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Journal of Health Informatics in Africa

Editorial to JHIA Vol. 11 (2024) Issue 3

Nicky Mostert

Nelson Mandela University, Port Elizabeth, South Africa

The Journal of Health Informatics in Africa (JHIA) is committed to publishing original, high-quality research focused on the application of information and communication technologies (ICTs) in the African healthcare sector.

To uphold the integrity and originality of the journal, each submission undergoes a thorough process that includes obtaining a Turnitin report prior to assignment to reviewers. Submissions are only considered for review if their Turnitin similarity index is below 15%. Any manuscript exceeding this threshold is immediately rejected. We strongly encourage authors to ensure that their work is original and has not been published elsewhere before submission to JHIA.

Once a paper is accepted for review, it undergoes a rigorous double-blind review process. This may result in either acceptance or rejection. In cases of acceptance, most submissions are subjected to a second round of peer review. Authors are required to revise their manuscripts based on reviewer feedback and resubmit them for further evaluation by the same reviewers. Only once both the reviewers and the editorial team are satisfied with the revisions is the paper formally accepted for publication.

This issue features three insightful papers:

- Eleke, Nwaneri, Okoronkwo, and Samuel present a comprehensive review comparing paper-based and software-assisted nursing documentation, focusing on data precision and timeliness.
- Kigombola and Mahundi explore the use cases, approaches, and challenges associated with the implementation of blockchain technology in the healthcare sectors of low- and middle-income countries.
- Mwogosi, Kibusi, and Shaoa share insights into primary healthcare practitioners' perceptions of the effectiveness of electronic health record systems for decision support in Tanzania.

I would like to extend my deepest gratitude to the editorial team, authors, and peer reviewers whose hard work has made this issue possible. I also encourage researchers engaged in health informatics to contact me about becoming reviewers for JHIA. The expertise of experienced researchers is crucial to maintaining the high quality of research published in our journal.

Thank you for your continued support of JHIA.

Nicky Mostert
December 2024

Journal of Health Informatics in Africa

Perceptions of Primary Healthcare Practitioners on the Effectiveness of Electronic Health Records Systems for Decision Support in Tanzania

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Background and Purpose: This study examined primary healthcare practitioners' perceptions of the effectiveness of Electronic Health Records (EHR) systems in providing decision support in Tanzania.
Methods: The study employed a quantitative research approach, utilising surveys and structured observations to collect data from healthcare practitioners in PHC settings. Descriptive statistical analysis was conducted to assess the functionalities and utilisation of EHR systems.
Results: The findings revealed that while EHR systems in PHC facilities offer certain benefits, such as facilitating access to patient information and improving administrative processes, there are limitations in their ability to support decision-making tasks effectively. Specific areas for improvement are identified, highlighting the need for targeted interventions to enhance the functionality of EHR systems in PHC settings.
Conclusions: This study underscores the importance of addressing the identified limitations in EHR systems to optimise their effectiveness in supporting decision-making tasks in PHC settings in Tanzania. Targeted interventions are essential to enhance EHR functionality and improve healthcare delivery outcomes.

Keywords: Electronic Health Records, Decision Support, Primary Healthcare, Tanzania, EHR systems, Implementation

1 Introduction

Digital technologies have revolutionised several industries worldwide, bringing a new era of productivity, accessibility, and operational efficiency. Technology developments, in particular, have created creative solutions that have transformed patient care and medical practice [1]. Electronic Health Records (EHR) are organised collections of digital health data for specific individuals or groups of patients. They originated from the first attempts to computerise medical data in the 1960s [2]. These technologies, which offer thorough records of patient contacts and streamline workflows in healthcare settings, are incorporated into network-connected information systems called EHR systems that span the healthcare enterprise [3]. EHR systems enhance safety through evidence-based decision support, quality management, and outcome reporting, improving care quality, efficiency, and continuity while fostering coordinated care among healthcare providers [4].

In addition to facilitating patient engagement and care coordination, EHR systems simplify population health management and research endeavours. Researchers and healthcare professionals can learn more about trends in population health, treatment effectiveness, and sickness patterns by combining identified patient data [5], [6]. Communities' health and well-being can be enhanced by using this data to identify public health problems, customise care, and allocate resources wisely. Moreover, seamless sharing among healthcare providers is made possible by the accessibility of medical records via EHR systems, which improves care transitions and raises the bar for safety and quality across the board [7], [8]. Technology

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integration, especially with EHR systems, improves individual patient care, advances population health management and research, and improves overall healthcare.

EHR systems enhance healthcare practitioners' decision-making capabilities by integrating clinical decision-support tools such as alerts, reminders, and recommendations embedded within EHR systems. It improves diagnostic accuracy and adherence to best practices, reducing errors and upholding clinical standards. Furthermore, EHR systems generate large volumes of data, which can be leveraged for analytics and predictive modelling, assisting healthcare practitioners in identifying patterns, assessing patient risk, and formulating treatment strategies. Moreover, EHR systems streamline care coordination by providing a centralised platform for accessing and updating patient data, ensuring effective collaboration among the care team and informed decision-making [9].

Tanzania's healthcare system operates within a well-structured pyramidal framework from local to national. Primary healthcare (PHC) services, including dispensaries, health centres, district hospitals, and community-based health services, serve as the foundation of this structure, emphasising prevention and health promotion. Health centres provide inpatient and outpatient care, while dispensaries focus on basic labour, delivery, and outpatient services. District hospitals handle referrals from health centres for medical and surgical procedures. In contrast, regional referral hospitals offer specialised care and serve as educational institutions [10]. The Ministry of Health (MoH) is responsible for health and social welfare services, setting policies, providing guidance, and mobilising resources. PORALG oversees service delivery at regional and council levels, with Regional Health Management Teams (RHMTs) monitoring and enhancing local government agencies' capacity. District Council Health Management Teams (CHMTs) offer support for preventive, rehabilitative, and curative health services through capacity building and supervision.

Both public and private healthcare organisations in Tanzania have embraced technology, particularly EHR systems, to enhance healthcare delivery. The government of Tanzania recognised the potential benefits of EHR systems. It developed the Government of Tanzania Health Operations Management Information System (GoT-HoMIS) to address challenges associated with paper-based systems [11]. Various hospitals in Tanzania utilise vendor-based EHR systems such as JEEVA and MedPro to manage hospital functions comprehensively, improving the standard of treatment by providing medical professionals with access to patient information stored across different locations. Moreover, systems like webERP, Care2x, Harmony, Bumi Expert, Daisa, and the locally developed Electronic Health Management System (eHMS) contribute to Tanzania's diverse electronic healthcare management environment, streamlining administrative procedures and improving care quality [12]. Private healthcare facilities have also implemented EHR systems, revolutionising patient data management and improving healthcare service delivery. Despite slower adoption in PHC facilities, recent efforts aim to incorporate EHR systems to enhance the effectiveness, accuracy, and accessibility of patient data, ultimately improving the standard of care provided at these facilities [13], [14].

Tanzania's adoption of EHR systems marks a significant advancement in healthcare technology. However, there remains a critical gap in understanding how PHC practitioners perceive the effectiveness of these systems, particularly in the context of decision support. In this study, "decision support" refers to the suite of functionalities within EHR systems designed to assist healthcare practitioners in making informed clinical decisions [15]. These functionalities include, but are not limited to, drug-allergy interaction checks, detection of duplicate treatments, and drug dosage warnings. Furthermore, decision support extends to tools that facilitate clinical data interpretation, such as preventive care reminders and diagnostic support [16], [17], [18], [19], [20]. While features like order administration and information retrieval are essential for overall workflow efficiency, this study focuses on those EHR functionalities that directly impact the quality and safety of clinical decision-making. Given these considerations, the central research question guiding this study is: How do primary healthcare practitioners in Tanzania perceive the effectiveness of EHR systems in supporting clinical decision-making, mainly through specific decision-support tools such as drug-allergy interaction checks, duplicate treatment detection, and dosage warnings? By examining PHC practitioners' perceptions of these specific decision-support tools, the study seeks to identify the strengths and limitations of current EHR implementations in Tanzanian PHC settings.

Understanding how frontline healthcare practitioners perceive these systems is crucial for identifying gaps in current EHR system implementations and guiding future improvements in EHR system design and training programs, ultimately enhancing patient care quality and safety in Tanzanian PHC settings.

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The rest of the paper is structured as follows: First, we present the synthesis of the literature review. Then, we describe the conceptual framework of our study. We describe the material and methods that guide this study, followed by the results. Finally, we discuss the implications of the findings and conclude the study.

2 Literature Review

The implementation and effectiveness of EHR systems in healthcare settings have been widely studied, particularly in developed countries[21], [22], [23], [24]. However, the unique challenges and opportunities in low-resource settings, such as those in Tanzania, remain underexplored. This literature review synthesises current research on the role of EHR systems in supporting clinical decision-making, focusing on their perceived usefulness, ease of use, and actual usage by healthcare practitioners in PHC facilities.

EHR systems are digital platforms designed to store, manage, and share patient health information across different healthcare settings[25], [26], [27], [28]. These systems are known for their potential to improve healthcare delivery by enhancing the accuracy and accessibility of patient data, streamlining administrative processes, and supporting clinical decision-making through integrated decision-support tools[5], [29], [30], [31]. According to Mwogosi [32], EHR systems are integral to modern healthcare, providing a comprehensive and accessible record of patient interactions that improve the continuity of care and facilitate coordinated treatment across providers.

In Tanzania, the adoption of EHR systems has been driven by the government's efforts to modernise healthcare delivery and address the inefficiencies of paper-based records [33]. The Government of Tanzania Health Operations Management Information System (GoTHoMIS) is one such initiative aimed at enhancing the management of patient information and improving healthcare outcomes[34], [35]. Despite these advancements, the effectiveness of EHR systems in supporting clinical decision-making, particularly in resource-constrained PHC facilities, has been mixed [36].

Studies have shown that when healthcare practitioners perceive EHR systems as valuable, particularly in supporting clinical decision-making, they are more likely to integrate them into their daily workflows. For instance, Kruse et al. [5] found that EHR systems that provided robust decision-support tools, such as alerts and reminders, were more likely to be used effectively in clinical settings. However, the ease of use of these systems also plays a significant role. Systems that are difficult to navigate or require significant time to input or retrieve data can hinder their perceived usefulness, leading to lower adoption rates[37].

Clinical decision support (CDS) systems embedded within EHR platforms are designed to assist healthcare providers in making more informed and timely decisions [15]. These tools can include drug-drug interaction checks, dosage recommendations, preventive care reminders, and diagnostic support [38], [39]. According to Sutton [40], effective CDS systems can potentially reduce medical errors, enhance diagnostic accuracy, and improve adherence to clinical guidelines. However, the integration and effectiveness of these tools vary significantly across different EHR systems.

The adoption and effectiveness of EHR systems in low-resource settings like Tanzania face several unique challenges. Infrastructure limitations, such as unreliable electricity and internet connectivity, can significantly hinder the implementation and use of EHR systems. Furthermore, the lack of technical support and training for healthcare practitioners further exacerbates the difficulties in effectively utilising these systems [41].

Moreover, cultural and organisational factors are crucial in accepting and using EHR systems [42]. For instance, resistance to change among healthcare practitioners, particularly those accustomed to paper-based records, can slow the adoption of EHR technologies [43]. Furthermore, the perceived complexity of the systems and concerns about data security and patient privacy may further discourage their use [44], [45].

There is limited knowledge about the effectiveness of EHR systems in supporting clinical decision-making within PHC facilities in Tanzania. While EHR systems have been implemented to modernise healthcare delivery, the extent to which these systems truly enhance decision-making processes at the PHC level remains underexplored. The scarcity of empirical data on how healthcare practitioners perceive and utilise these systems for decision support highlights the need for focused research to understand better and optimise the role of EHR systems in improving patient care in Tanzania's PHC settings.

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3 Conceptual Framework

The conceptual framework for this study is anchored in the Technology Acceptance Model (TAM), a well-established theory used to understand how users come to accept and use technology[46], [47]. TAM suggests that two primary factors, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), significantly influence an individual's intention to use and actual use of technology[45], [48]. In the context of this study, which examines the effectiveness of EHR systems in supporting clinical decision-making in PHC facilities in Tanzania, TAM provides a valuable lens through which healthcare practitioners' perceptions can be understood.

Perceived Usefulness (PU) in this framework refers to the degree healthcare practitioners believe EHR systems enhance their job performance, particularly in clinical decision-making[47]. The study measures PU by evaluating practitioners' perceptions of the effectiveness of various decision-support functionalities within EHR systems, such as alerts, reminders, drug-allergy interaction checks, and diagnostic support tools[16], [20], [49], [50]. These functionalities are critical as they directly impact the ability of healthcare providers to make informed clinical decisions, which is a crucial goal of implementing EHR systems in healthcare settings[51], [52], [53].

Perceived Ease of Use (PEOU) is another vital concept in this framework. It pertains to how healthcare practitioners find the EHR systems user-friendly[47], [54]. It includes the ease with which practitioners can navigate the system, access patient data, and use the available tools without undue effort. The study assesses PEOU through feedback on the usability of EHR systems like GoTHoMIS Lite, eHMIS, Care2X, and AfyaPro. Systems that are easier to use are expected to be perceived as more beneficial, thus influencing their overall acceptance and utilisation [47].

The concept of actual system use is also central to the framework. It represents the degree to which EHR systems are adopted and utilised in daily clinical practice. This is measured by the frequency of use of decision-support features, the duration of experience practitioners have with the systems, and the variability of system use across different facilities (public versus private). The framework posits that the more valuable and easier-to-use an EHR system is perceived, the more likely it is to be used regularly by healthcare practitioners [48].

Clinical decision support (CDS) within the EHR systems is another crucial component, encompassing tools designed to aid healthcare providers in making more accurate and timely clinical decisions [15]. The study evaluates the effectiveness of these CDS tools, including functionalities like drug-drug interaction checks, dosage warnings, and preventive care reminders [31]. The actual use of these tools is hypothesised to improve clinical decision-making and, ultimately, patient care quality in PHC settings.

In this framework shown in Figure 1, the relationships among these concepts are interconnected. The PEOU of an EHR system is expected to positively influence its perceived usefulness, which in turn impacts the actual usage of the system. The more a system is used, particularly its decision-support features, the more it is expected to enhance clinical decision-making processes. This conceptual framework not only guides the analysis of the data collected from healthcare practitioners but also helps identify areas for targeted improvements in EHR systems to optimise their effectiveness in supporting clinical decisions in Tanzanian PHC facilities.

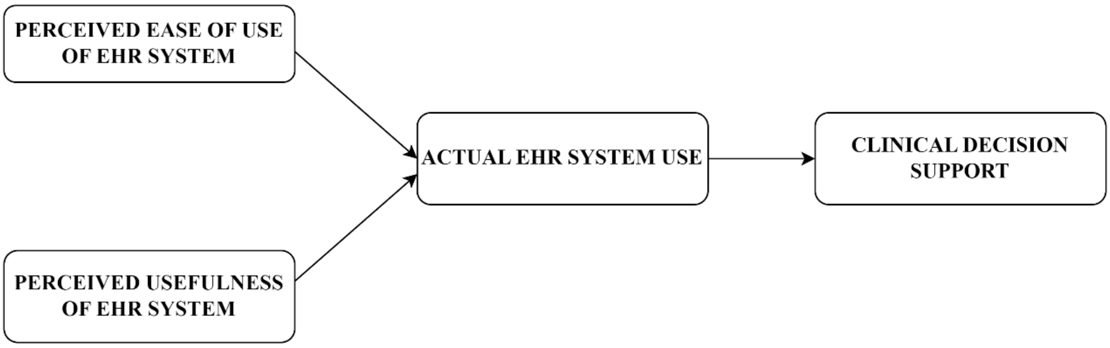

Figure 1: Conceptual Framework (**Source:** Researchers' work)

4 Materials and methods

4.1 Study Setting and Design

This study was conducted in the Dodoma region of Tanzania, a rapidly growing area with over 3 million residents and 644 healthcare facilities, including 475 PHC facilities. The region was selected due to its representative nature and the availability of diverse healthcare facilities, making it an ideal setting for evaluating the implementation and impact of EHR systems on decision-making processes in PHC settings.

A cross-sectional, quantitative research design was adopted to assess primary healthcare practitioners' perceptions of the effectiveness of EHR systems in providing decision support. This design was chosen for its ability to provide objective, quantifiable insights across a large sample of healthcare practitioners, enabling generalisable findings relevant to similar contexts.

4.2 Participants and Sampling

The study targeted a diverse group of participants, including medical doctors, clinical officers, nurses, laboratory staff, healthcare managers, health information personnel, IT professionals, and policymakers working in PHC facilities within the Dodoma region.

The inclusion criteria were:

1. Healthcare practitioners and administrators are directly involved in PHC delivery in the Dodoma region.
2. PHC facilities that had implemented and utilised EHR systems.
3. Facilities representing a mix of public and private ownership types

Exclusion criteria included:

1. PHC facilities that had not implemented or utilised EHR systems.
2. Facilities located outside the Dodoma region.
3. Facilities serving specialised populations exclusively.
4. Practitioners who did not consent to participate.

A multi-stage sampling procedure was employed, combining random, stratified, purposive, and snowball techniques to ensure a representative sample of PHC facilities. Initially, a comprehensive list of PHC facilities was compiled and categorised by facility type (e.g., district hospitals, health centres, dispensaries). Among the 475 PHC facilities in the region (see Table 1), only 49 had implemented and used EHR systems.

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Table 1: Number of PHC facilities in Dodoma region

Facility Type	Managing Authority	Total number of facilities	Facilities using EHR systems
District Hospital	Public	7	7
Hospital at the district level	Private	3	3
Health center	Public	55	20
	Private	6	6
Dispensary	Public	325	3
	Private	79	10
Total		**475**	**49**

Source: Researchers' work

4.3 Sample Size Calculation and Allocation

The sample size was determined to include 37 out of the 49 PHC facilities in the Dodoma region that had implemented EHR systems. This size was calculated to ensure a 95% confidence level with a 5% margin of error, providing a representative sample of facilities. The sample was then proportionally allocated across different facility types, as summarised in Table 2, to ensure that each type was appropriately represented in the study.

Table 2: Sample Size Calculation for each stratum

Facility Type	Managing Authority	N_i	$\frac{N_i}{N} * n$
District Hospital	Public	7	5
Hospital at the district level	Private	3	2
Health centre	Public	20	15
	Private	6	5
Dispensary	Public	3	2
	Private	10	8
Total		**49**	**37**

Source: Researchers' work

4.4 Data Collection Instruments

Data were collected using a structured questionnaire and an observation checklist. The questionnaire was developed for this study and aimed to capture detailed information on EHR system functionalities' use and perceived effectiveness, focusing mainly on decision-support capabilities. The questionnaire included closed-ended and open-ended questions to allow for comprehensive responses. The instrument was pre-tested with a small group of practitioners to ensure clarity and relevance before full deployment.

Structured observations were conducted in a subset of PHC facilities to assess how practitioners directly interacted with the EHR systems. Observations focused on critical activities such as data entry, navigation, patient information retrieval, and decision-support features.

4.5 Data Analysis

Descriptive statistics, including frequencies and percentages, were used to summarise the characteristics and functionalities of the EHR systems implemented in the PHC facilities. Crosstabulation analyses were performed to assess the decision-support capabilities of various EHR systems, followed by chi-square tests to identify any significant correlations between the type of EHR system used and its decision-support

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functionalities. Moreover, a One-Way Analysis of Variance (ANOVA) was conducted to determine if there were significant differences in the decision-support capacities among the various EHR systems employed in the studied facilities. These statistical methods were crucial in objectively evaluating the effectiveness of EHR systems in supporting clinical decision-making processes.

5 Results

5.1 Socio-demographic characteristics of the respondents

The demographic analysis revealed that most respondents were male (60.6%), with the largest age group being 18-34 (65.5%). Most respondents had attained an ordinary-level diploma (72.1%), followed by those with a university degree (24.2%). Clinical officers comprised the most significant proportion of healthcare workers (44.2%), followed by nurses (29.7%). The distribution of healthcare professionals across facility types showed that clinical officers and nurses were predominantly employed in dispensaries and health centres. At the same time, medical doctors and midwives were more commonly found in health centres and district hospitals. A significant association was observed between the healthcare workers' roles and the type of facility they worked in, indicating variations in their familiarity and capacity to use EHR systems effectively. Notably, district hospitals reported a higher presence of ICT officers (10.9%), reflecting a greater demand for technical support in these more extensive facilities. These socio-demographic characteristics suggest that the successful implementation and utilisation of EHR systems in primary healthcare facilities may depend on adapting training and support to different healthcare worker groups' specific needs and capabilities.

5.2 EHR systems implemented at the PHC facilities in Tanzania

The study revealed that GoTHOMIS Lite was the most commonly implemented electronic health record (EHR) system in Tanzanian PHC facilities, utilised by approximately 56.8% of surveyed facilities. eHMS was the second most popular system, adopted by 18.9% of facilities, while AfyaPro and Care2X were adopted by 8.1% and 5.4%, respectively. Various healthcare facilities also implemented other EHR systems like AfyaCare, Magnone, Medex, and Paracare (Table 4).

Table 3: EHR System Implemented in the PHC Facilities in Tanzania

EHR system	Frequency	%
AfyaCare	1	2.7
AfyaPro	3	8.1
Care2X	2	5.4
eHMS	7	18.9
GoTHoMIS Lite	21	56.8
Magnone	1	2.7
Medex	1	2.7
Paracare	1	2.7
Total	37	94.5

Source: Researchers' work

Publicly owned facilities predominantly utilised GoTHOMIS Lite (95.5%), while privately owned facilities favoured eHMS (53.3%). Significant differences in EHR system adoption between public and private facilities were noted ($\chi 2$ (37.926, n = 37) = 7; P = 0.000), as shown in Table 5.

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Table 4: Association between the type of EHR System and the Facility Ownership

EHR System	Facility Ownership				Total
	Public		Private		
	No	%	No	%	
Afyacare	0	0	1	6.7	1
AfyaPro	1	4.5	1	6.7	12
Care2X	0	0	2	13.3	8
eHMS	0	0	8	53.3	31
GoTHoMIS	21	95.5	0	0	95
Magnone	0	0	1	6.7	1
Medex	0	0	1	6.7	1
Parecare	0	0	1	6.7	1
Total	22	100	15	100	165

Pearson Chi-Square = 37.926a, DF = 7, P = 0.000

Source: Researchers' work

5.3 Years of using EHR Systems across different working Units

Descriptive statistics were used to summarise the distribution of years of experience using EHR systems across working units and healthcare facilities. The histograms in Figure 7 and Figure 8 were used to visualise the distribution of years of using the EHR System for each group. The visual representations of this distribution reveal varied experiences across different facilities and working units. General clinical services, health centres, and district hospitals exhibited higher concentrations of EHR system usage.

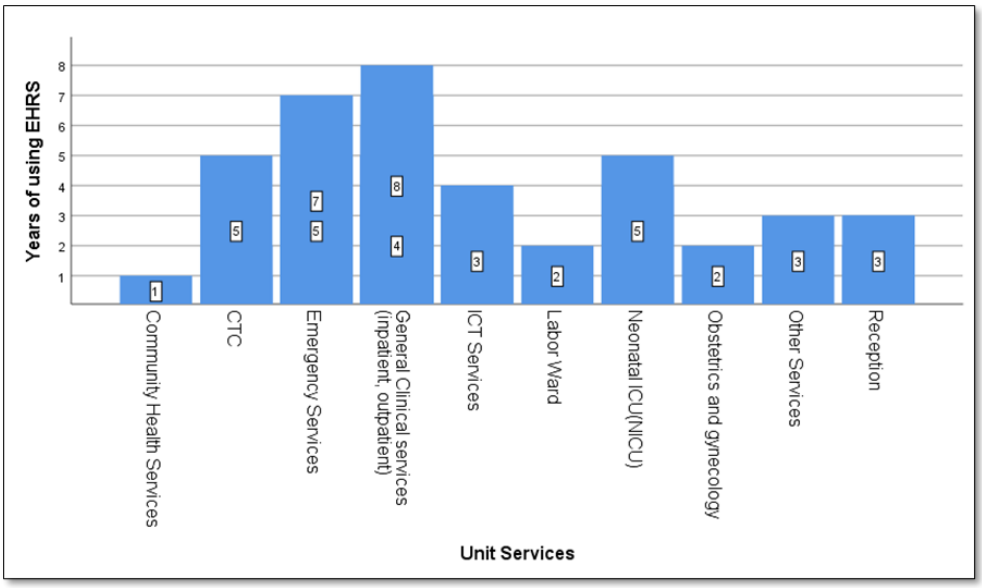

Figure 2: Distribution of years of using the EHR System across different working Units (

Source: Researchers' work

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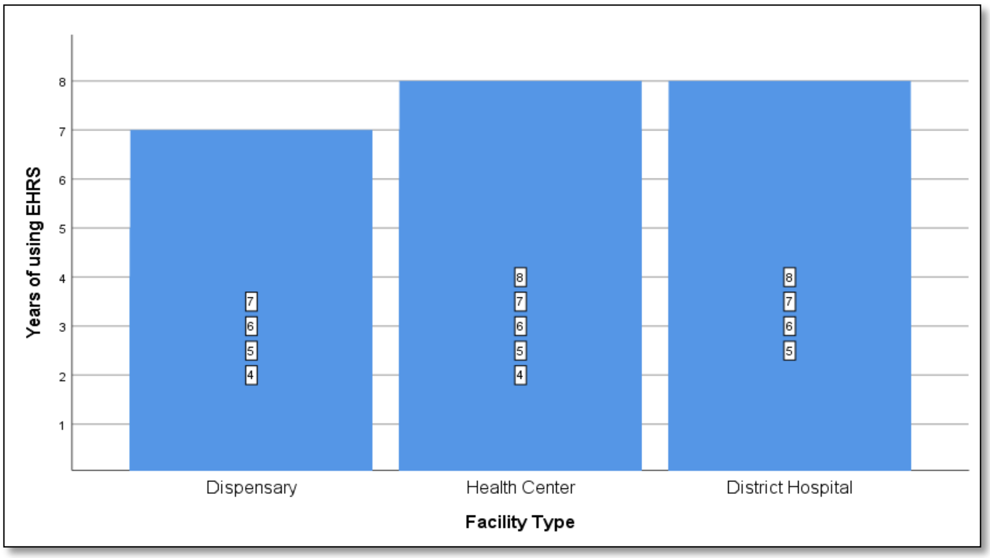

Figure 3: Distribution of years of using EHR System across different Healthcare Facilities

Source: Researchers' work

5.4 Years of using EHR Systems by ownership of Healthcare Facilities

Table 5 summarises the descriptive statistics for using EHR Systems by ownership of healthcare facilities. The results in Table 6 include the mean and standard deviation for each group (private and public). The histograms in Figure 4 and Figure 5 were used to visualise the distribution of years of using the EHR System for each group.

Table 5: Ownership of Healthcare Facilities and Years of Using EHR System

Ownership	Mean years of using EHR System	Standard Deviation
Private	2.77	1.823
Public	2.93	1.473

Source: Researchers' work

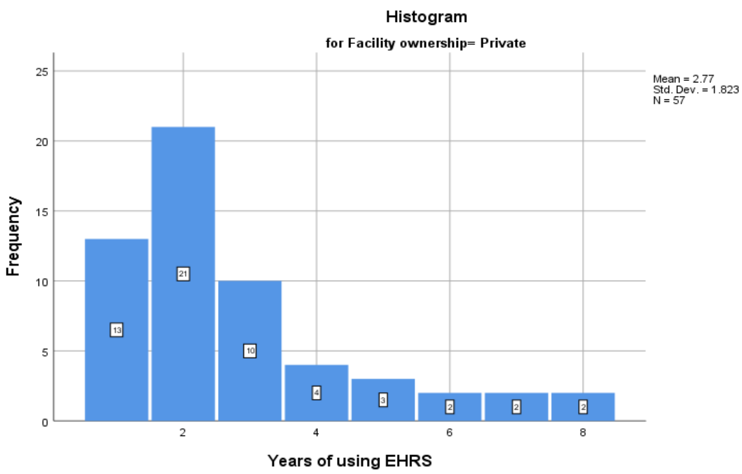

Figure 4: Distribution of years of using EHR System for Private Facilities

Source: Researchers' work

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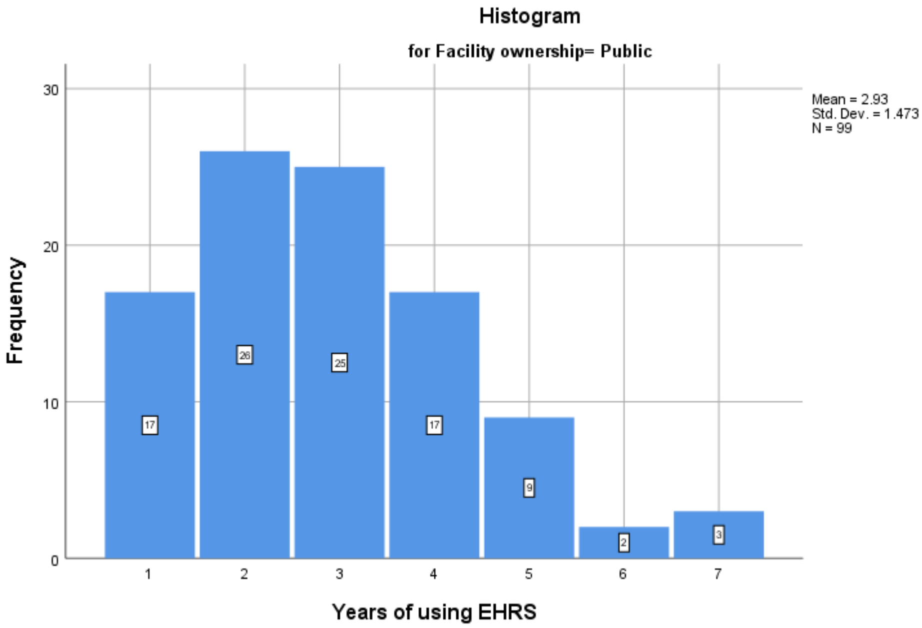

Figure 5: Years of using EHR System for Public Facilities

Source: Researchers' work

The boxplot in Figure 6 illustrates the distribution of years of using EHR Systems for private and public healthcare facilities. The boxplot for public facilities is skewed to the right, indicating a more extended EHR System use than public facilities. The mean years of using the EHR Systems for public facilities was 2.93 years, with a standard deviation of 1.473. In contrast, the mean years of use of the EHR Systems for private facilities was 2.77 years, with a standard deviation of 1.823.

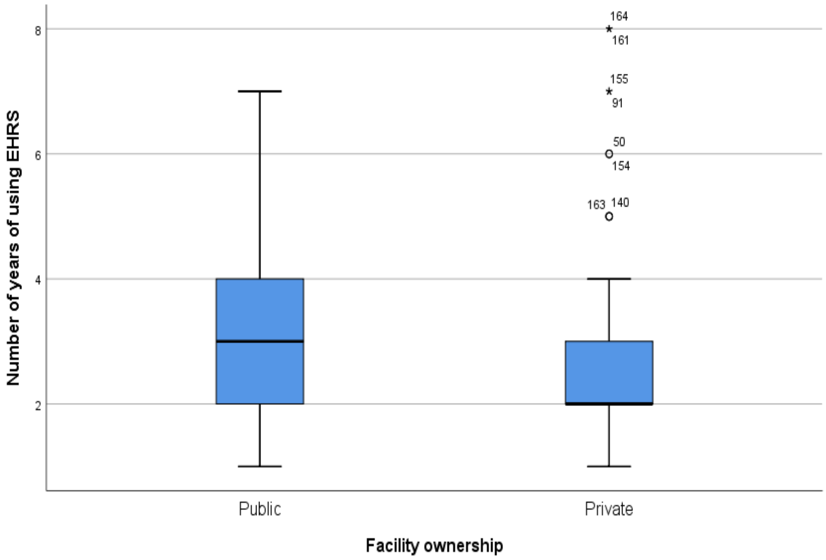

Figure 6: Boxplot of years of using EHR System by ownership of Healthcare Facilities

Source: Researchers' work

5.5 The perception of healthcare practitioners on the effectiveness of EHR System functionalities in providing decision support in PHC facilities in Tanzania

The study findings reveal that healthcare professionals in the Dodoma region view EHR systems as essential tools in healthcare delivery, particularly for their ability to facilitate quick access to patient information—a feature that 89.7% of respondents found beneficial. Moreover, 87.3% of respondents appreciated the ease with which laboratory results could be shared through these systems, and 81.2% recognised the systems' utility in managing orders. These functionalities are crucial for maintaining efficient workflows in healthcare settings and ensuring clinicians can access critical patient data on time. However, while these features are valuable for general healthcare delivery, they do not fully address the specific requirements of clinical decision-making.

Despite the overall utility of EHR systems, significant limitations were identified in their ability to support more complex decision-making processes. Only 24.2% of respondents felt that EHR systems effectively aided clinical decisions, suggesting that the systems are falling short in this critical area. Moreover, only 26.4% of respondents recognised the effectiveness of provider-to-provider communication features within these systems, indicating that the communication tools necessary for collaborative decision-making are not fully optimised.

Specific decision-support functionalities, essential for ensuring patient safety and preventing errors, were reported to be notably lacking. For instance, only 15.8% of respondents found the drug-allergy interaction checks compelling, and just 37.6% reported that the systems could reliably detect duplicate treatments. Furthermore, only 23.6% of respondents believed that the drug dosage warnings provided by the systems were adequate. These figures highlight a significant gap in the ability of EHR systems to support clinical decisions, as these tools are critical for guiding safe and effective patient care.

ANOVA was conducted to assess whether there were significant differences in the decision-support capabilities of various EHR systems used in PHC facilities. The analysis focused on crucial functionalities critical to clinical decision-making, including drug-drug interaction checks, drug-allergy interaction checks, dosage warnings, preventive care reminders, and diagnostic support. The results indicated no significant differences among the EHR systems in any of these decision-support functionalities, as reflected by p-values that all exceeded the threshold for significance (p-values: 0.467, 0.688, 0.410, 0.413, and 0.860, respectively).

These findings suggest that, across the board, the EHR systems evaluated in this study perform similarly in their decision-support roles, regardless of the specific platform or system used. This uniformity, however, does not point to strength but highlights a consistent shortfall across all systems in adequately meeting the decision-support needs of healthcare practitioners in Tanzanian PHC facilities. The lack of variability in performance underscores the pervasive issue that no current EHR systems provide the robust decision support required to enhance clinical outcomes significantly.

Direct observations further revealed specific strengths and weaknesses of the EHR systems. While all systems were praised for their usability, mainly their ease of access to patient data, there were notable differences in their decision-support functionalities. Care2X stood out for its comprehensive decision-making tools and functional direct messaging, facilitating better communication and clinical decisions, though it lacked predictive analytics. In contrast, systems like GoTHOMIS Lite and AfyaPro were lacking in these areas, with no observed direct messaging capabilities, clinical decision support algorithms, or predictive analytics tools. eHMIS, while slightly better with direct messaging, still fell short in providing robust decision-support functionalities and lacked advanced tools like comprehensive diagnostic support and integration with external data sources. These observations align with the feedback from healthcare practitioners and point to a need for targeted enhancements in the decision-support capabilities of these EHR systems, particularly those used in resource-limited settings.

Table 6: Summary of EHR System Systems' Usability, Functionality, and Decision-Making Tools

EHR system	Usability	Functionality	DSS features
GoTHoMIS Lite	Easy to use	Limited functionality for decision-making	No direct messaging, no clinical decision support algorithms, and no other communication tools observed
eHMIS	Easy to use	Limited functionality for decision-making	Direct messaging was observed but had limited functionality; it lacks advanced clinical decision support tools like predictive analytics and comprehensive diagnostic support.
Care2X	Easy to use	Robust decision-making tools	Direct messaging observed with good functionality; comprehensive clinical decision support tools, including diagnostic support
AfyaPro	Easy to use	Limited functionality for decision-making	No direct messaging, no clinical decision support algorithms, and no other communication tools observed

Source: Researchers' work

6 Discussion

This study aimed to explore PHC practitioners' perceptions of the effectiveness of EHR systems in providing decision support within Tanzanian PHC settings. The key findings highlight that while EHR systems are widely recognised for improving administrative processes and facilitating access to patient information, their effectiveness in supporting clinical decision-making remains limited. Only 24.2% of respondents agreed that EHR systems effectively support clinical decision-making, with significant gaps identified in functionalities such as drug-allergy interaction checks, duplicate treatment detection, and drug dosage warnings.

The limited effectiveness of EHR systems in supporting clinical decision-making can be attributed to several factors, such as the lack of advanced decision-support tools, including drug-allergy interaction checks and predictive analytics, which are critical for informed clinical decisions. The analysis highlights that while functionalities such as drug-allergy interaction checks and drug dosage warnings are crucial for effective decision-making, their underutilisation, as revealed through the study's statistics, suggests that EHR systems in Tanzanian PHC facilities may not be fully equipped to support these critical aspects of clinical care. This underscores the importance of not just the availability of these tools but also their integration and the training provided to ensure that healthcare practitioners can effectively utilise them in their decision-making processes. Moreover, insufficient integration of EHR systems with existing healthcare workflows and the absence of user-friendly interfaces can hinder practitioners' ability to utilise these systems efficiently. Moreover, inadequate training and support for healthcare practitioners and infrastructural challenges such as unreliable power supply and internet connectivity further exacerbate the limitations of EHR systems in these settings.

The analysis revealed that most EHR systems, particularly GoTHoMIS Lite and AfyaPro, lack comprehensive decision-support tools such as direct messaging capabilities and clinical decision-support algorithms. These deficiencies hinder the ability of healthcare practitioners to make informed clinical decisions, thus impacting the overall quality of care. The study's findings suggest that while these systems benefit data management and administrative tasks, they fall short in providing the necessary support for complex decision-making processes in clinical settings, consistent with findings from other low-resource settings.

The findings of this study align with previous research, indicating that the adoption and effectiveness of EHR systems are influenced by their perceived usefulness and ease of use resource settings [37], [55]. EHR systems often have robust decision-support features, such as drug interaction alerts, predictive analytics, and clinical decision algorithms, significantly enhancing clinical decision-making [53], [56]. For example, the United States and Europe have shown that well-integrated CDS systems within EHR platforms can reduce medical errors, improve diagnostic accuracy, and ensure adherence to clinical guidelines[57].

However, resource-constraints environments like Tanzania present a plain contrast. The lack of these critical functionalities reflects broader systemic challenges, including limited infrastructure, inadequate training, and resistance to technological adoption [36], [38]. This aligns with research in other low- and middle-income countries where similar issues, such as unreliable electricity, limited internet connectivity, and insufficient financial resources, often hamper the adoption of EHR systems[58]. Moreover, the cultural context, practitioners' familiarity with technology and organisational resistance to change further complicates the effective use of EHR systems for decision support [59].

The gap between the capabilities of EHR high- versus low-resource settings underscores the need for personalised solutions that address the specific challenges faced in environments like Tanzania. For instance, while EHR systems in developed countries are increasingly integrated with advanced AI-driven decision-support tools[60], [61], [62], [63], the systems in PHC facilities in Tanzania are often limited to basic functionalities, which may not meet the complex needs of clinical decision-making. This disparity calls for re-evaluating the strategies to implement EHR systems in resource-constrained settings, ensuring they are designed to overcome these unique barriers.

The study's findings underscore an urgent need to enhance the functionality of EHR systems in Tanzanian PHC settings by adding advanced decision-support tools such as predictive analytics, drug interaction alerts, and comprehensive diagnostic support and addressing critical usability and integration issues identified through practitioner insights. While specific functionalities, such as detecting duplicate treatments or providing drug dosage warnings, are essential, practitioners' perceptions reveal that these gaps extend beyond mere functionality. Issues like lack of user-friendly interfaces and limited integration into daily workflows hinder effective adoption, even when specific capabilities exist. Combining functionality assessment with practitioner insight, this dual approach clarifies how EHR systems can be optimised by aligning features with practitioners' real-world challenges. These findings suggest that developers focus on both functional enhancements and practical usability improvements, ensuring that decision-support tools are both present and effectively integrated, ultimately fostering a more supportive clinical environment in Tanzanian PHC facilities.

From a policy perspective, the findings suggest the need for a national strategy to standardise and improve EHR systems across all healthcare facilities. Policymakers should consider investing in the infrastructure to support more advanced EHR functionalities, including reliable internet access and power supply. Moreover, policies should promote the implementation of EHR systems with robust decision-support capabilities as a standard requirement in all PHC facilities. This could be supported by government incentives or funding programs to reduce the cost burden on healthcare providers in adopting these systems. Moreover, policies that mandate regular training and certification for healthcare workers in EHR systems could ensure consistent and effective utilisation nationwide.

Theoretically, this study contributes to understanding technology adoption in healthcare settings, particularly within low-resource environments. It reinforces the relevance of TAM in explaining the factors that influence the adoption and use of EHR systems. However, it also highlights the need to expand TAM to account for contextual factors unique to low-resource settings, such as infrastructure limitations and cultural resistance to technology. Future research could build on this by exploring how these additional variables impact EHR systems' perceived usefulness and ease of use in different contexts. Furthermore, the study calls for developing new theoretical models that integrate these contextual factors to predict better the successful implementation of health technologies in low-resource settings.

One of the critical limitations of this study is its focus on a single region in Tanzania, which may limit the generalizability of the findings to other regions with different healthcare infrastructures and resources. Moreover, the study relied on self-reported data from healthcare practitioners, which may be subject to bias. Observational data, while valuable, was limited in scope and may not capture the full extent of EHR system utilisation in real-world settings.

Future research should explore the impact of specific enhancements to EHR systems on clinical decision-making outcomes in PHC settings. Besides, expanding the study to include multiple regions across Tanzania could provide a more comprehensive understanding of the challenges and opportunities associated with EHR system implementation in diverse healthcare environments. Research should also investigate the role of continuous professional development in improving the use of EHR systems for decision support among healthcare practitioners.

While EHR systems in Tanzanian PHC facilities are valuable tools for data management and administrative tasks, their current limitations in supporting clinical decision-making highlight the need for targeted improvements. By addressing these gaps, EHR systems can be optimised to better support healthcare practitioners in delivering high-quality care, ultimately enhancing patient outcomes in Tanzania.

7 Conclusion

This study has provided valuable insights into the perceptions of healthcare professionals in the Dodoma region regarding the effectiveness of EHR systems in supporting clinical decision-making within PHC settings. While EHR systems are widely recognised for enhancing administrative efficiency and providing quick access to patient information, their effectiveness in directly supporting clinical decisions remains limited. Key decision-support functionalities, such as drug-allergy interaction checks, detection of duplicate treatments, and drug dosage warnings, were underutilised or inadequately implemented, raising concerns about the systems' capacity to improve patient safety and care quality.

As revealed in this study, healthcare practitioners' perceptions reflect a significant awareness of the limitations of current EHR systems. This perception is correct; the study's findings indicate that the current EHR systems lack the necessary decision-support functionalities to reduce errors and improve clinical outcomes. As such, these perceptions highlight a genuine need for system upgrades to include more robust decision-support tools, such as predictive analytics, comprehensive diagnostic support, and advanced alert systems.

However, the study also suggests that the underutilisation of existing functionalities may be partly due to a lack of awareness or insufficient training among healthcare practitioners. Therefore, it is essential to address this issue from both angles: upgrading the EHR systems to include the missing functionalities and providing comprehensive training to ensure that healthcare practitioners can fully leverage these tools in their decision-making processes.

In conclusion, while the current perceptions of EHR systems' decision-support capabilities are largely accurate, they also point to an opportunity for improvement. Policymakers and healthcare administrators should prioritise both the enhancement of EHR systems and the provision of targeted training programs. By doing so, it will be possible to fully realise the potential of EHR systems to support clinical decision-making, reduce errors, and ultimately improve the quality of healthcare delivery in Tanzanian PHC settings.

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Statement on conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Author Contributions

AM, SK, and DS conceptualised the study. AM conducted data collection, performed the analysis, and drafted the manuscript. SK and DS supervised the research. All authors (AM, SK, and DS) critically reviewed the manuscript and approved the final version for publication.

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Data Precision and Timeliness of Paper versus Software-Assisted Nursing Documentation: A Rapid Review and Meta-Analysis

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Background and Purpose: The nursing industry has progressively transitioned from paper-assisted documentation practices to software-assisted systems. Such a transition raises debates about its implications on the timeliness and precision of documented nursing data. This rapid review and meta-analysis examined existing literature on the effect of paper and software-assisted documentation systems on documentation precision and timeliness.
Methods: Utilizing the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines, this review and meta-analysis examined studies published in the past 50 years (1973 to 2023) and available in PubMed electronic database. The search methodology combined free-text search terms with Boolean operators for a more precise and sensitive search.
Results: The review and meta-analysis selected 15 studies from a pool of 314 articles after applying set inclusion criteria. The synthesis of evidence revealed that Software-assisted nursing documentation systems enhanced by twofold the precision of documented nursing data (Overall random effect Odds Ratio: 2.35, 95% CI: 1.32-4.17; $p = < 0.010$). Software-assisted nursing documentation systems reduced time spent on nursing documentation by nine minutes but was not significant (Overall random effects mean difference = 9.14 minutes; $p = 0.330$).
Conclusions: Software-assisted nursing documentation is valuable for enhancing nursing documentation precision but not timeliness. This study recommends software-assisted nursing documentation systems for improving the precision of nursing documentation.

Keywords: Nursing documentation, Paper records, Precision, Software, Timeliness.

1 Introduction

Nursing care documentation is an essential component of patient care. It archives nursing assessments, interventions, and outcomes [1]. Traditionally, nurses used pen and paper-assisted systems that involved handwritten notes on paper charts [2]. While this method sufficed for years, it posed inherent limitations: illegible handwriting, inconsistencies in nursing diagnosis codes, and extended time spent on documentation [3]. However, with the introduction of Electronic Health Records, software-assisted systems are quickly replacing the paper-assisted documentation system in healthcare facilities [4] [5].

Software-assisted nursing documentation systems have aimed to address the shortcomings of paper-assisted documentation [6]. The systems brought with them improved legibility of records, quick data retrieval and update capabilities [7]. It offers healthcare professionals a more efficient and organized means of recording patient information [8]. Yet, challenges persist regarding the perceived impact on the timeliness and precision of nursing data [9].

Precision is paramount in nursing care quality [10]. The precision of nursing documentation refers to the accuracy and specificity of the information recorded by nurses in patient care documents [11]. It entails capturing details with clarity and completeness, ensuring that the documented information accurately reflects the patient's condition, assessments, interventions, responses, and outcomes [12]. It involves using standardized language consistent with professional guidelines and healthcare standards [13]. Software-

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assisted systems incorporate features such as decision support tools and validation checks to improve data precision [6]. However, proponents of paper documentation argue in favour of its personalized and narrative approach, suggesting a deeper connection between nurse and patient [10].

Timeliness in nursing care documentation is crucial for effective patient care decision-making, care delivery, and inter-professional communication [14]. The timeliness of nursing documentation refers to the promptness with which the nurse records relevant information about patient care activities, assessments, interventions, and outcomes [15]. It indicates how quickly nurses document patient care and the subsequent updates to patient records [13]. Software-assisted systems facilitate instant access to patient information and real-time data recording [16] [17]. Conversely, paper-assisted documentation may delay accessing patient information and updating patient records, thus impacting nursing care decision-making and coordination [5] [10].

Although software-assisted systems offer some benefits, user-friendly challenges may also limit their utility to the nursing industry in terms of data precision and timeliness [12]. This debate raises the question of whether a complete departure from paper-assisted nursing documentation is justified, considering the need for precision and timeliness of documentation.

2 Materials and methods

This rapid review and meta-analysis examined evidence concerning the timeliness and precision of electronic and paper-based nursing care documentation on a global scale. This study utilized the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines [18] [19]. The PubMed electronic database was searched for related studies published between 1973 and 2023 (50 years). The search strategy employed Boolean operators (AND, OR, and NOT) and truncations (*) to combine free-text search terms as follows: (Timeliness OR Time* OR Efficiency OR Precision OR Accuracy) AND (Software OR Electronic) AND (Paper) AND (Nursing OR Nurs*) AND (Documentation OR Document*) NOT (Systematic Review). Hand searches for related studies referenced in retrieved articles were done using the descendant and ancestral approach. The inclusion criteria were as follows to ensure the selection of high-quality studies: (a) primary studies such as randomized controlled trials, quasi-experimental studies, and observational studies, (b) studies involving nurses as participants, (c) compared software to paper-assisted nursing documentation systems, (e) examined quality outcomes related to the timeliness and precision of nursing documentation, (f) published within the past fifty years (1973-2023), (g) available in English, (h) accessible in peer-reviewed academic journals and (i) presented in full-text format. This study excluded systematic reviews, case studies, protocols, and qualitative studies. Two authors (CE and JCS) independently conducted the search and study selection. Discrepancies between search results were discussed with co-authors (CAN and ILO) and resolved through consensus.

The search identified potentially relevant articles. Duplicate entries were removed from the initially retrieved articles. Subsequently, screening of titles and abstracts was done and articles with non-related titles and abstracts were excluded. The full texts of the remaining articles were examined for eligibility. Eligible studies were included in the review and meta-analysis. The quality of evidence in the selected studies was assessed with the help of the Johns Hopkins Evidence-Based Practice Model for Levels of Research Evidence [20]. Relevant data from the included studies were extracted using a data extraction form designed by the research team to extract and tabulate pertinent information covering author details, country, study design, sample characteristics, and study outcomes. Risk of publication bias across the studies was assessed statistically using a Funnel Plot supported by the Egger’s test. The data extraction process was carried out independently by two authors (CE and JCS) with the aid of Microsoft Excel 2007 software. Inconsistencies in data extraction were resolved through mutual agreement after deliberations with co-authors (ACN and ILO).

3 Results

Figure 1 depicts the study selection process. The application of data inclusion criteria in this review and meta-analysis resulted in the identification of 15 studies. The literature search yielded 314 articles, with PubMed providing 301 direct hits and 13 hits from manual searches. Screening titles and abstracts led to

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the identification of 40 potentially relevant articles. Upon examination of the full-text articles and application of inclusion criteria, 15 eligible studies were included in the review and meta-analysis. Of the selected 15 studies, four examined timeliness only, four examined both timeliness and precision, while seven examined only precision.

Figure 2 shows the funnel plot for risk of publication bias. The funnel plot indicated no potential risk of bias. The Egger's test did not support the presence of funnel plot asymmetry (Intercept = -1.58, 95% CI:-4.1 - 0.94, t = -1.227, p-value = 0.251).

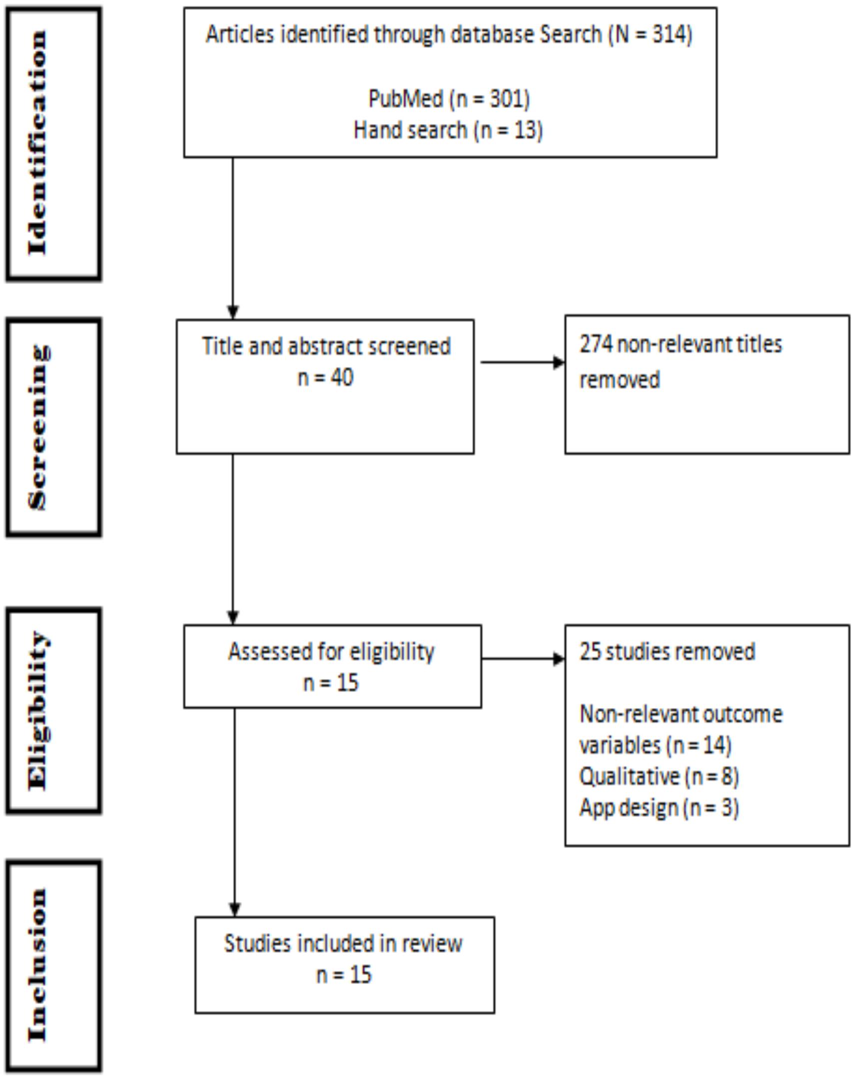

Figure 1: Study selection process (PRISMA flow diagram)

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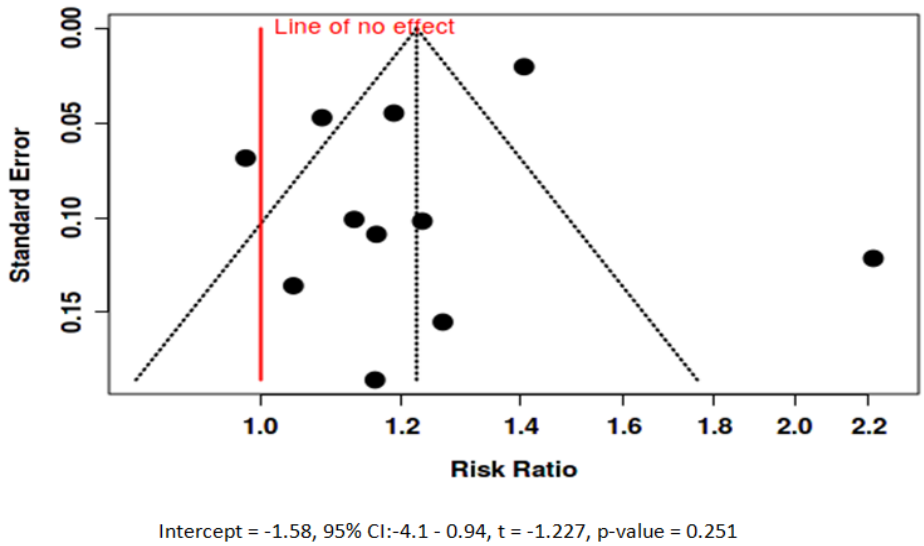

Figure 2: Funnel plot showing risk of publication bias

Table 1 provides an overview of the characteristics of the 11 studies concerning precision. The studies were conducted in Australia (n = 1), Canada (n = 1), Iran (n = 3), Italy (n = 1), Jordan (n = 1), the United Kingdom (n = 1), and the USA (n = 3). Seven of them utilized the single-group quasi-experimental design. The studies contained category II and III levels of research evidence.

Table 1. Precision of nursing documentation

Author	**Country**	**Design**	**Software assisted records**		**Paper assisted records**		**Level of evidence**
			n	***Precise***	***n***	***Precise***	
Jamieson *et al.* [8]	Canada	Single group quasi-experimental	21	19	21	15	II
Karp *et al.* [9]	USA	Single group quasi-experimental	904	470	904	434	II
Akhu-zaheya *et al.* [10]	Jordan	Single group quasi-experimental	434	166	434	75	II
Bertocchi *et al.* [11]	Italy	Single group quasi-experimental	198	105	198	93	II
Dean *et al.* [15]	USA	Single group quasi-experimental	998	998	998	709	II
Wilbanks *et al.* [21]	USA	Observational	30	24	30	23	III
Sefton *et al.* [22]	UK	Mixed method prospective	111	109	115	95	III
Wang *et al.* [23]	Australia	prospective	194	144	111	84	III
Tubaishat *et al.* [24]	Iran	Observational	52	43	52	37	III
Samadbeik *et al.* [25]	Iran	Single group quasi-experimental	50	29	50	25	II
Ranjbar *et al.* [26]	Iran	Single group quasi-experimental	40	37	40	30	II

Johns Hopkins Evidence-Based Practice Model for Levels of Research Evidence [20] was used, n = sample size, precise = accurately coding nursing diagnosis, interventions, and evaluations to accurately reflect the conditions of a patient.

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Table 2 provides an overview of the characteristics of the eight studies concerning timeliness. The studies were conducted in Germany (n = 1), Iran (n = 1), the United Kingdom (n = 3), and the USA (n = 3). Five of them utilized the single-group quasi-experimental design. The studies contained category II and III levels of research evidence based on the Nursing Johns Hopkins Evidence-Based Practice Model for Levels of Research Evidence criteria.

Table 2. Timeliness of nursing documentation (in minutes)

Author	**Country**	**Design**	**Software assisted records**			**Paper assisted records**			**Level of evidence**
			n	***Mean***	***SD***	***n***	***Mean***	***SD***	
Lucas *et al.* [5]	Germany	Single group quasi-experimental	17675	2.1	0.1	3962	1.4	0.1	II
Karp *et al.*[9]	USA	Single group quasi-experimental	904	2.6	1.7	904	9.3	4.7	II
Dean *et al.* [15]	USA	Single group quasi-experimental	998	20	0.5	1411	55	0.5	II
Sefton *et al.*[22]	UK	Mixed method prospective	111	1.1	0.1	115	1.6	0.1	III
Ranjbar *et al.* [26]	Iran	Single group quasi-experimental	40	5.2	1.1	40	8.2	2.1	II
Wong *et al.* [27]	UK	Single group quasi-experimental	296	2.5	0.5	281	3.6	0.5	II
Read-Brown *et al.* [28]	USA	Observational	188	9.3	2.7	58	7.5	2.8	III
Fieler *et al.* [29]	UK	Prospective	64	5.1	6.6	62	38.5	32.9	III

Johns Hopkins Evidence-Based Practice Model for Levels of Research Evidence [20] was used, n = sample size, timeliness = the amount of time taken in minutes to document a care plan record for one patient. Mean in minutes, SD = standard deviation.

Figure 3 revealed that software assisted systems significantly enhanced precision of nursing documentation by two folds compared to paper (Overall random effect Odds Ratio by 2.35, 95%CI: 1.32-4.17; $p = < 0.010$).

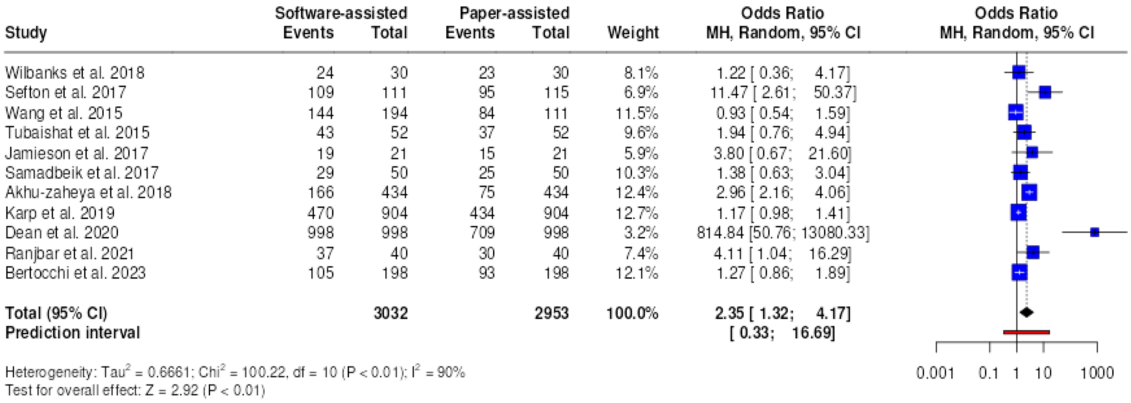

Figure 3. A forest-plot illustrating the synthesis of evidence on precision (Events = number of records with precise nursing documentation, CI = Confidence Interval)

Figure 4 reveals the synthesis of evidence from the reviewed studies on timeliness and demonstrated that although software-assisted systems reduced time spent on documentation by about nine minutes, the decrease was not significant (Overall random effects mean difference = 9.14 minutes; $p = 0.330$).

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Study	Software-assisted Mean	SD	Total	Paper-assisted Mean	SD	Total	Weight	Std. Mean Difference IV, Random, 95% CI
Wong et al. 2017	2.50	0.5000	296	3.60	0.5000	281	12.5%	-2.20 [-2.40; -1.99]
Read-Brown et al. 2013	9.30	2.7000	188	7.50	2.8000	58	12.5%	0.66 [0.36; 0.96]
Sefton et al. 2017	1.10	0.1000	111	1.60	0.1000	115	12.5%	-4.98 [-5.51; -4.45]
Fieler et al. 2013	5.10	6.6000	64	38.50	32.9000	62	12.5%	-1.41 [-1.80; -1.02]
Karp et al. 2019	2.60	1.7000	904	9.30	4.7000	904	12.5%	-1.90 [-2.01; -1.78]
Lucas et al. 2019	2.10	0.1000	17675	1.40	0.1000	3962	12.5%	7.00 [6.93; 7.07]
Dean et al. 2020	20.00	0.5000	998	55.00	0.5000	1411	12.2%	-69.98 [-71.96; -68.00]
Ranjbar et al. 2021	5.20	1.1000	40	8.20	2.1000	40	12.5%	-1.77 [-2.29; -1.25]
Total (95% CI)			**20276**			**6833**	**100.0%**	**-9.14 [-29.65; 11.37]**
Prediction interval								**[-25.60; 7.32]**

Heterogeneity: $Tau^2 = 40.2096$; $Chi^2 = 28036.80$, df = 7 (P = 0); $I^2 = 100\%$
Test for overall effect: $t_7 = -1.05$ (P = 0.33)

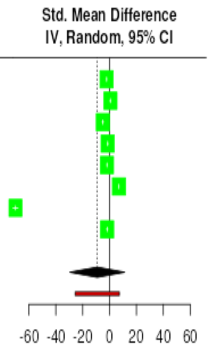

Figure 4. A forest-plot illustrating the synthesis of evidence on timeliness (*Mean in minutes, SD = Standard Deviation, CI = Confidence Interval*)

4 Discussion

This review and meta-analysis found evidence supporting the notion that software-assisted nursing documentation systems enhances documentation precision. The reason behind this observation can be attributed to various factors such as the organization of data within electronic systems, the reduction of human errors through built-in validation checks, real-time updates, and the integration of decision support tools, all contributing to a more precise recording of nursing care information [21]. Additionally, software-assisted systems often provide standardized templates, structured data entry, and automated prompts, minimizing ambiguity and ensuring consistent capture of essential details [6]. Improved legibility of electronic records also play a role in reducing errors associated with illegible handwriting, further enhancing documentation precision [22]. Furthermore, the dynamic nature of software-assisted documentation systems allows for immediate corrections and updates, facilitating ongoing accuracy throughout the care process [21]. The amalgamation of these features within software-assisted nursing documentation systems fosters an environment conducive to improved data precision.

The finding of this review and meta-analysis regarding the precision of software-assisted documentation is consistent with previous research by Akhu-Zaheya and colleagues [10], who found that software-assisted documentation's precision surpassed that of paper-based documentation. This consistency may be attributed to the required minimum nursing data set customization of the software systems [10]. The alignment with prior findings was unexpected, given Akhu-Zaheya's [10] lack of consultation with clinical nurses for desired system features before clinical deployment and evaluation. Utilizing the Pressman Five-Stage System Software Development Life Cycle (Waterfall Model), which requires qualitative information on desired software features from clinical nurses and literature before development and deployment, could enhance future research on this subject matter [30].

This review and meta-analysis uncovered evidence supporting the notion that software-assisted nursing documentation systems hold potentials to improve documentation timeliness by reducing the time from service to completion of nursing documentation, even though not significantly. The reason for this finding could be because nursing documentation software is equipped with features that support real-time data entry and updates, automated reminders and alerts [6] [15]. Moreover, electronic systems often feature timestamp functionalities, providing a clear chronological order of events [22]. The elimination of physical barriers associated with paper-based records further accelerates the documentation workflow [15]. Additionally, electronic systems facilitate simultaneous access by multiple healthcare providers, promoting collaborative and concurrent documentation efforts [21].

This finding contrasts with Lucas and colleagues [5], who reported better timeliness with paper-aided documentation compared to the electronic approach. The discrepancy may be attributed to specific limitations in the features of the software system examined by Lucas and colleagues [5], such as the inability to suggest nursing diagnoses. Conversely, Ranjbar and colleagues [26] reported reduced nursing documentation time with advanced electronic systems capable of suggesting NANDA nursing diagnoses. This finding aligns with previous research by Dean and colleagues [15], who demonstrated that software

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documentation systems are timelier compared to paper-aided documentation if nursing diagnoses and outcomes were programmed into the electronic design algorithm.

5 Limitations

This rapid review and meta-analysis is not without some limitations. The protocol for this review and meta-analysis was not registered in PROSPERO (An international database of prospectively registered systematic reviews in health science). Only one database (PubMed) was searched for this review and meta-analysis. While the searched database may contain a substantial amount of peer-reviewed literature, it may not have captured all relevant studies, particularly those published in non-indexed or non-traditional sources. Grey literature, which includes unpublished studies, conference abstracts, government reports, and dissertations, often provides valuable insights and data that may not be accessible through traditional research databases.

6 Conclusion

The software-assisted nursing documentation systems enhances precision by offering structured templates for data entry, validation checks, and real-time updates to ensure reliable recording of essential nursing care information. Nonetheless, software-assisted nursing documentation systems did not significantly improve timeliness of nursing care documentation. This use of software-assisted nursing documentation systems for improving the precision of nursing documentation is therefore recommended.

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Statement on conflicts of interest

The authors declare that there are no conflicts of interest.

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Ethical Consideration

The ethical review and approval for this study were waived by the University of Nigeria IRB since it involved secondary data.

Informed Consent

Not applicable.

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Implementing Blockchain for Health Sectors in Low- and Middle-Income Countries: Use Cases, Approaches and Challenges

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Background and Purpose: Despite its complexity and resource constraints, the healthcare sector in low- and middle-income countries (LMICs) faces a crucial challenge of ensuring data integrity, interoperability, and transparency. Blockchain technology emerges as a potential solution, offering secure and immutable platform for managing health information. This study investigates the use cases, approaches, and challenges of implementing blockchain in LMIC healthcare, focusing on health services and sector-wide management.
Methods: The study employed a systematic review methodology following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) to ensure transparency and reproducibility in the review process. Results show that while a number of African countries have embarked on the implementation of blockchain-based applications, most projects remain as proposals or experiments.
Results: The study found 26 (82%) projects had some form of implementation. Of these, 11 (42%) were simulations, 2 (8%) evolved into working prototypes, and only 3 (12%) achieved full-fledged deployments. The most implemented use case was Electronic Health Record systems (EHR), which constituted about 23% of all implementations, followed by Remote Patient Monitoring (15%).
Conclusion: The main challenge in the deployment of blockchain technology in the health sector in LMICs is the limited transition of simulations and prototypes into fully developed solutions. This issue is largely attributed to low levels of readiness, both technical and administrative, which hinder the successful implementation and integration of blockchain systems. Addressing these readiness gaps is crucial to overcoming barriers and unlocking the full potential of blockchain technology to improve healthcare outcomes in these settings.

Keywords: Blockchain, Health Sector, Technology Adoption, Low- and Middle-Income Countries

1 Introduction

The healthcare sector is inherently complex and heavily influenced by political dynamics (Aanestad & Jensen, 2011; Gedikci et al., 2023; Sheikh et al., 2015; Scott & Mars, 2015). It encompasses a multitude of interdependent institutions, each operating with distinct management structures (Braa et al., 2007; Kimaro & Titlestad, 2008). Effective health service provision necessitates seamless alignment and communication across these diverse institutions. To provide a complete and uninterrupted healthcare experience for a patient, it is necessary to coordinate between different departments involved in the process. For instance, the inpatient or outpatient department responsible for prescribing medications and interpreting test results, the laboratory that conducts tests and examinations, and the pharmacy that manages medical equipment and medications all need to work together seamlessly (Reichertz, 2006; Sittig et al., 2018). Data serves as the crucial link connecting these segments, encompassing patient information from outpatient departments, test results from laboratories, and details of medications dispensed by the pharmacy. Recognising the imperative for consistent data across different healthcare sections and ensuring its integrity, several scholars advocate for the integration of blockchain technologies (Haleem et al., 2021; Tandon et al., 2020; Elangovan et al., 2022; Agbo et al., 2019; Kuo et al., 2017) to streamline data management processes in the healthcare sector.

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The healthcare landscape in low- and middle-income countries (LMICs) is characterised by a myriad of challenges that hinder the delivery of effective and equitable care. Resource scarcity further compounds the problem, limiting access to essential medical supplies, diagnostic tools, and qualified healthcare professionals (World Health Organization, 2017; Frenk et al., 2014; Anyangwe & Mtonga, 2007). Inadequate data management systems contribute to the fragmentation of health information, making it difficult to establish comprehensive and interoperable health records (Mkayula et al., 2022). Blockchain technology emerges as a potential remedy to these challenges by providing a decentralised and secure platform for health data management (Mettler, 2016; Agbo et al., 2019; Kuo et al., 2017). In LMICs, the implementation of blockchain can streamline health data infrastructure, including secure storage of data, secure transactions and traceability in logistics and supply chain (P. Zhang et al., 2018).

The potential for using blockchain in the health sector has gained considerable attention (Mettler, 2016; Haleem et al., 2021). The immutable and decentralised nature of blockchain offers promising solutions to challenges such as interoperability, data security, and transparency in healthcare systems. For instance, blockchain can facilitate secure and interoperable health data exchange among diverse stakeholders, including healthcare providers, insurers, and patients (Mettler, 2016). Moreover, its ability to provide a tamper-proof and auditable record of transactions enhances data integrity, a critical aspect of healthcare data management (Iansiti & Lakhani, 2017). In LMICs, where traditional healthcare infrastructure may be limited, blockchain can enable efficient management of health records, streamline supply chain logistics for medical resources, and reduce fraud through transparent and traceable transactions (P. Zhang et al., 2018). The implementation of blockchain in healthcare, however, comes with its set of challenges, including technological barriers, regulatory uncertainties, and the need for skilled workforce training (Agbo et al., 2019). Addressing these challenges is crucial for realising the full potential of blockchain technology in improving healthcare outcomes and services in resource-constrained settings.

While the potential of blockchain in LMIC healthcare contexts is undeniable, its successful implementation is accompanied by distinct challenges. Inadequate infrastructure, especially limited internet access in rural areas, poses significant connectivity hurdles, hindering the seamless deployment of blockchain applications (Mars, 2013; World Bank Group, 2016; Scott & Mars, 2015). The challenges are further compounded by the need to navigate intricate regulatory frameworks governing health data and technology in LMICs, adding a layer of complexity to implementation efforts (Agbo et al., 2019; Kuo et al., 2017; Vazirani et al., 2020). Fostering interoperability between diverse blockchain platforms is crucial for ensuring the seamless exchange of health data across systems, necessitating careful consideration of standardisation efforts (Zhang et al., 2018; Jain et al., 2024) . Moreover, building trust and achieving user adoption among healthcare professionals and patients demand extensive stakeholder engagement and capacity-building initiatives to address concerns related to data privacy, security, and the overall reliability of blockchain systems (Mettler, 2016; Esmaeilzadeh & Mirzaei, 2019; Hasselgren et al., 2019). Following these many huddles, this study gives an account of the extent of the adoption of blockchain in LMICs as well as the types of blockchains involved. The study contributes to the existing body of knowledge by reviewing the use of blockchain technologies in managing the healthcare sector, with a focus on health services management and sector-wide management.

In specific terms, this study aimed to comprehensively examine the use cases, adoption approaches, and associated challenges of implementing blockchain technologies in the health sector, with a specific focus on LMICs. While existing reviews, such as those conducted by Hasselgren et al. (2019), Saeed et al. (2022), and Adere (2022), have provided valuable insights into the utilisation of blockchain technology in healthcare, they predominantly offer generic perspectives and do not adequately scrutinise the unique situations and challenges faced by healthcare systems in LMICs. Hasselgren et al. (2019) delved into the overall landscape of blockchain in healthcare, Saeed et al. (2022) explored its applications and benefits, and Adere (2022) conducted a systematic review of blockchain and IoT technology in healthcare. However, the specific challenges and approaches in adopting blockchain technology in LMICs have yet to be extensively addressed in these reviews, warranting a dedicated investigation to bridge this gap in the literature. This study aimed to address this void.

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Research Question(s).

i. How is blockchain technology applied in healthcare within low- and middle-income countries?
ii. What implementation approaches are utilised for blockchain in healthcare in low- and middle-income countries?
iii. What challenges arise in implementing blockchain for healthcare in low- and middle-income countries?
iv. What are the recommended strategies for successful blockchain implementation in healthcare in low- and middle-income countries?

2 Methodology

This study used a systematic literature review to investigate the implementation of blockchain technology in the health sectors in LMICs. The systematic review used follows the guidelines outlined by Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) to ensure transparency and reproducibility in the review process (Moher et al., 2009). Four reputable literature databases were chosen to gather relevant papers related to blockchain technology in healthcare. These were (1) PubMed: A well-known database for biomedical literature, (2) IEEE Xplore (IEEEX): A comprehensive resource for engineering and technology research, (3) ACM Digital Library: A prominent source of computer science publications, and (4) ScienceDirect: A leading database covering various academic disciplines. The search strategy involved using a combination of relevant keywords and Boolean operators to retrieve relevant papers. The search phrase used was: ("blockchain" OR "block chain" OR "block-chain") AND ("health" OR "healthcare" OR "medicine" OR "medical").

2.1 Inclusion Criteria

To ensure the relevance and quality of the papers, strict inclusion and exclusion criteria were applied during the screening process. The inclusion criteria were as follows:

i. Papers published between the years 2015 - 2022.
ii. Papers related to the application of blockchain technology in the healthcare sector.
iii. Full-text papers available in English.
iv. Studies conducted in LMIC setting

2.2 The exclusion criteria were as follows:

i. Papers not directly related to blockchain technology in healthcare.
ii. Papers not available in full text or not written in English.
iii. Reviews and editorials, only original articles and empirical research were considered.
iv. Articles that discuss the blockchain technology itself rather than its implementation

2.3 Screening Process

The screening process involved two stages: title/abstract screening and full-text screening. Initially, duplicate papers were removed from the search results. Subsequently, two independent reviewers conducted title and abstract screening based on the inclusion and exclusion criteria. Papers that met the criteria were then subjected to full-text screening. During the full-text screening phase, the same two reviewers independently assessed the content of each paper to determine its suitability for inclusion in the review. Any discrepancies were resolved through discussion and consensus.

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2.4 Data Extraction and Analysis

A standardised data extraction form was used to extract relevant information from the included papers. The data extraction process included information on study details (e.g., authors, publication year, country of origin), methodology, blockchain implementation type, healthcare use cases, and main findings. The extracted data from the included papers were synthesised and analysed to identify common themes, trends, and insights related to the application of blockchain technology in the healthcare sector. Seven (7) categories were selected to systematically analyse and evaluate the adoption of blockchain technologies in the health sectors of low- and middle-income countries (LMICs). The categories and corresponding reason for selection are briefly described below:
Solutions Implementation for identifying whether existing blockchain-based solutions are still theoretical or there are practical implementation, providing insight into the maturity of the technology in LMIC contexts.
Level of Implementation for assessing whether the implementation is at experiments pilot, or full rollout. This category highlights the extent of deployment within LMIC healthcare systems, shedding light on the challenges faced at different levels.
Implementation Details Provided for examining the depth of information shared about implementation, such as technical specifications, challenges faced, and strategies used.
Use Cases Implemented e.g., electronic health records, supply chain, or patient identity verification to highlight areas where blockchain technology is most impactful in LMICs.
Blockchain Technology Used for identifying the type of blockchain commonly used e.g., Ethereum or Hyperledger which influence factors such as scalability, security, and cost-efficiency which are critical in resource-constrained environments.
Integration with Other Technologies like IoT, AI, or cloud computing to assess how these synergies enhance functionality, solve complex healthcare challenges, and optimize resource use in LMICs.
Country of Origin of Papers provides insights into geographic trends, potential biases, and the need for more localized studies across different LMICs.

2.5 Limitations

This review acknowledges certain limitations, including the potential omission of relevant papers due to database constraints. Additionally, the scope of the analysis may have been restricted by the availability of full-text articles and the focus on studies published in English.

3 Results

The systematic review process scrutinised a total of 5,485 research papers extracted from selected databases PubMed (487 papers), IEEEX (371 initial papers), ACM Digital (267 papers), and Science Direct (4,360 papers) during the search phase. Following a screening process, a refined set of 31 papers emerged for in-depth examination, categorised across the selected databases as follows: PubMed (4 papers), IEEEX (14 papers), ACM Digital (10 papers), and Science Direct (3 papers). These selected papers were further reviewed, with data systematically collected and organised into 7 categories selected to systematically analyse and evaluate the adoption of blockchain technologies in the health sectors of low- and middle-income countries (LMICs). A summary of the analysis for each retrieved article is included in the appendix.

Table 7: Systematic Review Results

S/N	Category	Implementation	Number of papers
1	Solution Implementation	Yes	19
		No	6

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2	Level of implementation	Algorithm	2
		Simulation	1
		Lab experiments	11
		Working prototype	2
		Full implementation	3
3	Implementations details provided	Clear	7
		Not clear	12
4	Use cases implemented	Electronic Health Records	13
		Remote Patient Monitoring	4
		Payments	1
		Birth/Death Registration	2
		Healthcare Management System	2
		Supply Chain Management	3
5	Blockchain technology used	Ethereum	4
		Hyperledger	8
		Bitcoin	1
		Others	2
		Unspecified	3
6	Integration with other technologies	Artificial Intelligence	1
		IoT	3
		Cloud computing	2
		Machine Learning	1
		Big Data	1
7	Country of Origin of papers	South Africa	4
		Tunisia, Morocco	3
		Kenya	2
		Nigeria, Ghana, Guinea, Algeria, Namibia, Cameroon, Egypt	1

The analysis revealed that 19 out of 25 projects (76%) had implemented some form of solution. While 6 projects remained in conceptual stages (24%), the majority progressed beyond theoretical foundations, demonstrating a growing commitment to practical applications as summarised in Figure 1.

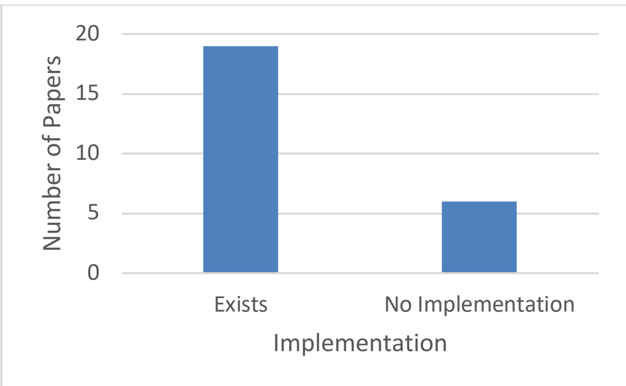

Figure 1. Implementation Exists or Not

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The level of implementation also varied, with 14 projects residing in algorithm, simulation or lab experiments (74%), two (2) evolving into working prototypes (11%), and only 3 achieving full-fledged deployments (15%). The analysis highlights significant progress in the implementation of blockchain solutions in LMIC healthcare systems, with more than three quarters of the reviewed projects moving beyond the conceptual stage as summarised in Figure 2.

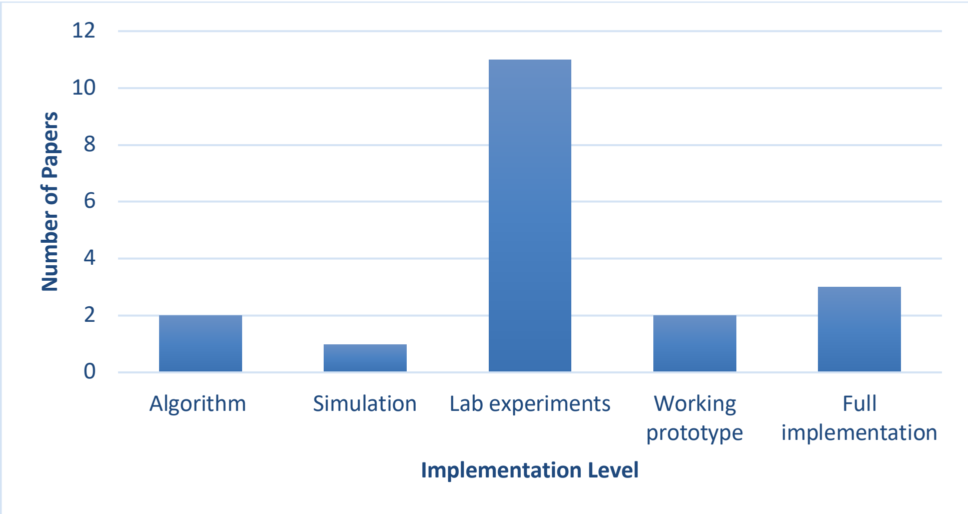

Figure 2. Implementation Level for Reviewed Articles

Examining the specific use cases targeted by the implemented projects, Electronic Health Records systems (EHRs) emerged as the primary focus, with 13 projects aiming to address secure patient data storage, data privacy and data exchange challenges (52%). Remote patient monitoring (4 projects, 16%) and supply chain management for drugs and vaccines (3 projects, 12%) were also key areas, underscoring the potential of blockchain to contribute to telehealth and supply chain assurance in resource-constrained settings. Other projects explored diverse applications including payments, birth/death registration, and healthcare system management (all representing 20% of projects), demonstrating the wide range of issues that can be potentially addressed by the blockchain technology as shown in Figure3.

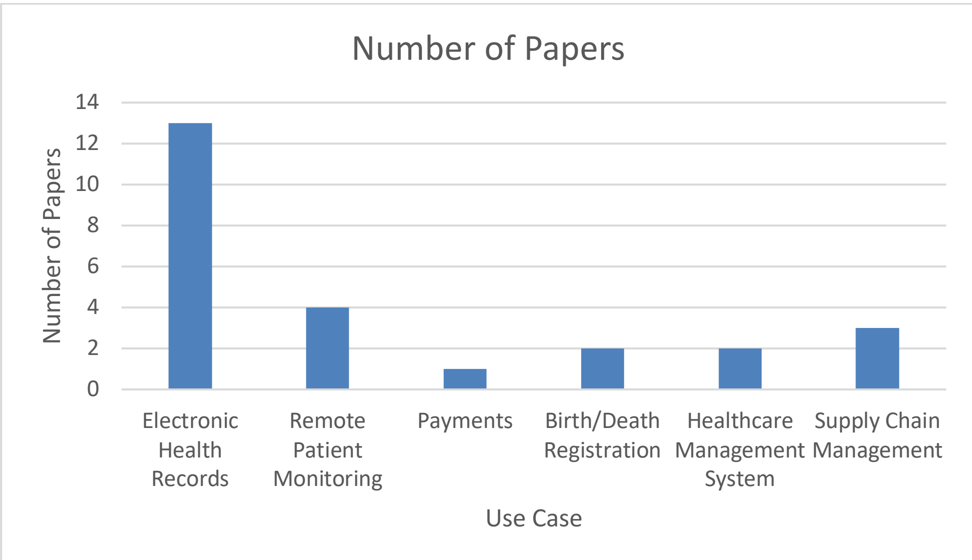

Figure 3. Implemented Use Cases

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From a technological perspective, established platforms dominated the implemented projects, with Ethereum (4 projects, 21%) and Hyperledger (8 projects, 42%) being the most preferred choices as shown in Figure 4. This suggests a focus on stability and reliability for real-world applications. However, the presence of projects utilising Bitcoin and other technologies (3 projects, 16%) indicates ongoing exploration and innovation in the LMIC context. Additionally, 3 projects successfully integrated blockchain with IoT sensors, showcasing the potential for real-time data collection and remote patient care. Cloud technology was integrated in 2 projects, further addressing challenges with data storage and accessibility. These integrations highlight the collaborative power of emerging technologies to drive impactful healthcare solutions.

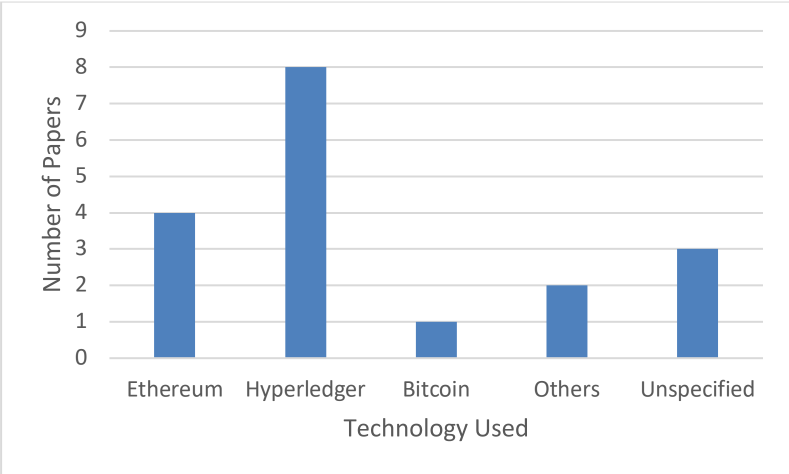

Figure 4. Blockchain Technology Used

4 Discussion

The results of the research demonstrate a growing interest and active exploration of blockchain technology in the health sector across Africa. A considerable number of projects have progressed beyond theoretical concepts, with 15 successful implementations reported. These implementations primarily consist of simulations and lab experiments, indicating a cautious approach to real-world adoption. The diversity of countries contributing to this research highlights the regional interest and collaborative efforts in harnessing blockchain technology for healthcare applications. Each country's unique socio-economic and healthcare challenges influenced the choice of use cases and technologies adopted. Below, the answers to research questions are provided.

Research Question 1: How is blockchain technology applied in healthcare within low- and middle-income countries?
Answer: The results from the analysis reveal that blockchain technology in healthcare within low- and middle-income countries (LMICs) is primarily applied in the implementation of Electronic Health Record (EHR) systems that aim to address data security and interoperability challenges. Beyond EHR, the technology finds more applications in remote patient monitoring and patient data privacy systems. The emergent of Electronic Health Records (EHRs) as the dominant use case reflects the urgent need for secure patient data storage, enhanced privacy, and streamlined data exchange in contexts where fragmented and insecure data management often undermines healthcare delivery. Additionally, the implementations of blockchain in supply chain management for drugs and vaccines highlights the need to enhance supply chain integrity, a vital consideration in resource-constrained environments. Other projects addressing payments, birth/death registration, and healthcare system management demonstrate blockchain's adaptability to diverse healthcare challenges.

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Research Question 2: What implementation approaches are utilised for blockchain in healthcare in low- and middle-income countries?
Answer: The implementation approaches for blockchain in healthcare in LMICs show a rather exploratory approach with 74% of projects residing in simulated or lab environments, indicating that most projects are still in the exploration stage. Additionally, 11% of projects have evolved into working prototypes, while only 15% have achieved full-fledged deployments. This suggests a progression from theoretical exploration to practical applications, emphasising the need for targeted support to bridge the gap between theory and real-world implementation. The results highlight a growing recognition of blockchain's potential and a commitment to translating theoretical concepts into practical applications. However, the varying levels of implementation underscore the challenges in achieving full-scale deployment. The majority of projects remain confined to controlled environments such as simulations or lab experiments, reflecting the technical and logistical complexities of real-world implementation. This calls for more robust strategies to address barriers such as infrastructure, regulatory hurdles, and stakeholder readiness.

Research Question 3: What challenges arise in implementing blockchain for healthcare in low- and middle-income countries?
Answer: The main challenge in the implementations of healthcare-based solutions in LMICs is the majority (74%) of implemented projects remain limited to controlled environments such as algorithms, simulations, or lab experiments. This suggests that while there is a strong commitment to exploring blockchain's potential, significant barriers prevent many initiatives from transitioning to practical, real-world applications. Key factors limiting successful deployment of blockchain based healthcare applications includes; inadequate infrastructure in LMICs such as limited internet connectivity and power reliability, which are essential for blockchain systems to operate effectively. Regulatory frameworks which in most countries either do not recognise or ban the use of crypto technologies. Overcoming these regulatory frameworks and addressing stakeholder concerns around data privacy, security, and interoperability is still a significant challenge. Another significant challenge is the lack of technical and administrative readiness. Many organizations lack the specialized expertise needed to design, develop, and maintain blockchain-based solutions, primarily due to the technology's inherent complexity.

Research Question 4: What are the recommended strategies for successful blockchain implementation in healthcare in low- and middle-income countries?
Answer: Recommended strategies for successful blockchain implementation in LMIC healthcare include addressing the challenges identified. One area that can be immediately addressed is building capacity for technology implementers to equip them with the necessary skills to develop blockchain solutions. Capacity building should also be extended to the administrative layer and decision-makers to create awareness of the benefits of using blockchain technology in the health sector. Additionally, strategies should be developed to enhance resource availability and navigate regulatory frameworks to ensure the smooth adoption of blockchain technology in LMIC healthcare. Lastly, as seen from the analysis, emphasis should be put on deploying blockchain with collaborative emerging technologies, such as IoT sensors and cloud integration, to drive successful healthcare solutions in these resource-constrained settings.

5 Conclusion

This study provides a review and analysis of the implementation of blockchain technology in the health sectors for low- and middle-income countries (LMICs), highlighting its potential to address critical challenges while also uncovering key barriers to widespread adoption. The findings reveal promising advancements, with most projects progressing beyond conceptual stages, demonstrating the growing commitment to practical applications. However, the predominance of projects still in controlled environments, such as simulations or lab experiments, indicates that significant challenges remain in achieving full-scale deployment. Blockchain technology shows promise in areas such as electronic health records, remote patient monitoring, and supply chain management, offering innovative solutions to enhance data security, privacy, and operational efficiency. Additionally, its potential extends to diverse use cases, including payments, healthcare system management, and vital statistics registration, showing its capability in addressing a wide range of issues in LMIC healthcare systems. Despite these opportunities, the study highlights substantial obstacles, including inadequate infrastructure, limited technical expertise, and complex regulatory frameworks. Addressing these challenges will require a concerted effort involving capacity building, collaborative policymaking, and the development of context-specific solutions tailored to LMIC environments. This research contributes to the existing body of knowledge by providing insights into the current state of blockchain implementation in LMICs and highlighting the necessity of addressing the gap between theoretical potential and practical application. Future research should extend its focus beyond the healthcare sector, examine regulatory frameworks relevant to blockchain technology, and investigate strategies for integrating blockchain with other emerging technologies.

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APPENDIX

Summary of Analysis for the Retrieved Articles

S/N	Article Title	Implementation Level	Use Case	Blockchain Technology Used
1	Implementation of Blockchain Enabled Healthcare System Using Hyperledger Fabric (Jain & Jat, 2022)	Lab experiment	Health care management system	Hyperledger
2	Patient-Centric Mobile App Solution (Khurram & Sardar, 2020)	Full application	Remote patient monitoring, electronic health records	Not specified
3	Secure Mobile Agents for Patient Status Telemonitoring Using Blockchain (Alruqi et al., 2021)	No implementation (Design proposed)	Remote patient monitoring	Not applicable
4	A Blockchain-Based Framework for Drug Traceability: ChainDrugTrac (Kambilo et al., 2022)	Lab experiment	Supply chain management	Ethereum
5	Improving Vaccine Safety Using Blockchain (Cui et al., 2021)	Lab experiment	Supply chain management	Fisco Bcos
6	Temporal Analysis of Cooperative Behaviour in a Blockchain for Humanitarian Aid during the COVID-19 Pandemic (Ba et al., 2022)	Full application	Payments	xDai
7	Enabling Privacy-Preserving Sharing of Genomic Data for GWASs in Decentralized Networks (Y. Zhang et al., 2019)	Algorithm developed	Electronic health records	Not applicable
8	A Permissioned Blockchain Approach to Electronic Health Record Audit Logs (Adlam & Haskins, 2020)	Lab experiment	Electronic health records	Hyperledger
9	A Framework for the Adoption of Blockchain Technology in Healthcare Information Management Systems: A Case Study of Nigeria (Azogu et al., 2019)	No implementation (Framework proposed)	Electronic health records	Not applicable
10	How Blockchain Helps to Combat Trust Crisis in COVID-19 Pandemic? (Abid et al., 2020)	Working prototype	Electronic health records	Ethereum
11	A Novel Decentralized Blockchain Architecture for the Preservation of Privacy and Data Security against Cyberattacks in Healthcare (Kumar et al., 2022)	Simulation	Electronic health records	Bitcoin
12	Blockchain-Secured Recommender System for Special Need Patients Using Deep Learning (Mantey et al., 2021)	Algorithm developed	Electronic health records	Not applicable
13	Addressing Care Continuity and Quality Challenges in the Management of Hypertension: Case Study of the Private Health Care Sector in Kenya (Walcott-Bryant et al., 2021)	No implementation (Framework proposed)	Healthcare management	Not applicable
14	A Novel Block Chain Method for Urban Digitization Governance in Birth	Full application	Birth/death registration	Ethereum

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	Registration Field: A Case Study (Shi et al., 2022)			
15	Potential Adoption of Blockchain Technology to Enhance Transparency and Accountability in the Public Healthcare System in South Africa (Ndayizigamiye & Dube, 2019)	No implementation	Health care management, supply chain management, electronic health records	Not applicable
16	Design of a Credible Blockchain-Based E-Health Records (CB-EHRS) Platform (Xu et al., 2019)	Lab experiment	Electronic health records	Hyperledger
17	Enabling Care Continuity using a Digital Health Wallet (Osebe et al., 2019)	Lab experiment	Electronic health records	Hyperledger
18	CP-BDHCA: Blockchain-Based Confidentiality-Privacy Preserving Big Data Scheme for Healthcare Clouds and Applications (Ghayvat et al., 2022)	Lab experiment	Electronic health records	Not specified
19	Secure and Privacy-aware Blockchain-based Remote Patient Monitoring System for Internet of Healthcare Things (Zaabar et al., 2021)	Lab experiment	Remote patient monitoring	Hyperledger
20	DSMAC: Privacy-Aware Decentralized Self-Management of Data Access Control Based on Blockchain for Health Data (Saidi et al., 2022)	Lab experiment	Electronic health records	Hyperledger
21	DASS-CARE 2.0: Blockchain-Based Healthcare Framework for Collaborative Diagnosis in CIoMT Ecosystem (Ayache et al., 2022)	No implementation (Framework proposed)	Healthcare management system	Not applicable
22	A Blockchain-based secure PHR data storage and sharing framework (Ghani et al., 2020)	Lab experiment	Electronic health records	Ethereum
23	Blockchain application to improve Vendor management replenishment in Humanitarian supply chain (Lahjouji et al., 2021)	No implementation (Framework proposed)	Supply chain management	Not applicable
24	A Novel Patient-Centric Architectural Framework for Blockchain-Enabled Healthcare Applications (Singh et al., 2021)	Working prototype	Supply chain management	Hyperledger
25	An IoT and Blockchain-Based Multi-Sensory In-Home Quality of Life Framework for Cancer Patients (Rahman et al., 2019)	Lab experiment	Remote patient monitoring, electronic health records	Hyperledger

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