Asia Pacific Journal of Health Management

Volume 21 Issue 2 2026

The Journal of ACHSM & SHAPE



ACHSM | Australasian College of Health Service Management

CONFERENCE ARTICLES Vol21(2) 2026

International Conference on SMART Technologies for Medical & Health Sciences: AI-Driven Health Care Innovation & Integration - 13th to 15th March 2026

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ACHSM Asia-Pacific Journal of Health Management

CONFAB 360 DEGREE 2026

THE ONE-SIZE-FITS-ALL FALLACY IN AI IMPLEMENTATION - WHY HOSPITALS AND PRIMARY CARE REQUIRE DIFFERENT STRATEGIES: COMMENTARY

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ABSTRACT

OBJECTIVE:

This viewpoint paper aimed to challenge the universal Artificial Intelligence (AI) implementation in healthcare, and based on empirical studies, ascertained that hospitals and primary care require context-sensitive implementation strategies.

ISSUE:

The one-size-fits-all AI implementation and adoption in healthcare adversely affects it comprehensive integration.

OUTCOMES:

AI implementation must consider varying governance structures, workflow dynamics, resource availability, and technical maturity in different healthcare settings.

CONCLUSION:

While usability, affordability, and workflow fit should be the focus of AI implementation in primary care, hospitals must emphasise governance, infrastructure, and integration.

KEYWORDS

Artificial Intelligence; AI Implementation; Hospitals; Primary Care; Context-Sensitive Strategies; Healthcare Governance.

INTRODUCTION

Healthcare industry is undergoing AI (Artificial Intelligence)-driven transformation, marked by accurate diagnosis, enhanced workflow efficiency, and better patient outcomes. This evolution in the last decade has guided considerable research concerning AI implementation in healthcare, particularly in the context of identifying barriers and enablers.

Recent systematic and scoping reviews have continued to document common challenges, including explainability issues, trust deficit, lack of workforce readiness, regulatory uncertainties, and data integration difficulties. While such syntheses have been valuable in consolidating knowledge, the problem lies in unclear understanding on how these challenges will manifest in various contexts of healthcare delivery [1, 2, 3]. To an extent, this gap has reinforced the assumption that similar strategies can be applied across diverse healthcare environments [4]. Moreover, AI adoption remains underdeveloped, with the dominant focus continuing to be on identifying barriers rather than understanding *how* and *why* they are being implemented across hospitals and primary care.

This viewpoint challenges this one-size-fits-all approach, simultaneously focusing on *why* hospitals and primary care need separate and specific AI implementation strategies, and not uniform models. Hospitals represent structured socio-technical systems offering specialised treatment for critical and complex diseases, whereas primary care systems are usually the first point of contact in community-based basic care, emphasising long-term well-being, disease prevention, and health management. Apparently, hospitals and primary care settings differ significantly in clinical complexity, governance, resource limitations, and workflow. While hospitals are characterised by coordinated multidisciplinary teams in high-pressure situations, primary care is organised around systems that are resource-constrained, time-limited, and focused primarily on the care of their patients. Such distinctions in two different care settings influence primary factors driving AI implementation, like trust, user-friendliness, cost, integration and governance [1,2,4,5]. This requires context-sensitive AI implementation across hospitals and primary care settings differently to pave the way for effective AI adoption. Having set this background, this viewpoint paper argues that the ongoing challenges in AI implementation can be partly attributed to a one-size-fits-all fallacy, whereby heterogeneous healthcare contexts are treated as functionally equivalent in implementation strategies. For effective implementation, there is a need to co-align strategies concerning AI and the contextual drivers of each care setting (hospitals and primary care). The paper, therefore, reconceptualises the challenges of AI adoption as one of context-strategy misalignment, rather than merely a list of known obstacles, to help fuel existing debates around AI implementation in healthcare.

THE PROBLEM WITH UNIVERSAL AI IMPLEMENTATION THINKING

Global research by Oleribe et al. [6] in hospitals and primary care shows a higher willingness to adopt AI in healthcare, with over 90% of respondents recognising its importance. Yet, the translation of these perceptions into hospitals and primary care is not differentiated in the study. This is reflected in the recent literature, including Allen et al. [7], who observed that the continuity, diversity, clinical time constraints and interactions with the patient are distinguishing features of primary care. The key considerations highlighted by Ranjbar et al. [8] are the need for dedicated resources in healthcare settings, effective financial management, and strict adherence to confidentiality principles in implementing AI in hospitals. Collectively, these results indicate that although many of the same barriers exist for using AI in healthcare, the implementation conditions vary widely depending on the setting. This is a reminder that studying AI in hospitals and primary care is important as separate areas of study, instead of bundling them into aggregate healthcare adoption.

AI IMPLEMENTATION GAPS IN HOSPITALS

Maimaitiaili et al. [9] proposed a five-layer architectural model for hospital AI deployment (across infrastructure, data, algorithm, application, security, and compliance) to assess its applicability. This multi-layered implementation is an institutionalised, organised attempt to embed AI into hospital systems, but it has a lack of coherence in governance and in relation to clinical workflow integration. For instance, even in the presence of more sophisticated information systems, a lack of robust governance can restrict clinician confidence and contribute to implementation challenges. Moreover,

integration issues in Electronic Health Records (EHR) systems also limit the operational deployment, reflecting the challenges in operationalising AI in complex socio-technical environments. Beyond this, Kamel Rahimi et al. [4] indicate that the success of AI implementation in hospitals relies on socio-technical systems that are interoperable, clinician and workflow-ready, and effectively integrated. Hence, hospitals may have built the structure but are still not mature in terms of operationalisation and smooth AI adoption. This echoes the previously made point that simply confirming the feasibility of tech is not enough; realising the benefits of AI within a hospital also needs to happen from multiple levels of organisation, one that involves governance, infrastructure, and clinical integration.

AI IMPLEMENTATION GAPS IN PRIMARY CARE

The use of AI in primary care is mostly limited to pilot studies, conceptual models, and restricted versions of decision support systems, and is not fully deployed in clinical practice [10]. Primary care is a very broad, time-limited, undifferentiated patient group in an environment where the structure of the relationship between the patient and primary care provider is of critical importance. On the contrary, as shown in Table 1, in hospital settings, to some extent, there is more differentiation in the patient group, a more hierarchical relationship, and there is generally a structure to the pathway of care. Furthermore, a study by Katonai et al. [11] indicates that the extent of algorithm sophistication is not as important as workflow, ease of use, and disruption of clinician-patient interactions in determining implementation success in primary care. This is supported by the concerns of Alamoudi et al. [12], who report inadequate real-world safety and continuity of care. In addition, primary care systems often lack the digital infrastructure, funding, or assistance to implement at scale.

TABLE 1: AI IMPLEMENTATION IN HOSPITALS AND PRIMARY CARE: WHY SEPARATE STUDY

Dimension	Hospitals	Primary Care	Why a Separate Study is Necessary
Implementation Stage	Structurally mature but operationally immature; it is supported by formal architectures (such as multi-layer AI systems) [9]	Primarily developmental; only used in pilots, prototypes, and small-scale deployment [10]	Evaluation frameworks and research concerns vary by stage of maturity.
Core Implementation Challenge	Multi-layered alignment – governance, infrastructure, integration and clinical workflows	The ability to fit into time-critical workflows shaped by relationships.	The challenges are driven by distinct system constraints, not common challenges
Primary Driver of Adoption	Governance, Accountability, Interoperability & Risk Management [8]	Continuity of care, usability, workflow fit and efficiency [11]	In other contexts, adoption is driven by different dominant factors that render unified models unenforceable
System Structure	Coordinated, hierarchical, and well-regulated systems	Decentralised, flexible and resource-constrained environments	Organisational designs influence the implementation and scale of AI.

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Data Environment	High volume clinical & diagnostic information (imaging, labs) is structured.	Unstructured, narrative, and context-rich patient data	Design & validation requirements for AI vary vastly
Workflow Characteristics	Coordinated multi-speciality approach: (aligned with defined clinical pathways and complex)	Rapid consultations, high variability, and continuity of care.	The challenges of workflow integration vary in type and impact
Resource Availability	Rigorous investment capacity, IT infrastructure, and technical support.	Lack of financial, digital and human resources.	Factors such as disparities in technical resources can affect the sustainability and scalability of AI solutions.
Governance Requirements	Formal governance structures, compliance with regulations and accountability systems	Few governance bodies; new challenges regarding safety, equity, and oversight.	Governance maturity varies and needs different governance policies and governance research.
Nature of AI Integration	System-level integration across departments and platforms	Tools within consultations for Point of Care (PoC).	There are different approaches to integration, scale vs. mode
Implementation Risk	A high clinical risk and medico-legal implications.	Risk is associated with disruptions in care, inequities in care, and disruptions in continuity of care.	Risk profiles vary, impacting adoption decisions and what is measured

Source: Compiled by Authors

ANALYSIS TOWARDS CONTEXT-SENSITIVE AI IMPLEMENTATION STRATEGIES

HOSPITAL IMPLEMENTATION STRATEGIES: GOVERNANCE-LED AND INTEGRATION-ORIENTED

The case study in the Canadian hospital underscored the importance of creating multidisciplinary governance committees, accountability measures and operational policies that can support the hospital's clinical workflows and existing team capacity [13, 14]. Hospitals should implement a robust digital infrastructure to maintain data privacy and security. Co-design with multidisciplinary teams, improved team communication, and defining design standards for AI output can make the implementation seamless in hospitals. Moreover, governance-led implementation can assist in restructuring the existing models using insights from AI analytics and leverage hospital leaders to drive AI adoption.

PRIMARY CARE IMPLEMENTATION STRATEGIES: WORKFLOW FIT AND LOW-FRICTION ADOPTION

The application of a "workflow-aligned" AI tool in "AI Consult" made in 15 primary care clinics in Kenya delivered a 16% reduction in diagnostic error, 13% reduction in treatment error, without reducing the autonomy of clinicians, and with continued trials [15]. Similar strategies can be applied in primary care to implement AI seamlessly. Clinicians in primary care should spend their time shortlisting AI tools that can be tested within a limited number of consultations before starting the adoption process in multiple areas together. Measurable workflow improvement must be focused on instead of spending excessive time on clinical notes and documentation. This example supports Katonai's perspective that AI tools must be strategically designed to integrate with workflows and minimise friction, fostering greater acceptance and usage.

TABLE 2: ACTION-ORIENTED STRATEGIES

Implementation Focus	Hospitals (Integration & Governance Oriented)	Primary Care (Workflow & Usability Oriented)
Starting Point	High risk / high impact use-cases (e.g., diagnostics, imaging)	Low risk / high frequency use-cases (e.g., documentation, triage support)
Implementation Approach	Requests that decisions be made in phases and as part of a broader department-based implementation	Incremental, practice-level implementation during consultations
Technology Integration	Significant integration with EHR / Hospital IT Systems	Plug-and-play tools that fit in with existing practice software.
Governance & Oversight	Formal governance structures, validation protocols, and accountability frameworks	Minimal but essential oversight focused on safety, usability, and continuity of care.
Workflow Strategy	Integrate AI into clinical workflows across multiple specialities	Ensure AI fits into the time-constrained consultation without disrupting the workflow
User Engagement	Clinician training, plus multidisciplinary collaboration	Co-design with clinicians, ease of use, and minimal training
Resource Strategy	Scalable infrastructure and data systems investments	Dedicated AI oversight teams that will fit a resource-constrained environment at low cost
Adoption Driver	Trust through governance, explainability, and reliability	Efficiency, usability, time saving
Scaling Strategy	Resources are scaled in a system-wide and standardised way	Resources are scaled by replication while localising the resources to meet local needs
Key Risk	There are a number of misalignments between governance, systems and workflow.	There are some key risks, including misalignments between governance, systems and workflow.

Source: Compiled by Authors

As shown in Table 2, AI applications in healthcare differ between hospitals and primary care, and the rationale behind them is distinct. Hospitals need integration through complex systems with established governance and robust infrastructure in place; primary care needs low-friction integration and interoperability with workflows. These variations highlight the importance of context-grounded approaches when implementing rather than standard approaches.

CONCLUSIONS

This paper addressed a burgeoning debate in healthcare: how should healthcare industry respond to AI evolution, and what should be the approach for effective AI implementation. The discussion centred on context-sensitive aspects of primary care and hospitals, explicitly suggesting and reinforcing the need to move beyond one-size-fits-all approach to AI integration across context-sensitive decision-making processes. Governance-led and workflow-aligned AI implementation strategies must be considered as key drivers of AI implementation in hospital and primary care clinical processes, respectively.

While this research sets the tone for effective AI implementation, further studies, guided by more comprehensive data-driven and primary approaches, are required to validate and reinforce this perspective further.

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ACHSM Asia-Pacific Journal of Health Management

CONFAB 360 DEGREE 2026

IMPLEMENTING ARTIFICIAL INTELLIGENCE IN CLINICAL DECISION SUPPORT, DIAGNOSTICS AND PREDICTIVE ANALYTICS IN HEALTHCARE: A DOMAIN-CONTINGENT AI IMPLEMENTATION MODEL

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ABSTRACT

OBJECTIVE:

The study aimed to analyse Artificial Intelligence (AI) techniques for clinical decision support, diagnostic analysis and predictive analytics for better implementation in healthcare.

DESIGN:

The study adopted a systematic literature review guided by Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to identify 17 studies related to three domains: clinical decision support, diagnostic analysis and predictive analytics. Thematic analysis was conducted to propose a conceptual model, the Domain-Contingent AI Implementation Model in Healthcare, to suggest that AI effectiveness relies on the domain-specific drivers, constraints, and system-level enablers.

MAIN OUTCOME MEASURES:

The study evaluates AI implementation against the drivers and constraints of three domains, derived through thematic analysis in healthcare settings.

RESULTS:

Findings emphasised the nature of AI as a domain-contingent capability across the three healthcare domains. AI effectiveness in healthcare is driven by interpretability, data intensity and forecasting power, while it is constrained by trust, black-box models and a validation gap in clinical decision support, diagnostic analysis and predictive analytics, respectively.

CONCLUSION:

The study concluded that AI's effectiveness in healthcare implementation is driven by adaptation factors, including usability, infrastructure, and reliability.

KEYWORDS
artificial intelligence; clinical decision support; diagnostics analysis; predictive analytics; healthcare

INTRODUCTION

The role of Artificial Intelligence (AI) is growing as transformative in healthcare, with evidence suggesting it can improve diagnostics, aid clinical decision-making and provide predictive insights. Beyond technical skills, quality issues like interpretability, data quality, and system readiness are among those that have a crucial role in outcomes, as emphasised by Nalla [1]. Others, such as Sani et al. [2] and Pesqueira, Sousa and Pereira [3], identify integration complexity and organisational constraints, and lack of trust, as being one of the key factors that limit healthcare in adopting the system to some degree. While the evidence base is growing, it is still disjointed with isolated applications, so that there is limited insight into the performance and implementation of AI in healthcare areas. This study, therefore, aims to use a systematic literature review to synthesise evidence from three key areas: Clinical Decision Support (CDS), Diagnostics Analysis (DA) and Predictive Analytics (PA) to gain a structured, evidence-based understanding of AI applications, their effectiveness and factors influencing their deployment in healthcare systems.

The novelty of the work is a domain-contingent conceptual model for the implementation of AI in health care. It includes an understanding of the interactions between the various domain-specific drivers, constraints, and system-level enablers, and not just on standalone performance metrics, which turns the spotlight on effectiveness in context.

RESEARCH QUESTIONS

RQ1: How is AI applied within clinical decision support, diagnostics, and predictive analytics, and what domain-specific benefits and limitations emerge?
RQ2: What factors influence the adoption and effective implementation of AI across these domains in healthcare systems?

LITERATURE REVIEW

AI IN CLINICAL DECISION SUPPORT

AI is increasingly applied in how people approach healthcare by providing new methods for identifying patients' illnesses, devising appropriate treatment strategies, and managing patient care. Jiang et al. [4] analysed the use of AI devices such as Machine Learning (ML) and Natural Language Processing (NLP) in stroke care and found that patient permission is required to collect their information into the AI systems. Only then can data be sent to physicians to assess with their clinical decision support. However, stroke care is a chronic disease, and its management is a rather complicated process. This highlights a key limitation of AI-driven decision support systems and their dependence on rich, longitudinal datasets, which may not be consistently available across healthcare settings. Similarly, a study by Yu [5] reported that physicians' willingness to use AI-driven clinical decision support systems is strongly influenced by perceived usefulness and individual innovativeness. It clearly indicates that, beyond technical capability, human factors such as trust and usability play an important role in determining the effectiveness of AI in decision-support contexts.

AI IN DIAGNOSTICS

AI techniques are finding their application to support disease prediction and diagnosis through the integration of extensive biological data to identify genomic lesions, proteins, and immunological states. Klumpp et al. [6] show various use cases of AI techniques in diagnosis, enhance patient cases, reduce the number of hospital visits and assist doctors in the diagnostic process during the pandemic. AI use in European hospitals has been studied in wearable sensors, evaluating the risk of a patient having prognostic Coronary Artery Disease (CAD), and the accurate prediction of fetal hypoxia. It has helped in identifying the level of acceptance for AI techniques among patients, further identifying the potential for

enhanced patient privacy, issues with pre-existing hospital systems in AI integration, and user acceptance. While diagnostic applications of AI show stronger performance in data-sensitive environments, the findings also reveal persistent barriers related to scalability and system integration, probably due to patient apprehension. It indicates that technological advancements alone do not ensure successful deployment as organisational and infrastructural constraints continue to limit real-world impact.

AI IN PREDICTIVE ANALYTICS

Predictive analytics analyses potential vulnerabilities based on historical data through AI techniques like ML and NLP to document security weaknesses and forecast future outcomes. Bhuiyan and Mondal [7], using a set of 1,338 healthcare insurance records, studied healthcare spending and the ability to forecast resource allocation differences using classification and XGBoost Regressor. The results indicated that AI-based predictive analytics can be useful for resource allocation and enhancing the efficiency of healthcare systems. But there are restrictions that need to be overcome as far as clinical validation and authorisation are concerned. The potential translation from experimental to clinical settings raises concerns about the reliability and regulatory approval of predictive models. Just as in the field of decision-support systems, poor data quality, limited generalisability, and non-integration within the health care workflow affect the capability of predictive analytics.

A consistent pattern emerges across these domains, i.e., AI's efficacy is context dependent. White technical maturity is needed; challenges related to trust and validation also need to be addressed. This study integrates findings across these domains to provide a comprehensive understanding of AI in healthcare.

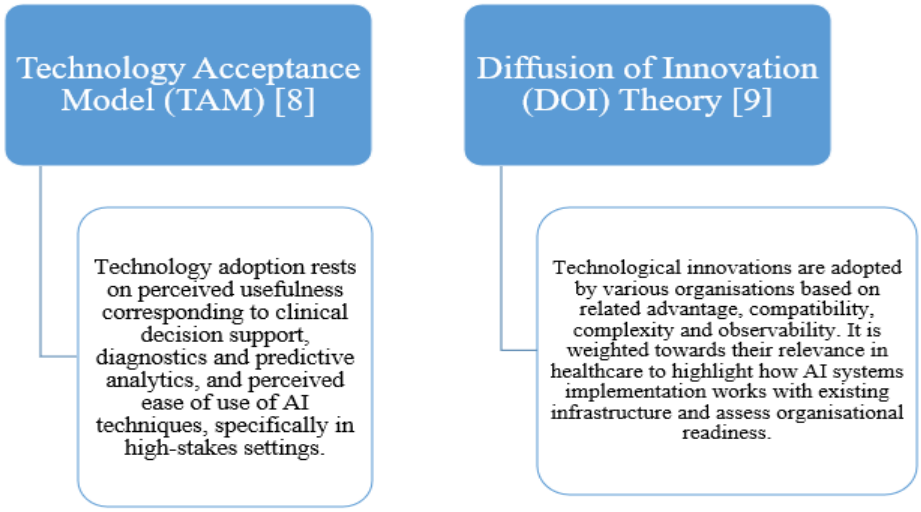
RESEARCH GAPS

- Limited evidence transferability of the DA in AI from one clinical environment and healthcare system to another with limited resources.
- Existing literature on CDS systems has addressed issues such as interpretability and physician trust; however, these have been explored less at the operational level, impacting real-world decisions and adoption.
- PA has been shown to be effective in yielding outcomes, but they are rarely clinically validated or aligned with regulations in high-stakes clinical care.
- Lack of understanding of the operational considerations for integration into current clinical workflows in all areas, including interoperability with legacy systems.

Overall, data privacy and patient acceptance issues are addressed conceptually rather than empirically examined, highlighting the gap in understanding their practical implications in large-scale AI deployment.

THEORETICAL FRAMEWORK

FIGURE 1. TAM AND DOI MODELS



Source: Created by Authors based on [8, 9]

This study combines TAM and DOI (Figure 1) to introduce a dual perspective from the individual level of acceptance by clinicians and users' level on the system level of acceptance in healthcare organisations. This integrated framework assists in guiding the thematic analysis by providing a construct of interpretability, data dependency, trust, integration and regulatory alignment.

METHODS

The study adopts Systematic Literature Review (SLR) to comprehensively investigate the implementation of AI in healthcare domains (i.e., CDS, DA and PA). The review process comprised identification, screening, eligibility evaluation, and inclusion of relevant literature sources. The methodology has been inspired by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach, which aims to increase transparency and enable a more comprehensive understanding of research identification, selection, and analysis of results.

SEARCH STRATEGY AND SEARCH STRING

Researchers used a systematic search to identify scholarly articles that investigated AI implementation in healthcare settings through academic databases, namely Scopus, Web of Science, Google Scholar, and PubMed. The search strings were developed based on the major themes of the study: artificial intelligence, healthcare, decision support, diagnostics, predictive analytics, and empirical implementation. The Boolean search string which was used is given below:

("artificial intelligence" OR "machine learning" OR "deep learning" OR "natural language processing") AND ("healthcare" OR "medical" OR "clinical") AND ("decision support" OR "clinical decision support system" OR "diagnostics" OR "medical diagnosis" OR "predictive analytics" OR "risk prediction") AND ("empirical study" OR "clinical evaluation" OR "validation" OR "implementation" OR "real-world evidence" OR "case study")

INCLUSION CRITERIA

- Peer-reviewed journal articles from 2016 to 2026 in the English language
- Studies focusing on AI applications in a healthcare environment
- Studies emphasising the use of AI techniques related to clinical decision support/diagnostics/predictive analytics

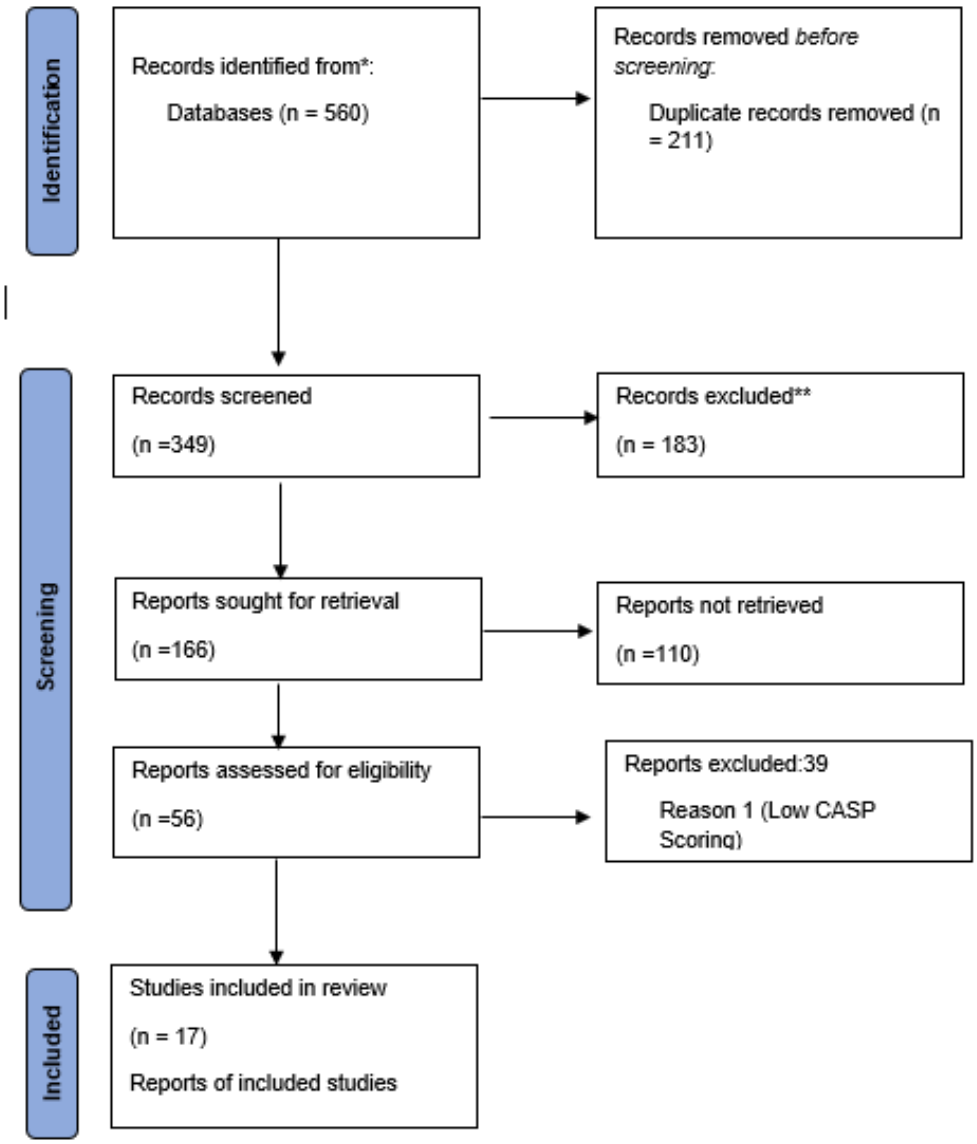
EXCLUSION CRITERIA

- Studies focusing on non-healthcare applications of AI
- Low Critical Appraisal Skills Programme (CASP) score
- Non-accessibility of full papers

STUDY SCREENING AND SELECTION PROCESS

The initial search yielded 560 studies relevant to the current research, out of which 211 duplicate records were removed. The remaining 349 records were screened. 183 records were removed at this stage because they did not align with the study's main aim. A further 166 records were sought for retrieval, of which only 56 were retrieved, as shown in Figure 2. These 56 records underwent a complete eligibility test based on the abstract and full text, using the CASP criteria framework. Each study that met CASP criteria was categorised as high quality, meaning strong methodological rigour and empirical evidence were present; moderate, meaning an adequate level of quality with some limitations; or low, meaning sufficient methodological reliability was not present. This screening left 17 studies for inclusion in the SLR. Figure 2 shows the entire selection process.

FIGURE 2. PRISMA FLOWCHART



Source: Constructed by Author

DATA EXTRACTION AND COMPARATIVE SYNTHESIS

A structured review matrix (Table 1) was used for data extraction. The data that were extracted from each of the studies identified: domain of healthcare, type of application (e.g., clinical application), source of the data (including sample sizes), performance (metrics) of AI models, clinical outcome & implications and limitations within studies. Synthesis of identified evidence from the extracted data occurred in a thematic framework, whereby the studies were grouped into three major categories of AI implementation in healthcare:

- Clinical Decision Support (CDS)
- Diagnostic Accuracy (DA)
- Predictive Analytics (PA)

TABLE 1. SUMMARISATION OF LITERATURE

Author(s)	Year	Study Type	Objective	Key Findings	Domain	Quality Rating
Somashekhar SP et al.	2018	Empirical	Evaluate IBM Watson Oncology recommendations	93% agreement with multidisciplinary tumour board	CDS, DA	High
Park T et al.	2023	Empirical	Assess Watson Oncology in urologic oncology	92.7% concordance with tumour board decisions	CDS, DA	High
De Fauw J et al.	2018	Empirical	Diagnose retinal disease using (Optical Coherence Tomography) OCT images	Performance comparable or superior to that of clinicians	CDS DA	High
Lee CS et al.	2019	Empirical	Generate retinal blood flow maps from OCT	Improved diagnostic imaging interpretation	CDS, DA	High
Alam M et al.	2019	Empirical	Classify retinal diseases	Improved screening and disease classification	DA, PA	High
Parchure P et al.	2020	Empirical	Predict near-term in-hospital mortality	AUC of 85.5% for mortality prediction	PA	High
Cheng FY et al.	2020	Empirical	Predict ICU transfer among COVID patients	Approximately 76% prediction accuracy	PA	High
Friedman JI et al.	2025	Empirical	Predict delirium risk in hospital patients	High predictive accuracy (AUC 0.94)	PA	High
Miotto R et al.	2016	Empirical	Predict diseases using EHR data	Improved prediction of diabetes and cancer	PA	High
Wanyan T et al.	2021	Empirical	Improve prediction of critical	Better prediction of mortality and ICU transfer	PA	High

			COVID events			
Jiang F et al.	2017	Conceptual Review	Examine the evolution of AI in healthcare	Identified present and future applications of AI in diagnosis and treatment	CDS, PA	Moderate
Currie G et al.	2019	Conceptual Review	Explore AI in medical imaging	Highlighted ethical, regulatory and implementation concerns	CDA, DA, PA	Moderate
Adlung L et al.	2021	Conceptual Review	Assess ML integration in clinical decision-making	Discussed benefits, risks and validation needs	CDS	Moderate
Lee D & Yoon SN	2021	Conceptual Review	Analyse opportunities and challenges of AI in healthcare	Found AI useful in diagnosis and decision support	DA	Moderate
Yu KH et al.	2018	Conceptual Review	Review AI applications in medicine	Highlighted the expanding role of AI in healthcare	PA	Moderate
Badawy M et al.	2023	Survey Review	Review ML and DL in predictive healthcare	Summarised predictive models and challenges	PA	Moderate
Topol EJ	2019	Perspective/ Conceptual	Explore the convergence of human expertise and AI	Discussed clinician-AI collaboration	CDS	Moderate

Source: Constructed by Author

THEMATIC ANALYSIS

Clarke and Braun's thematic analysis is used to systematically analyse findings from selected studies [10], [11]. It was guided by a three-stage coding procedure (Table 2), open coding, axial coding, and selective coding to enhance transparency and analytical rigour around theme development.

TABLE 2. THREE-STAGE THEMATIC CODING PROCEDURE

	Stage 1: Open Coding	Stage 2: Axial Coding (Clustering and Domain Alignment)	Stage 3: Selective Coding (Theme Development)	Theoretical Contribution (TAM + DOI)
Process	The included articles were checked line by line to identify common ideas with respect to the usage and employment of AI technologies for healthcare. This process of coding was inductive, producing a	The second step was to group similar codes into higher-order categories. In the course of doing this analysis, we noticed a clear pattern that the codes did not seem to be distributed randomly; rather, they	In the last step, the domain-aligned categories were synthesised into higher-order themes shaped by the dominant patterns within each domain. Instead of imposing generic themes throughout all studies, this	TAM and DOI were used as sensitising frameworks to interpret patterns, particularly in understanding how user acceptance, usability, and system compatibility

	set of initial codes that were data-derived rather than category-defined.	seemed to cluster around three specific application contexts in healthcare.	analysis maintained domain specificity, which produced the following three core themes.	influenced the clustering of codes.
Output	Most occurring codes- • interpretability and explainability; • clinical trust and the physician; • acceptance model accuracy and performance; • data requirements (volume, quality, annotation); • generalisability and validation; • regulatory and ethical concerns; • workflow integration and interoperability	i) Codes such as interpretability, trust, and physician acceptance were predominantly associated with clinical decision support systems. ii) Codes such as model accuracy, large dataset requirements, and black-box limitations were strongly linked to diagnostic applications. iii) Codes such as prediction accuracy, generalisability, and validation gaps were concentrated within predictive analytics.	1. Clinical Trust and Interpretability in Decision Support Systems (analysing CDS) 2. Data-Intensive Accuracy and Transparency Constraints in Diagnostics (analysing DA) 3. Predictive Capability versus Validation and Generalisability in Predictive Analytics (analysing PA)	Codes such as trust and usability align with TAM (perceived usefulness & ease of use), while integration, complexity, and compatibility align with DOI. This explains why certain codes are clustered within specific domains.
Insight	These codes encapsulated technical characteristics (e.g. accuracy, dependence on data) as well as implementation-related factors (e.g. trust, integration).	This also highlighted that AI challenges and capabilities are heterogeneous across domains rather than uniform, allowing for the alignment of categories with three healthcare domains.	For each domain, choose themes based on the frequency across studies, conceptual coherence and power of explanation in terms of both strengths and limitations of AI were chosen across studies.	TAM explains individual-level adoption (trust, usability), while DOI explains system-level diffusion (integration, compatibility). Together, they clarify why AI adoption varies across decision support, diagnostics, and predictive analytics.

Source: Compiled by Authors

ANALYSIS AND RESULTS

THEME 1: CLINICAL TRUST AND INTERPRETABILITY IN DECISION SUPPORT SYSTEMS

The analysis indicates that AI in CDS systems primarily serves as an assistive decision-making aid, facilitating clinicians' diagnostic and treatment planning by combining structured and unstructured clinical data. The effectiveness of AI for CDS is not solely based on predictive accuracy but also depends on the level of interpretability and clinical appropriateness of its outputs, as reflected in 8 of the 17 studies [4, 12-18]. Overall, the research points to the potential benefits of AI in improving decision-making processes, dealing with the consistency of decisions, and supporting expert reasoning. But accuracy is not the sole criterion of a CDS system. One of the studies puts an accent on interpretable outputs, visualising the decision process, such as OCT segmentation, to allow clinical interpretation and verification of AI decisions [14]. This highlights the fact that trust in the clinical setting is dependent on transparency, especially in high-risk

decision settings. Therefore, AI shows evident advantages in enhancing decision support but is limited by the inability of the outputs to be explainable or clinically justified.

In line with TAM, a higher degree of interpretability would result in a firmer belief in usefulness and ease of use and thus affect clinician acceptance. At the same time, along the lines of DOI theory, AI systems are more acceptable to be adopted when they fit into current clinical reasoning procedures.

THEME 2: DATA-INTENSIVE ACCURACY AND TRANSPARENCY CONSTRAINTS IN DIAGNOSTICS

AI in diagnostics is most commonly utilised as a pattern-recognition tool leveraging data analysis, often in the context of imaging diagnosis for disease identification. 7 out of 17 show that AI can enhance imaging interpretation by generating clinically relevant insights (e.g., retinal flow maps) from existing OCT data [12-16], [19-20]. But DA relies heavily on extensive and rich data sets and is not scalable when resources are scarce. Furthermore, the black-box nature of AI models, such as deep learning models, is problematic for clinical accountability and transparency, and integration capabilities limit the opportunity for routine clinical use.

In an analytical sense, the results support the TAM, as high DA increases perceived usefulness, which facilitates the adoption of AI, whereas limited explainability is used by clinicians to lower and temper perceived ease of use, decreasing trust in AI. Moreover, the DOI theory aids in comprehending the integration and complexity of AI systems into current clinical settings, such as healthcare environments with inadequate data infrastructure, thereby enhancing the likelihood of successful diffusion. Lastly, AI usage in DA is used as a high-performance, data-driven detection system (RQ1) which brings accuracy and efficiency, yet suffers from data dependency, limited transparency and integration barriers (RQ2).

THEME 3: PREDICTIVE CAPABILITY VERSUS VALIDATION AND GENERALISABILITY IN PREDICTIVE ANALYTICS

AI in PA is used as a tool for prediction and foresight, using extensive Electronic Health Records (EHRs) to anticipate disease outcomes and make resource planning decisions. The use of AI for clinical forecasting and risk stratification is supported by 10 of the 17 studies [4, 16, 19, 20-27]. However, limited validation and generalisability put a barrier on AI's efficacy, as models can often perform well within specific datasets only, which might be difficult to obtain in diverse healthcare settings. In addition, models are complex, decreasing interpretability and concerns over accountability and clinical reliability. High predictive performance would have a positive impact on perceived usefulness (TAM), whereas limited transparency would hinder clinician trust, which in turn would impact adoption from an analytical perspective.

At the same time, models can negatively impact diffusion through the healthcare system due to their poor validation and complexity (DOI). In sum, using AI in PA for outcome (RQ1) forecasting and risk prediction (RQ2) has demonstrated valuable predictive power, while these limitations are sufficiently substantial to warrant further research, development, and validation.

Together, the 3 themes define the domain-contingency of AI in health care as a function of trust in CDS, data intensity in DA, and validation in PA, and will support efforts towards integrated and contextually developed models going forward for the successful and continuous addition of AI to the healthcare domain.

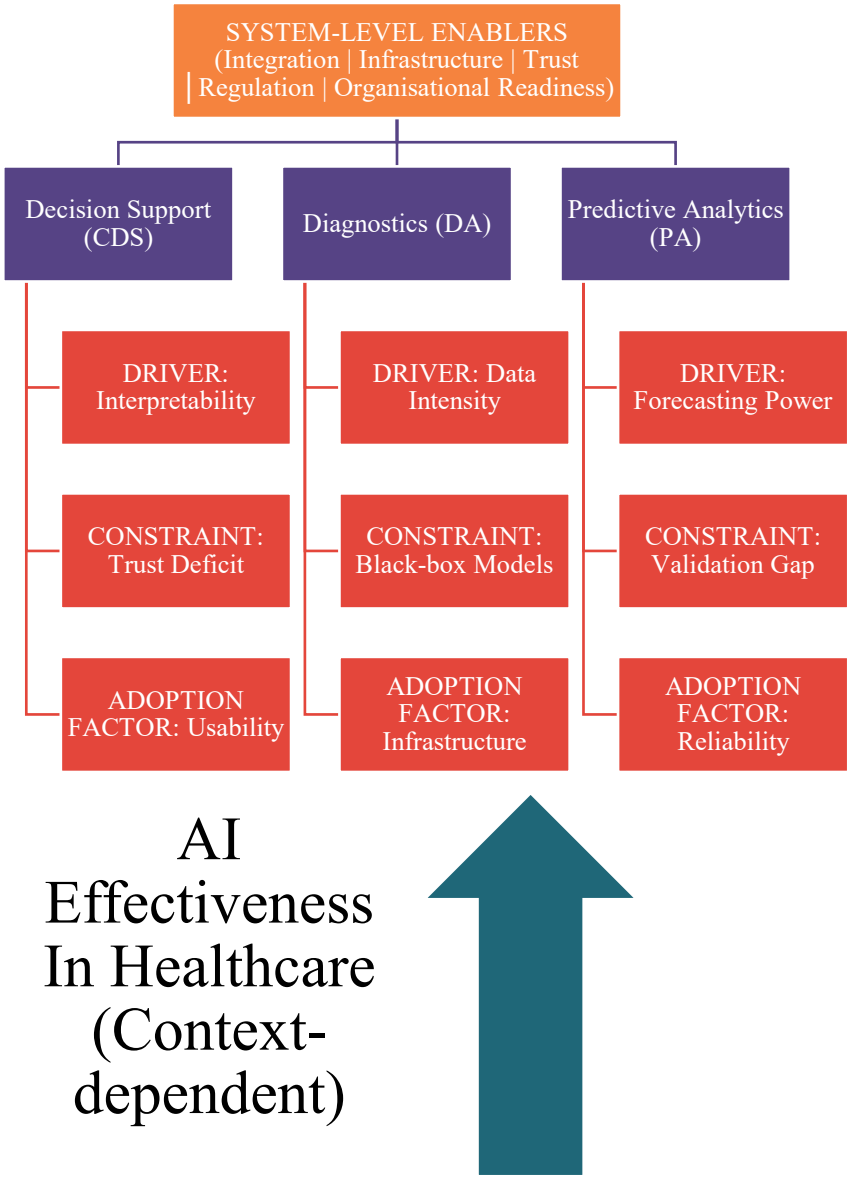
PROPOSED CONCEPTUAL MODEL

The Domain-Contingent AI Implementation Model in Healthcare represents a data-driven abstraction of the thematic findings, rather than a theoretically imposed structure, ensuring alignment between empirical evidence and conceptual contribution.

Figure 3 shows that each domain is driven by a different primary value mechanism: interpretability in decision support, data-intensive accuracy in diagnostics, and forecasting capability in predictive analytics. However, each also faces a distinct constraint, trust deficit, black-box opacity, and validation gap, respectively, which directly shape adoption outcomes.

Crucially, these domain dynamics do not operate in isolation. System-level enablers, including data infrastructure, workflow integration, regulatory clarity, and organisational readiness, mediate whether AI moves from technical capability to real-world effectiveness. The model thus goes beyond the traditional "which AI is best?" to "which AI will fit where and under what conditions."

FIGURE 3. DOMAIN-CONTINGENT AI IMPLEMENTATION MODEL IN HEALTHCARE



Source: Constructed by Authors

The model resolves the fragmentation in existing literature by providing a structured explanation of how AI effectiveness emerges through the alignment of domain-specific requirements and system-level conditions.

DISCUSSION

The study develops a conceptual model that examines the drivers and constraints of the three domains to identify adaptability factors that can support AI implementation in healthcare. It extends TAM and DOI by integrating AI adoption in domain-contingent rather than uniform across healthcare applications. It shifts the evaluation of AI from performance-centric metrics to context-driven effectiveness. Policymakers and healthcare professionals can adopt this as a tool to expand their horizon in meeting patient care needs and forecasting data-driven solutions for accurate diagnostics. Not only can they align with local implementation processes, but they can also make informed, well-aligned decisions within healthcare. Future researchers can use the analysis as a long-term validation and interdisciplinary efforts towards the

effective implementation of AI in clinical settings. However, the research is supported by only 17 studies, and it would be beneficial to explore all three domains with a primary data-driven perspective.

CONCLUSION

The study develops a domain-contingent conceptual model to assess the effectiveness of AI in healthcare across three domains: clinical decision support, diagnostic analysis, and predictive analytics, only to find that the adoption factors play an important role in its implementation.

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ACHSM Asia-Pacific Journal of Health Management

CONFAB 360 DEGREE 2026

UNPACKING ETHICAL, PRIVACY, AND GOVERNANCE RISKS IN AI-IOT BASED HEALTHCARE ENVIRONMENTS: A THEMATIC ANALYSIS

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ABSTRACT

OBJECTIVE

The paper aims to examine ethical, privacy, and governance challenges in AI-IoT (Artificial Intelligence-based Internet of Things) healthcare environments.

DESIGN

A total of 39 peer-reviewed open-access studies were screened and used for a systematic review using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework. A multi-stage thematic analysis was used for identifying recurring patterns within the literature and answering the research questions.

RESULTS/OUTCOMES

The identified challenges in the AI-IoT healthcare ecosystems, arising from the thematic analysis, are privacy and continuous surveillance, algorithmic bias and lack of explainability, limitations for informed consent, and fragmented governance and accountability.

CONCLUSION

The findings, in sync with STS theory, indicate that challenges in AI-IoT healthcare systems cannot be addressed solely through technological innovations. In response, the study proposed an Integrated Human-Centric Trust Framework to integrate human intervention with technological advancements.

KEYWORDS

Internet of Things; Artificial Intelligence; Healthcare; Thematic Analysis; Law and Governance

INTRODUCTION

The healthcare industry is advancing due to continuous developments in digital technology, specifically Artificial Intelligence (AI) and the Internet of Things (IoT), creating smart healthcare networks that enable real-time tracking, predictive analysis, and customised medical treatment. IoT is benefitting the healthcare industry through increased innovation (80%), visibility across the organisation (76%), and cost savings (73%) through the use of devices, such as smart inhalers, connected medication dispensers, and wearable sensors [3]. Their applications lie in tracking vital signs and gathering large amounts of patient information for better diagnosis and treatment procedures. Even the introduction of the Internet of Medical Things (IoMT) in healthcare has led to uninterrupted communication between patients and healthcare providers. IoMT applications in portable diagnostic deliver patient care, allowing for remote care, disease prevention, and continuous patient monitoring, particularly for chronic disease patients and senior citizens [3]. However, the reliability of such technologies on a network makes them vulnerable to cyberattacks, creating privacy issues for personal information like identification and health status [4]. Also, continuous collection of large amounts of sensor data in healthcare settings might improve the quality of care but pose continuous ethical challenges in terms of data management, bias and fairness, and informed consent [5].

The continuous flow of data enabled by IoT technology creates an ecosystem of constant surveillance, raising concerns about patients' privacy [5]. In addition, the lack of transparency in medical AI development, also known as the 'black box' problem, raises concerns about trust, accountability, and fairness in healthcare services [6], [7]. This further reinforces the point of informed consent to understand why/how patient data is utilised by the governing bodies in AI-IoT-enabled healthcare [8]. Additionally, the conventional understanding of consent can no longer be applied to the healthcare system, given the constant flow of information enabled by IoT technology, which is reused for various purposes in healthcare settings [9], [10].

Taken together, there is a strong need for explainability in governance and opening the black box has become essential to provide a watershed moment unpacking ethical, privacy, and governance concerns, including trust in AI-based IoT healthcare. While existing literature has extensively discussed privacy, explainability, ethical AI, and governance concerns in healthcare technologies, these discussions remain fragmented across technical, legal, and ethical domains. This study contributes by providing an integrated thematic synthesis of interconnected challenges, thereby presenting an Integrated Conceptual Human-Centric Trust Framework that positions trust, accountability, patient autonomy, and governance as central dimensions of AI-IoT healthcare implementation. The two research questions are:

RQ1: What are the major ethical, privacy, and governance challenges associated with AI-IoT-enabled smart healthcare systems?
RQ2: How do ethical, privacy, and governance challenges within AI-IoT healthcare ecosystems influence patient trust, accountability, and human-centred healthcare delivery?

THEORETICAL LENS

The study is conceptually led by Socio-Technical Systems (STS) Theory, emphasising the interdependent relationships between technological systems and social, institutional, and human environments within the healthcare industry. In this study, STS guides the thematic exploration of governance, trust, explainability, and human-centred healthcare delivery.

LITERATURE REVIEW

AI and IoT technologies have combined to become a transformative area of development in healthcare today, as they provide effective patient care through improved clinical delivery and accurate diagnosis. Rushabh et al. [1] found increasing applications of AI and IoT technologies, including patient monitoring systems, disease detection, and wearable devices, further highlighting the need for system accuracy, security, data collection and management, and privacy protection to support their continued development. Wearable devices and IoT-based healthcare systems enable

individualised and remote care by providing continuous monitoring of multiple physiological parameters and facilitating early disease detection [11], [12]. AI-based healthcare models have demonstrated similar reliability in predicting patient health outcomes and supporting clinicians' decisions [13].

Smart healthcare ecosystems focus on the contributions of AI-based IoT systems to addressing societal and healthcare issues, such as population growth, resource scarcity, and the management of chronic health conditions [14]. Emerging technologies have created new paradigms in personalised healthcare; however, IoT devices and their data collection processes have been recognised as potential sources of data privacy and security breaches [15], [16]. Various studies have highlighted the need to ensure security by implementing security models such as encryption and blockchain [17], [18].

Furthermore, privacy is also at risk due to the widespread use of IoT monitoring systems that often operate without user consent or knowledge, challenging traditional healthcare models [8]. The integration of AI into these IoT monitoring systems raises further privacy concerns about algorithmic bias and fairness. Bias in the input data used to train the algorithms, and in the way algorithms are designed, means that individuals will receive inaccurate predictions and outcome measures, especially those belonging to disadvantaged populations [7], [19].

In response to these concerns, Explainable AI (XAI) has emerged as a useful way to provide transparency and show how AI processes clinical decisions [20], [21]. Clinicians who use XAI methods such as Shapley Additive Explanations (SHAP) and Local Interpretable Model Agnostic Explanations (LIME) have a better understanding of the model's output, in addition to trust in AI systems for patient treatment [22]. Another challenge in AI-IoT-based healthcare systems concerns informed consent. The traditional concept of consent is found to be inadequate in situations where data is constantly being created and reused [9]. New concepts such as dynamic consent and blockchain technology are proposed to address this challenge and provide users with better control and transparency in data usage [23]. Research highlights the importance of integrated governance and trustworthy AI models in the context of healthcare systems based on AI [24, 25]. The challenges with AI-IoT systems in terms of ethics are not only issues of technological limitations but rather of governance concerns that involve patient autonomy, compliance, accountability, and the overall trust in healthcare delivery, by combining the points from the literature. Finally, patient trust and acceptability are essential for AI-based healthcare systems. Research has shown that although patients acknowledge the benefits of AI-enabled health care systems, they are apprehensive about the consequences of losing personal data, personal autonomy and human interaction in the decision-making process [26].

RESEARCH GAPS

Existing research studies have proposed XAI privacy-preserving technologies and dynamic consent models as effective solutions. Their relevance and implementation within healthcare have not been fully developed. Available studies provide a limited understanding of the combined impact of these ethical and governance issues on accountability, trust and the overall quality of healthcare delivery.

METHODS

RESEARCH DESIGN

The study focuses on understanding AI and IoT-based ethical, privacy, and governance issues in healthcare, interrelating these constructs subjectively (guided by STS theory) and qualitatively (through a Systematic Literature Review).

SEARCH STRATEGY

A literature search was conducted using various databases, including Scopus, Springer, ScienceDirect, IEEE Xplore, and PubMed. These databases were considered for their broad coverage of interdisciplinary research involving healthcare technology applications, ethical AI, the IoT, and digital governance.

The search strategy employed Boolean operators and carefully selected keyword combinations to identify relevant scholarly literature related to Artificial Intelligence (AI), the Internet of Things (IoT), and healthcare ethics. Boolean operators such as "AND" were used to refine and narrow the search results by combining multiple concepts. The search string was:
(("Artificial Intelligence" OR AI) AND ("Internet of Things" OR IoT OR "Internet of Medical Things" OR IoMT) AND (Healthcare OR "smart healthcare" OR "digital healthcare")) AND ("healthcare ethics" OR "ethical issues" OR "ethical challenges" OR "AI governance in healthcare" OR "Explainable AI" OR XAI OR "healthcare data privacy" OR "data protection" OR "algorithmic bias in healthcare AI" OR "informed consent in AI healthcare systems"))

These combinations enabled the identification of studies focusing on technological integration, ethical challenges, governance frameworks, transparency, privacy concerns, bias in AI-driven decision-making, and patient consent within intelligent healthcare environments.

INCLUSION CRITERIA

- English-language publications
- Literature focusing on AI, IoT, IoMT, machine learning, or explainable AI in healthcare contexts
- Peer-reviewed journal articles, conference proceedings, and scholarly book chapters discussing ethical, legal, governance, privacy, transparency, consent, or accountability dimensions
- Studies published between 2017 and 2025

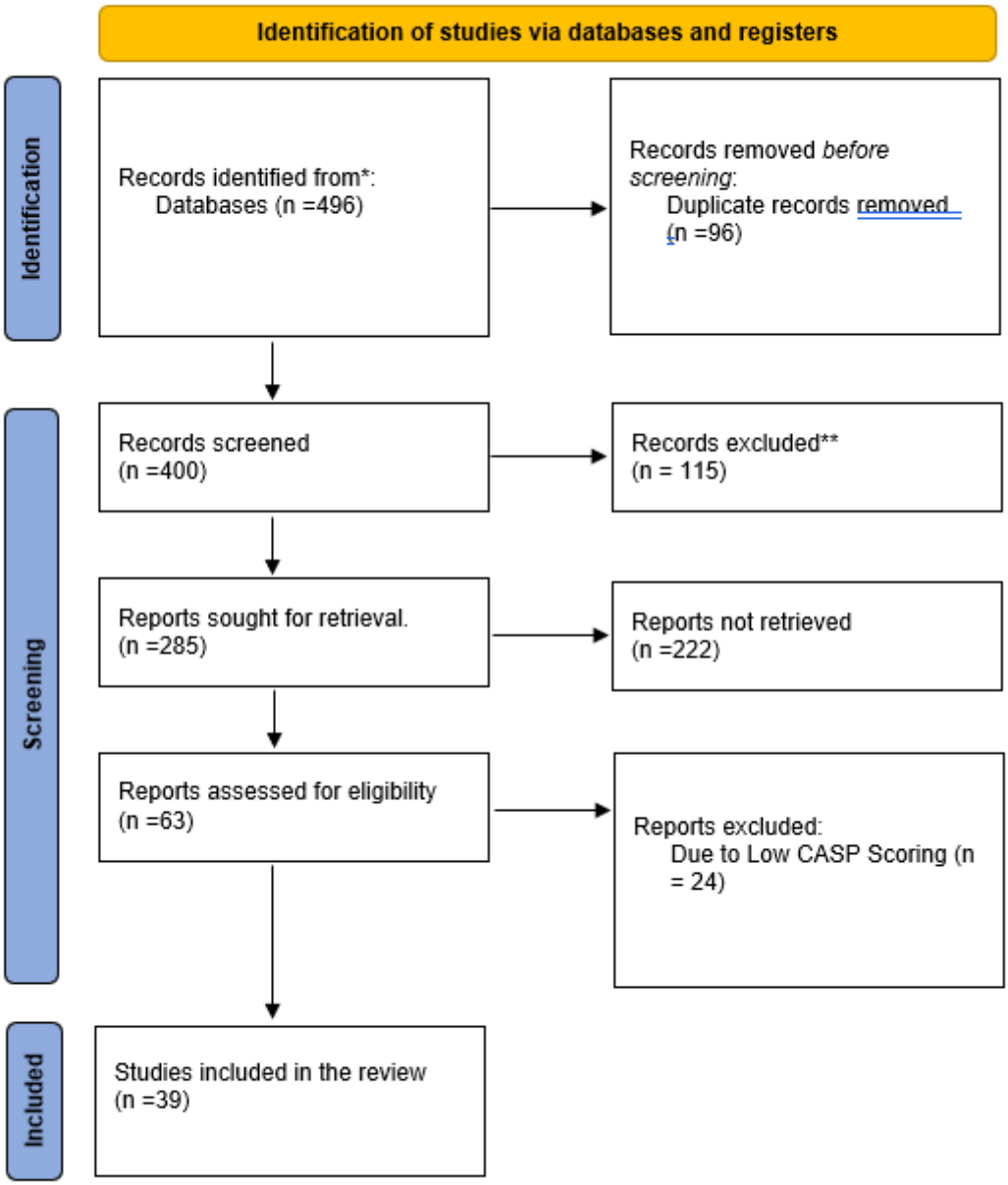
EXCLUSION CRITERIA

- Studies unrelated to healthcare applications
- Purely technical engineering studies without ethical or governance implications
- Non-peer-reviewed sources, editorials, blogs, or news reports
- Duplicate studies across databases
- Articles lacking an accessible full text

STUDY SELECTION PROCESS

Based upon the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework (Figure 1), the initial search was started using the Boolean search strings. The initial search yielded 496 articles for the contemporary period. Upon screening, it was found that out of 496 articles, 96 articles were duplicates and were thus removed. Moving forward, the 96 articles were further screened on the basis of inclusion and exclusion criteria. This resulted in the removal of 115 studies. The remaining 285 studies were then sought for report retrieval. Only 63 studies were retrieved. These 63 studies were then assessed on the basis of CASP (Critical Appraisal Skills Programme). Lastly, 39 studies were selected for the systematic literature review (Table 2).

FIGURE 1. PRISMA FLOWCHART



Source: Constructed by Authors

QUALITY APPRAISAL

The CASP framework provided a means to ensure the methodological quality and credibility of included studies by assessing them against common criteria, including: clearly defined study objectives, adequate methodological rigour, apparent validity of findings, relevance of findings to the research problem, ethical considerations, and transparency of analysis.

THEMATIC ANALYSIS

A multi-stage coding process was followed to ensure thematic consistency and analytical transparency. During the initial open coding stage, recurring concepts such as surveillance, explainability, bias, accountability, and governance were identified in the literature. In the second stage, these descriptive codes were grouped through axial coding into conceptual categories, i.e., ethics, privacy, and governance (Table 1). Finally, refinement was conducted using selective coding to categorise codes into analytical themes, which formed the foundation of this research's thematic interpretation.

TABLE 1. THEMATIC CODING AND CATEGORISATION

Category	Codes	Themes	Description
Privacy	privacy, surveillance, consent, data misuse, continuous monitoring	Theme 1 (RQ1)	Focuses on the protection of patient data, confidentiality, continuous IoT monitoring, informed consent practices, and risks associated with unauthorised access or secondary use of healthcare data.
Ethics	bias, explainability, transparency, trust, fairness, autonomy, human-centred care	Theme 2 (RQ1)	Covers ethical implications of AI-driven healthcare systems, including algorithmic bias, black-box AI, fairness in healthcare outcomes, transparency of decision-making, patient autonomy, and trust in AI systems.
Governance	governance, accountability, regulation, compliance, ethical oversight, liability	Theme 3 (RQ1)	Relates to regulatory frameworks, accountability mechanisms, AI governance structures, legal responsibility, policy compliance (e.g., GDPR), and institutional oversight of AI-IoT healthcare systems.

Source: Compiled by Authors

TABLE 2. SUMMARISATION OF LITERATURE

Year	Study Focus/Objective	Methodology/Approach	Key Findings	Codes	Themes	CASP Appraisal
[1]	AI and IoT integration in healthcare	Systematic literature review	AI-IoT improves monitoring and diagnostics	surveillance, governance	**Governance**	High
[2]	AI-IoT Healthcare 4.0 monitoring	Conceptual framework	Real-time predictive healthcare enhanced	surveillance, governance	**Governance**	Moderate
[3]	IoMT, AI, ML and smart healthcare future	Conceptual review	Smart technologies improve healthcare efficiency	surveillance, governance	**Governance**	Moderate
[4]	AI-enabled wearable IoT systems	Survey study	Wearables support continuous monitoring	surveillance, privacy	**Privacy**	High

[5]	Ethical issues in ambient intelligence healthcare	Ethical review	Surveillance threatens autonomy and privacy	privacy, surveillance, consent	**Privacy**	High
[6]	Explainability in healthcare AI	Multidisciplinary review	XAI improves transparency and trust	explainability, transparency	**Ethics**	High
[7]	Privacy challenges in AI healthcare	Literature review	Patients fear misuse of health data	privacy, accountability	**Privacy**	High
[8]	Privacy-by-design in smart healthcare	Conceptual analysis	Existing consent systems are inadequate	consent, governance	**Privacy**	High
[9]	AI, big data and consent	Theoretical analysis	Traditional consent models fail in AI systems	consent, accountability	**Ethics**	High
[10]	Legal and ethical concerns in healthcare AI	Review study	Responsibility for AI decisions remains unclear	accountability, governance	**Governance**	High
[11]	ML for healthcare wearables	Technical review	ML improves predictive monitoring	surveillance	**Governance**	Moderate
[12]	AI-IoT for critical healthcare	Applied review	AI enables real-time healthcare response	surveillance, accountability	**Governance**	Moderate
[13]	Secure wearable healthcare systems	CPS and IoT review	Security essential for healthcare trust	Privacy, governance	**Privacy**	Moderate
[14]	IoT and ML in smart healthcare	Review article	Predictive AI supports healthcare efficiency	Surveillance/ governance	**Governance**	Moderate

[15]	ML for healthcare-IoT security	Risk mitigation review	IoT vulnerabilities threaten healthcare systems	Accountability, governance	**Governance**	High
[16]	Data privacy in AI healthcare	Narrative review	AI challenges healthcare privacy norms	Privacy/surveillance	**Privacy**	Moderate
[17]	Secure IoT healthcare systems	Conceptual review	Secure architecture improves trust	governance	**Governance**	Moderate
[18]	ML anomaly detection in healthcare IoT	Experimental study	ML enhances security monitoring	Surveillance/ governance	**Governance**	High
[19]	IoT and ML for personalized healthcare	Conference study	Personalized care faces interoperability challenges	Accountability/governance	**Governance**	Moderate
[20]	Explainable AI diagnostics	Conceptual analysis	XAI improves accountability	Explainability/ accountability	**Ethics**	Moderate
[21]	XAI and healthcare trust	Review study	Transparency strengthens trust	explainability, transparency, trust	**Ethics**	High
[22]	XAI and ethical compliance	Conceptual review	Ethical AI requires transparency	explainability, governance, accountability	**Ethics**	Moderate
[23]	Blockchain-based dynamic consent	Technological framework	Dynamic consent improves patient control	consent, privacy	**Privacy**	High

[24]	Trustworthy AI in healthcare	Ethical review	Governance pathways are essential	governance, accountability	**Governance**	High
[25]	AI governance framework in healthcare	Multimethod protocol	Governance frameworks support safe AI adoption	governance, accountability	**Governance**	High
[26]	Public perception of healthcare AI	Survey study	Public expresses privacy and ethical concerns	privacy, trust, consent	**Ethics**	High
[27]	Ethical conundrums in AI healthcare	Scoping review	AI raises fairness and accountability concerns	bias, accountability, governance	**Ethics**	High
[28]	AI ethics under GDPR	Comprehensive review	GDPR stresses transparency obligations	governance, privacy, accountability	**Governance**	High
[29]	Security and privacy in IoT healthcare	Review article	Smart healthcare vulnerable to cyber threats	privacy, surveillance	**Privacy**	High
[30]	IoT communication security in healthcare	Technical review	Security mechanisms strengthen privacy	privacy, governance	**Privacy**	Moderate
[31]	Big data and predictive analytics	Perspective article	Predictive analytics may threaten patient interests	privacy, accountability, trust	**Ethics**	High
[32]	XAI with ML for disease prediction	Empirical review	Explainability improves trust and transparency	explainability, transparency	**Ethics**	High

[33]	Actionable ethics in digital health	Ethical framework analysis	Ethical oversight should be operationalized	governance, accountability, consent	**Governance**	High
[34]	AI ethics and managerial foresight	Conceptual review	Ethical imperatives shape sustainable healthcare	governance, accountability	**Governance**	Moderate
[35]	Safe and trustworthy AI systems	Review article	Trustworthy AI requires accountability and ethics	governance, accountability, trust	**Governance**	High
[36]	AI, IoT and wearable healthcare	Book chapter review	Emerging technologies improve diagnostics	surveillance, governance	**Governance**	Moderate
[37]	AI for IoT medical systems	Conceptual chapter	AI enhances intelligent healthcare systems	governance, surveillance	**Governance**	Moderate
[38]	Health Industry 4.0,5.0 trends	Bibliometric analysis	AI-healthcare research rapidly expanding	governance	**Governance**	Moderate
[39]	Digital healthcare disease prediction	Review study	Predictive systems improve diagnosis	surveillance, accountability	**Governance**	Moderate

Source: Constructed by Authors

ANALYSIS AND RESULTS

THEME 1. PRIVACY AND CONTINUOUS DATA SURVEILLANCE (RQ1)

Theme 1 aligns with patients' private information, including physiological data, behavioural patterns, and lifestyle details being collected through AI-IoT devices. Cyberattacks and vulnerabilities in connected networks directly or indirectly challenge data surveillance, increasing risks of breaches, illegal access, and misuse. The use of centralised data storage, together with cloud computing services, further exacerbates risks because both storage systems and communication protocols have security weaknesses. The process of collecting data without notifying users results in patients experiencing invisible data extraction. The situation creates an unequal distribution of power between patients and healthcare providers, resulting in privacy issues. Moreover, the reuse of data for secondary purposes, such as research, data analysis, or business, has increased the complexity of informed consent.

THEME 2. ALGORITHMIC BIAS AND LACK OF EXPLAINABILITY (RQ1)

Ethical challenges of AI-IoT systems are a lack of explainability and algorithmic bias that can arise for many reasons, including imbalanced datasets, lack of validation and weakness in governance measures during deployment. Biases shape and drive the unequal experiences of health care and significantly impact underrepresented patient populations. Additionally, the lack of understanding of AI-generated recommendations (in some cases) results in the black box property of AI systems and transparency issues. XAI could be a potential solution to increase transparency in the healthcare system, but it has to be paired with continuous ethical oversight and organisational accountability/prejudice checks. STS Theory suggests that these moral dilemmas should be approached not merely as a technical problem, but as a consequence of the closed relationships between technology, governance, healthcare organisations, and human decision-making.

THEME 3. GOVERNANCE, REGULATION, AND ACCOUNTABILITY GAPS (RQ1)

Theme 3 reflects the fact that AI-IoT systems deployed in health care settings are often subjected to governance and accountability issues. When the current regulatory and institutional frameworks don't evolve as quickly as AI technologies, the issues escalate into problems of patient safety, transparency, and institutional accountability. Rather, these governance issues, in the STS perspective, are not exclusively caused by the technological innovation itself, but by the complex interplay of factors, including AI systems, regulatory frameworks, healthcare contexts, and human decision-making processes. Only an integrated governance approach can help address these issues and enhance transparency, compliance, patient trust and human-centred care.

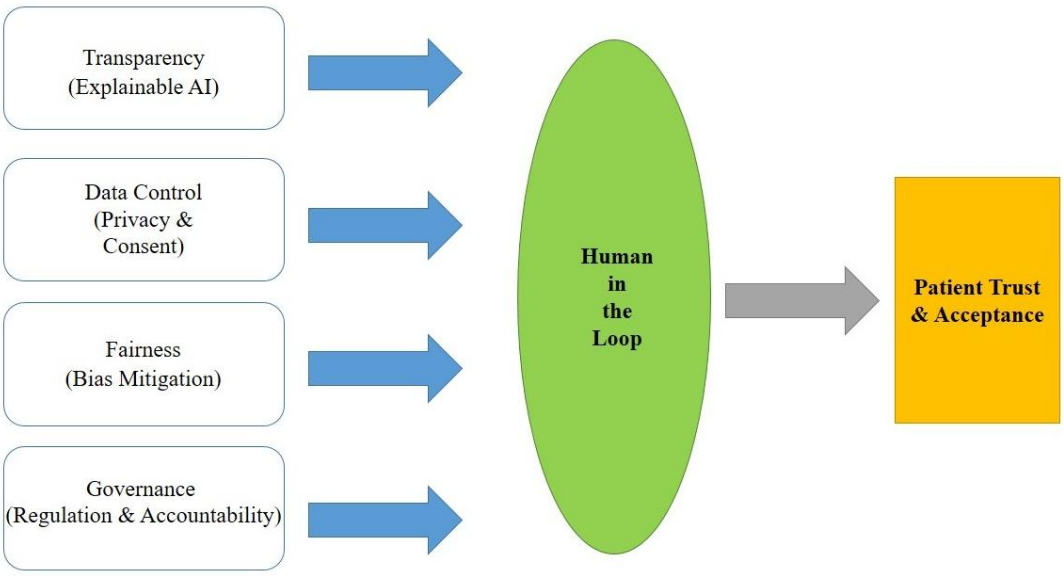
TRUST, ACCOUNTABILITY, HUMAN-CENTRED HEALTHCARE DELIVERY (RQ2)

Thematic analysis collectively reveals that lack of trust in AI-IoT-based healthcare systems exists because of issues with surveillance, biased algorithmic methods and governance. Concerns about privacy introduced problems relating to autonomy and informed consent, and institutional control of patient data. Similarly, the opacity of AI also posed challenges to operational processes, impacting the accountability of healthcare professionals for patient outcomes. Moreover, roles to be held accountable are not clearly specified, leaving room for doubts about ethical responsibility, particularly in the case of wrong diagnosis or prognosis and adverse clinical results. All these factors significantly affect transparency, compliance and public confidence in AI-supported healthcare delivery. The research, therefore, suggests that accountability in AI-IoT systems is not merely a technical issue but also an institutional governance challenge (STS perspective). In this context, the Integrated Conceptual Human-Centric Trust Framework emerges as a socio-technical governance approach, aiming to strengthen ethical AI implementation, institutional trust, and patient-centred healthcare delivery in digitised healthcare environments.

The Integrated Conceptual Human-Centric Trust Framework, as shown in Figure 2, builds a foundation for digital healthcare by outlining four fundamental elements of trust and how they impact transparency, patient control of data, fairness, and governance. Transparency supports clinical confidence because it enables stakeholders to make effective decisions using AI-IoT-supported systems. Patient control over data emphasises informed consent, privacy protection, and meaningful control over personal healthcare information. Fairness addresses the ethical risks of unequal healthcare outcomes caused by opaque AI decision-making processes. Governance functions as the foundational mechanism that supports institutional accountability, compliance and responsible AI deployment. At the centre of the frameworks is the Human-in-the-loop approach, suggesting that continued involvement of healthcare professionals is necessary in validating AI-supported decisions. From the STS perspective, it means that trustworthy healthcare requires a fine balance between technological innovations, human interventions, institutional accountability, patient-centred healthcare approaches and ethical oversight.

This holistic framework combines patient autonomy, fairness, governance and human oversight, unlike current frameworks which tend to focus on one or the other or on technical transparency in isolation. It makes trust a governance and management issue, rather than a technical matter. Nevertheless, the framework is still conceptual and needs to be validated in various healthcare environments for its practical application and operational effectiveness.

FIGURE 2. HUMAN CENTRIC TRUST FRAMEWORK FOR IOT ENABLED SMART HEALTHCARE SYSTEMS



Source: Constructed by Authors

Whereas, given the current state of frameworks and literature, such as WHO Ethical guidelines, trustworthy AI models, and GPR principles, there is a lack of unified socio-technical perspectives, particularly with concepts of patient autonomy, transparency and fairness in place as well as governance and human oversight (Table 3).

TABLE 3. COMPARISON BETWEEN EXISTING FRAMEWORKS

Existing Frameworks	Primary Focus	Limitation	Contribution of the Proposed Framework
WHO Ethical AI Guidance	Ethical AI principles	Broad healthcare ethics orientation	Integrates governance and trust within AI-IoT healthcare ecosystems
GDPR Principles [28]	Data privacy and compliance	Focused mainly on data governance	Incorporates institutional accountability and human oversight
Trustworthy AI Frameworks [35]	Transparency and fairness	Limited healthcare operational focus	Contextualises trust within healthcare delivery systems
Healthcare Governance Models [25]	Institutional accountability	Limited AI-IoT integration	Synthesises governance, ethics, and socio-technical trust dimensions

Source: Compiled by Authors from [25, 26, 35]

LIMITATIONS AND CONCLUSIONS

Some of the limitations of this research are as follows:

- The study relies on secondary literature and thematic analysis, which may introduce some subjectivity and bias in identifying and interpreting themes.
- The small sample of 39 studies may not fully capture the rapidly evolving nature of AI-IoT technology.
- The proposed framework is conceptual and is not empirically validated.

These limitations call for future empirical studies to validate the findings and enhance the practical implementation and operational efficacy of the proposed framework. Given these findings, continued research is needed to fully grasp the intricate interplay between healthcare facilities, AI systems, governance, and human decision-making processes, and

shift the norms and expectations of AI use. Further studies are necessary to build a balance between technological advancements and human interventions.

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ACHSM Asia-Pacific Journal of Health Management

CONFAB 360 DEGREE 2026

BRIDGING THE GAP BETWEEN RESEARCH AND PRACTICE: A SYSTEMATIC LITERATURE REVIEW OF IOT AND MACHINE LEARNING APPLICATIONS IN MENTAL HEALTHCARE SYSTEMS

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ABSTRACT

OBJECTIVE

This study conducts a systematic review of Internet of Things (IoT) and Machine Learning (ML) applications to identify existing gaps and scope for improvisation.

DESIGN

Databases such as Scopus, Web of Science, PubMed, IEEE Xplore, and ScienceDirect were searched to find relevant studies focusing on IoT and ML in mental healthcare. Using Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines, 18 studies were selected for the final review. Cyber-Physical Systems (CPS) theory and thematic analysis were employed to answer research questions.

RESULT/OUTCOMES

Four dimensions were identified as: continuous behavioural monitoring, ML-driven predictive analytics, real-time adaptive mental healthcare interventions, and responsible clinical deployment. IoT and ML technologies were found to have significantly improved patients' monitoring, predicting risks, and enhancing interventions using digital phenotyping, wearable data sensing, digital phenotyping and AI-driven analytics. However, some challenges in effective implementation of IoT and ML applications included explainability, ethical governance, interoperability, and clinical integration.

CONCLUSION

An Operational Framework for Real-Time IoT-ML Mental Healthcare Systems is proposed to bring together sensing, analytics, and interventions. This framework recommends taking adequate actions to support either scalability or clinically sustainable mental healthcare delivery.

KEYWORDS

Internet of Things; Machine Learning; Mental Healthcare System; Artificial Intelligence; Real-Time Implementation; Operational Framework

INTRODUCTION

Given the rise of mental health conditions, such as chronic stress, depression, anxiety, and behavioural dysfunction, the existing scenario of episodic consultations cannot be considered efficacious in the long run [1]. Mental health conditions have notably affected the quality of life and overall well-being of people across diverse populations. On top of that, current gaps in traditional psychiatric evaluations leave several people undiagnosed, leaving them either without any monitoring or with minimal interventions. Internet of Things (IoT), smartphones, wearable devices, and other advanced technologies have appeared in recent scholarly discussions in their potential to gather behavioural and physiological signals related to mental health. These signals often relate to speech and sleep patterns, Heart Rate Variability (HRV), and social interactions.

For example, a hybrid Machine Learning (ML) model can effectively interpret voice, facial expressions, and speech patterns, identifying the level of stress [2]. In sync with this, Del-Valle-Soto et al. [3] asserted a possibility of real-time feedback, gamification, and personalised interventions by integrating digital platforms with mental health. Growing research on digital phenotyping, one of the most effective processes to quantify individual-level human traits, confirms the predictive capabilities of wearable devices and smartphones in predicting the symptoms of insomnia, stress, depression, and other similar aspects [4, 5].

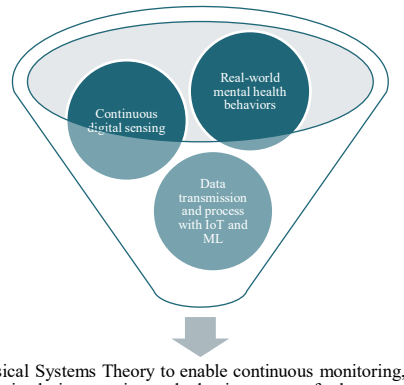
In spite of these developments, existing research is largely focused on technological aspects, which, to an extent, ignore the analytical and implementation-oriented synthesis of IoT and ML applications in mental healthcare delivery. The contribution of this research lies in integrating not only technological aspects, but also ethical dimensions and clinical implementation to address the gap between research and practice. To fulfil this objective, this study proposes an Operational Framework for Real-Time IoT-ML Mental Healthcare Systems to demonstrate phase-wise implementation of IoT and ML models.

RQ1: What are the major applications of IoT and ML in mental healthcare systems?
RQ2: How can IoT and ML technologies guide intervention-oriented mental healthcare delivery, and what are the challenges in their practical implementation?

THEORETICAL FRAMEWORK

Cyber-Physical Systems (CPS) theory provides the foundation for this research. This theory discusses the integration of computational systems, intelligent analytics, and sensor technologies, and how this integration is useful for creating interdependent real-time systems [6]. This theory aims to merge physical (sensors, human environments, mechanical parts) with cyber (internet, computation) through constant feedback loops (Figure 1). This unifying factor of this theory closely aligns with this research study, which also focuses on improving real-time mental healthcare delivery by a combination of digital information and behavioural and computational aspects.

FIGURE 1. CPS THEORY



Source: Constructed by Authors

SYSTEMATIC LITERATURE REVIEW

EVOLUTION OF MENTAL HEALTHCARE SYSTEMS

As per the World Health Organization (WHO) [7] report, approximately 970 million people suffered from mental health issues in 2019. Research by Queensland Brain Institute [8] suggests that more than 50% of people across the globe are likely to experience anxiety or depression at some point in their lives. Such statistics are concerning because depression and anxiety affect all realms of an individual's life, be it personal, professional, social, emotional, and more. Because of these all-encompassing adverse effects of mental health problems, early detection, real-time monitoring, and effective intervention have become a necessity to manage the stigma surrounding psychological issues and promote the overall life quality of people [9].

DIGITAL PHENOTYPING AND IOT IN MENTAL HEALTHCARE

While IoT devices such as smartphones, biosensors, and wearable sensors allow personalised care and real-time monitoring, cost-effective digital phenotyping can collect a wealth of data on digital phenotypes [10]. These are two significant aspects of transformation in mental healthcare systems because research has revealed significant potential in continuous anxiety and stress assessment using wearable devices [11]. Still, some authors, including Onnela and Rauch [12], have emphasised patients' consent in capturing their data. Similar issues, such as privacy, autonomy, confidentiality, need to be considered because of ethical issues in real-time surveillance.

ML AND PREDICTIVE MENTAL HEALTH ANALYTICS

With the continuously gathered data from the sensing devices based on Internet of Medical Things (IoMT), ML algorithms can be used to detect psychological patterns in people with depression, anxiety, stress, disorders, emotional stability and suicidal tendencies [13]. Specifically, Random Forest (RF) algorithms, Decision Trees, and Support Vector Machines (SVM) have demonstrated high potential in structuring behavioural datasets, and classifying and predicting risks.

Affirming this, Khoo et al. [14] have directly stated that these models can effectively classify depression, stress, and anxiety according to their severity levels, depending on sleep and voice patterns, along with social interactions and mobility of patients. Contrasting this, a study by Tuan [15] highlighted difficulties faced by clinicians in interpreting the results given by black-box Deep Learning (DL) models, causing trust issues. Additionally, many of these predictive models are based on biased or unbalanced datasets, which significantly affects the generalisability of findings and creates algorithmic bias. Overall, these challenges surrounding predictive models highlight notable gaps in these models' transition to intervention-oriented and clinically reliable systems.

INTERVENTION-ORIENTED SMART MENTAL HEALTHCARE SYSTEMS

Another key area is real-time intervention systems that can trigger emergency alerts to manage emotional crises, ongoing stress, and suicides [16]. In a study conducted by Zhang et al. [17], a real-time alert detection system achieved detection consistency of more than 95% across 12000 concurrent devices. This example reinforces the possibility of similar developments in mental healthcare delivery. These advanced developments should integrate psychosocial monitoring, behavioural analytics, and contextual awareness to improve personalised care. However, these intervention-oriented systems are still in pilot or experimental stages and have not so far shown sufficient clinical deployment. Furthermore, reliance on automated alerts raises concerns surrounding false alarms, limited human engagement, and ethical decision-making [18], [19], highlighting substantial gaps between technological innovation and practical implementation.

Overall, though existing research has demonstrated a fast evolution of advanced technologies, issues like lack of interpretability, limited accountability, and algorithmic bias remain large [18]. These challenges directly question ethical governance, emotional surveillance, explainability, and clinical validation of IoT-ML technologies, which can affect their implementation in healthcare on a large scale and on a sustainable basis.

RESEARCH GAPS

Key gaps across the reviewed studies include:

- Fragmented research surrounding ML prediction, IoT sensing, and digital phenotyping
- A limited number of studies with longitudinal data
- Less focus on intervention-orientation
- Limited studies focusing on clinical validation

METHODS

REVIEW PROTOCOL

The systematic review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 [20] guidelines to ensure transparency and rigour in identifying, screening, and synthesising studies. Inclusion and exclusion criteria were predefined, and the quality of studies was assessed based on the Critical Appraisal Skills Programme (CASP).

SEARCH STRATEGY

A comprehensive search was conducted across academic databases, including Web of Science, Scopus, ScienceDirect, and PubMed, to shortlist relevant articles (based on inclusion/exclusion criteria, Table 1) between 2016 and 2026.
An extended search string was used across databases:
(("mental health*" OR anxi* OR depress* OR stress* OR "behavio* disorder*" OR psychiatr*) AND ("deep learning" OR "machine learning" OR "artificial intelligence" OR AI OR SVM OR CNN OR LSTM OR "random forest*") AND ("Internet of Things" OR IoT OR IoMT OR wearable* OR smartphone* OR biosensor* OR "digital phenotyping") AND (monitor* OR predict* OR intervention* OR telepsychiatr*)) where * denotes variations in the specific term.

TABLE 1. INCLUSION AND EXCLUSION CRITERIA

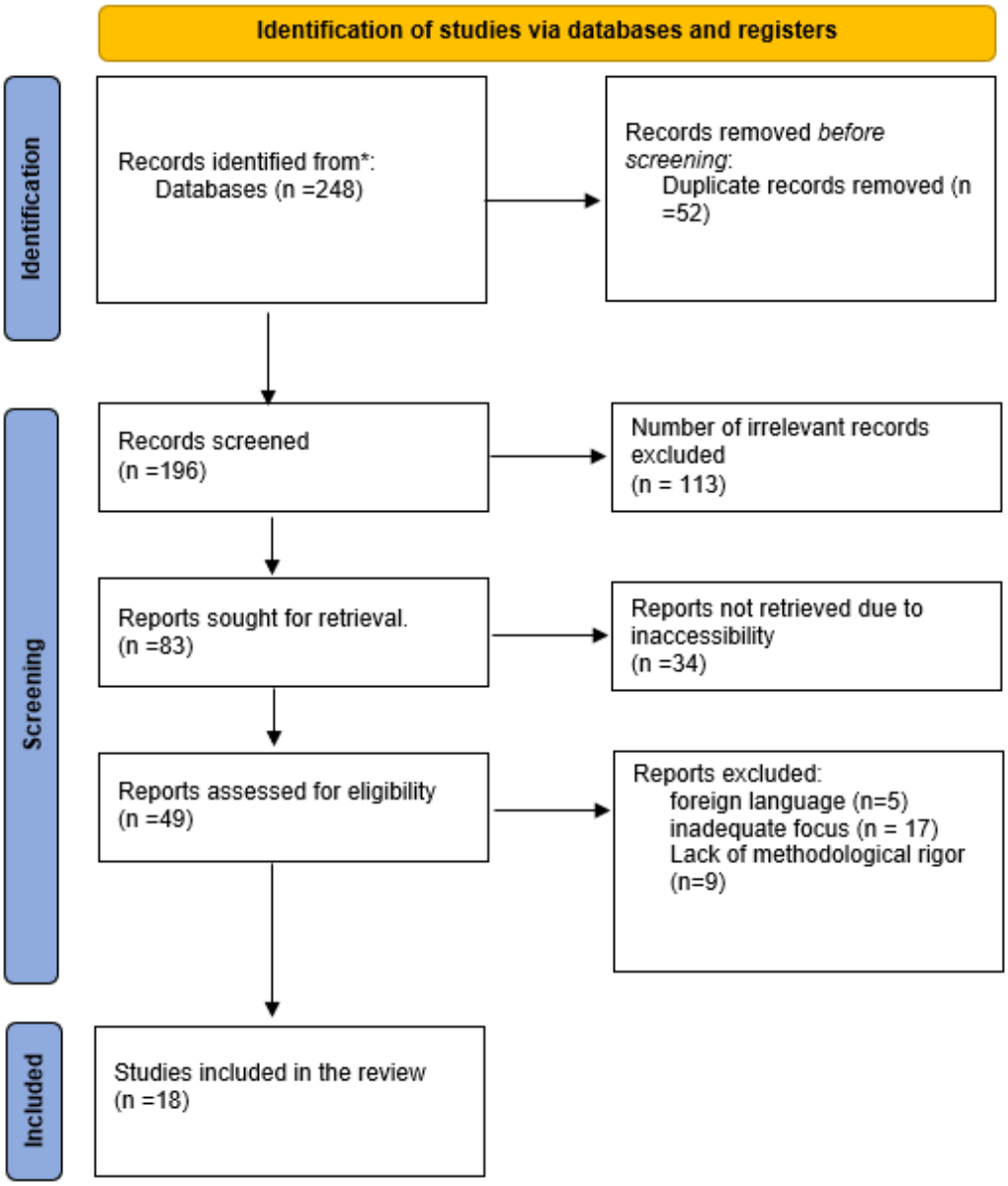
Inclusion Criteria	Exclusion Criteria
Peer-reviewed journal articles	Editorials, opinion papers, and conference abstracts
Studies published in English	Non-English publications
Studies published between 2016 and 2026	Studies published before 2016
Empirical studies involving IoT and ML/DL in mental healthcare systems	Studies unrelated to mental healthcare applications and implementation
Studies reporting implementation outcomes, predictive performance, clinical validation, interoperability, scalability, or patient monitoring evidence	Conceptual papers without empirical validation
Pilot, longitudinal, experimental, observational, and real-world deployment studies relevant to mental healthcare	Duplicate studies, incomplete reports, and studies lacking sufficient methodological information

Source: Compiled by Authors

STUDY SELECTION PROCESS

Initially, 248 records were identified from different databases using the Boolean search string. After removing 52 duplicate records, the remaining 196 abstracts were screened. 113 studies were excluded as they did not meet the inclusion criteria; out of the remaining 83 records, 34 could not be retrieved. 49 records were assessed for eligibility based on their titles and abstracts; 31 were excluded after assessing the full text, and the remaining 18 were considered for the final review process (Figure 2).

FIGURE 2. PRISMA CHART



Source: Constructed by authors

CASP FRAMEWORK

The CASP assessment tool was used to evaluate studies on 7 dimensions (2 scores for each and a maximum score of 14) as listed below:

- Clear objectives
- Appropriate methodology
- Valid datasets
- Analytical rigour
- Evidence-based
- Ethical concerns
- Reproducibility

Studies between 12–14 were classified as high quality, 8–11 as moderate quality, and 0–7 as low quality (Table 2).

TABLE 2. SUMMARISATION OF LITERATURE

Author(s)	Technology / Model	Mental Healthcare Application	Key Findings	Relevance to the Present Study	Theme	Code	CASP Score
[1]	Mental health intervention review	Mental health challenges and interventions	Highlighted the increasing global burden of mental health disorders and limitations of existing intervention systems	Establishes the need for intelligent and scalable mental healthcare systems	Need for continuous and intervention-oriented healthcare	M3	11 (Moderate)
[2]	Wearable devices + physiological analytics	Real-time stress prediction	Demonstrated effectiveness of physiological signals for stress monitoring using wearable devices	Supports IoT-enabled continuous behavioural monitoring	IoT-based monitoring systems	M1	13 (High)
[3]	Wearable biometric systems	Behavioural and physiological monitoring	Explored wearable technologies for biometric sensing and behavioural assessment	Provides evidence for IoT sensing infrastructure in mental healthcare	IoT-based monitoring systems	M1	12 (High)
[4]	Passive sensing + ML	Mental health monitoring	Showed that wearable and smartphone sensing can support continuous behavioural	Supports digital phenotyping and continuous monitoring systems	IoT-based monitoring systems	M1	13 (High)

			monitoring and prediction				
[5]	Digital phenotyping	Stress, anxiety, and depression detection	Identified smartphone behavioural indicators associated with psychological disorders	Supports behavioural analytics and passive sensing approaches	IoT-based monitoring systems	M1	12 (High)
[6]	Cyber-Physical Systems (CPS) Theory	Intelligent integrated systems	Defined CPS as the integration of sensing, computational systems, and real-time analytics	Form the theoretical foundation of the present study	Intelligent healthcare ecosystems	M3	9 (Moderate)
[7]	Global healthcare evidence	Mental health prevalence	Highlighted the growing global burden of mental health disorders	Justifies the need for scalable mental healthcare solutions	Need for continuous and scalable healthcare	M3	10 (Moderate)
[8]	Epidemiological evidence	Mental health prevalence	Reported that nearly half the global population may experience mental disorders	Establishes urgency for preventive and continuous mental healthcare systems	Need for continuous and scalable healthcare	M3	10 (Moderate)
[9]	Mental health prevention strategies	Mental health promotion and prevention	Emphasised the need for early intervention and preventive healthcare approaches	Supports intervention-oriented mental healthcare systems	Intervention-oriented mental healthcare	M3	11 (Moderate)

[10]	IoT and digital healthcare technologies	Monitoring and intervention systems	Demonstrated IoT-based innovations for mental health monitoring and support	Supports operational and intervention-oriented healthcare frameworks	Intervention-oriented mental healthcare	M3	12 (High)
[11]	Wearable AI systems	Anxiety detection	Meta-analysis showed wearable AI systems can effectively detect anxiety through physiological data.	Supports ML-driven predictive analytics	ML-driven predictive analytics	M2	13 (High)
[12]	Smartphone digital phenotyping	Behavioural mental health analytics	Established smartphone sensing as a tool for continuous behavioural monitoring	Foundational evidence for digital phenotyping	IoT-based monitoring systems	M1	12 (High)
[13]	Passive sensing + ML	Continuous mental health monitoring	Highlighted predictive capabilities of smartphone and wearable sensing systems	Supports Theme 1 and Theme 2 development	ML-driven predictive analytics	M2	13 (High)
[14]	Multimodal ML models	Mental health detection	Demonstrated multimodal sensing improves prediction robustness	Supports ML-based behavioural intelligence systems	ML-driven predictive analytics	M2	12 (High)

			and accuracy				
[15]	Explainable AI (XAI)	Clinical AI implementation	Highlighted trust and transparency challenges of black-box AI systems	Supports ethical and explainability challenges	Ethical and implementation challenges	M4	11 (Moderate)
[16]	AI-driven mental healthcare systems	Addiction and complex mental health management	Demonstrated role of AI in adaptive and personalised mental healthcare interventions	Supports the intervention-oriented healthcare theme	Intervention-oriented mental healthcare	M3	11 (Moderate)
[17]	Predictive analytics + AI	Suicide risk and emotional distress prediction	Demonstrated predictive AI systems for crisis detection and prevention	Supports real-time intervention and crisis management systems	Intervention-oriented mental healthcare	M3	12 (High)
[18]	Generalizable ML systems	Stress monitoring from wearables	Identified limitations in dataset generalizability and real-world implementation	Supports implementation and validation challenges	Ethical and implementation challenges	M4	11 (Moderate)

Source: Compiled by authors

ANALYSIS AND RESULTS

THEMATIC ANALYSIS

A three-stage thematic analysis, comprising open coding, category formation, and theme generation, was employed to ensure analytical and methodical rigour and transparency of the research process (Table 3 and Table 4).

TABLE 3. THREE-STAGE CODING

Stage	Process Conducted	Example from Reviewed Studies	Output Generated
Stage 1: Open Coding	Key concepts, technologies, applications, and challenges were extracted from each study based on repeated ideas and research focus areas. Initial labels (codes) were assigned to recurring concepts.	Studies discussing wearable devices, passive sensing, smartphone monitoring, and physiological tracking were coded as "monitoring", "behaviour tracking", and "wearable sensing". Studies focusing on Random Forest, CNN, and stress prediction were coded as "prediction models" and "AI analytics".	Initial recurring codes related to monitoring, prediction, intervention, and implementation issues were identified.
Stage 2: Category Formation (Axial Coding)	Similar codes were grouped together based on conceptual similarity and operational function within mental healthcare systems.	Codes such as wearable sensing, behavioural tracking, passive sensing, and physiological monitoring were grouped under "IoT-based monitoring". Codes related to depression prediction, anxiety detection, and multimodal AI models were grouped under "predictive analytics".	Broader analytical categories representing core research areas were developed.
Stage 3: Final Theme Development (Selective Coding)	The broader categories were synthesised into higher-level themes that represent the major dimensions of IoT- and ML-enabled mental healthcare systems.	Monitoring-related categories formed Theme M1, prediction-related categories formed Theme M2, intervention-focused categories formed Theme M3, and governance/privacy-related categories formed Theme M4.	Four final analytical themes were generated: M1 (Monitoring Systems), M2 (Predictive Analytics), M3 (Real-Time Adaptive Mental Healthcare Interventions), and M4 (Responsible and Clinically Sustainable Mental Healthcare Deployment).

Source: Compiled by authors

TABLE 4. CODES

Code	Theme
M1	IoT-Based Monitoring Systems
M2	ML-Based Predictive Analytics
M3	Real-Time Adaptive Mental Healthcare Interventions
M4	Responsible and Clinically Sustainable Mental Healthcare Deployment

Source: Compiled by authors

The frequency analysis of studies demonstrated in Table 5 reveals the concentration of literature surrounding four broad dimensions, i.e., M1, M2, M3, and M4. M3, the most predominant dimension appearing in more than 40% of the studies, relates to real-time adaptive mental healthcare interventions, which reflects the growing research orientation in real-time, intervention-based models. IoT-based monitoring systems (M1), appearing in approximately 27 % of the studies, highlighted that wearable sensing, digital phenotyping, and passive behavioural tracking are frequent approaches when

it comes to mental health assessment. In contrast, relatively fewer (approximately 16 %) studies talked about ML-driven predictive analytics, and only 2 studies out of 18 discussed ethical and implementation challenges.

This analysis directly shows that while innovation in technologies is growing, ethical concerns remain a concern requiring comprehensive attention. The analysis also reinforces the need for more analytically integrated and implementation-oriented mental healthcare frameworks that combine continuous monitoring, predictive intelligence, ethical governance, and actionable intervention mechanisms.

TABLE 5. FREQUENCY ANALYSIS

Code	Theme	Number of Studies	Percentage (%)	Interpretation
M1	IoT-Based Monitoring Systems	5	27.8%	Literature strongly focuses on wearable sensing, passive monitoring, and behavioural data collection for mental health assessment.
M2	ML-Driven Predictive Analytics	3	16.7%	Several studies emphasise predictive modelling, multimodal analytics, and AI-based mental health detection systems.
M3	Real-Time Adaptive Mental Healthcare Interventions	8	44.4%	The majority of studies highlight the growing need for scalable, preventive, and intervention-oriented mental healthcare ecosystems.
M4	Responsible and Clinically Sustainable Mental Healthcare Deployment	2	11.1%	Compared with other studies, fewer critically address explainability, privacy, validation, and implementation barriers.

Source: Compiled by Authors

THEME 1: REAL-TIME ADAPTIVE MENTAL HEALTHCARE INTERVENTIONS (M3) (RQ2)

Real-time adaptive interventions have been shown to improve continuity of care, accessibility of health services, risk management, and personalised mental healthcare delivery [10], [16], [18]. From the CPS theory's perspective, intervention systems combine computation and sensing as IoT devices monitor behavioural and physiological conditions, and ML models detect psychological risks. Thus, CPS-based ecosystems ensure smooth and continuous workflows not only in a predictable way but also in an action-oriented manner. However, these intervention systems are still in an experimental stage, and their large-scale clinical use is not yet established.

THEME 2: CONTINUOUS BEHAVIOURAL MONITORING SYSTEMS (M1) (RQ1, RQ2)

IoT-enabling monitoring systems are the foundation of smart mental healthcare solutions because continuous sensing is beneficial in detecting mental health risks over periodic assessments [2], [4], [5]. These systems, being CPS-based interconnected infrastructures, generate continuous digital data and ensure computational analysis by making that data measurable. Thus, monitoring systems ensure continual mental healthcare by effective physiological and behavioural monitoring, signifying a promising application of IoT.

THEME 3: ML-DRIVEN PREDICTIVE MENTAL HEALTH ANALYTICS (M2) (RQ1, RQ2)

Various algorithms, including SVM, RF, CNN, and LSTM, are frequently used for the classification of depression, prediction of stress, classification of emotions, and suicide risk prediction. According to the studies by Abd-Alrazaq et al. [11] and

Khoo et al. [14], the advantages of multimodal ML systems are that they leverage on behavioural, physiological, and contextual data to achieve predictive robustness. CPS theory underpins this theme with a focus on the dynamic interplay between sensing and computational decision-making subsystems, in which the continuously generated behavioural data are translated into predictive healthcare intelligence. However, the literature also reveals tensions regarding explainability, algorithmic bias, and limited clinical validation, indicating that predictive performance currently advances faster than practical implementation reliability.

THEME 4: RESPONSIBLE AND CLINICALLY SUSTAINABLE MENTAL HEALTHCARE DEPLOYMENT (M4)

Adverse impacts are observed on clinician trust with the use of Black-Box AI and emotional surveillance; consent issues and sensitive data security are raised with continued IoT-based behavioural monitoring. The findings of other studies, including those by Tuan [15] and by Vos et al. [19], also reveal a lack of diversity in datasets and a lack of adequate longitudinal validation that limits the confidence in implementing those studies in the real world. In the CPS paradigm, there is a need for secure, transparent and reliable interaction among the sensing infrastructures, computational systems and healthcare environments to build a sustainable mental healthcare ecosystem. To ensure effective implementation, predictive capability must also be combined with explainable AI architectures, interoperable healthcare systems, trusted data governance, and clinically rigorous decision-support tools. The results indicate that the rate of technological innovation in the realms of IoT and ML is outpacing that of ethical and clinical deployment, resulting in a significant disparity between the development of the technology and its practical application in healthcare.

Collectively, existing literature has significantly advanced across M1, M2, M3, and M4 themes; however, it predominantly focuses on isolated technological functions rather than explaining how sensing, analytics, intervention, and governance interact within mental healthcare systems. From a CPS perspective, this gap limits the full realisation of operational mental healthcare systems, indicating a need for a proposed action-oriented conceptual framework. Operational Framework for Real-Time IoT-ML Mental Healthcare Systems integrates continuous monitoring, predictive intelligence, adaptive intervention mechanisms, and responsible clinical implementation into a unified intelligent mental healthcare architecture.

PROPOSED CONCEPTUAL FRAMEWORK

After analysing, based on the CPS theory, the framework outlines the continuous sensing through IoT devices, the conversion into computational intelligence using ML analytics, the generation of adaptive healthcare actions and the anchoring through responsible clinical implementation mechanisms. The framework, therefore, demonstrates the real-time interaction between sensing infrastructures, predictive analytics, intervention systems, and governance structures within intelligent mental healthcare ecosystems. The framework is intentionally structured into four operational phases to ensure implementation clarity. As indicated in Table 6, Phase 1 involves persistent behavioural acquisition from the use of wearable devices, mobile phones, biosensors and tele-sensing. In Phase 2, AI- and ML-powered analytics engines that are able to detect stress, depression, anxiety, emotional instability and suicide-risk patterns are placed in operation, enabling predictive mental state detection. Phase 3 translates predictive outputs into adaptive healthcare interventions such as telepsychiatry consultations, AI-based Cognitive Behavioural Therapy (CBT) systems, behavioural recommendations, and emergency escalation workflows. Phase 4 ensures responsible clinical integration through explainable AI, cybersecurity protocols, interoperability standards, clinician oversight, governance systems, and long-term clinical validation.

To improve practical applicability, the framework further identifies specific implementation tools, technologies, operational steps, and responsible entities required at each phase, as shown in Table 7. This provides healthcare organisations with a transparent implementation roadmap rather than a purely descriptive conceptual model. The framework, therefore, bridges the gap between technological innovation and real-world mental healthcare deployment by demonstrating how IoT and ML systems can be operationalised into scalable, adaptive, and clinically sustainable mental healthcare ecosystems.

TABLE 6. OPERATIONAL FRAMEWORK FOR REAL-TIME IOT-ML MENTAL HEALTHCARE SYSTEMS

Phase	Operational Layer	What It Does	Key Technologies / Processes	Real-Time Healthcare Outcome
Phase 1	Continuous Behavioural Acquisition	Continuously captures physiological, behavioural, and contextual mental health indicators.	Wearables, smartphones, biosensors, IoMT devices, passive sensing	Real-time behavioural visibility and patient monitoring
Phase 2	Predictive Mental State Detection	Identifies abnormal psychological patterns and mental health risks through computational analysis	ML/DL models (SVM, RF, CNN, LSTM), multimodal analytics	Early-risk detection for stress, anxiety, depression, and suicide risk
Phase 3	Adaptive Healthcare Intervention	Converts predictive outputs into immediate and personalised mental healthcare actions	Telepsychiatry systems, AI-based CBT, crisis alerts, behavioural recommendation systems	Real-time intervention and adaptive healthcare delivery
Phase 4	Responsible Clinical Integration	Ensures secure, explainable, interoperable, and clinically sustainable implementation	Explainable AI (XAI), governance systems, interoperability frameworks	Trustworthy and scalable mental healthcare deployment

Source: Compiled by Authors

TABLE 7. TOOLS, TECHNOLOGIES, OPERATIONAL STEPS, AND RESPONSIBLE ENTITIES REQUIRED AT EACH PHASE

Phase	Tools / Steps / Approaches for Implementation	Responsible Entity for Implementation
Phase 1	Deploy wearable devices (Fitbit, Apple Watch, EEG bands), integrate smartphone sensing apps, establish cloud-based behavioural data collection infrastructure, implement digital phenotyping protocols, and integrate APIs with EHR systems.	Mental health clinics, hospital IT departments, IoMT vendors, mobile health application developers, wearable technology providers, and clinical informatics teams
Phase 2	Train ML models on behavioural datasets, integrate predictive AI engines into healthcare platforms, establish AI-supported clinical dashboards, implement NLP-based emotional analysis, and automate clinician risk scoring systems	Data scientists, AI engineers, clinical data analysts, hospital AI research teams, healthcare analytics companies, and psychiatrists validating predictive outputs
Phase 3	Deploy AI-powered CBT chatbots, integrate telepsychiatry platforms, establish suicide-risk escalation workflows, implement automated alert systems, integrate clinician notification protocols, and enable mobile-based patient engagement systems	Psychiatrists, psychologists, telepsychiatry teams, crisis response units, behavioural therapists, hospital operations teams, mental health support staff
Phase 4	Implement explainable AI dashboards, establish clinician-in-loop review systems, deploy cybersecurity and encrypted storage protocols, adopt interoperability standards (FHIR, HL7), conduct clinical validation studies, and establish AI governance and bias-monitoring frameworks	Healthcare regulators, hospital governance boards, ethics committees, cybersecurity teams, compliance officers, AI governance bodies, healthcare policymakers, clinical auditors

Source: Compiled by Authors

DISCUSSION AND LIMITATIONS

IoT and ML technologies are changing mental healthcare from the periodical psychiatric evaluation model to a more continuous, predictive, and intervention-oriented approach to healthcare delivery. Although much literature highlights wearable sensing and predictive analytics, on the other hand, less work has been directed to the aspects of real-life implementation, accessibility, explainability and the deployment of such tools in a clinically sustainable approach.

One potential limitation of this study is that few studies are included (n=18), which could limit the generalisability and richness of the themes emerging across a wide range of mental health care settings. A number of reviewed studies have examined this in pilot/experimental settings, but were limited in longer-term clinical implementation, scalability and patient outcome assessment. Further, some of these studies are highly focused on the predictive value and the feasibility of technology, offering limited discussion of interoperability, clinician feasibility, cost feasibility, and organisation readiness to deploy. The proposed operational model is conceptually synthesised from existing literature, and as such, needs to be validated with empirical analysis in real-world healthcare systems offering mental health services. Future researchers can extend this study by empirically validating the proposed operational framework through pilot implementation within real-world mental healthcare settings to evaluate clinical effectiveness, scalability, interoperability, and patient outcomes.

CONCLUSIONS

This study illustrates how continuous monitoring, predictive behaviour analytics, adaptive interventions and scalable mental healthcare delivery can be achieved by embedding IoT and ML technologies within CPS-supported healthcare ecosystems. Operational Framework for Real-Time IoT-ML Mental Healthcare Systems unifies the architectures of sensing, analytics, intervention, and responsible deployment.

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ACHSM Asia-Pacific Journal of Health Management shape

CONFAB 360 DEGREE 2026

REIMAGINING HEALTHCARE DELIVERY: A COMPARATIVE ANALYSIS OF TRADITIONAL HEALTHCARE AND AI-ENABLED SMART HOSPITALS

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ABSTRACT

OBJECTIVE

This study aims to comparatively analyse traditional healthcare and AI-enabled smart hospitals across key dimensions of operational efficiency, clinical outcomes, and accessibility, with a focus on how institutional readiness influences the effectiveness of digital healthcare transformation.

DESIGN

The study conducted a comparative narrative review using WHO's Digital Health Reports from 2019 and 2023. In addition, a total of 23 peer-reviewed articles published between 2016 and 2026 have been synthesised thematically across key dimensions of Operational Efficiency (OE), Resource Optimisation (RO), Clinical Decision Making (CDM), Accessibility (AC), Diagnostic Accuracy (DA), and Healthcare Digital Transformations (HDT), along with the global trends in digital health maturity, infrastructure, and workforce readiness.

RESULTS/OUTCOMES

Findings indicated that AI-enabled smart hospitals showed efficiency in DA, OE, and patient management through predictive analytics and automation. Nevertheless, it has been found that these advantages are highly contingent upon institutional preparedness, workforce capacity, and online infrastructure. Traditional healthcare models, on the other hand, are dependent on human interventions, with limited physical capacity and workforce.

CONCLUSION

The study highlighted that healthcare transformation does not solely rely on technological advancement. A hybrid model integrating traditional healthcare with digital innovation is essential to ensure sustainable, equitable, and scalable healthcare delivery.

KEYWORDS

Artificial Intelligence; Healthcare; Smart Hospitals; Technology; Digital Health

INTRODUCTION

Emerging technologies such as Artificial Intelligence (AI), Information Technology (IoT), and data-centric medical technology have transformed patient care through early interventions, disease diagnosis, real-time monitoring, and personalised care. As hospitals face an ever-increasing patient population and a subsequent rise in healthcare expenditure costs, there is a strain being put on traditional healthcare facilities to meet such real-time needs. Nevertheless, new technologies in smart hospitals can offer the opportunity to automate the medical process and provide healthcare professionals with better data management capabilities to improve clinical decision-making [1]. Digital systems like telemedicine and Electronic Health Records (EHRs) enhance coordination, increase access and support the continuity of care [2]. However, the potential of these systems not only depends on technological capability but also on their adoption and integration by both patients and healthcare providers. For instance, AI-enabled smart hospitals are showing improvements in their operational performance, emergency response time and diagnostic accuracy [3], [4]. These developing technologies highlight the need to critically examine their integration, influencing efficiency, accessibility, and quality of care across healthcare systems.

RESEARCH QUESTIONS

RQ1: How do AI-enabled smart hospitals differ from traditional healthcare systems in terms of operational efficiency, accessibility, and clinical outcomes across varying levels of institutional readiness?

RQ2: How do institutional factors such as governance, infrastructure, and workforce capacity influence the effectiveness of AI-enabled healthcare systems?

LITERATURE REVIEW

The evolution of digital technology has significantly transformed healthcare delivery through emerging AI-enabled smart hospitals based on advanced tools like AI, IoT, and other intelligent information systems. These technologies not only improve the efficiency and patient outcomes but also enable real-time data sharing, clinical coordination, and the delivery of personalised care through EHR, telemedicine platforms, and predictive analytics [2, 5].

Empirical studies emphasise the importance of user acceptance and engagement in the successful implementation of smart hospital technologies [6]. Research based on the Technology Acceptance Model (TAM) shows that perceived usefulness, trust, and convenience are key factors in determining whether patients will adopt smart healthcare services [7, 8]. Moreover, evidence indicates that integration of AI, robotics and automated systems in hospitals can enhance service quality and improve patient satisfaction compared to the traditional healthcare model [3, 9, 10]. However, these benefits are tagged with challenges, including data privacy concerns, high implementation costs, and workforce capacity. Therefore, strategic planning and institutional readiness are critical to facilitate the successful implementation of smart hospital systems. The key findings in Table 1 are synthesised to chalk out thematic codes for analysis.

Abbreviations used in Table 1-
AC- Accessibility
CDM- Clinical Decision Making
DA- Diagnostic Accuracy
HDT- Healthcare Digital Transformation
OE- Operational Efficiency
RO- Resource Optimisation

TABLE 1. KEY FINDINGS SYNTHESISED FROM LITERATURE

Author(s)	Study Focus	Methodology	Key Findings	Thematic Coding
[1]	Intelligent speech technology in smart hospitals	AI model using federated learning	98.6% accuracy in medical transcription and diagnosis	DA, HDT
[3]	Smart emergency hospital technologies	Comparative case study	Emergency response time reduced by 75% and costs by 33%	OE, RO
[4]	Smart technologies and patient satisfaction	Survey study	Smart healthcare technologies improve quality and satisfaction	AC, HDT, RO
[5]	AI-based stroke prediction platform	Deep learning model	Achieved up to 99% accuracy in stroke prediction	DA, CDM
[6]	Telehealth and AI during COVID-19	Analytical study	Telehealth improved healthcare accessibility during the pandemic	AC
[7]	Patient acceptance of smart hospital services	Survey (202) respondents	Trust, usefulness, and convenience influence the adoption of smart services	DA, HDT, AC
[8]	Voice-based smart ward systems	Pilot survey	Perceived usefulness significantly influences patient adoption	OE, CDM, RO
[10]	Advanced medical technologies in healthcare	Analytical study	AI diagnostics improve healthcare efficiency and accuracy	DA, OE
[11]	Integrating 6G technology in smart hospitals	Comprehensive review and analysis	6G-based smart hospital model enhances patient care, real-time monitoring, and hospital operational efficiency	OE, RO, DA
[12]	Digital transformation in hospitals	Mixed methods	Leadership and digital readiness drive hospital digitization	HDT, OE, CDM
[13]	Enablers of AI adoption in hospitals	ISM-MICMAC analysis	Infrastructure, policy, and collaboration drive AI adoption	AC, DA, OE, RO

[15]	Digital twin technologies in healthcare	Technology analysis	Enables real-time monitoring and improved emergency response	CDM, OE, RO
[16]	AI megaprojects in healthcare systems	Case study	AI improves efficiency but raises privacy concerns	OE, CDM, AC
[17]	IoT-enabled virtual hospital systems	Machine Learning Framework	Improves healthcare data processing and diagnostic efficiency	DA, OE
[18]	AI in hospital information systems	Literature review	AI enhances imaging, telemedicine, and patient management	OE, RO, HDT
[19]	AI in hospital administration	Conceptual analysis	AI enhances scheduling and resource allocation	RO, HDT
[20]	Digital twin governance in hospitals	Simulation-based empirical study	AI auditing improves compliance monitoring	CDM
[21]	Digital hospital evaluation scale	Psychometric survey study	Developed a reliable scale for digital hospital performance	OE
[22]	Future development of smart hospitals	Delphi study	Smart hospitals emphasise personalised and digital healthcare	HDT
[23]	Smart hospitals in neurosurgery	Scoping review	AI enables precise diagnostics and personalized treatment	DA, CDM
[26]	Digitalisation and financing of smart hospitals	Case study analysis	Digital healthcare platforms enhance partnership and patient-centred services	RO, HDT
[27]	Wearables technologies in healthcare	Analytical study	IoMT devices enable continuous health monitoring	HDT
[28]	Digital transformation in radiology	Policy and literature analysis	Infrastructure and training support digital healthcare adoption	HDT, AC, OE

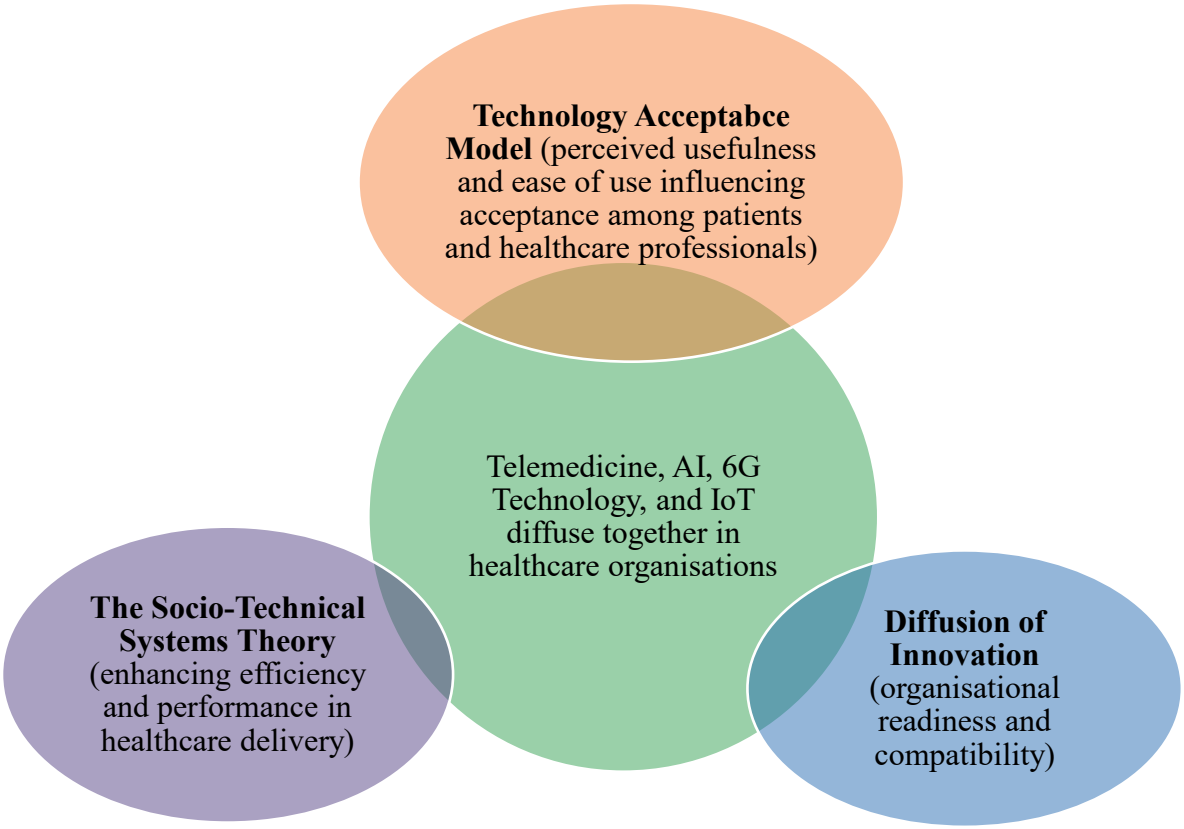
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THEORETICAL FRAMEWORK

This study is underpinned by the TAM, Diffusion of Innovation (DOI) Theory, and Socio-Technical Systems Theory, as represented in Figure 1, to account for the change from traditional healthcare services to AI-based smart hospitals. The

TAM argues that the adoption behaviour is a function of perceived usefulness and ease of use as key determinants influence acceptance among patients and healthcare professionals [7]. DOI Theory supports this by explaining how innovations like telemedicine, AI, 6G Technology, and IoT diffuse together in healthcare organisations driven by organisational readiness and compatibility [11, 12, 13]. The Socio-Technical Systems Theory, in parallel, focuses on the relationship between healthcare practitioners and technological systems to enhance efficiency and performance in healthcare delivery [2].

FIGURE 1. THEORETICAL FRAMEWORKS INTEGRATION



Source: Constructed by Authors

METHODS

A literature search was conducted using academic databases, including Google Scholar, PubMed, MDPI, and open-access journal databases. A total of 23 peer-reviewed academic publications between 2016 and 2026 were selected based on their focus on AI in healthcare, smart hospital systems, or digital healthcare delivery. The search strategy included combinations of keywords such as "artificial intelligence," "smart hospitals," "digital healthcare," "telemedicine," and "healthcare efficiency." Non-relevant and duplicate studies were excluded. Secondary data from the World Health Organization (WHO) digital health reports was utilised to identify technological and operational differences between the two healthcare models. The thematic narrative synthesis was applied to the selected studies, identifying patterns in the most important dimensions such as OE, RO, DA, CDM, AC, and HDT. Each dimension was then mapped to enable comparative interpretation of the study findings. The analysis of secondary data, WHO Digital Health Reports (2019, 2023), was performed to comprehend global trends in digital health maturity, infrastructure, and workforce capacity into perspective. Digital health maturing levels were analytically mapped to each dimension to integrate findings and understand differences between the two healthcare models. This allowed the connection of the literature understanding at the micro level (individual model) with the trends in the global system at the macro level (combination of both models).

RESULTS AND DISCUSSION

The findings of the study indicate that the integration of AI and digital technologies is fundamentally transforming healthcare delivery systems. However, the extent and effectiveness of this transformation vary significantly across contexts, depending on technological, organisational, and institutional factors.

THEMATIC ANALYSIS: RQ1 ANSWERED

Theme 1: Operational Efficiency (OE) and Resource Optimisation (RO)

Machine learning, IoT, and 6G technology, predictive analytics are some of the technologies that are used in smart hospitals to improve the performance of operations and their resource utilisation [11]. Smart hospitals can also enhance their OE with the introduction of automated logistics systems and AI-based technology for imaging and real-time data analytics [14-18]. The emergency response time of 75% reduction is achieved at emergency hospitals that adopt smart technology solutions, with their processes of RO being made 20% more efficient when compared to traditional healthcare models [3], [15]. Nevertheless, their efficacy depends on the integration of systems and the preparedness of infrastructure. The improvement of OE is restricted by a decentralised system that is not prominent in traditional settings. This is in conformity with the ideas of the Socio-Technical Systems Theory, which points out that alignment between the technical systems and the organisational processes is the key to technological effectiveness.

Theme 2: Diagnostic Accuracy (DA) and Clinical Decision Making (CDM)

Systems that are based on AI exhibit high DA in disease prediction and CDM. As an example, federated neural networks have demonstrated intelligent speech technology, with 98.6% DA and transcription accuracy showing potential of AI systems in CDM and minimising medical errors [1]. In addition, unlike traditional healthcare models, smart hospitals can rely on AI and deep learning-based prediction systems, demonstrating a level of DA up to 99% in disease detection systems [5]. These results suggest that AI can greatly improve CDM by minimising human error and enhancing data interpretation. But, within the frame of TAM, the adoption of AI systems can only be validated by governance and policymakers, as it is done in traditional healthcare systems. Results are governed by data quality, algorithm stability, contextual flexibility, biased or inaccurate datasets, making it necessary for the governing bodies to evaluate their perceived usefulness and trust between healthcare professionals.

Theme 3: Accessibility (AC) and Healthcare Delivery Transformation (HDT)

Digital technologies, e.g. telemedicine and remote monitoring, have increased access to health services and continuity of care. The role of digital infrastructure and the application of Management Information Systems (MIS) have played a pivotal role in the development and utilisation of traditional hospitals and the transition towards HDT [2]. These digital systems also ensure the use of remote patient monitoring and telemedicine, which have been critical in the development of HDT and the need to ensure the decongestion of hospitals. The perception and acceptance of HDT by patients are also factors of concern. Studies on patient perception of smart hospital services have revealed that patients are more likely to use smart hospital services when they think that the use of technology is trustworthy, convenient and beneficial to their healthcare needs [7], [19-23]. But the gains of AC are not evenly distributed over regions. The infrastructure and digital literacy levels are limited in many low and middle-income countries, limiting the efficacy of these solutions.

These three themes indicate that smart hospitals should adopt digitalisation and HDT because of the higher OE, RO, DA, and AC. In turn, it enables continuous flexibility in attending to patient needs. However, the implementation and CDM are still limited to governance and policymaking bodies due to their validated perceived usefulness and coordination among healthcare professionals.

WHO DATA ANALYSIS: RQ2 ANSWERED

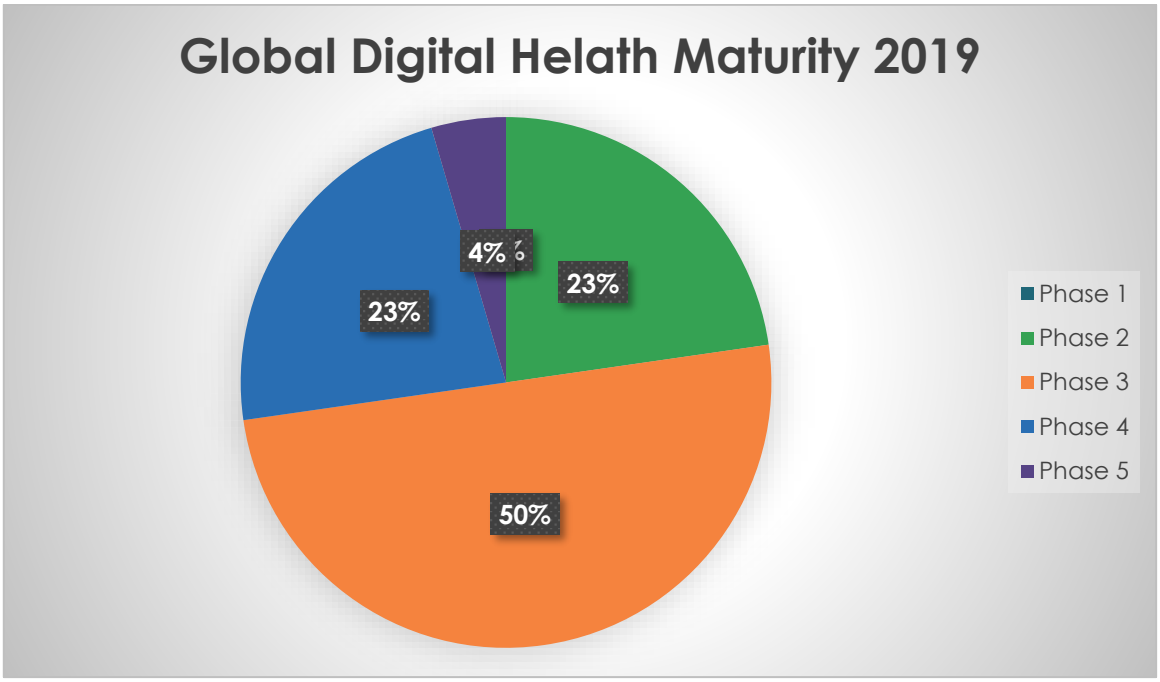
Institutional Readiness and Global Health System Context

The World Health Organization's (2019 and 2023) Digital Health reports show how the world is transforming from conventional health systems to digitally enabled health infrastructure. In the State of Digital Health 2019 report [24], which assessed 22 early adopter countries using the Global Digital Health Index (GDHI), it was established that the digital health ecosystem across the globe had reached an average level of maturity, which is referred to as Phase 3, indicating that it

is still at the developing stage. The most advanced component of the digital health ecosystem was leadership and governance, which had reached an average level of Phase 4, indicating that most countries had already adopted digital health strategies into their healthcare policies. However, other core components, such as standards and interoperability, are still at the developing stage. In addition, there was limited financial commitment and investment in digital health technologies.

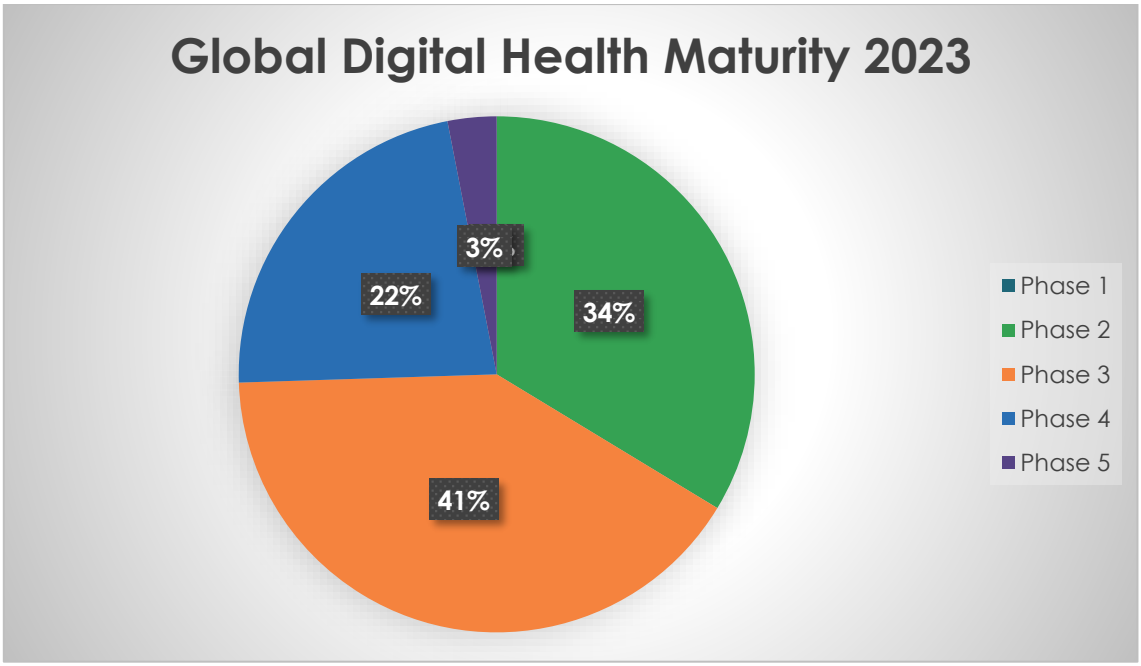
The report titled "The State of Digital Health 2023" [25] evaluates and compares the status of digital health within 67 different nations, serving as an indicator of the progressive, albeit somewhat uneven, advancement of the state of global digital health adoption. The majority of the countries are still at a Phase 3 maturity level, and the 22 countries that have already moved to Phase 4 maturity are experiencing a growing rate of national digital health infrastructure connectivity.

FIGURE 2. GLOBAL DIGITAL HEALTH MATURITY DISTRIBUTION FOR THE YEAR 2019



Source: Compiled by Authors from WHO Digital Health Reports

FIGURE 3. GLOBAL DIGITAL HEALTH MATURITY DISTRIBUTION FOR THE YEAR 2023

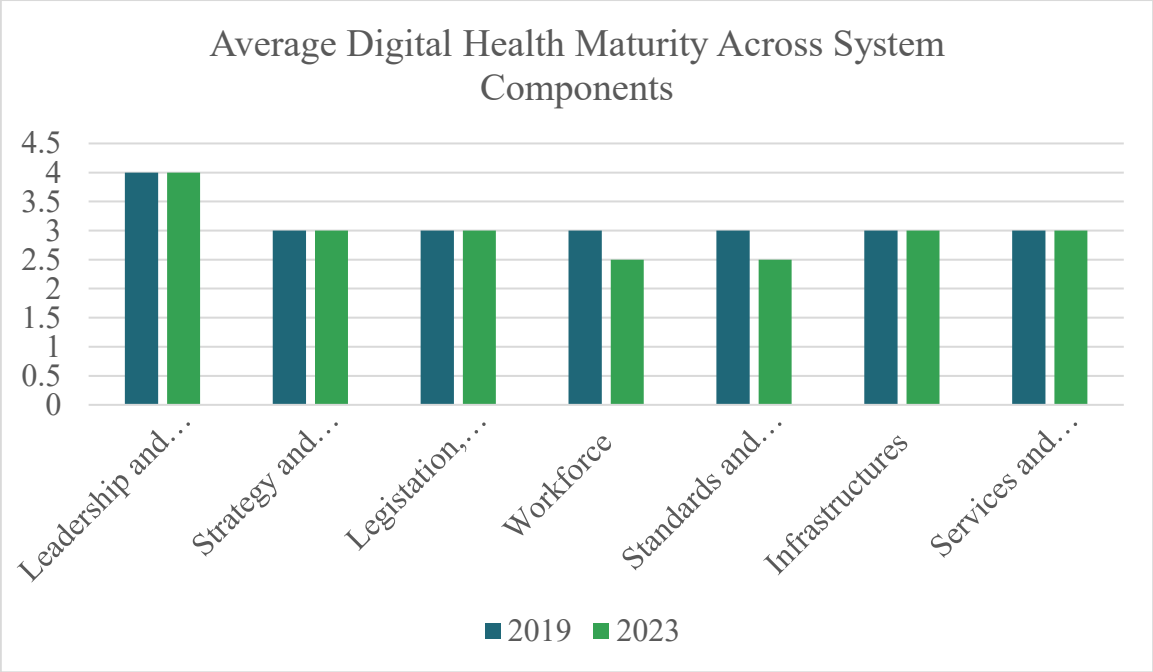


Source: Compiled by Authors from WHO Digital Health Reports

The global digital health maturity (Figures 2 and 3) indicates that most countries are still in Phase 3, which implies partial implementation of the digital health systems. Although the change towards higher maturity levels has been made, it is limited and unequal. Notably, those countries with higher levels of digital maturity (Phase 4 and above) are more inclined to successfully implement AI-enabled healthcare systems due to their improved infrastructure, governance, and workforce capacity. Conversely, less developed countries have structural limitations, which restrict the perceived usefulness of digital health interventions. Even from a TAM perspective, improvements in CDM and DA enhance perceived usefulness, while interoperability challenges reduce perceived ease of use, limiting adoption in Phase 3 systems. This indicates that despite the rising digital health adoption, institutional readiness is still immature, especially in such areas as interoperability, workforce capacity, and funding. Consequently, AI-enabled smart hospitals can only be as effective as they are technologically enabled but not limited by systemic or organisational constraints.

WHO data shows that countries at Phase 3 digital maturity are partially integrating digital innovations that directly impact RO and OE. In turn, such fragmented data infrastructures are showing limited real-time coordination and preventing DA and CDM, further reducing the effectiveness of automation and predictive systems. Uneven digital infrastructure and workforce capacity, as shown by the WHO report, directly impact the AC of telemedicine and remote monitoring in expanding HDT. However, countries at the higher maturity level of Phase 4 are showing better alignment between governance and workforce capabilities, moving towards AI-enabled smart systems.

FIGURE 4. AVERAGE DIGITAL HEALTH MATURITY ACROSS SYSTEM COMPONENTS BASED ON VARIOUS PHASES



Source: Compiled by Authors from WHO Digital Health Reports

Leadership and governance show a rather high level of maturity, whereas workforce capacity and interoperability are not yet at a high level of development (Figure 4). As the combination of leadership and governance shows great maturity (Phase 4), indicating that there are strong policy and strategic commitment, the use of systems to build workforce capacity and support the functions of standards/interoperability indicates only a moderate level of development (Phase 2.5). Hence, there is a significant loss in the capacity to develop digital health talent and connect to other health systems since there is still no development in these areas. According to the WHO reports, digital technology has experienced significant advances in providing AC to healthcare services and in delivering RO. Because of this, the healthcare industry is shifting from traditional systems to digital systems. Workforce capacity limitations further restrict the scalability of AI-enabled healthcare systems, as their effective implementation requires skilled personnel, interoperable systems, and long-term investment. The finding relates to the DOI theory that highlights the fact that adoption is based on organisational preparedness and systemic compatibility.

Moreover, the adoption of smart hospitals with AI-driven solutions is governed by challenges like high costs, data privacy issues, and cybersecurity threats [16]. These hurdles underscore the fact that digital transformation is not technological in nature, but institutional and socio-economic (The Socio-Technical Systems Theory) in nature. Also, the digital divide can contribute to disparities in healthcare access, especially in areas with a low level of infrastructure.

COMPARATIVE SYNTHESIS AND INTEGRATED INTERPRETATION

Based on the themes from 23 studies (Table 1) and WHO reports, the comparison is operationalised across OE, RO, CDM, DA, AC, and HDT between traditional and smart hospitals (Table 2).

TABLE 2. COMPARATIVE ANALYSIS OF TRADITIONAL HEALTHCARE SYSTEMS AND AI-ENABLED SMART HOSPITALS

Dimension	Traditional Healthcare Systems vs. AI-Enabled Smart Hospitals (RQ1)		Analytical Interpretation (RQ2)
	Traditional Healthcare Systems	AI-Enabled Smart Hospitals	
Decision-Making	Clinician-driven, experience-based	Data-driven, AI-assisted	Improves accuracy but depends on trust and perceived usefulness (TAM)
Operational Efficiency	Manual workflows, delays in processes	Automated systems, optimised resource allocation	Efficiency gains depend on infrastructure integration and system interoperability.
Diagnostic Accuracy	Dependent on human expertise	Enhanced through machine learning and predictive models	Reduces human error but introduces risks of algorithmic bias and data dependency
Data Management	Fragmented and siloed systems	Integrated, real-time data ecosystems	Effectiveness depends on interoperability and data governance (WHO findings)
Accessibility	Limited by physical infrastructure and location	Expanded through telemedicine and remote monitoring	Improves reach but varies across regions with differing digital maturity levels
Patient Engagement	Episodic, visit-based interactions	Continuous monitoring and digital engagement	Enhances adherence and satisfaction through sustained interaction
Workforce Capacity	Limited by physical capacity and workforce	High scalability through digital platforms	Enables population-level healthcare delivery with lower marginal expansion costs
Institutional Readiness	Established structures with lower digital dependency	Requires strong governance, workforce skills, and infrastructure	Primary determinant of success (DOI theory and WHO maturity data)
Cost Structure	Lower initial investment, but operational inefficiencies	High initial investment with potential long-term optimisation	Financial barriers may limit adoption in resource-constrained settings
Error and Risk Profile	Higher probability of human error	Reduced human error but increased cyber and ethical risks	Reflects the trade-off between automation efficiency and system vulnerabilities
Equity Impact	More accessible in low-resource settings	Risk of widening digital divide	Unequal digital infrastructure may exacerbate healthcare disparities

Source: Compiled by Authors

The comparison conducted in Table 2 indicates that the performance of AI-enabled smart hospitals is better than that of traditional systems in most aspects, primarily performance in terms of OE, workforce capacity, and DA. Based on the

comparative synthesis, the results indicate that the efficacy of AI-enabled smart hospitals is relative to their applicability and effectiveness in different contexts. High rates of improvement in the performance of the operation process and patient outcomes in high-resource settings with high rates of digital maturity characterise smart hospitals. On the other hand, the traditional healthcare systems are still essential in the context of resource-constrained settings since they are more available, versatile, and less dependent on the digital infrastructure. It implies that the future of healthcare lies in the development of hybrid models that would combine the advantages of the traditional healthcare system with the benefits of digital technologies. Such an approach will assist healthcare systems in accepting innovation without undermining inclusivity and resilience.

RESEARCH GAP AND FUTURE IMPLICATIONS

The literature on the AI-enabled healthcare systems identifies the transformative role of digital technologies, including AI, IoT, telemedicine, and wearable technology, in improving efficiencies in hospitals through better diagnosis and monitoring of patients [6, 26, 27, 5, 15]. However, the research was largely technology-focused and emphasised less on infrastructure preparedness, low data protection, the non-existence of interoperability among systems, and the lack of workforce capacity [16, 28]. Moreover, an integrated comparative analysis of digital health innovations in traditional healthcare systems and AI-enabled smart hospitals has not been done, as most studies examine digital health innovations separately. Limited evidence that exists in low and middle-income environments can also be found despite the large disparities in digital health maturity. Finally, policymakers and healthcare administrators must enhance digital infrastructure, governance, and workforce training that will help healthcare managers to adopt smart hospital systems [29-32].

POLICY AND MANAGERIAL IMPLICATIONS

The findings highlight that successful adoption of AI-enabled smart hospitals depends on strengthening institutional readiness, infrastructure, and workforce capacity. Table 3 summarises key policy and managerial implications derived from the comparative analysis and global digital health trends.

TABLE 3. POLICY AND MANAGERIAL IMPLICATIONS FOR AI-ENABLED HEALTHCARE SYSTEMS

Domain	Key Implication	Action Focus
Policy-Infrastructure	Strengthen digital infrastructure and interoperability	Invest in integrated health information systems and standardised data frameworks
Policy-Governance	Enhance data protection and regulatory frameworks	Establish clear policies for data privacy, cybersecurity, and ethical AI use
Policy-Workforce	Build digital health workforce capacity	Develop training programs and formal roles in health informatics and AI
Policy-Equity	Address uneven digital health maturity	Expand digital access and support underserved regions
Managerial-Implementation	Adopt phased technology integration	Prioritise high-impact areas (diagnostics, monitoring, admin automation)
Managerial-Alignment	Align technology with workflows	Integrate AI systems with existing clinical and operational processes
Managerial- Capability Building	Invest in staff training and change management	Enhance digital literacy and manage adoption resistance
Managerial-Data Utilisation	Leverage data for decision-making	Use analytics to improve efficiency and patient outcomes
Managerial-Risk Management	Strengthen cybersecurity and system resilience	Implement robust data protection and risk mitigation strategies

Source: Compiled by Authors

The implications indicate that digital transformation in healthcare is not solely technology-driven but requires coordinated action across policy and organisational levels. Although the enabling infrastructure, governance, and equity are important issues that should be considered by policymakers, the healthcare managers play an important role in

implementation, readiness of the workforce, and operational integration. This supports the main finding of the study that institutional readiness is the most significant factor of successful smart hospital adoption.

CONCLUSION

This study compared traditional healthcare systems with AI-enabled smart hospitals to examine differences in operational efficiency, accessibility, and overall healthcare digital transformations. The findings show that the performance of smart hospitals can greatly improve their diagnostic accuracy, operational efficiency, and scalability; however, they strongly depend on the institutional readiness. The importance of factors such as governance, infrastructure, and workforce capacity is more essential than technological solutions alone. The lack of digital maturity within the global population, as indicated by WHO statistics, also means that smart healthcare systems cannot be universal. The risks related to data privacy, cybersecurity, and digital inequality are also defined in the analysis. Overall, the study shows that hybrid models that incorporate technological innovation and the merits of the traditional systems are needed so as to sustain healthcare transformation and make it competent and just.

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ACHSM Asia-Pacific Journal of Health Management

CONFAB 360 DEGREE 2026

TELEMEDICINE IMPLEMENTATION AND VIRTUAL CARE TECHNOLOGIES IN RURAL HEALTHCARE: A CROSS-CONTINENTAL COMPARISON OF WEST AFRICA, AUSTRALIA, AND THE USA

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ABSTRACT

OBJECTIVE:

The research examines the role of governance capacity and infrastructure readiness in implementing telemedicine in various rural healthcare settings. The primary aim of the study is to create an empirical and context-sensitive framework for the sustainable implementation of telemedicine.

METHODOLOGY:

Secondary data were analysed using a qualitative cross-case comparative method, which involved identifying and reviewing open-access peer-reviewed articles (2015-2026) on telemedicine implementation in West Africa, Australia, and the United States. The analysis, based on a Context-Mechanism-Outcomes (CMO) logic, incorporated four dimensions: Governance Capacity (GC), Infrastructure Readiness (IR), Implementation Strategy (IS), and Outcomes and Sustainability (O) (S).

RESULTS:

Results demonstrate that telemedicine performance depends on contextual circumstances and the effectiveness of implementation strategies. Telemedicine implementation does not rely solely on technological aspects but highlights a non-linear, multi-level relationship among countries' policymaking, governance, socio-cultural climate, infrastructure, and collaboration with local bodies.

CONCLUSION:

The research proposes a comprehensive Context-Strategy Implementation Framework (CSIF-T), providing a practical roadmap to streamline telemedicine strategies and align them with the realities of the context to enhance scalability, sustainability, and equity.

KEYWORDS
Telemedicine, Rural Healthcare, Cross-Case Analysis, Digital Health, Implementation Framework, Healthcare Systems

INTRODUCTION

Geographic distance, lack of healthcare personnel and inadequate access to specialist services are some of the structural problems of rural healthcare systems globally. This leads to care delays, higher costs, and unequal health outcomes. The Australian Institute of Health and Welfare (AIHW) reports that remote areas experience 1.4 times the incidence of disease as urban areas [1]. In addition, implementation of health informatics solutions is challenging in a rural context where individuals seldom receive quality care [2]. Telemedicine has emerged as a high-quality, service-based, and cost-effective solution to healthcare issues experienced by people in rural regions [3][4]. With the continuous evolution and development of Information and Communication Technology (ICT), the introduction of telemedicine and virtual care technologies will play a major role in the healthcare sector to overcome the systemic constraints in delivering consultation, diagnosis, monitoring, and care remotely [5]. Digital innovations, including Artificial Intelligence (AI) tools, chatbots, and remote patient monitoring systems, have expanded the uses for telemedicine [6]. Despite all these advancements, telemedicine in rural settings is still contextually and unevenly applied.

The existing research studies have well-documented the benefits, barriers and enablers of the telemedicine adoption. Relevant challenges are unreliable connections, lack of digital infrastructure, regulatory challenges, employee dissent and digital illiteracy [6]. Conversely, facilitative issues such as policy assistance, technological assimilation and stakeholder interaction are enabling factors [1]. Nevertheless, the majority of research considers these issues as isolated constructs instead of studying their interaction in a particular contextual setting. Although it is a well-known fact that a one-size-fits-all approach cannot be effective, little is known about how the contextual conditions influence the implementation trajectories and results.

This study aims to fill this void by presenting a cross-case comparative study of the implementation of telemedicine in three widely different rural healthcare settings: West Africa, Australia, and the United States. The study aims to:

- Analyse how contextual factors influence telemedicine implementation strategies
- Compare outcomes across diverse healthcare systems
- Develop a framework for context-sensitive telemedicine implementation

While prior research has primarily focused on identifying barriers and enablers, this study provides a comparative and integrative perspective that explains how telemedicine implementation interacts within specific contexts to produce varied outcomes.

LITERATURE REVIEW

Telemedicine has been largely acknowledged as a transformative way of addressing the issues of healthcare access, especially in rural and less developed areas. It facilitates remote consultations, decreases travel strain, improves continuity of care and takes measures to address structural limitations in healthcare delivery [3]. Empirical research reveals the potential of overcoming the barriers, such as through facilitating rural older adults' access to teleconferencing and health portals and enhancing overall well-being [7]. Health centres are now available to older adults to provide low-cost, under $50 (in the USA), virtual visits 24 hours a day, 7 days a week [8]. Further, the integration of telemedicine with AI enables real-time monitoring of patient health data through wearable devices and mobile health apps, sending alerts to healthcare professionals. Such ongoing monitoring is crucial in the care of chronic diseases and helps keep complications at bay, minimising recurrent hospital visits [6].

Despite these promising developments, the implementation of telemedicine requires the availability and reliability of underlying technologies like the internet, ICT infrastructure and a continuous electricity supply. Virtual healthcare adoption in Africa includes a lack of knowledge and training, limited stakeholder engagement in health solutions, and low healthcare buy-in among medical practitioners to adopt telemedicine [9]. These challenges prevail in rural settings, where structural inequalities in access to technology and healthcare services persist. On the contrary, a study conducted by PwC Australia shows that with effective communication, purposeful planning, optimised organisational structure, and supportive government policies, the benefits of telemedicine are being recognised. Successful telemedicine models in Australia by the federal and state governments are successfully delivering specialist emergency care in remote health centres with the help of national funding of primary care services [10].

Telehealth should not be viewed as only a cost-saving measure, but it also means support for face-to-face care to reduce hospital visits. Still, challenges need to be considered for a comprehensive understanding. In a study conducted by Hawley et al. [11], older adults reported that the barriers to interest, access to care, access to technology, and a lack of confidence were prominent dimensions affecting telemedicine efficacy. Telemedicine has also shown great potential in specialised applications, such as in mental health care, where access barriers are especially high in rural areas [12]. Africa is opening up telemedicine for mental health and is joining the rest of the world in using social media tools like WhatsApp to provide telemedicine services. However, there are no standards of service delivery for telemedicine platforms in mental healthcare, and it lacks clarity regarding the liability, leaving the regulation of services in question [13]. Nevertheless, the success of these interventions is not entirely dependent on the availability of technologies but heavily relies on cultural acceptance, confidence in digital systems, and the willingness of both patients and providers to utilise virtual care. Such socio-cultural and behavioural aspects are poorly covered in the existing literature, which is more likely to lay stress on technological and infrastructural aspects. As a result of this, minimal awareness exists about the interaction of these contextual factors with implementation strategies to influence outcomes, and the need to develop a more integrative and comparative analysis approach.

This study is conceptually guided by a diffusion-based perspective and socio-technical systems theory, which emphasise that interaction between governance, infrastructure, and user context significantly shapes use adoption. These perspectives ask for analysing telemedicine implementation beyond isolated aspects, focusing on contextual adaptation.

METHODS

This study adopts a qualitative cross-case comparative approach to analyse the implementation of telemedicine in rural healthcare settings in West Africa, Australia, and the USA. To select individual cases, authors used Google Scholar, PubMed, and other open-access databases between 2015 and 2026 to ensure relevance to contemporary digital health developments. Three cases were chosen to ensure maximum variation, allowing for meaningful cross-context comparison and identification of implementation patterns across different levels of resource availability and institutional capacity. The cases were discovered through the case review process, but the final selection process involved their capacity to enable comparative analysis across different contexts. Further, using multiple cases from different contexts enhanced triangulation.

Peer-reviewed journal articles on telemedicine or virtual care implementation with relevance to rural healthcare were used to identify individual cases related to these three geographical regions.
The study moved beyond descriptive analysis to identifying patterns, strategies, and contextual variations in telemedicine implementation. The selected geographies represented variations in healthcare system capacity, governance structures, and implementation approaches, such as:

- West Africa, being a developing and resource-constrained economy, has limited fiscal capacity, infrastructural deficits, and fragmented governance structures. It helped understand the low-resource and community-based implementation of telemedicine.

- Australia, being a developed and sustainable economy, already has developed healthcare systems with higher institutional capacity. It helped understand high-capacity, rapid pandemic-driven telemedicine implementation.
- The United States, being a developed and technologically advanced economy, already has varying technological investments in AI and IoT. It helped understand structured governance and organisation-led telemedicine implementation.

KEY DIMENSIONS ACROSS CASES

For the purpose of systematic comparison across cases, the study identifies four dimensions:

- Governance Capacity (GC) to analyse policy support, leadership, and coordination mechanisms
- Infrastructure Readiness (IR) to analyse digital systems, connectivity, and technological resources
- Implementation Strategy (IS) to analyse speed, adaptability, and stakeholder engagement
- Outcomes (O) and Sustainability (S) to analyse access, efficiency, and long-term viability of telemedicine implementation

These dimensions allowed a comprehensive understanding of contextual factors aligned with socio-technical theory and a diffusion-based approach to shape implementation mechanisms. Further, the analysis applied a Context-Mechanism-Outcome (CMO) logic, where governance and infrastructure dimensions were discussed contextually to analyse structured implementation mechanisms.

RESULTS AND ANALYSIS

ANALYSING TELEMEDICINE IMPLEMENTATION ACROSS WEST AFRICA

Governance Capacity

Dodoo et al. [14] evaluated early telemedicine projects started in West African states, including Nigeria and Ghana's rural areas. Initiatives were taken by the government to implement telemedicine infrastructure by integrating cloud computing mechanisms to reach its full potential in smaller rural communities. Drone delivery mechanisms post-COVID-19 ensured progress in telemedicine implementation. However, telemedicine services remained limited to pilot-scale implementations, indicating lower levels of IS.

Analysis: Governance limitations restrict the transition from pilot projects to large-scale implementation, indicating weak institutional capacity to sustain telemedicine initiatives.

Infrastructure Readiness

A study by Agbeyangi et al. [15] confirms that low to moderate adoption of telemedicine in Nigeria is due to structural and infrastructural constraints. While urban populations are benefitting from broadband-enabled telehealth services, rural communities are still struggling with connectivity, affordability, and digital literacy barriers, indicating lower levels of O and S and affecting the viability of telemedicine implementation.

Analysis: Infrastructure gaps directly shape the feasibility of telemedicine due to the digital divide among rural people that limits its reach and scalability in rural settings.

Implementation Strategy

Omaghomi et al. [16] found that the health literacy in rural communication is low to effectively implement telemedicine. In addition to poor health literacy and a noticeable digital divide in African rural communities, there are unfamiliar regulations and a lack of policy integration. The availability of smartphones, computers, and other digital platforms is minimal, further adversely affecting people's interaction with telemedicine platforms.

Analysis: There is no alignment between infrastructure capacity and models of execution, as IS are still reactive and project-based, and not systematised.

Outcomes and Sustainability

The outcomes of telemedicine in West Africa are still inconsistent due to limitations. Although early applications have increased accessibility in particular settings, long-term sustainability is constrained by the infrastructural issues, low levels of digital literacy, and poor policy support.

Analysis: Weak GC and IR constrain IS (mechanism) as it limits policy coordination and funding continuity, while inadequate infrastructure reduces system reliability, leading to limited scalability and sustainability of outcomes.

ANALYSING TELEMEDICINE IMPLEMENTATION ACROSS AUSTRALIA

Governance Capacity

Bradford et al. [17] suggest that telehealth is a national priority for all states in Australia and, thus, a clear and realistic vision, consultative service rollout, and supportive management structures are needed to make telehealth a success. According to Smith et al. [18], face-to-face visits will be reduced by telemediated consultations without adversely affecting patient safety. Clinical involvement, particularly active engagement and leadership in service delivery, also strengthen GC.

Analysis: Australian governance is a strategic enabler that has systematic planning, policy congruency, and engagement of clinicians that encourage scale and implementation.

Infrastructure Readiness

Australia benefits from advanced digital infrastructure, including widespread broadband connectivity, integrated health systems, and access to necessary technical equipment. Palozzi et al. [19] showed that stronger telemedicine infrastructures and the quality of care in rural areas; however, issues like stroke care remained underserved. Kiburg et al. [20] researched the feasibility of ophthalmology in rural and remote communities of Australia. As a result, both patients and doctors showed positive implementation of telemedicine services at first, but due to reduced access to screening and treatment, distrust of the medical system, and lack of culturally appropriate care, telemedicine implementation to its full potential remains a challenge.

Analysis: While infrastructure enables scalability, access disparities and socio-cultural factors limit equitable utilisation, indicating that IR alone is insufficient for optimal outcomes.

Implementation Strategy

Telemedicine implementation in Australia reflects a flexible and adaptive approach. Training and educating stakeholders, using evaluative strategies, and developing stakeholder interrelationships are central to this strategy, according to Chapman et al. [21]. The effective engagement of rural and remote stakeholders, including healthcare professionals, services, and cross-sector partners, is essential to build trust, foster buy-in, and support more equitable outcomes, and should therefore be considered in all place-based healthcare research.

Analysis: A clearly defined process and efficient management systems support streamlined service delivery.

Outcomes and Sustainability

Telemedicine services in Australia have demonstrated positive outcomes in terms of improved access, efficiency, and patient value. Economic considerations, including cost savings and value-based service delivery, contribute to long-term sustainability. Importantly, sustainability is not solely determined by service volume but by the ability to deliver clinically effective care with efficient resource utilisation.

Analysis: Strong GC and IR (context) enable adaptive and well-coordinated IS (mechanism), resulting in scalable, efficient, and S telemedicine O.

ANALYSING TELEMEDICINE IMPLEMENTATION ACROSS THE USA

Governance Capacity

Salazar [22] showed a lack of telemedicine and quality healthcare in remote areas across the United States. The American Correctional Association (ACA) and the American Public Health Association (AHA) are striving tirelessly to establish healthcare norms and guidelines, but they are not able to because of fewer correctional facilities. Nevertheless, the American Telemedicine Association (ATA) has come up with guidelines that can help in addressing the high cost of care and facilitating access to patients who would have been otherwise underserved.

Analysis: The US GC is characterised by a structured but technologically underutilised system. However, differences in implementation across various sectors suggest policy design and IS gaps.

Infrastructure Readiness

Through the aid of BlueCross and BlueShield North Carolina Foundation and grants provided by Health Resources and Services Administration (HRSA) and the United States Department of Agriculture (USDA), the Centre of Rural Health Innovation (CRHI) is constantly working to bring improvements to access to Health-e-Schools programs in rural communities [23]. In Western North Carolina, the implementation of telemedicine is standardised using high-definition video conferencing with a focus on sports, behavioural health services and consultation on respiratory issues [24]. Brandford [25] justifies the fact that the Rural Health Care Program into Telecommunications and broadband, financed by the Federal Communications Commission (FCC), is made available to qualified health care providers. Moreover, digital literacy gaps still exist among social workers in rural communities.

Analysis: IR in the US is a powerful enabling factor, and it is supported by federal funding and investment in technology. Nevertheless, access and dependence on external resources show that there is no even distribution of infrastructure development.

Implementation Strategy

Abrams [24] underlines the concept of integrating virtual health infrastructure preparedness by a coordinating delivery process among various providers to make sure that workforce buy-ins are sustainable. Health-e-Schools is just one example of how IS is used by combining policy support, technological infrastructure and service integration to provide specific healthcare interventions in rural populations.

Analysis: The community, through its developmental efforts and relationships, focuses on the core of telemedicine and virtual care to empower civic engagement and the learning culture and skill set, as well as the dynamics of social relationships.

Outcomes and Sustainability

The implementation of telemedicine in the United States has led to better healthcare in rural and underserved populations, especially due to specialised programs facilitated by federal and institutional partnerships. Community and school-based interventions with telehealth programs show the possibility of delivering services in the long term. Nevertheless, there are still gaps in access and high-quality care in various groups of the population, especially those in marginalised environments [22].

Analysis: S is therefore influenced not only by IR and funding but also by equitable IS across diverse contexts.

INTERCONNECTION BETWEEN DIMENSIONS ACROSS WEST AFRICA, AUSTRALIA, AND THE US: A COMPREHENSIVE ANALYSIS

The comparative analysis reveals both shared patterns and context-specific differences in the implementation of telemedicine and virtual care technologies in rural healthcare settings, as shown in Table 1.

TABLE 1: CROSS-CASE COMPARISON

Dimension	West Africa	Australia	United States
GC	Fragmented, weak regulatory frameworks; pilot-driven initiatives; limited policy integration	Strong, coordinated national and state policies; high stakeholder engagement; clear strategic vision	Structured but complex governance; strong institutional frameworks; regulatory fragmentation across sectors
IR	Low; limited internet connectivity, electricity, and device access; significant rural–urban divide	High; strong broadband, integrated health systems; minor gaps in remote service delivery	High but uneven; advanced digital systems with persistent rural broadband and access disparities
IS	Adaptive but constraint-driven; fragmented, project-based, and non-scalable IS	Adaptive and capacity-driven; flexible, stakeholder-oriented, and continuously evolving IS	Structured and phased; system-driven, coordinated, and institution-led IS
O and S	Limited and uneven; improved access in pockets, but low long-term S	High impact; improved access, efficiency, and value; S is strong, but equity gaps remain	Stable and effective; improved access and continuity of care; S is influenced by policy and equity challenges

Source: Compiled by Authors

The cross-case analysis revealed that telemedicine adoption occurs along different pathways and does not necessarily follow a technical-viability-driven model. In the West African context, IS is constrained by weak GC and IR, resulting in limited adaptability and sustainability despite equity concerns. Australia has a strong GC and IR, which provides adaptability and sustainability for IS. The IS model in the United States is structured and stable, with institutional supports in place, but is hindered by certain access limitations, workforce shortages, and policy conditionality that hinder equity outcomes.

INTEGRATED CONTEXT-STRATEGY PROPOSED IMPLEMENTATION FRAMEWORK FOR TELEMEDICINE (CSIF-T)

The difference between developed and developing contexts highlights the need for a context-aligned approach to implementation. However, in developing economies, there is a lack of structured alignment, which is likely to result in further fragmentation and failure of telemedicine initiatives. In a developed system, misalignment can result in inefficiencies, inequities, and underuse of technological potential.

The proposed framework is therefore critical in guiding both contexts: enabling foundational system development in resource-constrained settings while supporting optimisation and equitable delivery in high-capacity healthcare systems. The framework, based on the insights presented above, combines Context–Mechanism–Outcome (CMO) logic with a sequential implementation pathway. It interprets empirical trends into a systematic yet adaptable framework that can inform telemedicine adoption across a wide variety of healthcare settings.

CONTEXT-STRATEGY IMPLEMENTATION PATHWAY

Step 1: Context Assessment (GC + IR)

This step aims to determine the background conditions under which telemedicine implementation will take place. Implementation of telemedicine starts with a GC and IR evaluation. This involves evaluating policy support, leadership, coordinating systems, connectivity, digital systems and accessibility to technological resources. Results show that

implementation potential is limited when contextual conditions are weak, but when governance and infrastructure are strong, then scalable solutions can be implemented.

Step 2: Strategy Alignment (IS)

Based on contextual assessment, implementation strategies (mechanisms) must be aligned accordingly:

- **Low GC + IR** → Adaptive, low-resource, community-driven strategies
- **High GC + IR** → Scalable, integrated, system-driven strategies
- **Structured systems (O+S)** → Phased, policy-driven implementation

In settings with limited resources (West Africa), adaptive, cost-effective models that are based on community-related practices and versatile delivery systems prove more suitable. In contrast, high-capacity systems (Australia) can successfully implement integrated and scalable models for telemedicine; a structured institutional environment (USA) can benefit from a phased and policy-driven approach to implementation. This alignment is based on empirical differences across the three cases and is at the heart of the framework's decision logic.

Step 3: Implementation Design

This stage involves operationalising telemedicine through:

- Engagement and collaboration of the stakeholders
- Training and capacity building of the workforce
- Adoption of technology in the workflows
- Process standardisation

Evidence from Australia and the United States highlights that structured planning and stakeholder alignment are critical for successful IS.

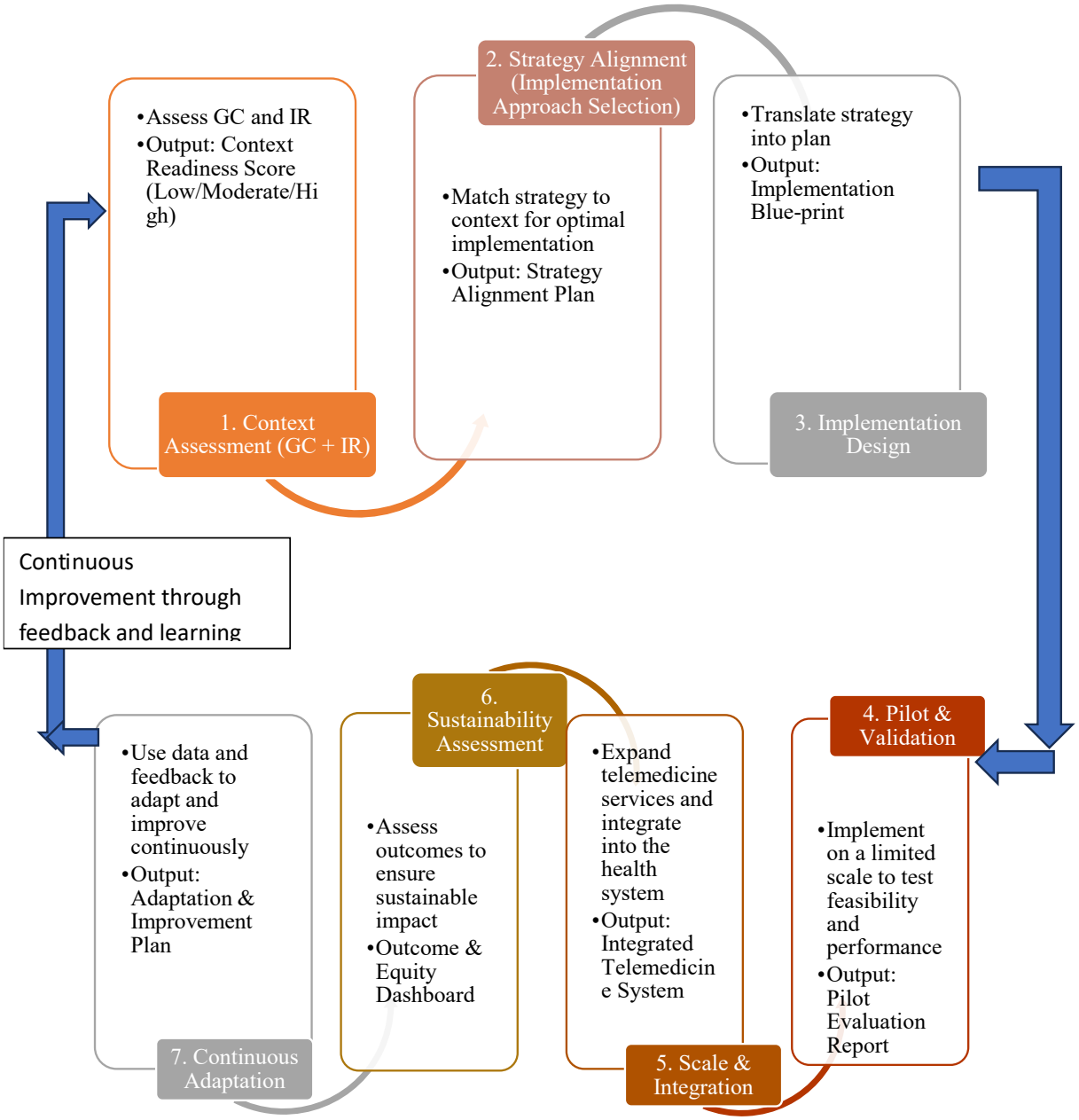
Step 4: Outcome Monitoring and Evaluation

Once the implementation design is in place, a pilot test is conducted to examine feasibility and implementation issues. Through a pilot implementation, the organisations can test interventions to make sure that they are contextually appropriate and operationally viable, before scaling up. The findings indicate that it is not sufficient to simply consider access, but equity and sustainability should also be included.

Step 5: Iterative Adaptation

If successful, telemedicine services will be scaled and integrated into healthcare systems. However, the model stresses that scale is not a key factor in success. An equity analysis is one of the major parameters of structure. This research shows that access and utilisation disparities still exist in high-capacity systems. Thus, telemedicine has to be evaluated not only regarding its efficiency and reach but also inclusivity and long-term sustainability. Adaptive models, especially in Australia, underscore the importance of continual learning for maintaining telemedicine services. Lastly, the system has an adaptation mechanism, considering that telemedicine systems operate in a dynamic environment, where iterations are possible.

FIGURE 1. INTEGRATED CONTEXT-STRATEGY PROPOSED IMPLEMENTATION FRAMEWORK FOR TELEMEDICINE (CSIF-T)



Source: Created by Authors

DISCUSSION AND RECOMMENDATIONS

The analysis highlights key considerations for implementing telemedicine. Enhanced GC and IR should be key enabling factors, and IS must be adapted to local realities, and cannot rely on uniform frameworks. High-capacity systems like Australia focus on speedy scalability, which usually translates into inequities in use and quality among people. In low-resource settings, on the other hand, less appropriate community-led approaches are used, which, though locally relevant, are less scalable. Governments in developing economies (such as Africa) are advised to manage the gap in the infrastructure to make telemedicine successful. On the other hand, the developed countries (like Australia and America) have to strengthen their decision-making by collaboration between the governments, NGOs, private sector organisations, and internal organisations, as well as the local communities. This highlights a fundamental tension between speed and sustainability, where rapid deployment may compromise long-term integration, while gradual approaches may delay access expansion. But, similar to socio-technical systems theory and diffusion-based theories, the

implementation of telemedicine is context-sensitive and influenced by varying degrees of system readiness, governance, and acceptance.

LIMITATIONS AND IMPLICATIONS

The study is limited by the secondary data used, publication bias, and geographical limitations. Future studies need to expand the vision of rural space in developed as well as developing economies to accentuate the likelihood of generalised results. New studies can overcome these drawbacks by expanding the ideas and theories evolved from this paper to both the developing and developed continents with a unified platform. This framework will assist researchers with extensive knowledge to also dig further into gaps in telemedicine implementation in an effort to match their strategies.

CONCLUSION

Finally, the study provides a telemedicine implementation pathway in rural healthcare by overlapping four dimensions: governance capacity, infrastructure readiness, implementation strategies, outcomes and sustainability, across West Africa, Australia, and the United States. The cross-case analysis integrated into both theory and policy is followed by the Context-Strategy Implementation Framework to guide a context-sensitive adoption of telemedicine.

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ACHSM Asia-Pacific Journal of Health Management

CONFAB 360 DEGREE 2026

FROM PREDICTION TO PREVENTION: A SYSTEMATIC REVIEW OF AI-DRIVEN PREDICTIVE ANALYTICS IN HEALTHCARE

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ABSTRACT

PURPOSE:

This study examined how Artificial Intelligence (AI)-enabled predictive analytics moves from technical prediction towards actionable preventive healthcare and identified the conditions that enable or constrain this translation.

DESIGN/METHODOLOGY/APPROACH:

A systematic literature review of 12 peer-reviewed studies published between 2021 and 2026 was conducted using Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)-guided screening, Critical Appraisal Skills Programme (CASP) quality assessment, and open, axial, and selective coding with frequency analysis.

FINDINGS:

Three themes emerged: predictive performance does not equal preventive value, timeliness and actionability shape preventive utility, and implementation conditions shape translation into practice. The findings show that preventive value depends on the alignment of predictive validity, timely action, workflow integration, decision ownership, and governance.

ORIGINALITY/VALUE:

The study introduces the prediction-to-prevention translation gap and develops a decision-oriented framework for evaluating AI beyond model performance.

KEYWORDS;

Artificial Intelligence, predictive analytics, preventive healthcare, machine learning, clinical decision-making, systematic literature review

INTRODUCTION

Healthcare systems increasingly use predictive analytics to identify health risks before they develop into severe and costly conditions. A major example of this challenge is noncommunicable diseases. World Health Organisation [1] reported at least 43 million deaths globally in 2021 caused by these diseases, including 18 million deaths among people younger than 70 years. Therefore, early detection and timely treatment are important for preventive healthcare. Artificial Intelligence

(AI) and Machine Learning (ML) offer new possibilities in this area because of their ability to analyse large and diverse health datasets to estimate future risk, identify emerging deterioration and support earlier healthcare decisions.

AI-enabled prediction is increasingly moving beyond experimental modelling into regulated healthcare settings. The United States Food and Drug Administration (FDA) maintains a public list of AI-enabled medical devices authorised for marketing in the United States [2]. These comprise technologies utilised in all areas of cardiovascular and neurological care, screening, as well as continuous monitoring, including devices for use outside the standard healthcare environment [2]. This trend simply indicates predictive and monitoring technologies that increasingly make their appearance in regulated healthcare settings. However, greater availability of tools does not necessarily mean AI-enabled tools provide preventive value. Such a differentiation matters because in healthcare, technical performance and usefulness measure different things. Performance indicators like accuracy, discrimination and others indicate whether a model can distinguish risk, but they do not establish whether its output arrives early enough to change care, corresponds to a feasible intervention or can be integrated into routine decision-making. However, complex ML approaches were not automatically superior to conventional modelling in predicting the risk of pancreatic cancer among adults with newly diagnosed diabetes, as found by Clift et al. [3]. Hinson et al. went a step further, however, using the ML model in a prospective validation study and integrating its results into workflows in the emergency department [4]. The difference between these studies highlights a broader issue. A model may predict well without demonstrating that the prediction can be translated into useful healthcare action.

Current assessment approaches of AI-based predictive analytics may then tend to focus on the predictive performance rather than on what happens once the prediction is made. Preventive value depends on a connected process. The model must produce sufficiently reliable information, the information must arrive within a useful intervention window, an appropriate response must exist, and the healthcare system must be capable of acting on it. Workflow integration, decision responsibility, interpretability and governance can consequently influence value just as strongly as technical performance.

The paper conceptualises the distance between predictive capability and preventive action as the prediction-to-prevention translation gap. Its contribution lies in examining AI-enabled predictive analytics not only by how accurately systems predict risk, but by the conditions under which prediction becomes timely and actionable preventive healthcare. For this, the paper addresses two Research Questions (RQs):

RQ1. How does predictive performance translate into actionable preventive healthcare across AI-enabled predictive analytics studies?
RQ2. What technological, clinical, organisational, and governance conditions enable or constrain this translation?
For this review, preventive healthcare includes anticipatory applications that identify emerging risk, support screening or early detection, enable timely monitoring or intervention, or inform prospective healthcare decisions before adverse outcomes intensify.

THEORETICAL LENS

The paper is guided by Socio-Technical Systems (STS) Theory, which argues that organisational performance depends on how well technical and social systems work together, rather than on technology alone [5]. Technical system components of AI-powered predictive healthcare are data quality, model design, validation, and predictive performance. Clinical judgement, workflow, decision responsibility, organisational readiness and monitoring are components of the social system. This matters because the prediction must have a preventative effect that the healthcare system can use to act on it. Meanwhile, even the best clinical processes cannot overcome an unreliable prediction. STS helps explain the prediction-to-prevention translation gap as an alignment problem between predictive technology and the people, processes, and organisational conditions needed to turn predictions into action.

LITERATURE REVIEW

The literature review underscores significant advancements in the development of AI-driven predictive health models; however, it also reveals a gap between their predictive capabilities and the potential benefit for prevention. Lin et al. [6] used large electrocardiogram (ECG) datasets to evaluate cardiovascular event prediction, and Lee et al. [7] used retinal images with conventional risk factors and evaluated the model in an independent population. Kalmady et al. [8] also analysed cardiovascular prediction from hospitals and patient subgroups. These studies help build confidence in model performance beyond a single development dataset. However, stronger technical performance does not mean greater clinical value. Clift et al. found that more complex machine-learning approaches did not provide better clinical utility than a conventional model for pancreatic cancer risk prediction [3]. This challenges the assumption that more sophisticated algorithms will yield superior preventive decisions.

Another concern is when a prediction turns into a supported action and a question arises about its usefulness. The shift toward screening and monitoring studies in the near future is toward preventive care, since these provide an opportunity to intervene while risk is not yet an issue. Khattab et al. [9] performed an external validation of the prediction process for personalised diabetes screening, whereas Hughes et al. [10] demonstrated that early prediction of cardiovascular risk using AI can change the classification of some patients, which in turn can inform treatment decisions. Decision curve analysis has also been applied to evaluate community-based screening systems [11] in addition to assessing model accuracy. But remote monitoring goes one step further in helping to determine predictive risk and then convert it into warning intensities that aid in early action [12]. Nevertheless, earlier predictions do not necessarily lead to better prevention. The value of the prediction is limited if it is taken outside the window of meaning, or outside of what is going to be done about it. Recent studies of wearable monitoring also show that prediction accuracy may vary depending on the predicted time [13].

Yet another issue pertaining to translation is its integration into the routine practice of health care. Imrie et al. [14] combined automated model development with interpretability and assessment of clinical net benefit. Hinson et al. [4] implemented a process for using ML to support their risk assessment in the emergency department and monitored this process in a prospective study. Coombs et al. [15] related risk classification to the perspectives of clinicians and future decisions in oncology. These studies illustrate the additional complexity of the process of implementation. Technically valid predictions cannot be directly translated into healthcare decisions without clinicians, a well-fitting workflow, interpretation, responsibility for taking action and monitoring after deployment. However, evidence on model implementation is less prevalent than performance-centric studies. The literature thus reflects the merits of predictive analytics but also confirms that the link between prediction and preventive action is not yet that clear.

RESEARCH GAP

Existing research provides strong evidence that AI can predict health risks but less is known about how those predictions become preventive healthcare actions. Predictive validity, timely actionability, and implementation are often investigated independently. The relationship between these stages is therefore missing. The paper fills this gap by examining the interaction between technical performance and timing, workflow, decision responsibilities, and organisational context. It then integrates these relationships into a Prediction-to-Prevention Translation Framework that explains how predictive capability can move towards preventive value.

METHODS

RESEARCH DESIGN

The study used a Systematic Literature Review (SLR) methodology to synthesise how AI-enabled predictive analytics contributes to preventive and anticipatory healthcare. An SLR was appropriate because the evidence spans different prediction targets, data environments, algorithms, and healthcare settings, making direct statistical pooling inappropriate. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [16] were followed to ensure methodological transparency and rigour, as shown in Figure 1.

SOURCE AND SEARCH SELECTION

Digital database research was undertaken for an extensive literature search, including PubMed and Web of Science. The research approach was supported by the extensive coverage of peer-reviewed articles based on the inclusion and exclusion criteria shown in Table 1. Boolean search string used was: ("artificial intelligence" OR "machine learn*" OR "deep learn*" OR "neural network*" OR "automated machine learn*" OR AutoML) AND (predict* OR prognos* OR "risk strat*" OR "risk scor*" OR "risk assess*" OR screen* OR "early detect*" OR "early warn*" OR monitor*) AND (health* OR clinic* OR patient* OR disease* OR hospital* OR "population health"). The asterisk was used for right-hand truncation as shown in Table 2 to capture lexical variants. Preventive terminology was not made a mandatory search field for databases.

TABLE 1. INCLUSION AND EXCLUSION CRITERIA

Inclusion criteria	Exclusion criteria
Peer-reviewed primary empirical studies published between 2021 and 2026	Reviews, editorials, commentaries, protocols, conference abstracts, or other non-primary studies
Studies published in English with full text available	Non-English or unavailable full-text studies
Studies applying AI or machine learning to human healthcare data	Studies without an AI or machine-learning component
AI used for prediction, risk stratification, screening, early detection, monitoring, or prospective clinical decision support.	AI used only for classification, segmentation, data extraction, or administrative purposes without predictive or anticipatory relevance.
Studies with preventive or anticipatory healthcare relevance, including early risk identification or support for timely clinical action	Studies with no preventive, anticipatory, or clinically actionable relevance
Studies reporting model performance, validation, clinical utility, or implementation evidence	Studies providing insufficient evidence to evaluate model performance, validation, utility, or implementation

Source: Compiled by Authors

TABLE 2. TRUNCATION

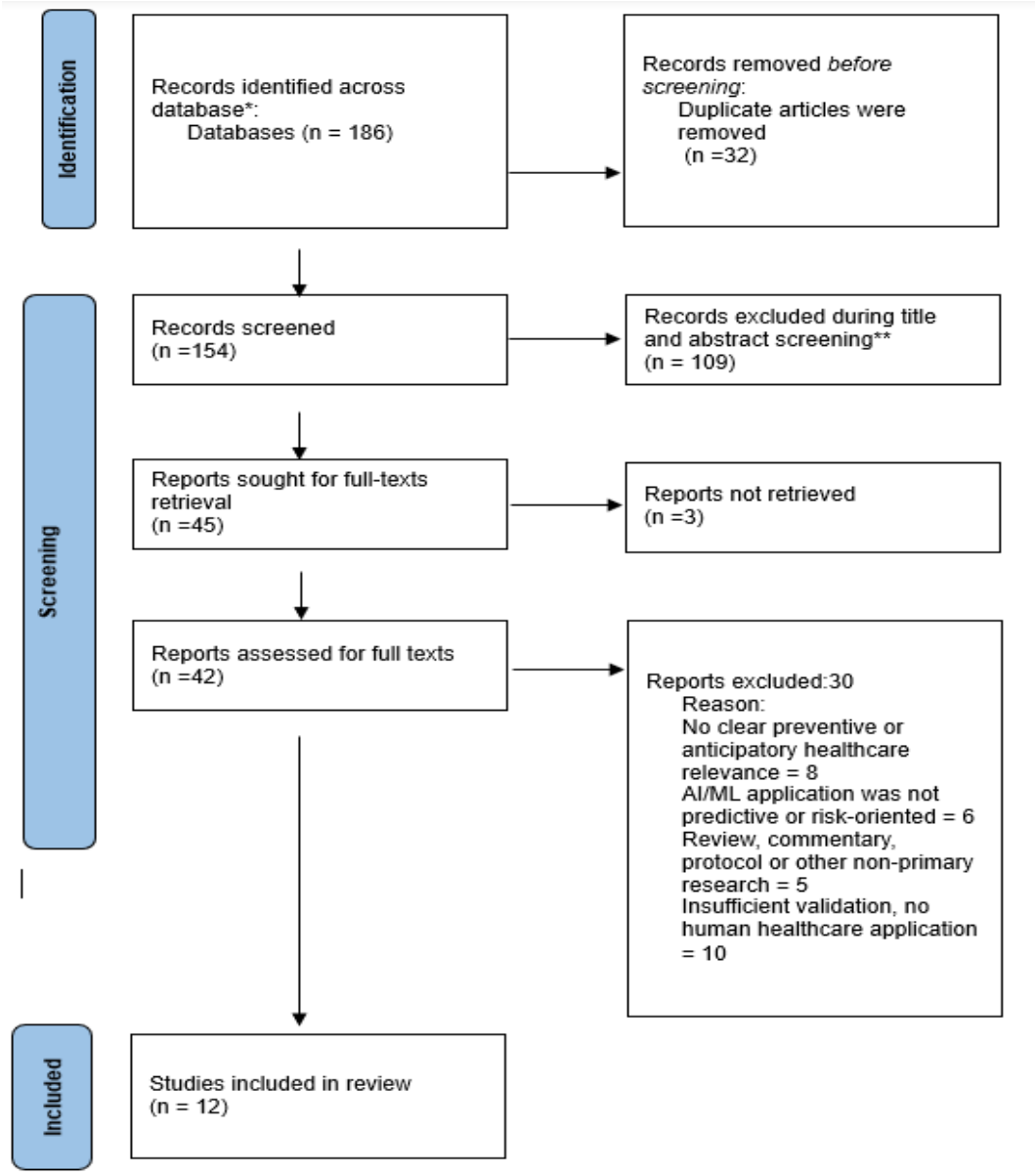
Search term	Captures examples such as	Purpose
machine learn*	machine learning, machine learner	ML terminology
deep learn*	deep learning	Deep learning terminology
neural network*	neural network, neural networks	Singular/plural
automated machine learn*	automated machine learning	AutoML
predict*	predict, predicted, predicting, prediction, predictive	Prediction variants
prognos*	prognosis, prognostic, prognostication	Prognostic variants
risk strat*	risk stratification, risk stratified	Risk stratification
risk scor*	risk score, risk scores, risk scoring	Risk scoring
risk assess*	risk assessment, risk assessments	Risk assessment
screen*	screen, screening, screened	Preventive screening
early detect*	early detection, early detecting	Early identification
early warn*	early warning, early warnings	Early-warning systems
monitor*	monitor, monitoring, monitored	Continuous/remote monitoring
health*	health, healthcare	Healthcare variations
clinic*	clinic, clinical, clinician	Clinical contexts
patient*	patient, patients	Patient populations
disease*	disease, diseases	Disease contexts
hospital*	hospital, hospitals	Healthcare settings

Source: Compiled by Authors

STUDY SELECTION AND PRISMA PROCESS

A total of 186 records were identified across the databases. After removing 32 duplicates, 154 records were screened based on their title and abstract. Of these, 109 were excluded because they did not meet the predefined eligibility criteria. Forty-five full-text articles were sought for full-text retrieval; three could not be retrieved. Forty-two full-text reports were assessed for eligibility, of which 30 were excluded for the reasons shown in Figure 1. The final qualitative synthesis included 12 studies that became part of the SLR table shown in Table 3.

FIGURE 1. PRISMA FLOWCHART



Source: Adapted from PRISMA 2020 [16]

Data were extracted from each included study using a structured matrix covering healthcare application, data or setting, AI/ML approach, key evidence, validation or performance focus, Critical Appraisal Skills Programme (CASP) score, and contribution to the thematic synthesis.

QUALITY ASSESSMENT

An adapted CASP framework was used to assess the methodological quality of the included studies [17]. Eight criteria were assessed: clarity of research aim, appropriateness of study design, adequacy of data and sample, transparency of AI/ML methods, model validation, consideration of bias, clarity of findings, and relevance to preventive or anticipatory healthcare. Each criterion was scored 1 if adequately addressed and 0 if not, for a maximum score of 8. Studies scoring

7–8 were classified as high quality, 5–6 as moderate quality, and 0–4 as low quality. Quality scores guided the strength of interpretation during evidence synthesis rather than excluding studies.

TABLE 3. SUMMARISATION OF LITERATURE INCLUDED FOR ANALYSIS

Study	Healthcare application	Data / setting	AI/ML approach	Key evidence / contribution	Validation / performance focus	CASP	Theme (T)
Khattab et al. (2026)	Type 2 diabetes screening	All of Us Research Program and UK Biobank	Two-stage ML / XGBoost	Supported personalised identification of individuals at risk of developing type 2 diabetes	External validation across independent cohorts; subgroup assessment	**8, High**	**T2**
Lin et al. (2025)	Major cardiovascular event prediction	Large-scale ECG data from multiple medical centres	Multitask deep learning	Demonstrated prediction of several future cardiovascular outcomes from ECG data	Independent external validation and comparison with conventional cardiovascular risk assessment	**7, High**	**T1**
Hughes et al. (2023)	Long-term cardiovascular risk	ECG datasets from multiple healthcare centres	Deep-learning ECG risk score	AI-generated risk information supported cardiovascular risk reclassification with potential implications for preventive treatment	Validation across independent healthcare centres	**8, High**	**T2**
Lee et al. (2023)	Cardiovascular risk prediction	Fundus images and conventional cardiovascular risk factors	Multimodal deep learning	Combining imaging and traditional risk factors improved cardiovascular risk estimation	External validation and comparison with conventional approaches	**7, High**	**T1**
Imrie et al. (2023)	Diagnostic and prognostic modelling	UK Biobank and clinical prediction applications	Automated machine learning	AutoML supported accessible model development, interpretation and clinical decision-	Comparison with established risk scores and assessment of clinical net benefit	**7, High**	**T3**

				support applications			
Zhang et al. (2024)	Community-based eye disease screening	Real-world community screening data	RETFound-enhanced deep learning	Demonstrated the value of AI for community screening across different service environments	Real-world evaluation and decision-curve analysis	**7, High**	**T2**
Capstick et al. (2024)	Early detection of urinary tract infection	Remote monitoring and home-sensor data	Explainable ML	Risk estimates were converted into actionable warning levels for early identification	Evaluation of sensitivity, specificity and alert burden	**6, Moderate**	**T2**
Gadaleta et al. (2021)	Early COVID-19 detection	Wearable sensor data	Explainable ML	Passive physiological monitoring supported detection before or around conventional clinical identification	Performance evaluated across different prediction windows	**7, High**	**T2**
Hinson et al. (2022)	Hospital admission and deterioration decisions	Multisite emergency department setting	Workflow-integrated ML	Model predictions were incorporated into electronic clinical workflows and used to support admission decisions	Prospective validation and implementation monitoring	**8, High**	**T3**
Coombs et al. (2022)	Oncology risk prediction and prospective care decisions	Oncology clinical setting	ML risk-prediction framework	Connected prediction with clinician review and prospective care decisions	Retrospective and prospective validation with clinician confirmation	**8, High**	**T3**
Clift et al. (2024)	Pancreatic cancer risk in adults with new-onset diabetes	Population-based healthcare data	Cox regression, XGBoost and neural networks	More complex ML did not necessarily provide superior clinical value	Internal-external validation, calibration and decision-curve analysis	**8, High**	**T1**

				compared with conventional modelling			
Kalmady et al. (2024)	Population-level cardiovascular prediction	Large multisite ECG dataset	ML algorithms	Predictive performance differed across cardiovascular outcomes and settings, highlighting limits of performance metrics alone	Patient-level and cross-hospital validation with subgroup evaluation	**8, High**	**T1**

Source: Compiled by Authors

THEMATIC SYNTHESIS AND FREQUENCY ANALYSIS

For thematic synthesis, a three-step coding procedure was followed, including open coding, axial coding, and selective coding across 12 studies, as shown in Table 4. These studies were grouped together according to their conceptual relationships based on recurring concepts as identified by open coding. Selective coding was then used to integrate these categories around the central issue of how AI-enabled predictive analytics translated into preventive healthcare value. Cross-study comparison was also used to identify convergent and contradictory findings, while CASP scores informed the strength placed on each pattern during interpretation. Each study was assigned to the theme representing its dominant contribution to the synthesis. A study-level frequency analysis was subsequently conducted, with each study counted once, to show the distribution of evidence across the three themes.

TABLE 4. THEMATIC SYNTHESIS AND FREQUENCY ANALYSIS

Open codes identified across studies	Axial coding category	Selective coding interpretation	Final theme	Studies, n	Frequency
Predictive accuracy, discrimination, calibration, internal validation, external validation, generalisability, model comparison, subgroup performance	**Predictive validity and robustness**	Strong prediction establishes technical capability, but predictive performance alone does not demonstrate preventive or clinical value	**T1. Predictive Performance Does Not Equal Preventive Value**	**4**	**33.3%**
Early detection, screening, risk stratification, prediction horizon, early warning, timely alerts, intervention opportunity, clinical net benefit	**Timeliness and actionability**	Prediction becomes more useful for prevention when it is generated early enough and is linked to a feasible healthcare response	**T2. Timeliness and Actionability Shape Preventive Utility**	**5**	**41.7%**
Workflow integration, clinician involvement, decision support, explainability, organisational readiness, bias assessment,	**Implementation and governance conditions**	Translation from predictive capability into healthcare action depends on the clinical and organisational	**T3. Implementation Conditions Shape Translation into Practice**	**3**	**25.0%**

implementation monitoring, human review		conditions surrounding model use			
		Total		**12**	**100%**

Source: Compiled by Authors

FINDINGS AND ANALYSIS

THEME 1. PREDICTIVE PERFORMANCE DOES NOT EQUAL PREVENTIVE VALUE

Findings indicate that strong technical performance creates predictive capability, but not preventive value. External validation showed that models could be applied usefully to achieve scores beyond those from their original development datasets. The results also indicated that more refined and complicated models do not necessarily lead to more clinical value. However, Clift et al. [3] found that more complex ML methods did not generate greater clinical utility than conventional modelling. This differentiation is directly related to RQ1. Accuracy and discrimination are not enough to infer Preventive value. Reliability of the identification of risk does not mean the model changes the outcome of the patient. In an STS perspective, these measures reflect the technical system's strength but not whether the social and clinical system will utilise the information. The finding thus translates the concept of predictive validity not to the end of the translation process, but rather at the start. Technical reliability is important, but only if and when the prediction can inform a decision or intervention that allows for prevention.

THEME 2. TIMELINESS AND ACTIONABILITY SHAPE PREVENTIVE UTILITY

The synthesis shows that the utility of the prediction changes according to what's being predicted, when the information arrives and whether taking some action could follow. Prediction has become a possibility to prevent action with personalised diabetes screening [9], cardiovascular risk reclassification [10], community screening [11], as well as remote warning systems [12] and wearables [13]. Previous prediction, however, should not be assumed to be superior to prevention. A risk signal has limited utility if it comes too late, too early to support a reliable decision, or if there is no feasible response. Actionability, in turn, is an important connection between the technical prediction and the use of healthcare. This addresses RQ1 as it demonstrates that translation is more about a meaningful intervention window than predictive performance. It also helps to answer RQ2, as time, communication, and how the participant can respond are turning conditions for success in translation. The STS perspective considers actionability to be the point of convergence between the technical and the social systems. The function of the model is to provide information; however, preventive value can only be gained when the information is appropriate and in time for the healthcare decision context.

THEME 3. IMPLEMENTATION CONDITIONS SHAPE TRANSLATION INTO PRACTICE

There is an important gap in maturity, as evidenced by a few studies that focus on implementation. While evidence of routine use of technical prediction in healthcare processes seems less developed, prediction seems to be more advanced than technical prediction. This directly answers RQ2. The extent to which a prediction becomes an operational decision depends on workflow fit, clinicians' involvement, responsibility for action, interpretability and post-deployment monitoring. Related governance evidence was found in the form of biases assessed, human review and monitoring, but not as advanced as technical validation. STS helps explain this pattern clearly. Predictive technology cannot generate preventive value without being embedded in a particular healthcare system. Therefore, the process of translation should ensure that the outputs of the models correspond to the people, responsibilities, and processes involved in their use. The discovery changes the deployment problem to one of effectiveness at the time of deployment.

PREDICTION-TO-PREVENTION TRANSLATION FRAMEWORK

Table 5 outlines the Prediction-to-Prevention Translation Framework to guide the translation of predictive capability and value in the context of preventive healthcare driven by AI. The themes identified in the review were then organised in accordance with the logic of STS Theory. Predictive validity underscores the need to predict before preventing, as the

framework begins with that criterion. Then it turns to the challenges of preventative actionability and timely delivery that enable an actionable response to the prediction. The second phase, decision and workflow alignment, focuses on the intended target audience for the prediction, who is carrying out the action, and how the target audience's healthcare process involves the prediction. Governing implementation concludes with human oversight, control, bias assessment, accountability, and continuous monitoring. This framework is not to be followed in a step-by-step sequence. Failure can occur at any stage of the translation process, and the model, workflow, or decision will be subject to change as a result of feedback from the implementation. The predictive efficacy, therefore, is not enough to guarantee the preventive value; it is necessary to understand the social conditions together with the technical conditions.

TABLE 5. PREDICTION-TO-PREVENTION TRANSLATION FRAMEWORK

Framework stage	Key question	Main condition	Decision rule
Predictive validity	Can the prediction be trusted in the intended population and setting?	Reliable performance, validation, subgroup robustness	Do not move towards implementation if predictive performance is weak, unstable, or not adequately validated
Preventive actionability	Does the prediction identify a risk that can realistically be acted upon?	Clear link between predicted risk and a feasible healthcare response	High predictive performance alone is insufficient when no meaningful preventive action follows
Timely delivery	Does the prediction arrive within a useful intervention window?	Appropriate prediction horizon and timely communication	A prediction has limited preventive value if it arrives too late or too early to support a reliable response
Decision and workflow alignment	Who receives the prediction and who is responsible for acting on it?	Clear decision ownership, workflow fit, clinician involvement	Predictive outputs should be linked to an identified decision maker and response pathway before routine use
Governed implementation	Can the system be used safely and responsibly over time?	Human oversight, bias assessment, accountability, monitoring	Deployment should include review of model performance, unintended effects, subgroup differences, and workflow consequences
Preventive value	Has prediction been translated into useful healthcare action?	Alignment across technical and social conditions	Preventive value is achieved only when valid prediction, timely actionability, workflow integration, and governance operate together.

Source: Compiled by Authors

IMPLICATIONS

Predictive AI needs to be considered as a part of the healthcare management system and not just a tool or technology. Organisations need to address four practical questions before using a model: 1) Is the model validated, 2) can any action that may result in a decreased outcome to the prediction be taken, 3) will any person take the action, and 4) will the action be carried out within a meaningful time to the model or prediction. Reaction, alert burden, workflow and side effects should, therefore, be part of the assessment, in addition to accuracy when pilot testing. For instance, if a hospital implements an algorithm to stratify patients who are at risk of diabetes, the algorithm's output should be associated with a standardised and formalised protocol, e.g. linked to a recommendation for confirmatory testing and then a call to a clinician or to a diabetes prevention counselling pathway. If prevention is used, it will have value only if assertive follow-up is directly involved in the process. The framework can thus be applied to procurement, pilot testing, and pilot implementation decisions.

LIMITATIONS

Different performance evaluations in the reviewed studies were combined into one synthesis, including various diseases, datasets, and healthcare contexts, which provides broader coverage but may limit direct comparability of model performance. Evidence of prediction and validation was also more well-developed than evidence of long-term implementation, governance and post-deployment outcomes. The differences reflect the fact that the field is still a maturing one. Future studies should therefore pay greater attention to plans for future implementation, cross-setting validation of the impact of the outputs of the predictions on the various facets of the preventive decision, workflow, equity and patient outcomes.

CONCLUSION

This paper shows that accurate prediction alone does not create preventive healthcare value. Predictive validity provides the technical foundation, but value depends on whether the prediction is timely, actionable, integrated into workflow, assigned to a responsible decision maker, and appropriately governed. The Prediction-to-Prevention Translation Framework brings these conditions together and explains where translation can succeed or break down. By separating predictive capability from preventive value, the study moves the discussion beyond model performance and towards the practical conditions required for AI-enabled prediction to support preventive healthcare.

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