A Systematic Review of Leveraging Enterprise Architecture to Overcome Blockers in AI-CDSS Implementation

Anthony Lua
University of Melbourne
anthonykp.lua@gmail.com

Ching Yi Chan
University of Melbourne
cy@invisiontech.com

Takeichi Gushiken
University of Melbourne
gushikentakeichi@gmail.com

Zong-Han Hsieh
University of Melbourne
zonghan.bryan@gmail.com

Vivek Kothary
University of Melbourne
vivek.kothary@icloud.com

Rod Dilnutt
University of Melbourne
rpd@unimelb.edu.au

ABM Nayeem
University of Melbourne
abm.nayeem@student.unimelb.edu.au

Abstract

This systematic review analyses a set of articles to explore how Enterprise Architecture (EA) can resolve five key barriers to adopting AI-powered Clinical Decision Support Systems (AI-CDSS) in healthcare: data governance, ethical challenges, AI reliability, organisational resistance, and system interoperability. The findings showcase EA's ability to provide a well-organised framework that transforms disjointed healthcare systems into cohesive digital solutions. EA aligns AI integration with clinical objectives, ensures adherence to regulations, reduces risks, and enhances stakeholder trust. Consequently, EA emerges as both a technical solution and a strategic enabler for comprehensive digital transformation.

Keywords: Artificial Intelligence, Clinical Decision Support Systems, Enterprise Architecture

1. Introduction

Artificial Intelligence (AI) is rapidly growing within the healthcare sector, with one of its most promising applications being in Clinical Decision Support Systems (CDSS) (Alanazi, 2023). These systems are designed to enhance clinical decision-making using healthcare information and patient data (Baron & Haick, 2024). It does so by providing predictive insights and actionable recommendations (Zhang et al., 2023), by enhancing diagnostic accuracy and personalising treatment plans (Aguirre & Cha, 2025) with machine learning (ML) techniques (Adler-Milstein et al., 2022; Janbi et al., 2022). When integrated effectively, they can improve clinical decisions, improve clinical workflows, inform diagnostic decisions through analysing large datasets to anticipate patient diagnosis, treatment planning, and real-time data analysis for timely interventions (Baron & Haick, 2024; Deng et al., 2024).

Despite these advantages, AI-CDSS adoption in hospital settings remains uneven and is fraught with blockers. This paper does not aim to identify all blockers but instead focuses on the recurring themes that emerged from the existing literature as a foundation for deeper exploration. These blockers include:

1.1. Clinical Data Governance and Quality Assurance

Fancy et al. (2024) notes that healthcare datasets can be voluminous and change rapidly, making it difficult for healthcare providers to compute and interpret. Adler-Milstein et al. (2022) recognise that AI models are often developed using limited data samples and may not be representative. Furthermore, Gedefaw et al. (2023) recognise the limitations on the use of AI from completely replacing manual diagnosis, such as limited databases, a lack of standardisation and validation, systemic errors and biases. AI is trained on data; if the data contains bias and is not representative, it may produce inaccurate or biased results (Gedefaw et al., 2023).

1.2. Ethical, Legal, and Regulatory Challenges

Ethical concerns around AI include biases in predictive algorithms and the potential for job displacement amongst healthcare workers (Hajiheydari et al., 2025). Gedefaw et al. (2023) raise concerns around the significant threats to patient privacy and security from AI systems, with a call for strict laws to be applied to ensure the security of

Electronic Health Records (EHR). Adler-Milstein et al. (2022) highlight the slow pace of regulators with the US Food and Drug Administration (FDA)'s approach to regulating AI/ML clinical decision support and device decision support software remaining a work in progress, almost six years after the Cures Act[1].

1.3. Explainability and Reliability of AI Outputs

Shin et al. (2025) states that AI models face issues with "inaccuracies caused by incorrect, biased, outdated or misleading information" and "hallucinations where the model produces fabricated content". Patients perceive AI as a 'black box' incapable of explaining its reasoning or rationale behind its recommendations, with patients preferring their clinicians' diagnoses (Hajiheydari et al., 2025; Yang et al., 2022). Clinicians have raised concerns about the need for the careful development and testing of AI-integrated EHR systems to ensure the accuracy and trustworthiness of AI in clinical decision-making for patient treatment (Alanazi, 2023).

1.4. Organisational Resistance and Change Management

EHR AI implementation often stalls when leadership hesitates or lacks technical expertise because of the long periods, complex processes, and high costs (Mwogosi, 2024; Yang et al., 2022). Deng et al. (2024) showcase that clinician satisfaction is key to adoption, and clinicians often resist adopting new AI systems due to task-technology fit concerns and computer proficiency.

1.5. Interoperability and Integration with Legacy Infrastructure

Interoperability between AI systems and existing healthcare systems is a significant challenge with the lack of interoperability leading to fragmented care and inconsistencies in treatment recommendations (Gedefaw et al., 2023). Ensuring interoperability between AI tools, existing EHR systems, and related platforms is often complex due to incompatibility (Janbi et al., 2022; Adler-Milstein et al., 2022), with many organisations struggling to integrate AI with their existing Information Technology (IT) infrastructure and clinical workflows (Yang et al., 2022).

Our exploration of the research underscores the need for a more holistic framework that can bridge these gaps and ensure safe, transparent, and integrated AI adoption. Enterprise Architecture (EA), with its structured methodologies and layered architectural models, provides a promising lens through which AI-CDSS implementation can be strategically governed (Chaczko et al., 2010). Frameworks like The Open Group Architecture Framework (TOGAF®) offer an iterative, stakeholder-driven approach to align IT initiatives with clinical goals, regulatory requirements, and operational constraints (Chaczko et al., 2010).

These now lead to our Research Question: ***How can Enterprise Architecture (EA) overcome blockers when augmenting Artificial Intelligence (AI)-powered clinical decision support systems for Hospitals?***

2. Methodology

A Systematic Literature Review (SLR) approach was undertaken to investigate our Research Question. We adopted this comprehensive approach because of its utility in highlighting underdeveloped research areas (Møller et al., 2018), and hence appropriate for future scientific inquiries.

2.1. Search Term

Based on topics arising from our Research Question, Table 1 depicts all search terms that formed the basis of our SLR process. These search terms were chosen because of their close relevance with our Research Question.

Topics			
EA	AI & Clinical Decision	Blockers	Healthcare

[1] The 21st Century Cures Act ("Cures Act") specifies and implements a new type of health IT system interoperability, that requires that Electronic Health Records (EHRs) have an application programming interface (API) that grants access to patient records with no excessive effort (Adler-Milstein et al., 2022).The Cures Act aims to increase the exchange and availability of health data.

	Support Systems		Institutions
(Enterprise Architect* **OR** EA)	(Artificial Intelligence Clinical Decision Support System **OR** Artificial Intelligence CDSS **OR** AI Clinical Decision Support System **OR** AI CDSS)	(Clinical Data Quality Governance **OR** Clinical Data Quality Assurance **OR** Ethical Challenges with AI Integration **OR** Challenges with AI Integration Ethics **OR** Legal Challenges with AI Integration **OR** Regulatory Challenges with AI Integration **OR** Challenges with AI Integration Regulations **OR** Explainable AI **OR** AI Reliability **OR** Reliability of AI **OR** Organisation* Resistance **OR** Resistance to Change **OR** Change Resistance **OR** Interoperability with Legacy Infrastructure **OR** Integration with Legacy Infrastructure)	(Hospital **OR** Hospitals)

Note. **Bold** words represent a search operator.

Table 1. *Search Terms*

2.2. Inclusion Criteria

We thoroughly evaluated and included articles that met all the following criteria:

1. All peer-reviewed articles of the following types - Original research, case studies, methodology papers, case reports, perspectives, clinical trials, and conference papers.
2. All published peer-reviewed articles from 2022 onwards.
3. If the peer-reviewed article has keywords included, it should contain at least one or more of the following keywords (see Table 2).

Keywords		
Enterprise Architecture (EA)	Interpretable and Explainable AI	Legal Considerations
Enterprise Architect	Clinical Decision Support Systems	Regulations
Architecture	AI-Clinical Decision Support Systems	Regulatory Considerations
TOGAF®	Healthcare Professionals	Systems Integration
Zachman Framework	Clinicians	Interoperability
Artificial Intelligence (AI)	(Clinical) Data Management	Change Management
Machine Learning	(Clinical) Data Quality	Change Resistance
Generative AI	(Clinical) Data Assurance	Resistance to Change
Explainable AI (XAI)	Ethics	Health Information Systems
Interpretable AI	Legal	Hospitals

Note. Words in '()' represents an optional term that is inclusive of the whole keyword.

Table 2. *Considered Keywords*

2.3. Exclusion Criteria

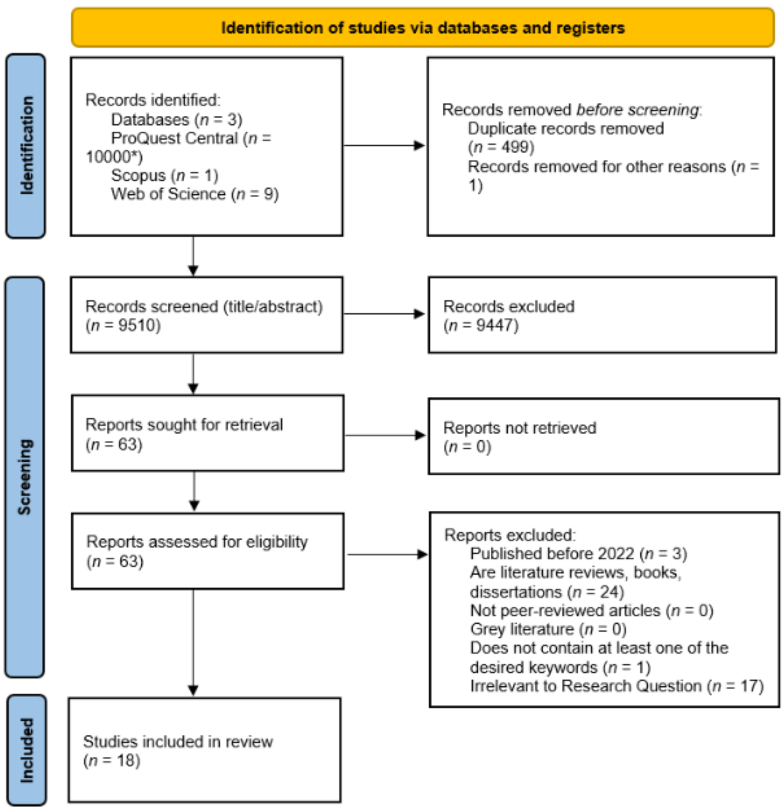
We thoroughly evaluated and excluded articles that met all the following criteria:

1. All types of literature review articles (e.g., systematic reviews, meta-analyses, scoping reviews, narrative reviews, normal reviews etc), editorials, books, and all retracted articles.

2. All non-peer reviewed articles.
3. All Masters' and PhD dissertations.
4. All grey literature.

2.4. Search Strategy and Study Selection

Consolidating the search terms and eligibility criteria together, the **AND** search operator was used to connect search terms from each topic. Articles were then searched from across three digital bibliographical databases in April 2025. No search filters were applied to preserve integrity. Once completed, duplicates were identified and removed. Subsequently, the titles and abstracts of remaining articles were screened to determine preliminary relevance with the Research Question. After shortlisting relevant articles, their full text was evaluated against the eligibility criteria to exclude those that did not meet it. In the end, 18 articles remained. Figure 1 illustrates the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA; Page et al., 2021) approach that was undertaken as part of our SLR.



Note. '*' ProQuest Central originally returned 56787 articles. But due to search limit and licence constraints, we could only view and include the first 10000 articles.

Figure 1. *PRISMA Diagram*

From the final 18 articles, each author independently conducted inductive thematic analysis on a non-overlapping subset of articles to examine and identify key solution-driven insights to tackle the five major blockers. After all analyses were completed, all authors came together and presented their respective findings, which sparked insightful discussions. Disagreements between authors were settled by having all authors read the whole article in question followed by continuous discussion until a consensus was reached. Discussions ceased once all analyses had been critiqued and a consensus reached.

3. Key Themes Analyses

To address the research question, this section dives into five recurring themes, with each representing a major blocker to AI-CDSS adoption. For each theme, this section examines how an EA framework can be strategically applied to overcome these challenges.

3.1. Clinical Data Governance and Quality Assurance

Data quality issues, particularly biases in data, are extremely problematic in healthcare (Wang et al., 2023; Pinsky et al., 2024). In the context of AI-CDSS, these biased data are reflected in generated medical advice, which in turn compromises patient safety as clinicians might make incorrect decisions and thus put patient lives at risk. In hospitals, these biased data are typically stored in fragmented clinical data sources with each having different formats and types (Doutreligne et al., 2023). Hence, this is the ideal starting point for Enterprise Architects to make significant contributions towards enhancing clinical data governance and ensuring data quality when integrating AI-CDSS into existing hospital IT infrastructure and clinical workflows. Alongside clinical data governance, regulatory compliance is also a key aspect for appropriate data management.

To merge all fragmented clinical data sources, Enterprise Architects must create a list of data quality guidelines that dictates the format and type in which data is currently written and stored across various hospital systems. Ideally, these guidelines should be developed into a clinical data governance framework. As a typical data governance framework should reflect the structure of systems across an organisation (Doutreligne et al., 2023), it is justified for Enterprise Architects to use their hospital's current data architecture as the basis to map out the future data architecture. Furthermore, if data sharing between healthcare organisations is necessary, Enterprise Architects can draw knowledge from the European Union Data Governance Act (Kondylakis et al., 2023) to supplement its development.

Once a clinical data governance framework has been developed, Enterprise Architects can recommend changes be made to seamlessly combine clinical data from all data sources into a centralised clinical data warehouse (Doutreligne et al., 2023). In accordance with the data architecture layer of TOGAF®'s Architecture Development Method (ADM) Information Systems (IS) Architecture phase, Enterprise Architects must settle on an established common data model that defines the format and data type for all data (Wong et al., 2025). For example, all patient data must adhere to HL7[2] FHIR[3] formatting standards to ensure data consistency and compliance with regulatory standards, which are key in ensuring data quality. Consequently, these enable AI-CDSS to be appropriately trained with high-quality data.

To conclude, Enterprise Architects can spearhead the design of a comprehensive clinical data governance framework that assists them in managing and structuring clinical data to input into a clinical data warehouse. Most importantly, Enterprise Architects should leverage TOGAF®'s ADM as part of its design to facilitate smooth digital transformation for their respective hospital's future data architecture.

3.2. Ethical, Legal, Regulatory Challenges with AI Adoption

Ethical issues with AI include the loss of 'human touch' in clinical care, prejudice and bias by patient demographics, and issues about transparency and explainability. Patients are concerned about reduced empathy and personalised care, which are crucial for maintaining patient-clinician trust (Maris et al., 2024). Algorithmic biases can perpetuate existing inequalities, and opaque algorithms can undermine patient trust and autonomy (Wang & Beecy, 2024; Comeau et al., 2025). Thus, patients should be involved in decision-making, especially when implementing AI-powered clinical decisions (Maris et al., 2024). TOGAF®'s ADM Business Architecture phase can assist with aligning AI systems with organisational values, emphasising transparency, fairness, and patient centric care (Alomari et al., 2024). Implementing digital solutions and virtual clinics within TOGAF® ADM can enhance care quality, reduce biases, and preserve clinical empathy.

[2] HL7: Health Level Seven, a set of international standards for the exchange, integration, sharing and retrieval of electronic health information (Health Level Seven International, n.d.).

[3] FHIR (Fast Healthcare Interoperability Resources): A free to use modern standard developed by HL7. It uses web technologies like REST APIs and JSON/XML to enable faster, simpler and more flexible data exchange between health systems (Health Level Seven International, n.d.).

Legal issues include accountability and privacy concerns. The ambiguity in legal responsibility, when AI-powered decisions lead to patient harm, is a concern. The handling of sensitive patient data also necessitates strict compliance with regulations such as HIPAA[4] (Moodley, 2024; Wang et al., 2023). Countries like the US are looking into an AI Bill of Rights that protects people and clarifies agency over data (Moodley, 2024). TOGAF® emphasises robust data governance and clear delegation of responsibility, thereby addressing legal requirements and accountability (Alomari et al., 2024). This structured framework offers a safe and reliable approach that addresses these legal issues as it evolves throughout its lifecycle.

Regulatory challenges include establishing precise oversight mechanisms to ensure the safety and efficacy of AI systems, risking patient safety due to a lack of rigorous validation and inadequate performance monitoring (Chouvarda et al., 2025; Arbelaez Ossa et al., 2024). Comeau et al. (2025) state that stakeholders must participate actively in AI oversight to manage these risks. TOGAF® ADM provides a structured methodology for systematic AI application validation, monitoring, and compliance (Alomari et al., 2024). Its phased implementation and continuous change management ensure that adherence to regulatory requirements enhances AI safety and effectiveness at each critical phase.

In conclusion, integrating AI into CDSS requires addressing patient-centric decision-making, policies protecting humans, and active stakeholder participation. By leveraging on methodologies like TOGAF®'s ADM, healthcare operations can maintain improvements and efficiencies without compromising ethics, legal, and regulatory requirements.

3.3. Explainability and Reliability of AI Outputs

Transparency and explainability are essential for understanding AI decisions and are closely related to the reliability of AI (Wang et al., 2023), which are key factors for the successful implementation of AI in CDSS. EA enables standardised validation methods, transparency protocols, and continuous monitoring systems (Wang & Beecy, 2024; Moodley, 2023). These mechanisms ensure that AI systems meet clinicians' expectations for interpretability and reliability, thereby supporting effective integration with clinical workflows.

For explainability, EA facilitates the adoption of Explainable AI (XAI)[5] frameworks that align with clinical decision-making processes, offering clinicians clear and justifiable reasoning behind AI-generated recommendations (Wang & Beecy, 2024). Using the structured methodology of TOGAF®'s ADM, healthcare organisations can elicit explainability requirements from clinical stakeholders, align data and application architectures to support transparency, and select technologies that enhance interpretability (Alomari et al., 2024). By iterating through the ADM phases, organisations can ensure that XAI systems are developed with stakeholder input and remain adaptable to evolving clinical needs. With improved interpretability and situational awareness, these tools are more likely to be accepted at the bedside (Pinsky et al., 2024).

Regarding reliability, maintaining data quality and regularly updating AI models are essential to minimise risks associated with outdated information or model in evolving clinical practices (Wang & Beecy, 2024; Moghadasi et al., 2024). EA offers a systematic approach to support healthcare organisations building continuous validation and recalibration of AI models through data governance, monitoring mechanisms and the Human-in-the-Loop (HITL[6]) concept (Montomoli et al., 2024). Accurate and consistent data serve as the foundation for reliable outputs, while performance tracking and early detection of model drift ensure sustained accuracy. Additionally, EA supports the design of layered architectures that address explainability and reliability across technical, organisational, and operational dimensions (Moghadasi et al., 2024). For example, integrating auditability and validation capabilities at the application and data architecture layers ensures traceable and consistent AI decisions. By embedding these mechanisms, EA not only enhances model reliability but also ensures that AI systems remain responsive, trustworthy, and aligned with the dynamic nature of clinical environments.

[4] The Health Insurance Portability and Accountability Act of 1996 (HIPAA) is a US federal law that establishes national standards for the protection of individually identifiable health information, requiring covered entities to implement administrative, physical, and technical safeguards to ensure patient privacy and data security (Health Insurance Portability and Accountability Act [HIPAA], 1996).

[5] Explainable AI: Explainable AI refers to a set of methods and techniques that enable human users to understand and trust the output of AI models (Wang & Beecy, 2024).

[6] Human-in-the-Loop: Human-in-the-Loop is a design principle in AI systems where human judgment is actively integrated into the model's decision-making process (Montomoli et al., 2024).

3.4. Organisational Resistance and Change Management

Organisational resistance is a common barrier to digital transformation, and effective change management is essential for anticipating, addressing, and reducing this resistance during the adoption of AI-CDSS (Ratta et al., 2025; Wong et al., 2025).

EA can serve as a strategic integration tool to address this challenge. By promoting standardisation across organisational systems and clinical pathways, EA facilitates clear communication of system roles and benefits to various stakeholders (Mutasa et al., 2025). For example, by applying TOGAF®, organisations can standardise clinical workflows within the business architecture layer to align AI-CDSS integration with established processes. At the application architecture layer, AI-CDSS modules and role-based user interfaces can be defined to support interactions among different users. In the information architecture layer, aligning data formats like FHIR ensures high-quality, reliable data while addressing concerns about data bias (Wong et al., 2025). EA also enables the development of tailored training plans to equip user groups with a clear understanding of how AI supports their clinical roles (Asiri et al., 2025; Wang et al., 2024). Collectively, these elements strengthen trust in AI-generated output and reduce implementation resistance.

EA supports phased implementation by piloting AI-CDSS in controlled settings to show value and build user confidence (Mutasa et al., 2025). EA also emphasises stakeholder engagement during the design and planning stages by involving key stakeholders, such as physicians and administrators, to promote ownership, increase trust, and reduce implementation resistance (Pinsky et al., 2024). Before full integration, a "silent validation[7]" phase can compare AI outputs with historical decisions without exposing them to end-users, ensuring alignment with retrospective evaluations and reducing perceived risk (Wang & Beecy, 2024). In EA, this phase serves as a transitional interaction strategy within the application architecture layer to enhance user understanding and guide continuous system refinement.

EA facilitates the integration of AI into clinical workflows through phased adoption, embedded training, clear role definitions, and structured feedback mechanisms. These enhance transparency, preserve clinical autonomy, and strengthen change management efforts, resulting in reduced organisational resistance towards AI-CDSS adoption.

3.5. Interoperability and Integration with Legacy Infrastructure

Interoperability hurdles and integration challenges with legacy infrastructure hinders the implementation of AI-CDSS across hospitals (Mutasa et al., 2025). EA, particularly when guided by TOGAF®, provides a structured, scalable approach to address these issues and translate them into actionable design and governance principles.

EA helps overcome fragmented systems by providing a high-level blueprint for aligning IT capabilities with business needs. For example, Mutasa et al. (2025) recommended a phased technical architecture plan to guide the procurement and implementation of IT infrastructures to integrate disparate legacy Health Information Systems within Namibia's national strategy, aligning with TOGAF®'s Migration Planning and Technology Architecture phases. Similarly, the TOGAF®-based case study by Alomari et al. (2024) at Jordan's National Center for Diabetes demonstrated how integrating clinical and pharmacy modules using an EA roadmap streamlined operations and improved system interoperability by using an Electronic Health assistant and the digitalisation of services to improve existing processes, falling within TOGAF® ADM's IS Architectures and Opportunities and Solutions phases.

Comeau et al. (2025), Doutreligne et al. (2023) and Kondylakis et al. (2023), advocate for open-source tools, audit trails, transparency standards and encryption measures to protect patient health from a governance perspective. These principles are directly aligned with TOGAF®'s Implementation Governance and Architecture Change Management phases. Chouvarda et al. (2025) stress the need for organisations to perform internal validation and clinical evaluation on AI-CDSS. It is also important to have harmonised validation methodologies and reporting guidelines to standardise integration with legacy infrastructure.

Linking to TOGAF®'s IS architectures, Tanković et al. (2025) suggest multimodal systems and standardised datasets to address schema variability in EHRs. Pinsky et al. (2024) highlight the need for rigorous planning,

[7] Silent validation takes place prior to the model being integrated into the clinical workflow. Throughout this phase, end-users cannot access the model's results. The aim is to document the data input and model output to confirm alignment with the retrospective evaluation (Wang & Beecy, 2024).

stakeholder involvement and interface design to ensure compatibility across vendors, reflecting TOGAF®'s ADM Architecture Vision and Business Architecture phases. Finally, Montomoli et al. (2024) recommend creating structured data flows (ETL[8] pipelines) and having dedicated teams – Clinical AI Departments – to manage and unify health data. This aligns with the IS Architecture and Technology Architecture phases in TOGAF®'s ADM.

In conclusion, only a systematised approach can enable wider AI-CDSS adoption beyond isolated pilots. EA and TOGAF®'s ADM offer a vital scaffolding from the Architecture Vision to Implementation Governance phases that can systematically help address legacy system fragmentation, AI tools that do not provide a functional fit into current clinical workflows, and inconsistent data structures across varied EHR platforms.

4. Discussion

This study systematically reviewed 18 high-quality articles to examine how EA can address five recurring blockers to AI-CDSS adoption in healthcare: data governance, ethical challenges, AI reliability, organisational resistance, and system interoperability. Although each blocker presents distinct issues, they collectively reflect systemic fragmentation within hospital environments, primarily due to insufficient coordinated governance and a lack of strategic alignment between clinical priorities and digital transformation objectives.

Importantly, these blockers are deeply interconnected. For instance, weak data governance often leads to biased or unreliable AI outputs, increasing ethical concerns and resistance from clinicians. Similarly, a lack of explainability reduces trust in AI technologies, posing further adoption challenges even when technical performance is adequate. EA's primary strength is its ability to offer an integrated, comprehensive framework, enabling hospitals to transition from fragmented, isolated implementations to cohesive digital transformation strategies.

Leveraging on TOGAF®'s ADM, EA provides a structured pathway for aligning technological solutions with organisational goals, regulatory demands, and operational workflows (Wong et al., 2025; Alomari et al., 2024). Its layered architecture and phased approach help standardise governance through centralised data and model repositories and robust validation procedures (Moghadasi et al., 2024; Wong et al., 2025; Mutasa et al.,2025). This mitigates reliability and interoperability challenges while supporting secure and scalable integration of AI technologies.

Additionally, EA facilitates stakeholder alignment through iterative requirements gathering and structured engagement processes (Wang & Beecy, 2024; Comeau et al., 2025; Pinsky et al., 2024). This is critical for ensuring that AI solutions meet transparency, explainability, fairness, and compliance expectations, which serve as key prerequisites for clinician trust and adoption. Standardisation of these governance elements is especially valuable for generating explainable and auditable AI outputs, thus reducing resistance from clinicians and patients.

The findings underscore the importance for hospitals and broader health systems to adopt EA frameworks not just as technical tools, but as strategic enablers for digital transformation. Consequently, health Chief Information Officers (CIO) and clinical leaders are encouraged to embed EA within their digital health governance frameworks. EA guided implementation not only enhances alignment between AI tools and clinical workflows but also ensures regulatory compliance, mitigates operational risk, and builds critical stakeholder confidence.

4.1. Limitations and Future Directions

The section below describes several limitations of this review. Due to the use of highly specific search terms, this review may have excluded relevant papers using different or broader keywords. While this approach closely aligned with our examination of EA within AI-CDSS, the findings may not fully capture the extent of existing literature in this domain. Additionally, the review encountered a challenge due to limited literature specifically addressing EA in the healthcare context. This suggests that the area remains relatively unexplored, which constrained the review to a narrow selection of case studies and examples. Therefore, generalisations about the efficacy and broader application of EA frameworks across varied clinical settings may be limited.

Future research should use broader search criteria to include a wider range of articles to address these limitations. This could potentially uncover diverse insights and additional blockers not identified in this review. Furthermore, expanding the search may verify the generalisability of EA frameworks, such as TOGAF® or Zachman™, within

[8] ETL: Extract, transform, and load (ETL) is the process of using a set of rules to clean, organise and combine data from multiple sources into a large, central repository called a data warehouse (Amazon Web Services, Inc., n.d.).

different environments. Moreover, given the abovementioned scarcity, future empirical research should conduct case studies to validate the application and efficacy of the EA frameworks. This could significantly strengthen the evidence base for EA as a mechanism for overcoming common blockers when integrating AI-CDSS in healthcare.

5. Conclusion

In conclusion, our findings illustrate that Enterprise Architects can overcome the five recurring blockers when integrating AI-CDSS into hospital IT infrastructure. The proposed solutions enable alignment between clinicians' needs and healthcare business objectives. Moving forward, a potential path is the development of a comprehensive novel AI-powered TOGAF® framework for Enterprise Architects to successfully integrate AI CDSS into existing hospital IT systems. We are confident that our findings will enable Enterprise Architects to create lasting impact in the digital transformation of healthcare.

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