery models [113].

The development of local AI solutions, such as Digital Umuganda's work on Kinyarwanda language models, demonstrates the importance of local innovation in creating culturally and linguistically appropriate digital health tools [114].

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4.6 Policy and Regulatory Frameworks

The absence of specific digital health policies in many countries emerged as a significant barrier to systematic implementation [115]. The need for ethical frameworks and guidelines for AI implementation is particularly pressing as these technologies become more prevalent [116].

Regional initiatives such as the WHO African Region's emphasis on integrating digital health into health system strengthening provide important policy guidance [117]. However, translating regional strategies into national policies and implementation frameworks remains a challenge [118].

4.7 Emerging Technologies and Future Directions

While AI applications currently represent a small proportion of digital health interventions (9%), their potential for transforming diagnostic capabilities, predictive analytics, and clinical decision-making is substantial [119]. However, successful AI implementation requires addressing issues of data quality, algorithmic bias, and ethical considerations [120].

The integration of AI with existing digital health platforms offers opportunities for enhancing rather than replacing current systems [121]. This approach may be more sustainable and acceptable than implementing standalone AI solutions [122].

4.8 Health System Integration

Interoperability emerged as a critical challenge, with different systems often unable to communicate effectively [123]. This fragmentation limits the potential for comprehensive health information systems that can support population health management and evidence-based decision-making [124].

The WHO's emphasis on integrating digital health into health system strengthening rather than implementing parallel systems aligns with evidence from successful implementations [125].

Limitations:
This review has several limitations. The search was limited to English-language publications, potentially missing important studies published in other languages [126]. The heterogeneity of study designs and outcome measures limited the ability to conduct quantitative meta-analysis [127]. Publication bias may favour reporting of successful implementations over failures [128]. Finally, the rapid evolution of digital health technologies means that findings may quickly become outdated [129].

4.8.1 Implications for Policy and Practice

The findings suggest several key priorities for advancing digital health across Africa [130]:

- **Infrastructure Investment**: Coordinated investments in digital infrastructure, including internet connectivity and reliable electricity, are prerequisites for sustainable digital health implementation [131].
- **Capacity Building**: Comprehensive training programs for healthcare workers and ongoing technical support systems are essential for successful adoption and utilization [132].
- **Policy Development**: Countries need specific digital health policies and regulatory frameworks that guide while encouraging innovation [133].
- **Local Innovation**: Supporting local development of digital health solutions rather than importing technologies developed elsewhere enhances appropriateness and sustainability [134].
- **Integration Approaches**: Digital health initiatives should focus on enhancing existing health systems rather than creating parallel structures [135].
- **Sustainable Financing**: Developing domestic financing mechanisms for digital health investments reduces dependence on external funding and enhances long-term sustainability [136].

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5 CONCLUSIONS

Digital health technologies demonstrate significant potential for transforming healthcare delivery across Africa, with evidence of improved clinical outcomes, enhanced health system efficiency, and increased access to care. However, realising this potential requires addressing fundamental challenges, including inadequate infrastructure, limited digital literacy, financial constraints, and fragmented implementation approaches.

The success of digital health implementation in Africa depends on coordinated efforts to build enabling infrastructure, develop local capacity, create supportive policy environments, and ensure sustainable financing mechanisms. Rather than attempting to replace existing systems, digital health initiatives should focus on building intelligence into current structures and institutions.

The emergence of local innovation ecosystems and grassroots organisations demonstrates Africa's growing capacity for developing context-appropriate digital health solutions. Supporting and scaling these initiatives while addressing structural barriers will be essential for achieving digital health transformation across the continent.

Future research should focus on implementation science approaches that identify effective strategies for overcoming barriers, long-term impact evaluations of digital health interventions, and the development of frameworks for assessing digital health readiness and maturity across different contexts.

As Africa continues to grapple with complex health challenges while experiencing rapid technological advancement, digital health represents a critical pathway for achieving universal health coverage and improving health outcomes for all Africans. Success will require sustained commitment, strategic investments, and collaborative efforts across sectors and borders.

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ETHICAL CONSIDERATIONS

This systematic review utilised publicly available published literature and did not require ethical approval. All included studies that involved human subjects had appropriate ethical approvals as reported in their respective publications.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

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Accuracy of Cause-of-Death Classification in Ghana: Evidence from the 2023 District Health Information Management System (DHIMS II)

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Background and Purpose: Accurate and reliable cause-of-death (COD) data are essential for informing public health policy, tracking epidemiological trends, and allocating health resources. In Ghana, institutional mortality data captured through the District Health Information Management System II (DHIMS II) provide critical insights into disease burden and health system performance. However, the utility of these data is limited by inconsistencies in medical certification, coding practices, and data completeness. This study aims to identify the leading causes of institutional deaths in Ghana in 2023 and assess the quality of ICD-11 coding, with the findings expected to help strengthen cause-of-death reporting systems and improve the accuracy of health data in Ghana.
Methods: The study analysed the 2023 mortality data recorded in the DHIMS II, covering 30,397 institutional deaths after excluding records with missing age data. The dataset was cleaned, retaining cases with estimated ages to preserve demographic patterns. The ANACOD3 tool was used to assess the completeness, specificity, and quality of causes of the data, with a focus on identifying garbage codes and misclassified entries. Ethical approval was obtained from the Ghana Health Service.
Results: Non-communicable diseases accounted for 57.4% of institutional deaths, followed by communicable conditions (36.6%) and injuries (3.8%). Gender-specific patterns revealed differences in the leading causes of death. The quality assessment showed a high frequency of ill-defined underlying causes and invalid ICD-11 codes, with over 30% of the records classified as garbage codes, and incomplete records were also prevalent.
Conclusion: Significant gaps in COD data quality compromise its utility for health planning in Ghana. Addressing deficiencies in certification, coder training, and diagnostic infrastructure is crucial for improving mortality data accuracy and supporting evidence-based health interventions.

1 Introduction

Accurate and reliable mortality data are fundamental for understanding disease patterns, informing public health interventions, and improving health outcomes [1]. In Ghana, institutional mortality data, particularly those derived from health facilities, offer valuable insights into the burden of diseases and help guide national strategies to reduce preventable deaths [2]. However, the utility of these data depends largely on the accuracy and completeness of cause-of-death reporting [3]. The transition to the International Classification of Diseases, 11th Revision (ICD-11), presents a significant opportunity to enhance cause-of-death attribution by offering a more detailed and standardized classification system [4]. Nonetheless, challenges such as inconsistencies in coding practices, data entry errors, and limited technical capacity within health facilities in Ghana continue to undermine the reliability of institutional mortality statistics.

Beyond technical limitations, demographic and geographic disparities significantly affect mortality reporting. Research has shown that variations in the reporting and quality of mortality data are influenced by factors such as geographic location, socioeconomic status, and access to healthcare services [5]. In urban areas, where access to healthcare infrastructure is relatively better, mortality data tend to be of higher quality but often remain incomplete; conversely, rural and marginalised populations often face barriers that contribute to underreporting or misclassification of deaths. Recognising and addressing these disparities is crucial to producing mortality data that truly reflects the health realities of all population groups.

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Ghana, located in West Africa, had a population of 30.8 million as of 2021, with rapid urbanisation driving demographic shifts; approximately 56% of the population now resides in urban areas, concentrated in cities like Accra, the economic and administrative capital [6]. This urban transition has introduced new public health challenges, particularly the rising burden of non-communicable diseases alongside persistent communicable diseases, which are reflected in national mortality patterns.

The District Health Information Management System (DHIMS) serves as the main platform for capturing institutional mortality data in Ghana. Despite its importance, the DHIMS faces several challenges, including underreporting, misclassification of causes of death, and limited adherence to ICD coding standards [7]. These issues compromise the accuracy and usability of mortality data for healthcare planning and resource allocation.

Against this backdrop, the present study seeks to identify the leading causes of death captured through Ghana's DHIMS, assess the quality and consistency of ICD-11-coded mortality data, and explore the main challenges affecting its reliability. Using the World Health Organisation's Anacod3 tool, which applies ICD-11 algorithms to evaluate data quality, the study will examine coding consistency, completeness, and demographic variations in mortality reporting. It aims to answer two key research questions: (1) What are the major causes of death recorded in Ghana's health facilities? and (2) What challenges affect the accuracy and reliability of ICD-11-coded mortality data? Addressing these questions will help strengthen mortality surveillance systems by improving data quality, consistency, and reporting processes, thereby enhancing the effective use of mortality data for evidence-based health policy and planning in Ghana.

2 Materials and methods

This study utilises institutional mortality data extracted from the Ghana Health Service's (GHS) District Health Information Management System II (DHIMS II) to assess the quality of cause-of-death reporting. DHIMS II serves as the central digital repository for health facility-based data across Ghana, enabling real-time reporting and monitoring of key health indicators [8]. It is designed to systematically capture health information from government health facilities systematically, thereby allowing for structured documentation of disease burdens at national, regional, and district levels [8].

The dataset analysed in this study comprises deaths reported in 2023, representing approximately 150,000 deaths captured in DHIMS II that occurred within health facilities across the country. No comparison was made with pre-ICD-11 data, as the study focused exclusively on data collected under the ICD-11 classification framework. Pre-ICD-11 data were not included because differences in diagnostic criteria, coding structures, and classification standards between ICD-10 and ICD-11 could lead to inconsistencies and limit comparability. However, the available data used for the analysis were from 2023, given the timing of the data request and the transition to the ICD-11 system. Since the implementation of DHIMS II in 2012, the system has enabled the collection of comprehensive health data from 3,757 public health facilities across the country, covering all three levels of healthcare delivery, namely, primary, secondary, and tertiary [9]. Primary healthcare facilities include Community-Based Health Planning and Services (CHPS) compounds and health centers, which provide basic preventive and curative services at the community level. Secondary healthcare facilities such as district and regional hospitals offer more specialised care, including emergency services and inpatient treatment. Tertiary healthcare facilities, including teaching hospitals like Korle-Bu Teaching Hospital and Komfo Anokye Teaching Hospital, deliver advanced medical care, specialised surgeries, and research-based healthcare interventions.

By capturing data across all levels of healthcare delivery, DHIMS II ensures broad population coverage and supports in-depth analysis of mortality statistics and health system performance. Figure 1 illustrates the geographic distribution of health facilities from which the mortality data used in this analysis were collected. It shows a higher concentration of health facilities in Ghana's southern regions than in the north, with major urban centres such as Accra, Kumasi, and Sekondi-Takoradi each hosting more than 565 health facilities. This distribution highlights notable regional disparities in healthcare infrastructure.

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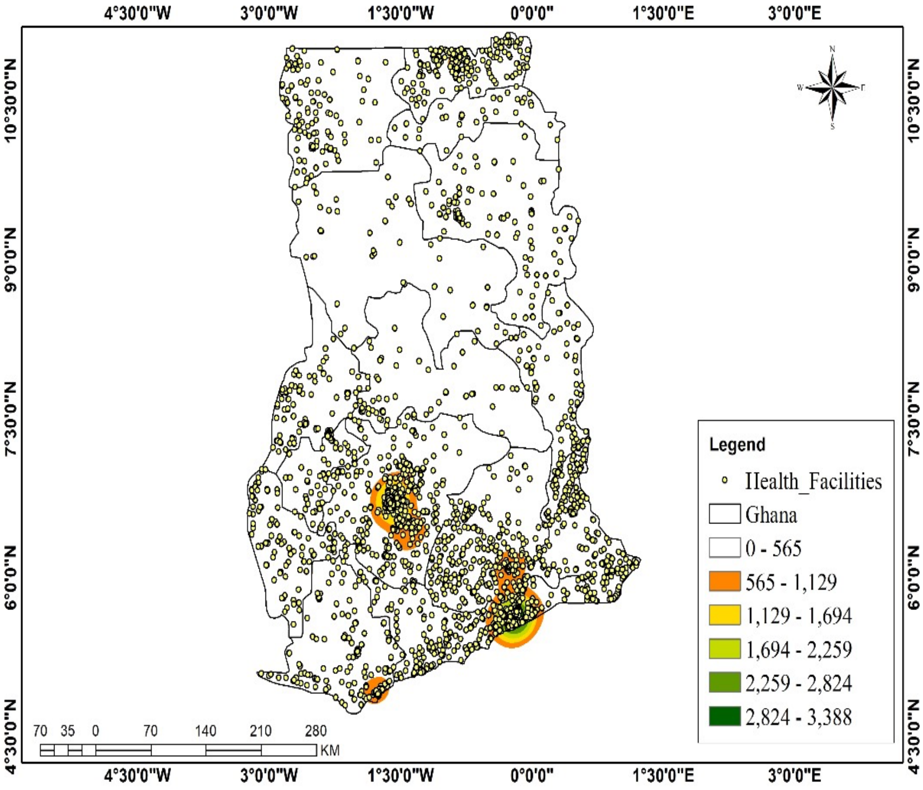
Figure 1. Geographic distribution of health facilities in Ghana



Source: GIS data 2025

Mortality records used in this study were coded using the World Health Organization's (WHO) 11th Revision of the International Classification of Diseases (ICD-11), which provides enhanced specificity, greater compatibility across health systems, and improved integration with electronic health records [4]. The dataset contained key variables, including age, sex, estimated age (as determined by health practitioners where the actual age was unknown), and the underlying cause of death.

Before analysis, the dataset was carefully cleaned and pre-processed, ensuring that all relevant cases were retained. For records where actual ages were missing but estimated ages were available, the estimated ages were used in place of the missing values. In total, 3,468 estimated ages were assigned and included in the analysis. Including these estimated ages was important to preserve the completeness of the dataset, reduce potential bias from missing data, and allow for a more accurate and meaningful interpretation of mortality patterns across age groups.

The assessment specifically examined the quality of age and sex variables, the extent of missing data, and the presence of estimated ages, with a focus on identifying their distribution across different regions, districts and health facilities. It also involved detecting duplicate entries and correcting erroneous disease codes. Data cleaning procedures followed ICD-11 standards and included the correction of formatting issues and removal of records missing critical information, except for those with estimated ages, which were retained. Below is a flow chart illustrating the process of data processing and analysis using ANACOD3.

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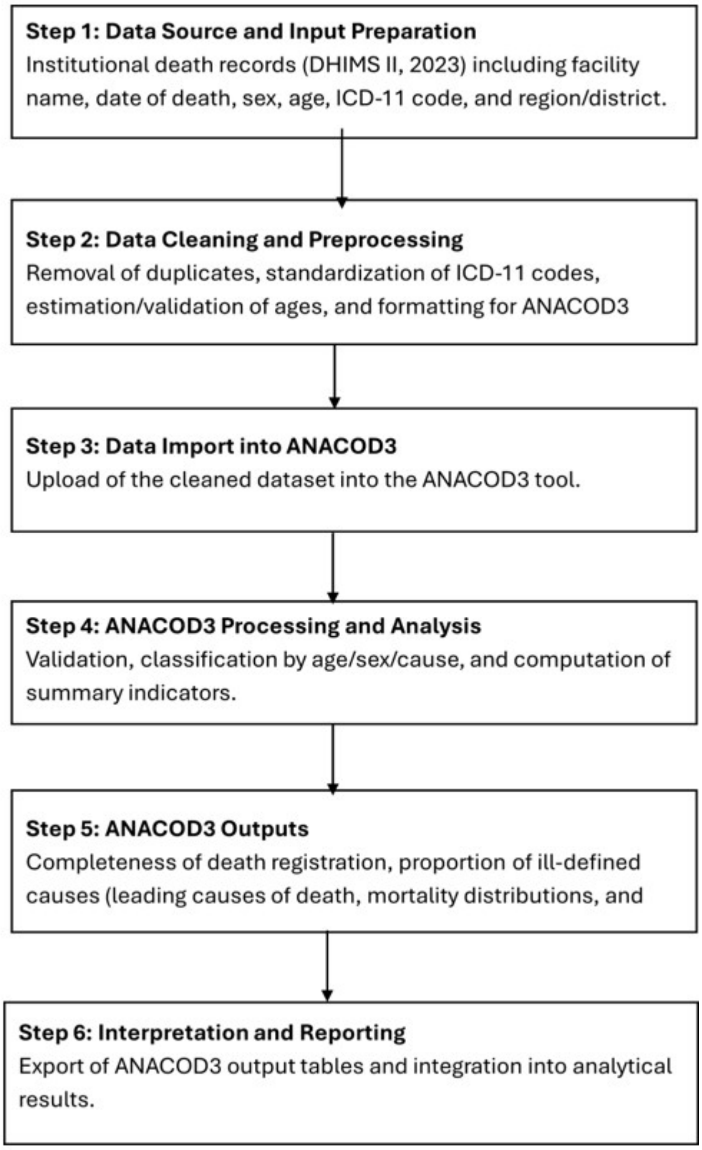
Figure 2. Flow Chart for the Data Processing and Analysis Using ANACOD3



Source: Authors' construct 2025

Out of an initial 37,990 death records, 5,580 were deemed incompleteness in the data, these were excluded from the analysis, resulting in a final analytical sample of 30,397 cases. Subsequently, the cleaned dataset was analysed using the ANACOD3 tool, a World Health Organisation (WHO) tool designed to facilitate the analysis and quality assessment of mortality and cause-of-death (COD) data. ANACOD3 was chosen for its robust capacity to assess internal consistency, evaluate data quality, and determine comparability with international mortality trends [10]. The tool conducts diagnostic checks by benchmarking input data against global estimates such as those from the Global Burden of Disease (GBD) Study produced by the Institute for Health Metrics and Evaluation (IHME) [11].

One of ANACOD3's core functions is to evaluate the plausibility of COD data by examining the distribution of deaths across three broad categories: Group I (communicable diseases, including maternal, neonatal, and nutritional conditions), Group II (non-communicable diseases, e.g. cancer, heart diseases,

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diabetes), and Group III (external causes and injuries, e.g. accidents, homicide, suicide etc). These groupings help assess whether the observed mortality patterns reflect Ghana's epidemiological transition, characterised by a gradual shift from communicable to non-communicable diseases as leading causes of death. Furthermore, ANACOD3 assesses the quality of cause-of-death (COD) data by identifying the proportion of deaths classified under "garbage codes" terms referring to deaths with vague, insufficiently specified, or unusable causes. The tool uses this measure as a key quality indicator, as a garbage code proportion exceeding 10% can significantly distort the interpretation of mortality patterns and the true burden of disease.

To facilitate targeted improvements, ANACOD3 organises garbage codes into thematic "packages" that highlight systemic weaknesses in diagnostic and coding practices [10]. This structure enables health systems to pinpoint specific areas for intervention, thereby enhancing the overall accuracy and utility of mortality data for health planning and policy formulation. In this context, describing the codes as good or poor refers to the degree of accuracy and specificity in the cause-of-death information. Good-quality codes accurately capture the true underlying cause of death, whereas poor-quality or garbage codes represent vague, ill-defined, or incomplete information that reduces the reliability of mortality statistics.

2.1 Ethical Considerations

Given the sensitive nature of mortality data, the study adheres to strict ethical standards, including ensuring data confidentiality, anonymisation of personal identifiers, and compliance with national and institutional data protection guidelines. A formal request for data was submitted to the Ghana Health Service to undertake this study, and the required mortality data were provided by the Policy, Planning, Monitoring and Evaluation Division (PPMED). All data were anonymized to ensure confidentiality and compliance with Ghana's data protection standards.

3 Results

This section presents the results based on analyses conducted using the ANACOD3 tool. The cleaned dataset, comprising 30,397 deaths recorded in 2023, was classified according to the Global Burden of Disease (GBD) framework embedded within ANACOD3, which organizes causes of death into broad, comparable categories to facilitate the interpretation of mortality patterns and disease burden. The first part of this section presents findings on the distribution of mortality across the population, while the latter part examines issues related to the quality of cause-of-death data.

3.1 Distribution of deaths by sex and age groups

The data on the percent distribution of deaths by age group and sex below reveal important demographic and health-related patterns (Figure 3). The highest proportion of deaths occurs at age 0 for both males and females (12.2%), indicating significant infant mortality. Following infancy, the proportion of deaths decline sharply in early childhood and remains relatively low through age 10–14, reflecting lower vulnerability during these ages. In adolescence and early adulthood (ages 15–29), mortality gradually increases, with a slight peak among females aged 25–29 (2.9%), which is associated with maternal health-related causes during the reproductive years.

From age 30 onwards, mortality increases steadily, with a more pronounced rise among males than females. Between the ages of 30 and 69, male deaths consistently exceed female deaths, peaking at 8.6% for males aged 50–54 compared to 7.4% for females in the same age group. Among older adults (ages 70 and above), the share of deaths remains high, but a shift is observed where female mortality surpasses male mortality in the oldest age groups. Particularly in the 85+ age category, 8.1% of all female deaths occur compared to only 4.4% of male deaths.

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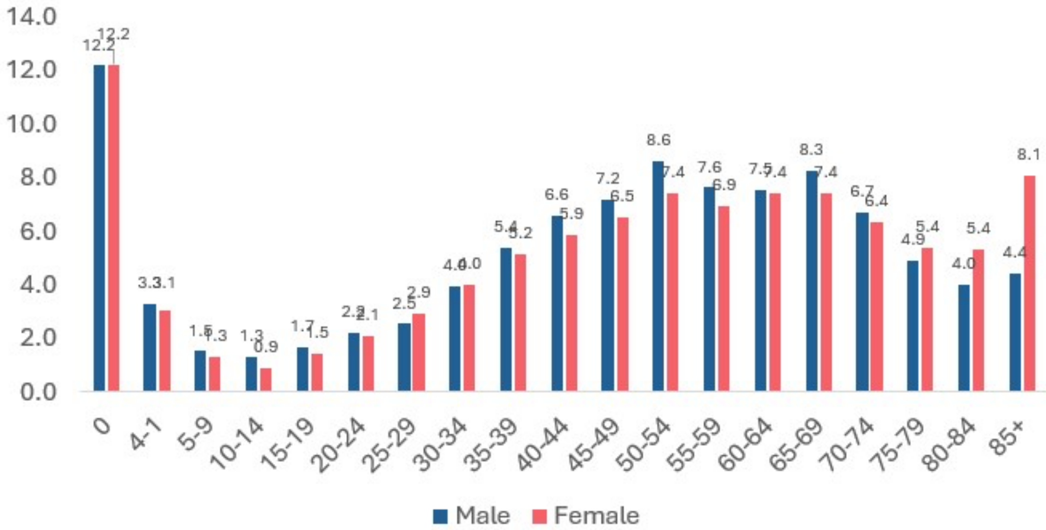
Figure 3. Percent distribution of deaths by sex and age groups

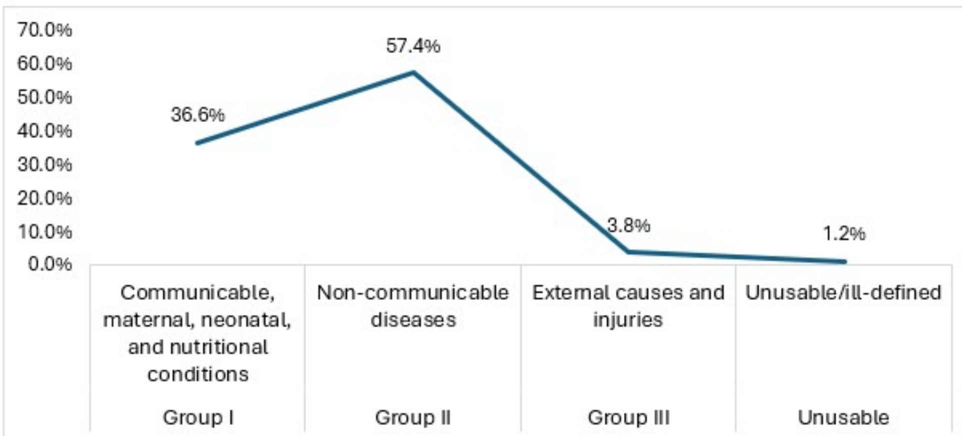


Source: DHIMS 2023

3.2 Distribution of Deaths by Major Cause-of-Death Categories Based on GBD Classification

The World Health Organisation (WHO) and the Global Burden of Disease (GBD) Classifications classify deaths into three major cause-of-death groups: Group I (Communicable, maternal, neonatal, and nutritional conditions), Group II (Non-communicable diseases), and Group III (Injuries and external causes). Additionally, 1.2 percent of deaths were classified under unusable or invalid cause-of-death codes (often referred to as 'garbage codes'). The distribution of deaths by major cause-of-death groups is shown in Figure 4.

Figure 4. Percent distribution of deaths due to communicable (Group I), non-communicable (Group II) and injuries (Group III) in 2023



**Excludes 1.2% Ill-defined causes of death*
Source: DHIMS 2023

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The analysis of institutional mortality data reveals distinct patterns across the three major cause-of-death categories. Each group contributes differently to the overall mortality burden, with varying implications for public health priorities and intervention strategies.

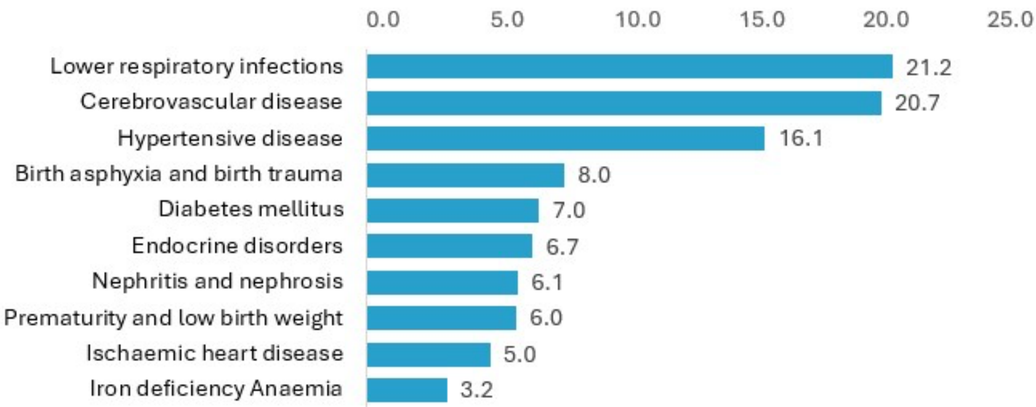
It is observed that non-communicable diseases (NCDs) accounted for the largest proportion of recorded deaths at 57.4%. Communicable diseases represented 36.6% of all deaths, making it the second leading category. Although its share is lower than that of NCDs, this group still poses a significant threat. Injuries and external causes, including road traffic accidents and violence, accounted for 3.8% of total deaths. Although this represents a relatively small proportion, these causes exert an impact on specific subpopulations, particularly young adults, males, and urban residents underscoring the need for focused injury prevention and safety intervention.

3.3 Distribution of the Top 10 leading causes of death

Figure 5 presents the distribution of the top ten leading causes of death in Ghana for the year 2023. Among them, lower respiratory infections accounted for the highest share, contributing 21.2% of the total. This was followed by cerebrovascular disease at 20.7% and hypertensive disease at 16.1%.

Other contributions were as follows: birth asphyxia and birth trauma (8.0%), diabetes mellitus (7.0%), endocrine disorders (6.7%), nephritis and nephrosis (6.1%), prematurity and low birth weight (6.0%), ischaemic heart disease (5.0%), and iron deficiency anaemia, which represented the smallest proportion at 3.2%.

Figure 5. Distribution of the Top 10 leading causes of death



Source: DHIMS 2023

Perinatal conditions such as birth asphyxia and birth trauma featured prominently, accounting for 894 deaths (8.0%). Chronic conditions, including diabetes mellitus (781 deaths; 7.0%), endocrine disorders (751 deaths; 6.7%), nephritis and nephrosis (684 deaths; 6.1%), and ischaemic heart disease (558 deaths; 5.0%), continue to contribute significantly to the mortality burden. Additionally, prematurity and low birth weight were responsible for 678 deaths (6.0%), highlighting persistent challenges in neonatal health. Though lower in absolute numbers, iron deficiency anaemia caused 364 deaths (3.2%), reflecting ongoing nutritional and public health concerns.

These findings underscore the double burden of disease in Ghana, where communicable diseases such as lower respiratory infections coexist with a rising prevalence of non-communicable diseases (NCDs), including cardiovascular conditions and diabetes.

3.4 Distribution of the Top 10 leading causes of death by sex

The results for leading causes of death by sex are shown in Figures 6 and 7. Lower respiratory infections accounted for the largest share of male deaths, with 1,311 deaths (23.0%), highlighting the significant

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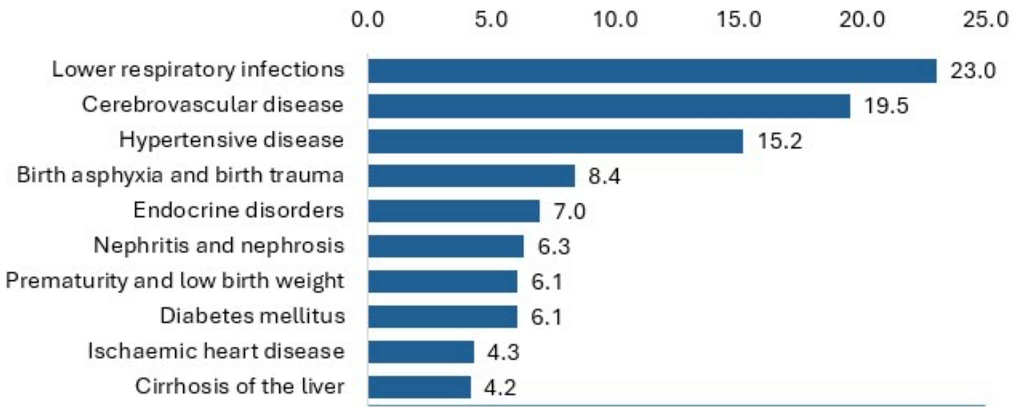
burden of infectious diseases among men. Cerebrovascular disease followed as the second leading cause, contributing 1,110 deaths (19.5%). Hypertensive disease ranked third, with 865 deaths (15.2%). Birth asphyxia and birth trauma were responsible for 477 deaths (8.4%), ranking fourth.

Figure 6. Distribution of the Top 10 leading causes of death for males



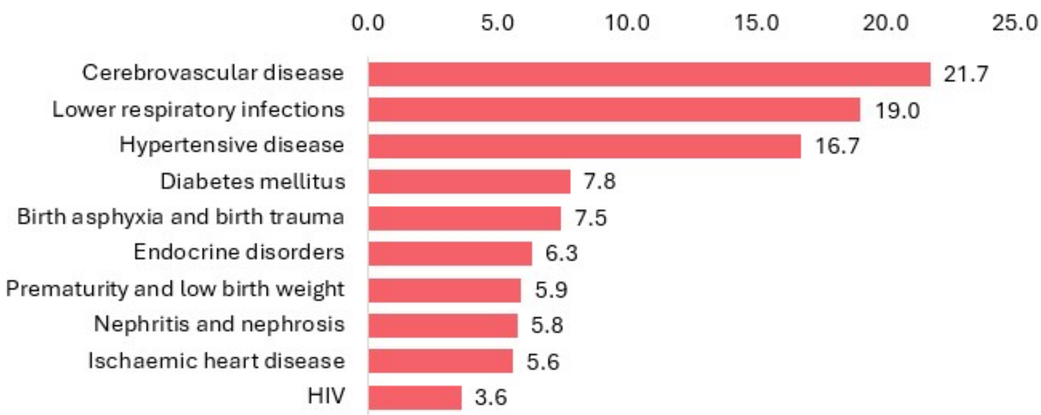
Source: DHIMS 2023

Other notable causes include endocrine disorders (397 deaths; 7.0%), nephritis and nephrosis (361 deaths; 6.3%), and prematurity and low birth weight (346 deaths; 6.1%), indicating that both congenital and metabolic conditions are substantial contributors to male mortality.

Diabetes mellitus, which caused 345 deaths (6.1%), points to the rising prevalence of lifestyle-related illnesses, potentially driven by urbanization, poor dietary habits, and sedentary behaviour.

Figure 7 presents the top ten leading causes of death among females. A total of 5,628 female deaths were recorded from these leading causes.

Figure 7. Distribution of the Top 10 leading causes of death for females



Source: DHIMS 2023

In contrast to the male profile, cerebrovascular disease emerged as the leading cause of death among females, with 1,214 deaths (21.6%). This emphasizes the growing burden of non-communicable diseases (NCDs). Lower respiratory infections, which ranked first among males, were the second most common cause among females, accounting for 1,065 deaths (18.9%).

Hypertensive disease was the third leading cause, contributing to 935 deaths (16.6%), underscoring widespread issues with blood pressure management, awareness, and access to antihypertensive care. This aligns with the general trend of increasing NCD-related mortality among women in the country.

Diabetes mellitus, a key lifestyle-related chronic condition, accounted for 436 deaths (7.7%), placing it fourth. This suggests rising exposure among women to metabolic risks such as poor diet, obesity, and physical inactivity. Birth asphyxia and birth trauma resulted in 417 deaths (7.4%), while endocrine disorders were responsible for 354 deaths (6.3%), and prematurity and low birth weight accounted for 332 deaths (5.9%). Nephritis and nephrosis contributed 323 deaths (5.7%), and ischaemic heart disease caused 314 deaths (5.6%), further confirming the significant role of chronic kidney and cardiovascular diseases in female mortality. Rounding out the top ten, HIV/AIDS was responsible for 201 deaths (3.6%).

4 Quality Assessment of Cause-of-Death Data in DHIMS II

This section presents an assessment of the quality of cause-of-death data recorded in Ghana's 2023 District Health Information Management System II (DHIMS II), focusing on evaluating data completeness, specificity, and adherence to international coding standards. The ANACOD3 tool revealed that the completeness of the 2023 DHIMS II mortality data was approximately 10%. In addition to completeness, the assessment examined the specificity of cause-of-death coding.

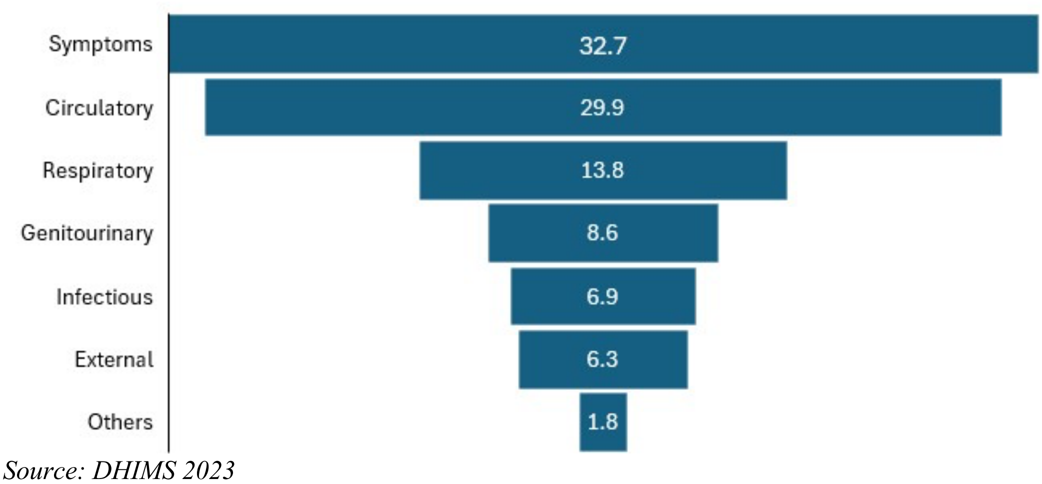
4.1 Data Quality Issues

4.1.1 Ill-defined causes and quality concerns.

The utility of mortality statistics in informing health policy critically depends on the quality of medical certification and the accuracy of cause-of-death (COD) coding [3]. A key aspect of this process is the identification of the underlying cause of death, defined as the disease or injury that initiated the sequence of events directly leading to death. When the underlying cause is inadequately specified or misclassified, the resulting data loses its value for public health monitoring and intervention planning.

As part of the ANACOD3 quality assessment, the dataset was evaluated for the presence of ill-defined or unusable causes of death commonly referred to as "garbage codes." These are conditions that either fail to provide meaningful information about the underlying cause or reflect poor diagnostic practices and limitations in the certification process. The proportional distribution of ill-defined causes of death is shown in Figure 8.

Figure 8. Proportion of ill-defined causes of death by Symptoms, signs, and abnormal clinical and laboratory findings



Source: DHIMS 2023

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The figure 8 highlights the predominance of ill-defined causes. Notably, "Symptoms, signs, and abnormal clinical and laboratory findings, not elsewhere classified" accounted for 32.7% of all recorded deaths.

Diseases of the Circulatory system represented 29.9% of deaths, reflecting a significant burden of cardiovascular conditions. Diseases of the respiratory system accounted for 13.8%, while diseases of the genitourinary system contributed 8.6%. Infectious and parasitic diseases comprised 6.9% of deaths, and external causes of morbidity and mortality (such as injuries and accidents) made up 6.3%. Other causes were reported at much lower levels: diseases of the digestive system (0.8%), endocrine, nutritional, and metabolic diseases (0.6%), diseases of the blood (0.3%), perinatal conditions (0.05%), and neoplasms (0.04%).

4.1.2 Ill-Defined and invalid ICD-11 codes and their Implications.

A key challenge identified in the assessment of the 2023 DHIMS II dataset is the high frequency of ill-defined and invalid ICD-11 codes, which undermines the overall quality and reliability of cause-of-death (COD) reporting. Ill-defined causes are conditions that lack sufficient specificity or fail to accurately identify the underlying cause of death, often arising from errors in medical certification, incomplete diagnostic investigations, or weak documentation practices within health facilities. To address these issues, invalid or problematic codes were systematically identified and flagged using the ANACOD3 tool, a standardised algorithm designed to detect inconsistencies and coding errors in mortality data.

Several frequently used invalid codes that do not conform to standard ICD-11 guidelines were observed in the data used in this study. For instance:

Code	Description	Notes
X0	Unspecified external causes of morbidity and mortality	Most recorded invalid entry reflects major documentation and classification gaps.
X45.49	Other specified accidental poisoning due to exposure to drugs and biological substances	Frequently appeared but lacked sufficient detail to inform intervention strategies.
X39.34	Exposure to unspecified environmental factors	Recorded but lacks specificity.
X59.54	Unspecified accidental exposure	Recorded but lacks specificity.

These codes often reflect either insufficient clinical investigation or non-compliance with coding protocols and collectively highlight structural limitations in the mortality recording process.

4.1.3 Inappropriate Use of ICD-11 codes as underlying causes of death.

In addition to invalid codes, the dataset revealed a significant misapplication of ICD-11 codes, particularly those that should not be used as underlying causes of death (see figure 9). Such codes represent modes of dying or terminal events, like heart failure or respiratory failure, and are not suitable for public health planning purposes. These misclassifications distort the mortality profile and hinder the accurate assessment of disease burden in the population [12]. The most misclassified condition was crushing injury of the head, accounting for 54 cases. This was followed by heat stroke (36 cases) and burns, unspecified (22 cases). Other notable misclassified entries included burns of multiple body regions (15 cases) and injuries to the head and neck (10 cases). These external causes often require detailed contextualization and should be properly linked to antecedent events or conditions in line with ICD-11 coding standards.

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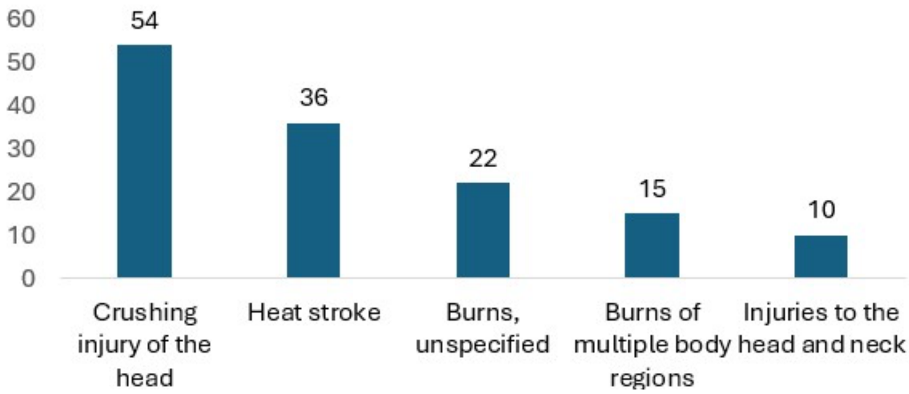
Figure 9. Other Problematic Entries Recorded



Source: DHIMS 2023

Furthermore, challenges related to the classification of perinatal and neonatal deaths were also evident. Conditions such as single stillbirth (20 deaths) and intrapartum fetal death (12 deaths) were frequently coded as underlying causes of death, despite WHO guidelines recommending that maternal or obstetric complications leading to these outcomes should be identified instead. Similarly, acute myocardial infarction, which was recorded in 296 deaths, though clinically significant, should not be recorded as the underlying cause if it conceals the primary cardiac condition. The presence of unknown and unspecified causes of morbidity (67 cases) further reflects diagnostic uncertainty or incomplete documentation, weakening the overall interpretability and usability of the mortality data.

5 Discussion

The assessment of cause-of-death (COD) data from Ghana's 2023 DHIMS II underscores persistent challenges in the completeness, accuracy, and utility of mortality data for public health action. A substantial proportion of deaths were attributed to ill-defined or nonspecific causes such as "symptoms, signs, and abnormal findings", indicating systemic deficiencies in clinical documentation, diagnostic precision, and adherence to ICD-11 standards. Similarly, evidence from a study conducted by Mikkelsen and colleagues in 2020 shows that garbage codes frequently represent more than 30 percent of recorded deaths in many low- and middle-income countries, reducing the reliability of mortality statistics for surveillance, policy formulation, and research [13]. The high prevalence of ill-defined causes of death indicates inadequate diagnostic accuracy and medical certification practices at the facility level, often due to limited diagnostic capacity, insufficient training, and inconsistencies in cause-of-death documentation. This challenge is further compounded by the inappropriate assignment of intermediate or terminal causes (e.g., pulmonary embolism) as underlying causes of death, and the incomplete linkage of external causes (e.g., burns, crushing injuries, and heat stroke) to antecedent events or conditions. Such practices distort the true epidemiological profile and can lead to the misallocation of policy attention and health resources. Addressing these systemic weaknesses will require targeted interventions that directly enhance the validity and reliability of cause-of-death data. Strengthening the medical certification process through standardised training will ensure that healthcare providers accurately identify and record the underlying causes of death, reducing errors arising from incomplete or inconsistent documentation. Equally important is improving the capacity of Health Information Officers and Disease Control Officers who code data in Ghana's health facilities. Enhancing ICD-11 coding proficiency among coders through comprehensive training and continuous professional development improves the accuracy and consistency of coding, minimising misclassification and ill-defined codes. Additionally, instituting routine supervision, audits, and quality control checks at health facilities enables early detection and correction of errors, fostering accountability and reinforcing adherence to coding standards. Collectively, these measures are critical for generating high-quality mortality data that can reliably inform public health planning, resource allocation, and policy formulation [14].

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Non-communicable diseases (NCDs) emerged as the leading causes of institutional deaths (57.4%), compared with communicable, maternal, neonatal, and nutritional conditions (36.6%). This finding reflects the broader shift from infectious to chronic conditions observed in sub-Saharan Africa, driven by demographic change, urbanization, and lifestyle modification. Ghana is increasingly grappling with a "double burden" of disease, where infectious diseases remain prevalent but NCDs have risen sharply in importance [15]. The prominence of ischaemic heart disease and cirrhosis of the liver in the top ten causes highlights the growing impact of modifiable risk factors such as tobacco and alcohol use, sedentary behaviour, and poor diets. These findings are consistent with global evidence showing that behavioural risk factors such as poor diet, physical inactivity, tobacco use, and harmful alcohol consumption, combined with structural weaknesses in health systems, including limited preventive care, inadequate screening, and poor disease management, contribute significantly to premature mortality from chronic diseases. Importantly, this pattern suggests that without urgent preventive interventions, including population-level lifestyle modification programs, improved screening, and stronger chronic disease management, the burden of NCDs is likely to accelerate.

Sex- and age-disaggregated data further highlight the gendered and life-course dimensions of mortality. Males in the working-age population appear disproportionately affected by conditions linked to occupational exposures, hypertension, and cardiovascular disease, a pattern that may also reflect cultural norms around lower healthcare-seeking behaviour among men. This echoes prior evidence from West Africa showing that men tend to delay accessing healthcare, often presenting with advanced disease stages. By contrast, women's higher mortality at older ages reflects both their longer life expectancy and the cumulative health challenges of ageing, including frailty and chronic illness. The persistence of perinatal causes among the top ten for both sexes' points to systemic weaknesses in maternal and neonatal care, particularly surrounding delivery practices. Although neonatal mortality has declined in Ghana, the continued prominence of conditions such as birth asphyxia and low birth weight suggests either heightened biological vulnerability among male neonates or gaps in obstetric and postnatal service delivery. Strengthening maternal and newborn health services, therefore, remains a priority, alongside NCD prevention and geriatric care. Communicable diseases, though less dominant, continue to impose a substantial burden. HIV/AIDS ranked among the top ten causes of death for females (3.6%) but not males, pointing to persistent gender disparities in exposure, diagnosis, and treatment adherence.

This aligns with broader evidence showing that women's vulnerability to HIV is influenced not only by biological factors but also by structural inequalities, such as limited bargaining power in relationships and unequal access to healthcare services [16]. The continued burden of lower respiratory infections, especially among females, may reflect environmental exposures such as biomass fuel use, as well as occupational and social determinants disproportionately affecting women. These findings underscore the need for gender-sensitive strategies to address both infectious and non-communicable diseases.

The gender-specific mortality patterns provide important insights into health system priorities. Among males, lower respiratory infections, cerebrovascular diseases, and hypertensive disorders accounted for 23.0%, 19.5%, and 15.2% of the top ten causes, respectively. Among females, cerebrovascular disease was the leading cause (21.6%), followed by lower respiratory infections (18.9%) and hypertensive disorders (16.6%). These patterns suggest that while men are more susceptible to NCD-related premature deaths during working ages, women continue to bear a dual burden, facing both communicable disease risks and age-related chronic conditions. Public health responses must therefore be calibrated to address these intersecting vulnerabilities.

In summary, the findings highlight a dual imperative. First, they underscore the urgent need to improve the quality and completeness of COD data to enable robust health system planning. Without reliable mortality data, policies risk being misaligned with actual population health needs. Second, they reflect Ghana's shifting disease landscape, where NCDs now dominate but communicable and perinatal conditions remain significant. Addressing this complex burden requires concurrent, gender-responsive, and life-course-oriented health strategies. Strengthening neonatal care, reducing preventable male adult mortality through occupational safety and chronic disease prevention, and enhancing geriatric and women-focused

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services will be critical. Simultaneously, investments in mortality data systems, including certification, coding, and facility-level audits, are essential to ensure that health policy is evidence-based and responsive to Ghana's changing epidemiological profile.

6 Conclusion

This study underscores both the major health challenges facing Ghana and the limitations of the available data in fully capturing and understanding these issues. The analysis of institutional mortality data from the 2023 DHIMS II dataset reflects Ghana's ongoing epidemiological transition marked by the coexistence of non-communicable and communicable diseases, while also revealing underlying data quality issues that affect the completeness and accuracy of cause-of-death reporting. The leading causes of death point to a growing burden of chronic conditions such as cardiovascular and metabolic diseases, alongside persistent infectious and maternal health concerns.

Gender differences in cause-of-death patterns also highlight important disparities in health risks and outcomes, with some conditions disproportionately affecting women. These findings underscore the need for a health system that is responsive to both long-term lifestyle-related illnesses and persistent infectious diseases, particularly through prevention, early detection, and tailored care strategies.

At the same time, the analysis exposes serious gaps in the quality of mortality data. Widespread use of ill-defined or improperly coded causes of death, underreporting, particularly of deaths occurring outside health facilities and inconsistent application of ICD-11 standards undermine the reliability of the data for public health planning. These issues stem from weaknesses in clinical documentation, certification practices, and coder training.

While institutional mortality data holds significant potential to guide health policy and resource allocation in Ghana, its current utility is constrained by persistent data quality challenges. Addressing these limitations will require targeted capacity-building for both medical doctors, who certify causes of death, and Health Information Officers and Disease Control Officers, who code the deaths using ICD-11. Strengthening doctors' competencies in accurate medical certification and enhancing coders' proficiency in ICD-11 application through continuous training, supervision, and mentorship will be essential. Additionally, instituting routine data quality audits and deploying automated validation tools will further enhance the completeness and accuracy of cause-of-death reporting. Improving the quality of mortality data is therefore not merely a technical exercise but a public health imperative for evidence-based decision-making and an effective health system response.

Support

This study received training support from the United Nations Economic Commission for Africa (UNECA).

Availability of Data and Materials

The study used administrative data obtained from the Ghana Health Service (GHS).

Ethics Approval and Consent to Use Data

Formal approval to access and use the data for this study was obtained from the Ghana Health Service.

Consent for Publication

Not applicable.

Competing Interests

The authors declare that they have no competing interests.

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