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A Framework to Enhance the Adoption of Artificial Intelligence (AI) Decision Making among Workers of the Healthcare Sector

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Abstract

AI decision-making is transforming the healthcare industry by increasing efficiency and improving patient outcomes. Despite concerns about job displacement and data privacy, the use of AI is critical for improving healthcare systems and developing leadership in medical innovation. Thus, the goal of this study was to create a framework that identifies elements that improve AI decision-making and its impact on organisational performance, with organisational learning acting as a mediator, incorporating both direct and indirect relationships between these aspects. This paradigm analyses how AI adoption elements might improve decision-making processes and, as a result, boost overall performance, assisted by the organization’s constant learning and adaptability. To validate the framework, a questionnaire survey was administered to 1,033 employees at three Abu Dhabi hospitals which are the Tawam Hospital, Shaikh Khalifa Medical City (SKMC), and Ambulatory Healthcare Services (AHS). The validation was carried by utilising SmartPLS software. All five direct and indirect relationships were found to be statistically significant, demonstrating that organisational learning had partial mediation effects. This suggests that all of the identified characteristics have a major impact on AI decision-making tool adoption, with organisational learning serving as a key mediator. The framework highlights the relationships between the factors to boost AI adoption in the UAE healthcare business, solving concerns such as long wait times and administrative challenges through better technological integration.

Keywords: AI decision-making, Organizational learning, Healthcare adoption

1. Introduction

Conventional healthcare decision-making is complicated by varying degrees of medical expertise, encompasses numerous stakeholders, and often leads to misinterpretations (Higgs, & Jones, 2008). The significance of artificial intelligence (AI) decision-making in the healthcare sector is increasing to improve operational procedures due to the complexity of the circumstances. Utilising AI to address challenges such as prolonged wait times and inefficient processes may enable the United Arab Emirates to improve healthcare services. The United Arab Emirates' Vision 2030 plan aims for complete automation by 2020 through the initial integration of artificial intelligence (AI) into the public sector. Nonetheless, challenges persist regarding the adoption and integration of artificial intelligence within the UAE healthcare sector. The implementation of artificial intelligence is contingent upon several factors, the most critical of which is the perspectives of healthcare professionals. The intricacy of AI decision-making extends beyond the mere application of AI technologies.

This study aims to explore the perspectives of health professionals regarding the application of artificial intelligence in decision-making. Despite the UAE's efforts, there is a dearth of research on AI decision-making in the health sector, which emphasises the need for a strategic framework for AI implementation. By determining the elements that influence employees' intentions to use AI in healthcare, this study aims to develop a strategic framework to improve AI decision-making in the United Arab Emirates..

2. Literature Review

The principal objective of this research is to develop a comprehensive framework to enhance the adoption of artificial intelligence decision-making among healthcare professionals in Abu Dhabi. The framework categorises the elements affecting AI adoption in healthcare as distinct constructs. Organisational Learning is included as a mediating factor, with AI Adoption as the dependent variable.

2.1 Factors Influencing to Adopt AI in Healthcare

Decision-makers are more inclined to embrace AI if they perceive it as superior to current systems, offering expedited and more precise diagnoses that enhance healthcare outcomes (Vemuri, 2024). AI adoption increases when it is compatible with current processes and systems because it makes integration with current workflows and technologies easier (Putra, Badruzaman, & Supriadi, 2024). The perceived complexity of AI systems may hinder adoption because straightforward and user-friendly solutions are more enticing. External factors, such as market dynamics, regulatory policies, and technological infrastructure, have a significant impact on AI adoption decisions (Febriana & Mujib, 2024). Decision-makers' self-efficacy, or confidence in their capacity to comprehend, apply, and use AI technology, has an impact on adoption. Higher levels of self-efficacy were expected to lead to more proactive decisions regarding the adoption of AI (Scaccia, Cook, Lamont, Wandersman, Castellow, Katz, & Beidas, 2015). When taken as a whole, these factors affect how healthcare decision-makers evaluate, embrace, and apply AI technologies to enhance organisational performance and patient outcomes. This section's literature review breaks down the factors influencing AI adoption in healthcare into five major categories: relative advantage, compatibility, complexity, environment, and self-efficacy.

2.1.1 Compatibility Group

Compatibility is essential when incorporating technology into an organization's established processes, norms, and values. It evaluates the extent to which an innovation satisfies the requirements and experiences of users (Rogers, Singhal, & Quinlan, 2014). Enhanced compatibility with existing practices facilitates adoption and optimises user experience (Magsamen-Conrad & Dillon, 2020). The Diffusion Of Innovation (DOI) theory states that greater compatibility facilitates and expedites adoption. Little change is needed when AI fits in with current workflows; however, resistance may surface when major changes are implemented (Kakatkar, Bilgram, & Füller, 2020). AI requires a lot of data, and analysis and storage are made simpler by integrating it with enterprise data resources. In this context, compatibility refers to a person’s capacity to communicate with artificial intelligence..

2.1.2 Complexity Group

In healthcare, complexity refers to how challenging AI technologies are perceived to be in terms of understanding and application (Rogers, Singhal, & Quinlan, 2014). High complexity negatively impacts the adoption of AI in healthcare, as complicated technologies require healthcare workers to acquire new skills and knowledge. AI is considered a complex technology (Alsheibani, Messom, Cheung, & Alhosni, 2020), and different AI implementations can exhibit varying levels of complexity. This makes complexity a critical factor that can limit the adoption of AI in healthcare settings, potentially hindering the integration of AI security systems and other AI applications within healthcare organizations. This complexity can be resolved by providing adequate training and support for healthcare workers is essential to facilitate the successful adoption of AI technologies in healthcare (Loftus, Altieri, Balch, Abbott, Choi, Marwaha, ... & Tignanelli, 2023).

2.1.3 External Environment Group

In the healthcare sector, the external environment plays a crucial role in the adoption of AI technologies. This environment includes various conditions and pressures under which healthcare organizations operate (Chau & Tam, 1997). According to Rogers’ DOI theory, these external factors can be attributed to the social system, while Tornatzky and Fleischer in 1990 considered it a distinct context. By referring the external environment is essential for effectively adopting AI decision-making technologies in healthcare (Hoti, 2015; Arpaci, Yardimci, Ozkan, & Turetken, 2012).

External pressures, such as regulatory requirements, funding availability, and societal expectations, can significantly enhance the uptake and adoption rates of AI technologies in healthcare. Additionally, market uncertainty and competitiveness drive healthcare organizations to adopt advanced technologies like AI to stay ahead and improve their services. By acknowledging and adapting to these external factors, healthcare organizations can better integrate AI technologies into their operations, ultimately enhancing decision-making processes and patient care.

2.1.4 Relative Advantage Group

Relative advantage refers to the perceived superiority of an innovation compared to existing solutions. In the context of AI adoption, this concept is crucial as it determines how advantageous the new technology is perceived to be over traditional methods. Artificial Intelligence (AI) is proved a very effective technique in reducing complexity and making suitable quick decisions for achieving success. The organizational setting, which includes internal attributes such as resources and prevalent organizational characteristics, can either promote or hinder the effective use of AI technology (Aboelmaged, 2014). Professional networks significantly influence the formation of subjective norms within organizations, both before and after the adoption of new technology, as highlighted by (Rogers, Singhal, & Quinlan, 2014). Establishing and maintaining internal connectivity mechanisms enhances technology acceptance by linking defined units and broadening organizational boundaries. According to Alsheibani, Messom, Cheung and Alhosni (2020), the perceived relative advantage of AI plays a significant role in its adoption within an organization. The United Arab Emirates (UAE) is eager to capitalize on the benefits of artificial intelligence (Almarashda, Baba, Ramli, & Memon, 2022). When employees perceive AI to be superior to traditional methods, it greatly facilitates its acceptance and integration into the organizational workflow.

2.1.5 Self-Efficacy Group

Technology Self-Efficacy involves the skills and capacity of staff to use technology, including their abilities, education, and competence (Scaccia, Cook, Lamont, Wandersman, Castellow, Katz, & Beidas, 2015). Proper implementation of AI requires personnel with relevant expertise, including programming knowledge and organizational understanding (Pumplun, Tauchert, & Heidt, 2019). Firms face challenges in attracting skilled individuals due to high demand. Research indicates that organizations often prioritize technology over necessary knowledge and methodologies (Alsheibani, Cheung, & Messom, 2018). Staff talents and skills are crucial for the efficient application of AI to enhance community security.

2.2 AI Adoption in Healthcare

Health is a top priority for individuals, often outweighing other aspects of life such as family and relationships, as highlighted by (Chen, Lin, & Chang, 2009; Rogge & Kittel, 2016). This health-conscious mindset drives interest in AI-enhanced health products, despite concerns about AI’s ability to address individual needs (Longoni, Bonezzi, & Morewedge, 2019). Research shows a strong correlation between health interest and the adoption of portable health gadgets, with perceived health benefits significantly influencing usage intentions (Vickers,Lyon, Sepulveda, & McMullin, 2017).

The Health Belief Model indicates that perceived health risks and benefits are key drivers of adopting new technologies in healthcare (Zhang, Pezeshki, Brakel, Zhang, Bengio, & Courville, 2017). Women, in particular, perceive higher benefits from health knowledge, positively impacting their adoption of AI technologies. However, older adults face challenges in adopting portable devices, although they recognize the health benefits (Li, Feng, Meng, Han, Wu, & Li, 2019). The adoption of AI in healthcare is influenced by individuals' health priorities, perceptions of health benefits, and the ability of AI to enhance health outcomes.

2.3 Organizational Learning

Previous research has highlighted the importance of socio-technical elements in healthcare IT installations. Technological advancements in healthcare offer opportunities to analyze the inter-relationships between technology and organizational characteristics (Cresswell, & Sheikh, 2014).

Organizational Learning (OL) plays a crucial role in AI technology adoption in healthcare. OL involves adapting processes and skills to improve performance, making it a key factor in the successful implementation of AI technologies (Khamis & Njau, 2014; Chiva, Ghauri, & Alegre, 2014; Goh, Heng, & Lin, 2013; Darwish, Darwish, Darwish, AlHmoud, & Alshraideh). Research consistently shows that OL positively influences technology adoption and innovation performance (Khamis & Njau, 2014; Ugurlu & Kurt, 2016). Studies indicate that OL is vital throughout the innovation lifecycle, significantly affecting the successful implementation of AI decision-making technologies. Organizational learning enhances overall performance and facilitates the adoption of AI in healthcare settings (Khamis & Njau, 2014; Darwish, Darwish, Darwish, AlHmoud, & Alshraideh). Consequently, OL can mediate the relationship between various AI technology adoption factors and the adoption of AI decision-making technologies in healthcare organizations, underscoring its importance in achieving effective technology integration and improved healthcare outcomes.

3. Assessment of the Model

Data for developing the model was collected from 1,033 workers/employees across three hospitals in Abu Dhabi: Tawam Hospital, Shaikh Khalifa Medical City (SKMC), and Cleveland Clinic Abu Dhabi. The model was developed using SmartPLS software, which employs Partial Least Squares (PLS) computational techniques, suitable for theory development. The assessment of the model in SmartPLS involves two key steps: evaluating the measurement components and the structural components.

For the measurement component assessment, the PLS Algorithm function is run to ensure that the constructs meet criteria for reliability and validity, including construct reliability, validity, and discriminant validity (Memon, 2013). In the structural component assessment, the bootstrapping function is used to determine the significance of the paths within the model, providing t-values and confidence intervals for hypothesis testing. Additionally, the blindfolding function can be employed to assess the predictive relevance of the model.

These steps together provide a comprehensive evaluation of both the measurement and structural aspects of the model, ensuring its robustness and validity.

3.1 Organizational Learning

Measurement component assessment includes construct reliability and validity, as well as discriminant validity (Rahman, Memon, Abdullah, & Azis, 2013). Construct reliability ensures that assessment items consistently capture the underlying construct, which is frequently tested using Cronbach's alpha and composite reliability (CR) (Memon, Rahman, & Azis, 2013). Validity, on the other hand, assesses whether the measurement items accurately reflect the intended construct and is generally measured using convergent validity, which employs average variance extracted (AVE). Discriminant validity assures that the constructs are distinct from one another, and is commonly assessed using the Fornell-Larcker criterion and cross-loadings. These assessments collectively provide a full review of the measurement model, guaranteeing that the constructs are both trustworthy and valid (Hair, Hult, Ringle, & Sarstedt, 2022).

Table 1. Results of construct reliability and validity

Constructs	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
AI Adoption	0.754	0.836	0.509
Compatibility	0.812	0.869	0.571
Complexity	0.806	0.866	0.565
Environment	0.844	0.889	0.615
Organizational Learning	0.815	0.871	0.575
Relative Advantage	0.782	0.853	0.539
Self-Efficacy	0.832	0.882	0.605

Table 1 reveals that all constructs are very reliable and valid, with Cronbach's Alpha values ranging from 0.754 to 0.844, Composite Reliability values greater than 0.80, and Average Variance Extracted (AVE) values ranging from 0.509 to 0.615. This demonstrates that the constructs are regularly measured and capture adequate variance from their indicators.

Table 2. Results of discriminant validity using Fornell Laker

Constructs	AI Adoption	Compatibility	Complexity	Environment	Organizational Learning	Relative Advantage	Self-Efficacy
AI Adoption	0.813						
Compatibility	0.761	0.796					
Complexity	0.659	0.728	0.751				
Environment	0.756	0.707	0.733	0.784			
Organizational Learning	0.756	0.752	0.745	0.697	0.799		
Relative Advantage	0.738	0.728	0.728	0.644	0.777	0.834	
Self-Efficacy	0.751	0.61	0.738	0.72	0.617	0.659	0.788

Table 2 validates the constructs' discriminant validity using the Fornell-Larcker criterion. The square root of the Average variation Extracted (AVE) for each construct is greater than its correlations with other constructs, indicating that each construct is unique and shares more variation with its own indicators. For example, AI Adoption has an AVE of 0.813, showing strong discriminant validity. All constructions satisfy this requirement, proving their distinctness inside the model.

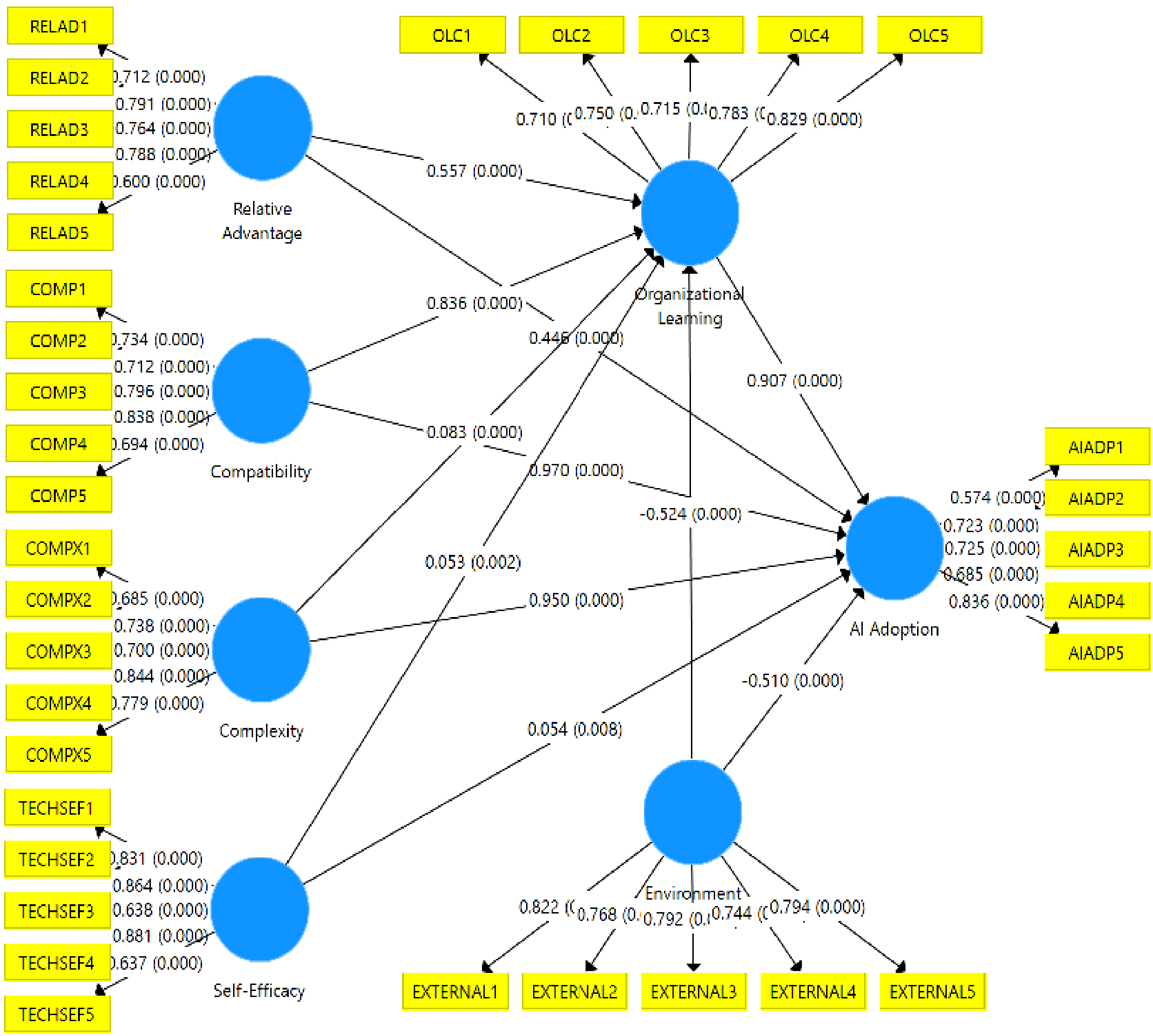

Figure 1. Conceptual Framework

The model in Figure 1 depicts five independent constructs: compatibility, complexity, environment, relative advantage, and self-efficacy. These constructs are linked directly to the AI Adoption construct, which serves as the dependent variable. Additionally, Organisational Learning acts as a mediator for the indirect relationships between the independent constructs and AI adoption.

3.2 Structural Component Assessment

In this structural component assessment, it involves three processes which are coefficient of determination, path analysis (Rahman, Memon, & Abd Karim, 2013) and predictive power of the model.

3.2.1 Coefficient of Determination

R^2 measures the extent of variance explained by the model, indicating structural model quality (Hair, Ringle, & Sarstedt, 2011; Hair, Gabriel, & Patel, 2014; Wong, 2016). Higher R^2 values suggest better model quality, with 0.25 considered low, 0.50 moderate, and 0.75 high (Hair, Gabriel, & Patel, 2014; Wong, 2016). In customer behavior studies, an R^2 of 0.2 is deemed substantial (Wong, 2016).

Table 3. R^2 assessment

Variable	R Square
AI Adoption [DV]	0.969
Organizational Learning [Mediator]	0.701

Table 3 summarises the R^2 values for AI adoption and organisational learning. An R^2 value reflects how much of the variance in the dependent variable is explained by the independent variables in the model. The R^2 for AI adoption is 0.969, indicating a solid model that explains 96.9% of the variance. The independent factors account for 70.1% of the variance in Organisational Learning (R^2 = 0.701). The high R^2 value indicates that Organisational Learning has a strong influence on the predictors in the model, suggesting its robustness as a mediator.

3.2.2 Path Analysis

Path analysis is used to evaluate assumptions regarding the relationships between variables in a hypothetical model. Bootstrapping techniques are utilised to determine path strength (path coefficients) and produce T statistics (Memon, Memon, Soomro, Memon, & Khan, 2023). A T statistic larger than 1.96 indicates statistical significance, implying that the association between variables is most likely genuine and not the result of chance. This significance testing is critical for validating the hypothesised model and ensuring the robustness of its routes (Hair, Hult, Ringle, & Sarstedt, 2022; Henseler, Hubona, & Ray, 2016). For this study, the results of the hypothesis testing on the mediation model include both direct and indirect correlations, as detailed in Tables 4 and 5. The direct relationships demonstrate the direct impacts of independent factors on the dependent variable, whereas the indirect relationships show the effects mediated by an intervening variable.

Table 4. Results of hypothesis testing of direct relationship

Direct relationship [IV to DV]	Path strength (beta value)	T Statistics >1.96	Remark
Relative Advantage -> AI Adoption	0.445	8.198	Significant
Compatibility -> AI Adoption	0.851	13.419	Significant
Complexity -> AI Adoption	0.935	33.127	Significant
Self-Efficacy -> AI Adoption	0.052	2.458	Significant
Environment -> AI Adoption	-0.499	7.814	Significant

Table 4 shows that all parameters have a considerable impact on AI adoption, albeit in varying degrees and directions. Relative advantage has a considerable positive link with AI adoption, as demonstrated by a beta value of 0.445 and a T statistic of 8.198. This shows that the perceived benefits of AI drive its adoption. Compatibility has an even bigger positive influence, with a beta value of 0.851 and a T statistic of 13.419. This means that when AI is seen as compatible with existing systems, its adoption is much higher.

Surprisingly, complexity shows a substantial positive correlation with AI adoption (beta value of 0.935 and T statistic of 33.127). This could indicate that more advanced AI solutions are used where they are absolutely needed, regardless of the issues they may provide. Self-efficacy, with a beta value of 0.052 and a T statistic of 2.458, has a smaller but still substantial positive effect on AI adoption. This demonstrates that individuals' trust in their capacity to use AI contributes to its adoption, but to a smaller level than other aspects.

Interestingly, environmental factors have a strong negative impact on AI adoption (beta value of -0.499 and T statistic of 7.814). This shows that external pressures or limits have a detrimental impact on AI adoption in healthcare. These findings emphasise the intricate interplay of numerous factors impacting the adoption of AI, having both positive and negative implications depending on the context and type of the elements involved.

Table 5. Results of hypothesis testing of indirect relationship

Indirect relationship [IV to Mediator to DV]	Path strength (beta value)	T Statistics >1.96	Remark
Relative Advantage -> Organizational Learning -> AI Adoption	-0.505	10.314	Significant
Compatibility -> Organizational Learning -> AI Adoption	-0.758	13.823	Significant
Complexity -> Organizational Learning -> AI Adoption	-0.076	4.944	Significant
Self-Efficacy -> Organizational Learning -> AI Adoption	-0.048	3.187	Significant
Environment -> Organizational Learning -> AI Adoption	0.475	9.736	Significant

Table 5 shows the indirect correlations between key factors driving AI adoption, as mediated by Organisational Learning. The findings indicate that Relative advantage has a substantial negative indirect association with AI adoption via organisational learning, as demonstrated by a beta value of -0.505 and a T statistic of 10.314. This implies that while relative advantage may favourably promote AI adoption directly, when mediated by organisational learning, the connection turns negative.

Compatibility has a substantial negative indirect association with AI adoption via organisational learning, with a beta value of -0.758 and a T statistic of 13.823. This means that, while compatibility may directly increase AI adoption, from the perspective of organisational learning, it has a major detrimental impact. Complexity also has a substantial negative indirect association with AI adoption through organisational learning, as evidenced by a beta value of -0.076 and a T statistic of 4.944. This shows that the complexity of AI solutions negatively effects their adoption when mediated by organisational learning; nevertheless, the intensity of this link is quite mild.

Self-efficacy has a strong negative indirect connection with AI adoption through organisational learning (beta = -0.048, T = 3.187). This implies that individuals' confidence in their capacity to use AI can have a detrimental impact on its adoption when mediated by organisational learning, though the effect is minimal. Environmental factors have a substantial positive indirect association with AI adoption through organisational learning (beta = 0.475, T = 9.736). This suggests that environmental factors have a favourable impact on AI adoption when mediated by organisational learning. These findings highlight the complicated role of organisational learning in the adoption of AI, demonstrating that it can drastically alter the effects of other contributing factors.

3.2.3 Predictive Power of the Structural Model

The structural model's predictive strength is tested using cross-validated redundancy, specifically applying Stone-Geisser's predictive relevance (Q^2), to determine if all indicators in the outer model of endogenous constructs can accurately predict data points (Wong, 2016). This method employs a sample re-use strategy that estimates model parameters, excludes a portion of the data matrix, and then uses these estimates to forecast the excluded portion (Hair, Ringle, & Sarstedt, 2011; Hair, Gabriel, & Patel, 2014). To be regarded predictively meaningful, the model's cross-validated redundancy (Q^2) value should be greater than zero (Chin, 1998). The study's final models were evaluated for cross-validated redundancy (Q^2) using the blindfolding approach and SmartPLS program (Ringle, Wende, & Becker, 2015). Table 6 shows the findings achieved using the blindfolding procedure.

Table 6. Cross-validated redundancy (CVR)

Constructs	SSO	SSE	Q^2 (=1-SSE/SSO)
AI Adoption [dependent construct]	1885	974.896	0.483
Compatibility	1885	1885	
Complexity	1885	1885	
Environment	1885	1885	
Organizational Learning [mediator]	1885	1141.426	0.394
Relative Advantage	1885	1885	
Self-Efficacy	1885	1885	

Table 6 shows a Q^2 value of 0.483 for the AI Adoption construct, indicating accurate data prediction. Organisational Learning's Q^2 rating of 0.394 indicates moderate predictive significance. AI Adoption and Organisational Learning are endogenous constructs with Q^2 values above zero, demonstrating the model's expected accuracy (Chin, 1998).

3.3 Status of the Mediation Effect

Referring to (Ghasemy, Teeroovengadum, Becker, & Ringle, 2020) study, full mediation is observed when the indirect relationship is significant, but the direct relationship is not. Partial mediation is identified when both the indirect and direct relationships are significant. No mediation occurs if the indirect relationship is not significant. Hence by comparing the significant level for direct and indirect relationships as Table 7 the mediation effect of the mediator is determined.

Table 7. Determination of mediation effect

Direct relationship	Remark	Indirect relationship	Remark	Mediation effect
Relative Advantage -> AI Adoption	Significant	Relative Advantage -> Organizational Learning -> AI Adoption	Significant	Partial
Compatibility -> AI Adoption	Significant	Compatibility -> Organizational Learning -> AI Adoption	Significant	Partial
Complexity -> AI Adoption	Significant	Complexity -> Organizational Learning -> AI Adoption	Significant	Partial
Self-Efficacy -> AI Adoption	Significant	Self-Efficacy -> Organizational Learning -> AI Adoption	Significant	Partial
Environment -> AI Adoption	Significant	Environment -> Organizational Learning -> AI Adoption	Significant	Partial

Table 7 investigates the mediating role of organisational learning in the links between key influencing factors and AI adoption in UAE healthcare. The findings reveal that the mediation effect is partial for all interactions, which means that while these characteristics directly drive AI adoption, their impact is greatly amplified through organisational learning (Lewis, Stachowicz-Stanusch, & Elshareif, 2023).

For example, variables like Relative Advantage and Compatibility directly improve AI adoption by aligning with organisational objectives. Complexity and self-efficacy are also important in promoting AI adoption by increasing confidence and lowering implementation obstacles. Furthermore, the external environment creates pressures that encourage adoption, which are reinforced by organisational learning processes.

4. Framework

The framework of this investigation is based on the findings of the model hypothesis testing and the determination of the mediation effects as mentioned earlier. It demonstrates how many factors influence AI adoption in two ways which are the independently and through the mediating effect of organisational learning. This approach emphasises the vital need of encouraging organisational learning to amplify these aspects' influence and ensure the successful integration of AI technologies in healthcare settings in the UAE.

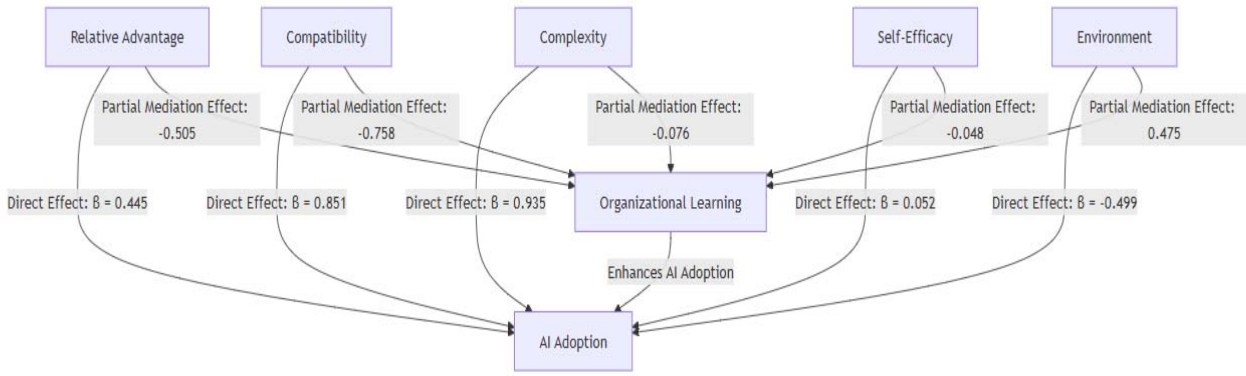

Figure 2. Conceptual Framework

Figure 2 illustrates the study's structure, which includes both direct and indirect linkages between major influencing factors and AI adoption in the UAE healthcare industry. In terms of direct links, Relative Advantage has a substantial path with a strength of 0.445, showing a favourable influence on AI adoption. Compatibility has an even higher direct association, with a substantial path strength of 0.851, implying that aligning with existing processes and beliefs improves AI adoption. Complexity has a major path with a strength of 0.935, highlighting its critical function. Self-Efficacy, with a path strength of 0.052, and Environment, with a negative path strength of -0.499, emphasise the differing influences of these elements on AI adoption.

It also demonstrates indirect links, with a focus on the partial mediation effects of organisational learning. Relative Advantage has a partial mediation effect of -0.505, indicating that aligning AI adoption with organisational goals can be greatly improved through organisational learning. Compatibility has an even greater partial mediation effect (-0.758), demonstrating significant benefits from organisational learning when aligning AI technologies with existing procedures and values. Complexity and Self-Efficacy have partial mediation effects of -0.076 and -0.048, respectively, indicating that while organisational learning helps attenuate difficulties and create confidence in AI adoption, its influence is rather minor. In contrast, the Environment has a positive partial mediation effect of 0.475, indicating that external pressures and conditions, when supported by effective organisational learning processes, greatly favour AI adoption.

The framework emphasises the necessity of supporting organisational learning in order to maximise the influence of these elements on successful AI implementation in UAE healthcare settings. The findings emphasise the impact of organisational learning, highlighting the necessity for healthcare organisations to invest in learning procedures that can boost the effectiveness of these influencing elements, eventually leading to more successful AI adoption.

5. Conclusion

It may be stated that AI decision-making had a substantial impact on the healthcare business, resulting in increased efficiency and better patient outcomes. Concerns were raised regarding job displacement and data privacy, yet implementing AI was critical for advancing healthcare systems and achieving leadership in medical innovation. This study created a framework for identifying elements that improve AI decision-making and its impact on organisational performance, with organisational learning acting as a mediating component. This paradigm highlighted how AI adoption may improve decision-making processes and overall performance by promoting continual learning and adaptability. It shown that all identified parameters had a significant impact on AI decision-making tool adoption, with organisational learning serving as a significant mediator. The framework emphasised the potential to promote AI adoption in the UAE healthcare business, solving issues including high wait times and administrative challenges through superior technology integration.

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