

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. While 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.

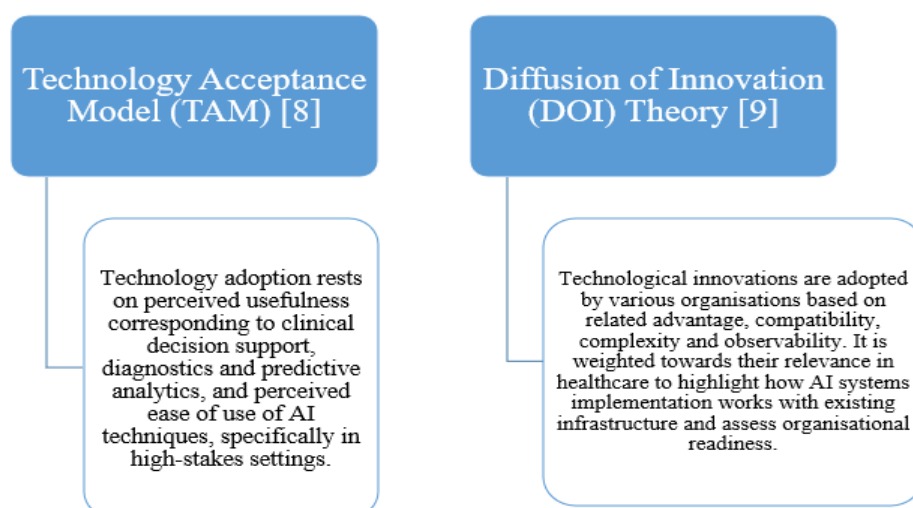
RESEARCH GAPS

- 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]

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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

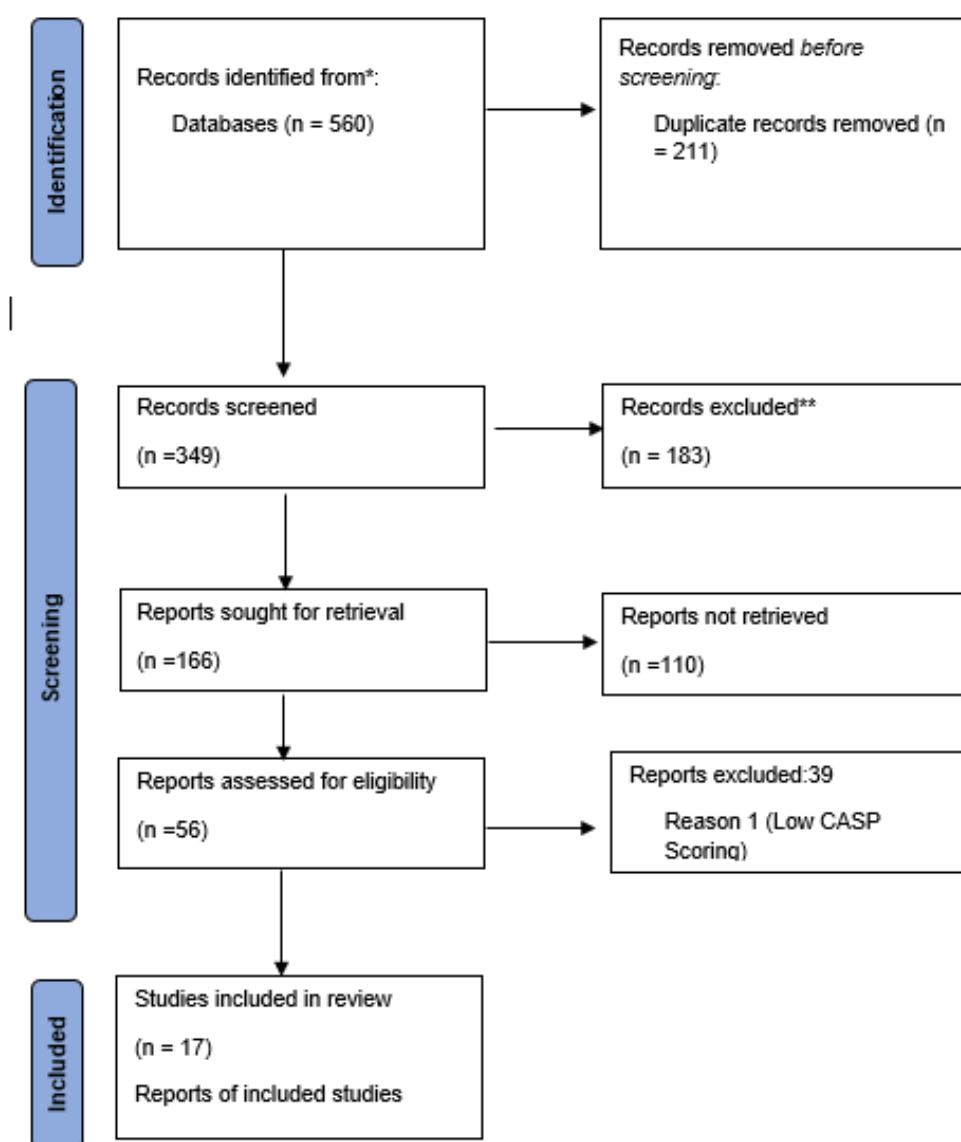
EXCLUSION CRITERIA

- 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
Somashekar 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	<p>Most occurring codes-</p> <ul style="list-style-type: none"> • 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 	<p>i) Codes such as interpretability, trust, and physician acceptance were predominantly associated with clinical decision support systems.</p> <p>ii) Codes such as model accuracy, large dataset requirements, and black-box limitations were strongly linked to diagnostic applications.</p> <p>iii) Codes such as prediction accuracy, generalisability, and validation gaps were concentrated within predictive analytics.</p>	<ol style="list-style-type: none"> 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.

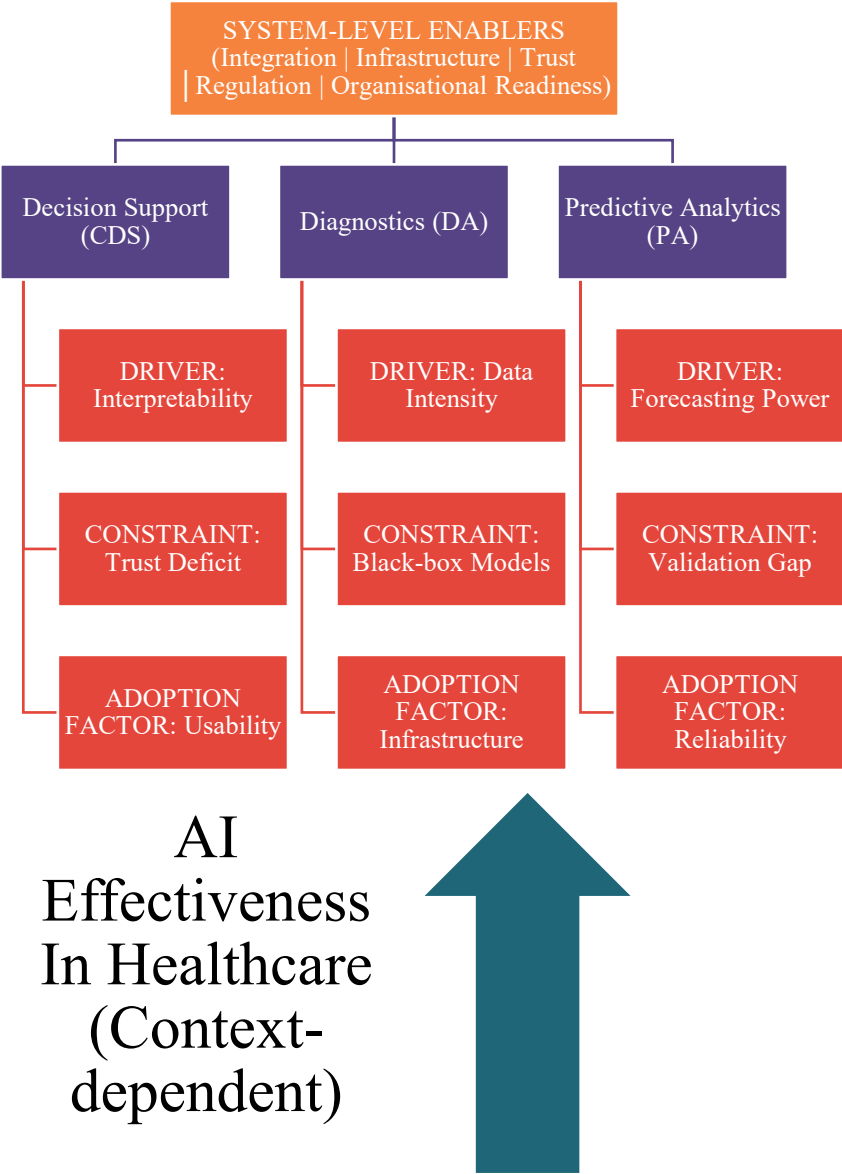
PROPOSED CONCEPTUAL MODEL

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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