Enterprise Architecture Framework and Artificial Intelligence Challenges in Healthcare

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Abstract

Over the past few years, there has been growing evidence of the potential of Artificial Intelligence (AI) in improving healthcare services. However, its actual adoption in healthcare practices is very limited. Based on some of the previously established research work, this paper identifies issues such as: major technical challenges and ethical concerns that are illustrated by researchers as the root cause for this limited adoption; and investigates the ability of three famous Enterprise Architecture Frameworks (EAF) to address these AI challenges in healthcare. The result of our investigation suggests that: TOGAF addresses the ethical concerns most comprehensively, Service Oriented Architecture (SOA) can eliminate technical challenges of interoperability and integration in the most systematic manner and Zachman, due to its ability to partially address the technical and ethical challenges, can only be adopted for maintaining and classification of important artefacts.

1. Introduction

In recent years, many healthcare organisations have replaced their paper health record systems with an electronic health record system (EHR) in an effort to improve healthcare services and reduce medical errors (Keuse et al., 2016; Tsai et al., 2019). These EHR systems generate an abundance of clinical data that can fuel advanced analytical systems such as Artificial intelligence (AI) technology (Car et al., 2019).

AI in healthcare is the use of digital technology to mimic human cognition in the analysis, presentation, and comprehension of complex medical and health care data (Briganti & Le Moine, 2020). Healthcare was initially identified as one of the most promising application areas for AI (Kun, 2018).

There is growing evidence in research of its potential in improving clinical decisions and diagnostic services, therefore, AI has received a great amount of attention in healthcare circles (Benjamens et al., 2020). Researchers argue that AI can contribute to adding the element of efficiency and personalised treatment through data management and analysis into the decision-making procedure (Paranjape et al., 2020). With AI, the data generated during various methods, structured or unstructured, can be used effectively to understand the treatment requirements and potential solutions (Strachna & Asan, 2020).

However, a systematic review of 23 research studies published between 2015 to 2018 reveals a gap existing between the significant academic AI advancements in healthcare and the comparably low level of AI practical application in preventive, diagnostic and therapeutic contexts (Alhashmi et al., 2020). Our review of the literature in the field of AI in healthcare has revealed three basic challenges: interoperability, integration and ethical issues that attribute to the existence of this gap. These three concepts are explained in detail in the next section.

Another field that received a growing interest over the past few years is the Enterprise Architecture, which studies the optimisation of disjoined processes across the whole enterprise to form an integrated environment that can sustain agility and support of the delivery of the business strategy (Sajid & Ahsan, 2016). The three major technical and ethical challenges of AI in healthcare have been addressed in the research literature through the Enterprise Architecture's point of view (i.e., enterprise architecture frameworks). However, there is a lack of studies in the literature comparing different enterprise architecture frameworks (EAF) to find the most suitable one to tackle AI challenges in healthcare. Therefore, this research gap leads to our following research question (RQ):

Which Enterprise Architecture Framework (EAF) best addresses Artificial Intelligence challenges in healthcare?

Through identification of the EAF, this research paper aims to serve the following objectives:

- Propose a potential solution to the challenges of interoperability, integration and ethicality of AI applications in healthcare.
- Propose an EAF for AI application in healthcare.

The structure for the rest of this research paper is as follows; section 2 provides an illustration of the methodology adopted for the identification and selection of the research literature. Section 3 provides the literature review conducted for identification of the major AI challenges in healthcare. Section 4 investigates the ability of the in-scope EAF to address the identified challenges. Section 5 is the last section and represents the conclusion of this report.

2. Research Method

A concept centric approach given by Webster & Watson (2002) was adopted for perforating the search of the already published scholarly work for this report. The search for the relevant literature was performed in two phases. In the first phase, search stream 1 was used to identify literature that discussed challenges of AI in healthcare. Whereas in the second phase, search stream 2 was processed to identify literature that addressed the challenges identified in phase 1 using EAFs.

Two search strings were used separately for identification of the desired literature results using the google scholar database as explained in the table below. oreover, keeping the time constraints for this research project in view, the scope of the search was limited to:

- Literature published in the last 10 years (2011 to 2021)
- Three Enterprise Architecture Frameworks: TOGAF, Zachman and Service Oriented Architecture.

The identification and filtration of the research is explained through a table given below using (Mathiassen et al., 2007) step wise approach.

Identification and Reporting Steps	**Phase 1** **Period under review (2011 – 2021)**	**Phase 2** **Period under review (2011 – 2021)**
Step 1: Identification of the search string	Search stream 1: "Challenges of Artificial Intelligence in healthcare"	Search stream 2: "Enterprise Architecture Framework" and "AI challenges in healthcare"
Step 2: Results retrieval after application of search stream in selected database.	Selected database (Google Scholar). Total search results produced = 93	Selected database (Google Scholar). Total results produced = 76
Step 3: Limiting the number of articles as per the time constraint involved.	Keeping the time constraint in view, initial 20 articles appearing in the search results were selected for scrutiny. Considered articles = 20	Keeping the time constraint in view, initial 20 articles appearing in the search results were selected for scrutiny. Considered articles = 20
Step 4: Initial scrutiny of research articles as per relevance.	The abstract and conclusion of the articles were reviewed for relevance. Criteria: most relevant articles. Result: Initial 16 articles	The abstract and conclusion of the articles were reviewed for relevance. **Note**: Articles that previously appeared in the phase 1 are considered as already identified and therefore are not represented in number. Criteria: most relevant articles. Result: Initial 5 articles
Step 5: Selection of authoritative venue's articles only.	Criteria: Peer reviewed articles published in credible lit sources. Result: 16 articles. All articles satisfied the mentioned criteria.	Criteria: Peer reviewed articles published in credible lit sources. Result: 7 articles. All articles satisfied the mentioned criteria.
Step 6: Total number of articles under review	Result of articles from search stream 1 + Result of articles from search stream 2 16 + 5 = 21	

Table 1: Literature Search and Identification Process

3. Literature Review

Our literature review identified challenges of AI in healthcare that can be broadly divided into two major categories: technical challenges and ethical challenges. These are discussed in detail below.

3.1 Technical Challenges

Our review of the literature under discussion identified two main technical challenges - Interoperability and Integration. Both are discussed in detail below:

3.1.1 Interoperability

Interoperability is the inability of an AI healthcare system to exchange, utilise, analyse and interpret the required information, in real time without the use of middleware, which is available from multiple systems/sources that are either isolated, hidden or incompatible to each other (HIMSS, n.d; Masuda et al., 2021). Since AI healthcare systems depend on multiple systems and data sources for requirement analysis and proposing solutions, interoperability has emerged as a major challenge (Adenuga et al., 2015; Masuda et al., 2021; Sajid & Ahsan, 2016).

The role of interoperability is being increasingly acknowledged but relatively low in comparison to AI (Lehne et al., 2019). It is now gaining attention as a prerequisite to fully functional digital healthcare among healthcare professionals. There are multiple data standards and nomenclatures used in healthcare such as SNOMED-CT, International Classification of Diseases, Tenth Revision, Clinical Modification (ICD-10-CM), logical observation identifiers, names and codes (LOINC), among the others (Lehne et al., 2019).

In order to stimulate efficient exchange of information among various systems, it is critical that semantic interoperability is established in the organisation (Luz et al., 2015). Some fundamental contributions of semantic interoperability to the anticipated future state of the healthcare system include (Lehne et al., 2019):

1. Structured and universally applicable data
2. Trusted and secure technology systems
3. Adequately validated data

In many instances, such as that of a rare medical condition or for precision medicine, when data is scarce or dispersed among various departments of the healthcare system (i.e., a GP, radiologist, pharmacies, etc.), data pooling for comparison and analysis becomes mandatory (Lehne et al., 2019). However, this analysis is often seen to be facing barriers such as unstructured or semi structured data, varying data formats and vague connotations (Kelly et al., 2019; Lehne et al., 2019). As a result, the organisation is forced to undergo time consuming amendments or removal of data. Besides, unstructured data may induce errors into the system, presumably causing it to crash or compromising the security of the system (Lehne et al., 2019).

Moreover, in the case of a clinical decision support system, to leverage maximum benefits out of the data acquired, the system needs to have complete ontological, spatial, and temporal information. This is known as operational semantic interoperability (Luz et al., 2015).

3.1.2 Integration

In the healthcare landscape, there are many sources of clinical data such as electronic health records and wearable devices (Peng & Goswami, 2019). With the increasing potential of the usefulness of these data in providing better healthcare, there is a need to integrate them into the clinical workflow (He et al., 2019). In this context, integration refers to the incorporation of patients' clinical data from heterogeneous resources into a data warehouse that is accessible by authorised parties (Bukowski et al., 2020; Peng & Goswami, 2019).

Data integration can help in implementing AI solutions, refer to *Figure 1* for more information. However, the nature of the digital systems in the healthcare ecosystem has many fragmentations and silos, which presents a major obstacle for AI implementation in the healthcare sector (Davenport & Kalakota, 2019). In this context, Yu and colleagues (2018) reported that the complicated environment of the health sector presents a critical barrier to integrate patient data into clinical routines. In the clinical routine, diagnostic data is derived from a variety of sources and is gathered by clinicians with various expertise such as pathologists, nuclear medicine specialists, and radiologists (Bukowski et al., 2020).

AI applications, therefore, face considerable challenges with the different IS/IT architecture and business procedures in different medical institutions (Sajid & Ahsan, 2016). These applications need systematic treatment to enhance medical diagnosis (Yu et al., 2018). Sun & Medaglia (2019) highlighted that AI performance depends on the quality of the provided data. AI technology cannot deliver value to healthcare with the absence of data integration (Sun & Medaglia, 2019). Therefore, healthcare institutions should establish an infrastructure that can support such solutions.

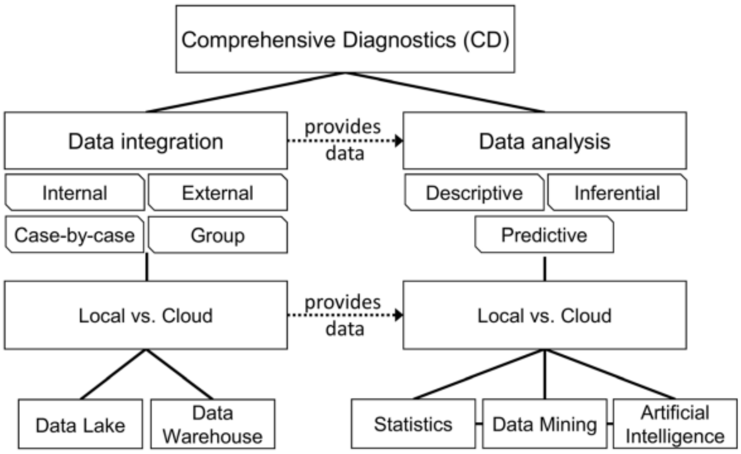

Figure 1: Use of Data Integration in developing AI Solutions (Peng & Goswami, 2019)

3.2 Ethical Challenges

Our review of the literature under discussion identified that AI models can pose three main ethical challenges to the healthcare institutions, healthcare professionals and patients. These are discussed in detail below:

3.2.1 Biased Decision-Making

The AI models require substantial sets of training data in order to process new input data and to provide useful outputs. An AI model can only provide outputs based on patterns formed with its training data. There could be a new pattern it faces that would provide it with a biased output due to its inability to assess the new input data (Matheny et al., 2019). Furthermore, the evolving medical landscape requires quick and updated decision-making, but as most AI models are trained on historic and limited data, the outputs produced could be outdated and catastrophic to patients (Sunarti et al., 2021). Therefore, insufficiencies in training data at the inception of AI models, could pose huge risks to decision-making of healthcare professionals and patients from minority groups, as the training data does not represent them (Schönberger, 2019).

3.2.2 Lack of Transparency

The decision outputs provided by AI models can be extremely difficult for a healthcare professional to explain to a patient. As these algorithms are like black boxes, there is no easy method of providing concrete reasoning behind why the AI model may have provided the said output (Reddy et al., 2019; Schönberger, 2019; Sunarti et al., 2021; Yu et al., 2018). The patients on the receiving end would not be confident, or may avoid taking into consideration output from an AI model, as there is no substantive explanation as to why. Additionally, patients would not be comfortable with their sensitive health information being processed by an AI model (Sunarti et al., 2021). The opacity in understanding AI models can deter patients from trusting its outputs, as patients would much rather trust in the healthcare professional’s reasoning behind a diagnosis.

3.2.3 Workforce Morality

The healthcare professionals utilising AI models would open the risk of dehumanisation of medicine, as many patients are most familiar with doctors providing them with diagnosis as mentioned previously (Briganti & Le Moine, 2020). Henceforth, the ethical implications of the AI models, can affect the workforce morality as they could lose their touch of empathy when working with patients, and the potential of AI overtaking decision-making powers (Matheny et al., 2019).

Section	Challenge	Identified as	Literature Source
3.1	**Technical Challenges**		
3.1.1	**Interoperability**	Identify interoperability as a challenge due to dependency on multiple systems and information sources.	Masuda et al., 2021 Sajid & Ahsan, 2016 Adenuga et al., 2015
		Identify semantic interoperability as a challenge due to mandatory data pooling for comparison and analysis.	Lehne et al., 2019
		Identify interoperability as a challenge due to unstructured or semi structured data, varying data formats, vague connotations.	Kelly et al., 2019
		Identify operational semantic interoperability as a challenge due to the needs to have complete ontological, spatial, and temporal information.	Luz et al., 2015
3.1.2	**Integration**	Identifies integration as a challenge due to fragmentations and silos in healthcare ecosystem has many.	Peng & Goswami, 2019 He et al., 2019
		Identifies integration as a challenge due to diagnostic data being derived from multiple sources e.g. pathologists, nuclear medicine specialists and radiologists.	Bukowski et al., 2020
		Identify integration as a challenge due to complicated environment of health sector resulting in critical barrier to integrate patient data into clinical routine.	Davenport & Kalakota, 2019 Yu et al., 2018
		Identify integration as a challenge due to different IS / IT architecture, business procedures in different medical institutions.	Sajid & Ahsan, 2016
		Identify integration as a challenge due to dependence of AI performance on the quality of the provided data.	Sun & Medaglia, 2019
3.2	**Ethical Challenges**		
3.2.1	**Biased Decision-Making**	Identifies biased decision making as a challenge due to AI system inability to assess new input data while decision making.	Matheny et al., 2019
		Identifies biased decision making as a challenge due to AI models being trained on historic and limited data.	Sunarti et al., 2021
		Identifies biased decision making as a challenge due to inability of the AI system to represent minority groups.	Schönberger, 2019
3.2.2	**Lack of Transparency**	Identify lack of transparency as a challenge due to AI system algorithms being black boxes concrete reasoning behind the AI system output can't be provided.	Reddy et al., 2019; Schönberger, 2019; Sunarti et al., 2021; Yu et al., 2018
3.2.3	**Workforce Morality**	Identify workforce morality as a challenge due to the risk of dehumanization of medicine in AI based systems.	Briganti & Le Moine, 2020
		Identify workforce morality as a challenge due to the loss of empathy in final decision making due to dehumanization.	Matheny et al., 2019

Table 2: Summary of Literature Sources Identifying the AI Challenges in Healthcare

4. Enterprise Architecture Frameworks (EAF) Addressing AI Challenges in Healthcare

This section illustrates how the EAF address the above identified AI challenges in healthcare. Although there are many EAF, the scope of this paper is limited to three commonly used frameworks: TOGAF, Zachman, and Service Oriented Architecture. These frameworks were selected because they were extensively researched in the literature.

4.1 TOGAF Addressing AI Challenges in Healthcare

4.1.1 Introduction to TOGAF

The Open Group Architecture Framework (TOGAF) is a standard that provides a methodology for sustaining an effective Enterprise Architecture in an organisation (The Open Group, 2018). The most recent version, TOGAF 9.2, consists of three main components: architecture development method (ADM), enterprise continuum, and content framework (Osei-Tutu & Song, 2020). TOGAF provides a holistic view into the enterprise by dealing with different architecture layers: business, data, application, and technology, refer to *Figure 2* (The Open Group, 2018).

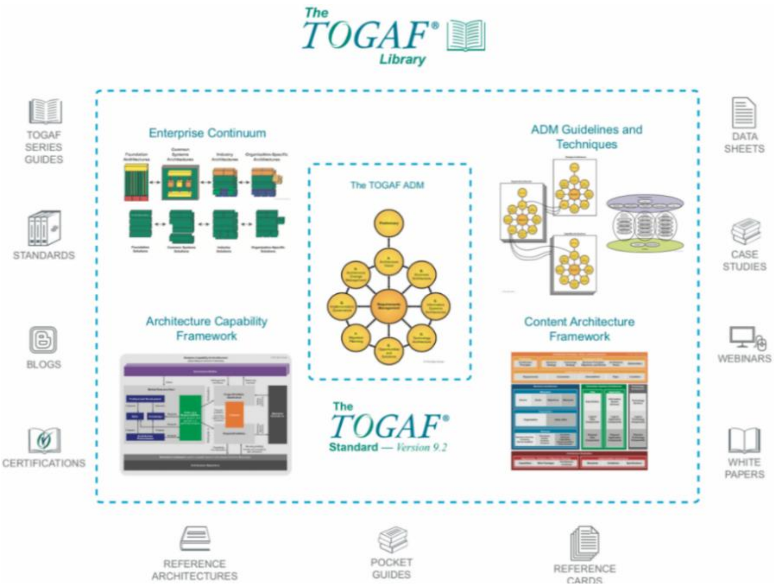

Figure 2: TOGAF 9.2 (The Open Group, 2018)

4.1.2 TOGAF Addressing Interoperability

Interoperability can be established with the TOGAF ADM which includes tasks such as elaborating on the information about how every part fits into the other, setting vocabulary and policies (Sajid & Ahsan, 2016). It divides the entire enterprise into four categories that evaluate the respective aspects of the architecture in detail (Sajid & Ahsan, 2016). Data Architecture emphasises the methods of data storage and retrieval. This could be beneficial in instituting common and verified standards for data collection and storage throughout the organisation. It also helps in building a shared vocabulary for everybody in the organisation, thus enhancing data sharing and data reliability (Sajid & Ahsan, 2016). Moreover, technical architectures define how different infrastructure (software or hardware) synchronise with each other and support applications. This could help in understanding the interlinked functionalities before deciding data standards (Mudaly et al., 2013).

4.1.3 TOGAF Addressing Integration

Integration issues can be reduced by allowing healthcare organisations using AI to conduct an ontology of the AI model architecture (Bikkulova, 2020). Using the TOGAF framework, the architecture is divided into four levels that gives a gradual process for designing an Enterprise Architecture model. These different layers represent the conduct of all components and the relation among them (The Open Group, 2018). The four-level model promotes an effective understanding of the business process and ICT components (Sajid & Ahsan, 2016). The Application Architecture layer offers a blueprint for the independent application systems to be deployed, for their relationships and their interactions to the basic business processes of an enterprise (Sandkuhl, 2019). Thus, TOGAF provides an effective solution to the AI systems integration issue.

4.1.4 TOGAF Addressing Ethical Concerns

The implementation of AI models requires initial training by AI experts, to meet the needs of the healthcare institutions at its inception stage (Schönberger, 2019). The use of TOGAF ADM phases A, B, C, D and E as indicated in *Figure 2* can reduce the impact of ethical concerns when it comes to data, transparency and workforce morality. These TOGAF ADM phases allow us to determine the scope, conditions of the business, data and human resource requirements (Sofyana & Putera, 2019). It is at the inception stage that the AI model can gain the trust of healthcare professionals and patients for sharing data and accepting decision outputs. This prepares healthcare institutions' AI models to mitigate ethical concerns as the planning and involvement of these stakeholders builds trust when being utilised (Yu et al., 2018).

4.2 Zachman Framework Addressing AI Challenges in Healthcare

4.2.1 Introduction to Zachman Framework

The Zachman Framework was first introduced in the late 1980s (Gerber et al., 2020). The framework provides architectural representations that demonstrate different perspectives of the Enterprise Architecture and facilitate communication among involved parties to increase the probability of achieving the desired outcome (Zachman, 1999). The recent version of Zachman Framework includes columns (i.e., data, function, network, people, time, and motivation) and rows (planner, owner, designer, builder, technician, and enterprise) where the cell represents an architectural representation of the intersection of a column and a row, refer to *Figure 3* (Gerber et al., 2020).

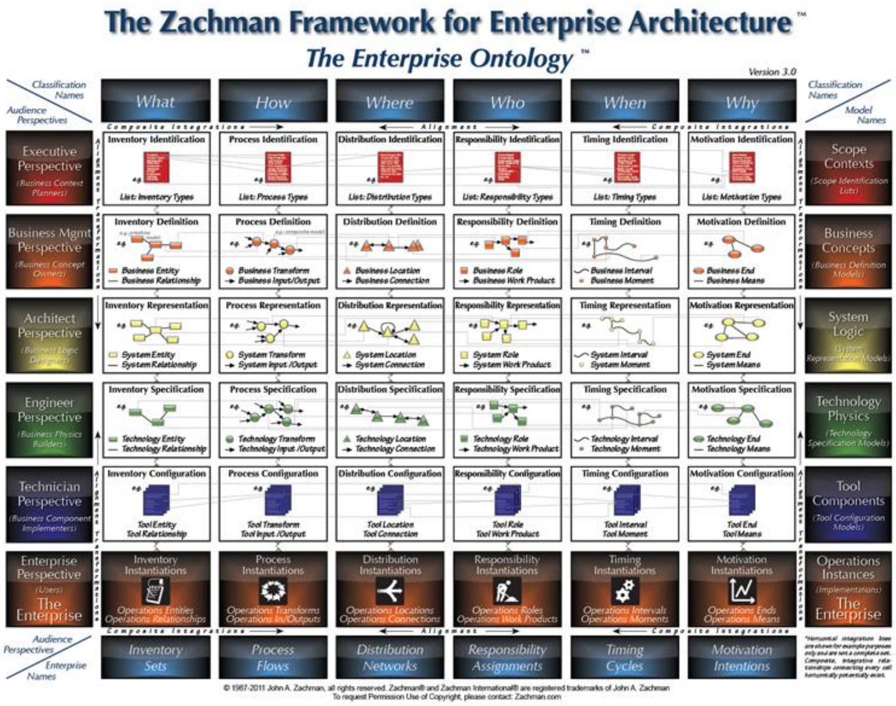

Figure 3: Zachman Framework (Gerber et al., 2020)

4.2.2 Zachman Framework Addressing Interoperability

Interoperability relies on efficient and constant exchange of information among various applications and departments. This implies a set of organisation wide data standards for the fully integrated systems (Masuda et al., 2021). Zachman partially establishes the issue of interoperability in an organisation as it predominantly focuses on promoting integration and accessing the required information for the same. It answers the problem through a six-by-six matrix with questions of what, where, how, when, and why from the perspective of different participants (Zachman, 1999). However, it fails to specify the measures to develop or highlight relationships among each block. Therefore, it might prove to be beneficial in developing a new architecture but may not be as efficient in upgrading an existing architecture (Sajid & Ahsan, 2016).

4.2.3 Zachman Framework Addressing Integration

The importance of integrating AI models lies in the ability to interact between resources to provide accurate and timely information to clinicians. The Zachman framework represents information technology (IT) in the enterprise and is typically designed as a six-by-six matrix, so it gives a comprehensive view of the entire organization. (Zachman, 1999). However, Sajid & Ahsan (2016) states that each row of the Zachman framework is separate and does not solve the problem of consistency between columns, rows, and cells. Thus, it is hard to comprehend how the structure reacts between the different parts. Furthermore, the framework does not resolve semantic conduct and for this purpose fails to identify the behaviour efficiency of interactions (Sajid & Ahsan, 2016).

4.2.4 Zachman Framework Addressing Ethical Concerns

The ethical challenges could be partially mitigated as it allows AI experts to prepare an ontology of the underlying architecture of an AI model. As the AI models will involve various stakeholders and data, the representation provided by the Zachman framework (Gerber et al., 2020), allows healthcare institutions to maintain appropriate documentation. The documentation could lead to transparency of the training data sets used, processes of AI models and decision outputs (Zachman, 1999), therefore making it easier for healthcare professionals to explain to patients the results obtained from AI models. Additionally, the Zachman framework’s clear taxonomy of all perspectives and involved parties will provide confidence to the healthcare professionals and improve workforce morale, as they would see AI as an opportunity to deliver better care to patients.

4.3 Service Oriented Architecture (SOA) Addressing AI Challenges in Healthcare

4.3.1 Introduction to Service Oriented Architecture

Service Oriented Architecture (SOA) is an approach for designing, building, and sustaining data and applications where components and functionalities of the system can be reusable (Ionita et al., 2013). This approach is characterised by a high level of adaptability and agility but requires clear documentation and standardised interfaces (Ionita et al., 2013).

4.3.2 Service Oriented Architecture Addressing Interoperability

The SOA addresses the issue of interoperability by using connectors. Data entered in various terminologies is converted into a standard format before storing it into the data repository. In this scenario, the SOA architecture can use two databases, namely, the patient service database and the service provider database (Dan et al. 2006). Patient and treatment information is updated in real-time, or as soon as the care is delivered to the patient, into the system which can then be extracted and converted into a common format with a data interchange agent (Batra et al., 2015), which is essentially a connector. SOA works based on the XML language. Furthermore, this architecture supports increased privacy that would help in building trusted systems.

4.3.3 Service Oriented Architecture Addressing Integration

The use of SOA can seamlessly integrate AI models in a healthcare organisation. According to Avila & colleagues (2017), the SOA framework has seven layers which are: the services layer, the access layer, the business process layer, the management and security layer, the enterprise component layer, and the integration layer. The integration layer allows the integration of distributed systems, as it assists the mediation and routing of services and flows using the Enterprise Service Bus (ESB), which is considered a major enabler of SOA (Arsanjani, 2004). The core function of an ESB is that it helps to communicate different technological resources, and appears as a connection point for each system, device, or application across the organisation (Keen et al., 2004). It offers a flexible method of mediation, routing and transformation possibilities (Arsanjani, 2004). We conclude the effectiveness of SOA solutions to the challenge of integrating AI models.

4.3.4 Service Oriented Architecture Addressing Ethical Concerns

The SOA would partially mitigate ethical concerns related to the transparency of decision-making for healthcare professionals to better deliver results to patients in an understandable approach. As SOA is a process-centric architecture (Mahmood, 2007), this will ensure AI models are developed to align with the needs of the healthcare institution and professionals. Hence allowing healthcare professionals to effortlessly extract and understand the AI's decision-making process and reasoning behind such outputs, this will eliminate the 'black-box model' of AI (Cohen et al, 2014). Furthermore, better scalability from an SOA would (Mahmood, 2007) provide AI models with a solid foundation upon which training data can be expanded to meet the needs of minority groups and further enhance the AI decision making process (Matheny et al., 2019).

AI Challenges in Healthcare	TOGAF	Zachman Framework	SOA
Technical	**Yes**	**Partial**	**Yes**
Interoperability	Yes - Establishing enterprise-wide common vocabulary and data standards through data and technical architecture.	Partial - Develops integrated systems, **however**, **does not** clarify the relationship between various units.	Yes - Converts different terminologies into a standard format using connectors before storing the data into repositories. Thus, increasing the scalability of usage and security of the data.
Integration	Yes - The Application Architecture layer provides a blueprint of standalone application systems and describes their relationships and interactions.	Partial - Provides a comprehensive view of the entire organization **but** there is **no** solution to the problem of consistency between columns, rows and cells - fails to identify the efficiency of interactions behaviour.	Yes - The integration layer allows to integrate distributed systems using the Enterprise Service Bus (ESB).
Ethical Concerns	**Yes**	**Partial**	**Partial**
Biased-Decision Making	Yes - Determining scope of the training data set.	Yes - Documentation of training data used.	Partial - Scalability **could** allow for expansion of training data for minority groups.
Lack of Transparency	Yes - Stakeholders involvement during inception stage. Builds trust in AI models assisting healthcare professionals, rather than eliminating decision-making powers.	Partial - Documentation of processes **may be too technical** for healthcare professionals to understand the decision making process of AI.	Yes - Process-centric architecture helps eliminate black-box model of AI for healthcare professionals to understand the underlying basis for decision making.
Workforce Morality	Same as Above.	Yes - Documentation of various perspectives provides opportunity to healthcare professionals to deliver better care to patients.	Yes - Clear understanding of the AI models decision making, allows healthcare professionals to see it as an opportunity than an unknown technology as a threat.

Table 3: Summary of EAF Addressing AI Challenges in Healthcare

5. Conclusions and Recommendations

The aforementioned discussion indicates that EAF can address AI challenges in the healthcare industry. TOGAF, for example, addresses ethical concerns effectively compared to the other two EAF. Therefore, its adoption before the implementation of AI systems can facilitate eliminating biased decision making and ensure active involvement of different stakeholders from early stages to avoid lack of transparency and impacts on workforce morality. Zachman framework, on the other hand, can be used by healthcare organisations when implementing AI to ensure continuous maintenance and production of required artefacts and their classifications, similar to another firm. However, it does not seem to address the AI specific challenges comprehensively. In contrast, SOA best addresses the technical challenges and therefore, should be adopted by the healthcare organisations to ensure ongoing support and smooth functioning of their AI systems. There is no single framework that comprehensively eliminates all AI challenges, however. This suggests a combination of these frameworks can be utilised by healthcare organisations in different time contexts for effective elimination of the barriers throughout the gradual adoption stages and long-term usage of AI.

While this research paper discussed the challenges of AI in the healthcare industry and how EAF can help in tackling them, there are some limitations presented, due to the narrative of the topic and the nature of the research method. Firstly, this paper has adopted a theoretical approach to the topic and lacked quantitative results that can show association between EAF adoption and measurable outcomes such as patient satisfaction or diagnosis accuracy. Secondly, the study scope only included three challenges of AI in healthcare and three EAF while there are many other challenges and EAF need to be covered. Thirdly, as this study is based on reviewing literature, the conclusions drawn were not tested in practice. Therefore, we recommend taking these limitations as an opportunity to further investigate this topic in the future studies.

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