# Understanding Healthcare Professionals' Adoption and Sustained Use of AI Medical Technologies in Saudi Arabia's Vision 2030 Context

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**Abstract:** Despite Saudi Arabia's Vision 2030 AI strategies, a significant gap remains between policy measures and the sustained clinical integration of AI in healthcare. This research employs a sequential exploratory mixed methods design to investigate the transition from initial adoption to continuous usage among practitioners. Currently, the qualitative phase is complete, with thematic analysis underway for interviews conducted with physicians, radiologists, and nurses across the Kingdom. Emerging findings reveal that trust in autonomous AI is not a static construct but evolves through distinct phases: from initial distrust to hesitant reliance, and finally to trustful integration. Preliminary data further suggests that workflow complexity and organisational readiness pose more significant barriers to sustained use than the technical performance of the AI itself. Theoretically, this study proposes a framework for "Adaptive Clinical Integration" that identifies key acceptance factors and explores how Agile project management practices can be adapted to manage the unique complexities of AI-Based Medical Devices (ABMDs). By bridging individual acceptance models with agile science, this research provides a context-specific roadmap for Saudi policymakers to ensure the successful, sustained assimilation of high-stakes healthcare AI.

**Keywords:** Artificial intelligence in healthcare, Technology adoption, Clinical decision support, AI-assisted robotic surgery, UTAUT2, Saudi Arabia

## 1. Introduction

In Saudi Arabia, healthcare is undergoing a radical transformation driven by Vision 2030, with a strategic mandate to leverage Artificial Intelligence (AI) for systemic improvement. Economic projections suggest AI could generate between $15 and $27 billion in value for the country's healthcare sector by 2030 (AlBasri et al., 2022). Currently, 77 per cent of Saudi healthcare leaders report active AI use a nearly twofold increase from the previous year and 96 per cent intend to expand their investments (Philips, 2023). However, this surge in investment and leadership optimism masks a critical implementation gap. Despite the rapid deployment of AI-Based Medical Devices (ABMDs), evidence suggests that high-level technological performance does not automatically translate into clinical utility. In Saudi Arabia specifically, while infrastructure is rapidly maturing, the transition from institutional acquisition to frontline practitioner integration remains precarious (Handayani et al., 2018; Cangelosi et al., 2025).

This gap is particularly acute in high-stakes autonomous technologies, such as robotic surgery and Clinical Decision Support Systems (CDSS). Unlike generic IT, these systems demand deep alignment with professional identity, complex clinical workflows, and significant organisational adaptation (Asan et al., 2020; Wenderott et al., 2024).

This research aims to investigate the key factors influencing selected medical professionals' acceptance of specific AI-Based Medical Devices adoption in Saudi Arabia's healthcare sector, centred on agile project management approaches tailored for AI-driven initiatives. To achieve this, the study addresses the following research questions:

*RQ1: What key factors influence medical professionals' acceptance of AI-Based Medical Devices adoption in Saudi Arabia's healthcare sector?*

*RQ2: How do identified factors interact and contribute to the successful adoption of AI-Based Medical Devices in healthcare settings?*

*RQ3: How can agile project management practices be adapted to effectively manage AI-Based Medical Devices adoption in Saudi Arabia's healthcare sector?*

## 2. Literature Review and Theoretical Background

### 2.1 AI Medical Technologies in Healthcare

AI technologies have proven their worth in various fields of medicine. According to Rajpurkar et al. (2022), much progress has been achieved in analysing medical images in radiology, pathology, gastroenterology, and ophthalmology. Topol (2019) claims that artificial intelligence can help optimise health care systems' functioning and predict patients' fates by adding to rather than substituting doctors' skills. On the other hand, Briganti and Le Moine (2020) cite some successes in detecting arrhythmias and analysing images; however, they correctly note the lack of sound design and external validation of many studies.

In Saudi Arabia, AI-based diagnostic technologies are in active clinical use (Philips, 2023), and this study focuses on two fields of technology that informed the selection of participant medical professionals.

**Table 1: AI-Based Medical Devices and target sample**

| Technology Category | Target Healthcare Professionals | Clinical Role & Interaction | Interaction Rationale for Study Inclusion |
|---|---|---|---|
| Autonomous Systems (AI assisted robotic surgery) | Surgeons | Primary Operators: Direct, real-time interaction where the AI provides precision guidance and automates specific surgical tasks | High stakes dependency; adoption hinges on the balance between AI autonomy and the surgeon's professional identity/control |
| AI Clinical Decision Support Systems (CDSS) | Physicians, Nurses, Radiologists | Interpretive & Advisory Users: Use AI for diagnostic imaging (radiologists) or therapeutic suggestions and patient monitoring (physicians/nurses) | CDSS integrates into daily cognitive workflows; successful adoption depends on how AI-driven insights are trusted and validated by the clinical team |

The most spoken about AI-based medical technologies globally and in Saudi Arabia are shown in Table 1 (Faisal, 2024). Firstly, the field of autonomy involves robotics systems with AI assistance being used for surgical operations to conduct minimally invasive procedures more accurately. Secondly, the utilisation of CDSS in Saudi Arabia is significantly on the rise to increase diagnostic accuracy, reduce medication errors, and improve adherence to treatment guidelines (Alqahtani et al., 2016).

### 2.2 Technology Acceptance in Healthcare Contexts

The adoption of healthcare technology depends on a complex interplay of user, organisational, and technological factors. The Technology Acceptance Model (TAM) and its successor, TAM2, established perceived usefulness and ease of use as primary determinants (Davis, 1989), with meta-analyses confirming their robustness across diverse fields (Granić & Marangunić, 2019). While TAM2 improved explanatory power by incorporating social influence and cognitive processes (Venkatesh & Davis, 2000), these generic frameworks often lack the granularity required for high-stakes clinical environments.

The Unified Theory of Acceptance and Use of Technology (UTAUT) attempted to harmonise these perspectives (Venkatesh et al., 2003), yet research highlights significant structural omissions. For instance, Dwivedi et al. (2017) found that UTAUT overlooks the central mediating role of attitude. Furthermore, while UTAUT2 introduced consumer-centric variables such as hedonic motivation and habit (Venkatesh et al., 2012), it remains insufficient for clinical AI. Critically, none of these models inherently account for trust the most vital predictor of adoption in medical decision-making where errors have dire consequences (Kaplan et al., 2023).

Recent evidence suggests that Generic models fail to capture clinical nuances such as professional identity, workflow complexity, and organisational readiness (Shachak et al., 2019; Dwivedi et al., 2020), with workflow integration identified as a primary barrier in radiology AI (Wenderott et al., 2024). Clinician-centred models like TrAAIT confirm that trust alone explains 36% of AI acceptance variance (Stevens and Stetson, 2023). These factors form an interrelated socio-technical layer: trust establishes the psychological condition for delegation, professional identity shapes its perceived boundaries, and organisational readiness determines whether individual acceptance can be sustained at the organisational level (Shachak et al., 2019; Kaplan et al., 2023).

The conceptualisation of trust as a dynamic, stage-like process has gained increasing traction in the human–automation literature. Madhavan and Wiegmann (2007) established, through an integrative review, that trust in automated systems operates through mechanisms distinct from interpersonal trust, evolving in response to performance cues and operator experience rather than the social reciprocity characteristic of human–human relationships. More recently, phase-oriented accounts have elaborated this trajectory. McGrath et al. (2025) propose the CHAI-T process framework, which situates trust evolution within collaborative human–AI teaming cycles and advocates active management of trust across performance phases rather than treating initial acceptance as a stable endpoint. In clinical settings specifically, Naiseh et al. (2022) demonstrate that the class and quality of explanation provided by AI systems materially affects clinicians' capacity to calibrate trust in CDSS tools, highlighting the importance of transparency mechanisms for enabling appropriate reliance rather than blanket scepticism. Notwithstanding this growing body of process-oriented work, existing phase models have been developed predominantly in Western, experimental, or general automation contexts; none has been empirically grounded in the lived experience of healthcare practitioners within a high-context, hierarchical, rapidly digitalising non-Western health system. This study's identification of a three-stage trajectory initial distrust, hesitant reliance contingent on perceived system performance, and trustful integration characterised by confident delegation responds to this gap by offering a contextually embedded account of how Saudi clinicians construct and move through sequential trust states during actual AI deployment.

While UTAUT2 focuses on adoption as a static, one-time event, this research employs agile project management as a conceptual bridge to address the dynamic, iterative processes required for sustained clinical integration.

### 2.3 Synthesis of Prior Research

A summary of key research on AI adoption in healthcare is presented in Table 1. They are derived from high-quality sources (Q1/Q2 in Scimago Journal Rank; 3/4 in ABS ranking). Some clear trends emerge. Performance Expectancy and Perceived Usefulness often influence intentions to adopt technology across different settings (Kim et al., 2024; Prakash and Das, 2021; Pan et al., 2019). Trust is seen both as an independent predictor and a mediator (Stevens and Stetson, 2023; Cornelissen et al., 2022; Kim et al., 2024). The impact of facilitating conditions and social influence varies by setting. According to Zhai et al. (2021), social influence predicts behaviour quite strongly among Chinese oncologists, but according to Cornelissen et al. (2022), it plays no role at all for Dutch physicians. Very few studies focus on sustained usage or analyse the specific context of Gulf healthcare.

**Table 2: Synthesis of Key Studies on AI Adoption in Healthcare**

| Study | Context | Region | Key Variables | Main Findings | Limitation |
|---|---|---|---|---|---|
| Prakash and Das (2021) | Healthcare AI (CDSS) | India | UTAUT, Trust, Resistance | Performance expectancy and trust; resistance significant | Pre-adoption focus |
| Zhai et al. (2021) | Radiation oncology | China | UTAUT, Social Influence | Social influence and facilitating conditions are strongest | Single centre; age bias |
| Cornelissen et al. (2022) | Care pathways | Netherlands | UTAUT, Professional Identity | Medical performance expectancy is dominant; gender moderates | Online volunteer sample |
| Jones et al. (2022) | CDSS | USA | UTAUT | Eight dominant themes were identified such as Alert fatigue, Automation and Redundancy | inpatient only.<br>trauma population |
| Stevens et al. (2023) | Oncology | USA | UTAUT, IS Success, Trust | Trust explains 36% of variance; system performance is critical | Single centre |
| Aljarboa and Miah (2023) | CDSS | Saudi Arabia | UTAUT + TTF | 13 factors identified as influencing CDSS acceptance, including: Performance expectancy, effort expectancy, facilitating conditions, task-technology fit. | Qualitative only; GP-focused |
| Wenderott et al. (2024) | Radiology | Germany | TAM, Workflow Integration | Positive attitudes: workflow barriers dominate | Single department |
| Kim et al. (2024) | Medical AI | South Korea | UTAUT, Trust Mediation | Trust mediates UTAUT factors and acceptance | Age-limited sample |
| Alsudairy et al. (2025) | Primary care AI | Saudi Arabia | TAM/UTAUT | 31% using AI tools; 54% lack training; 49.2% cite high costs; 48% concerned about human touch erosion. | Primary care only; mixed awareness levels |
| Shao et al. (2026) | DeepSeek LLM-CDSS | China | UTAUT + Perceived Risk Theory | Performance expectancy, effort expectancy and facilitating conditions reduce perceived risk. | Single hospital; convenience sample; emerging technology (LLM) |

Some key trends have been identified from this synthesis. Trust and workflow integration emerge consistently as highly relevant but less researched concepts within varying national settings. Research tends to concentrate on adoption intentions and not on the continued use of AI applications after the implementation phase.

### 2.4 Project Management Practices in AI Healthcare Projects

Traditional project management methods, designed for stable requirements, are poorly suited to AI healthcare projects. Agile approaches offer benefits through iterative development and ongoing value delivery (Kokol et al., 2022), though adoption remains limited. Technology acceptance and user behaviour influence implementation (Shetty and Joshi, 2024), while workflow integration and AI complexity demand flexible, adaptive strategies rather than fixed plans (Nair et al., 2024; Koçak et al., 2025).

### 2.5 Agile Principles for AI Healthcare Implementation

Agile principles offer a fitting framework for implementing AI in healthcare because they handle the uncertainty and complexity of AI projects. Unlike the traditional waterfall approach, agile methods encourage iterative development, ongoing stakeholder engagement, and flexibility in adjusting to changing needs (Kokol et al., 2022). In this study, agile principles serve as the implementation framework that operationalises the theoretical constructs of the extended UTAUT2 model. The success of agile AI projects depends on user acceptance and behavioural factors, which shows the importance of implementation methods that meet stakeholder needs (Shetty & Joshi, 2024). Specifically, agile project management contributes to AI adoption by fostering trust through iterative, small-scale deployments that allow clinicians to validate system performance before full-scale use. It further ensures sustained use by providing the structural flexibility needed to refine clinical workflows continuously as professional knowledge and AI capabilities evolve. Research highlights that successful AI implementation requires flexible methods to tackle workflow integration issues, improve processes, and adapt to organisational changes (Nair et al., 2024; Koçak et al., 2025). Agile methods also promote continuous learning and improvement through regular feedback, which boosts clinical value and aids effective change management (Leuba & Piricz, 2024; Nihi et al., 2025). In the context of Saudi Arabia's Vision 2030, agile principles like flexibility in implementation, stakeholder involvement, and continuous adaptation will likely play a key role in supporting AI adoption across healthcare organisations with varying levels of digital maturity.

Critically, the qualitative phase of this study has identified specific Agile-aligned patterns that emerged consistently across participant accounts and may offer potential directions for extending the UTAUT2 model. These emerging themes point to a recognised structural limitation of UTAUT2: its exclusive focus on individual-level variance, which leaves unexplained the team-level and process-level dynamics through which individual intention is or is not translated into sustained clinical use. Further exploration of these themes, including potential operationalisation and their relationships within the broader theoretical model, will be reported in a subsequent manuscript following completion of the full thematic analysis. The present paper signals this as a theoretical direction under active investigation.

### 2.6 Issues Surrounding Knowledge in AI Healthcare Adoption

Trust in clinical AI is an epistemic process through which practitioners collectively refine tacit knowledge about system reliability (Nonaka and Takeuchi, 1995), not merely a psychological disposition. Established frameworks such as UTAUT and TAM treat knowledge acquisition as an individual event, underestimating collective sensemaking through which institutional trust is built (Tamilmani et al., 2021; Shachak et al., 2019). Knowledge creation is geographically embedded: Western findings may not reflect Saudi Arabia's steeper hierarchies, collectivist culture, and directive policymaking (Argote and Miron-Spektor, 2011), with regional studies sparse (Nasseef et al., 2022; Aljarboa and Miah, 2023). Most studies measure initial acceptance but neglect double-loop learning (Argyris, 1977) through which practitioners revise assumptions during deployment; workarounds constitute acts of tacit knowledge creation and knowledge sharing that, if captured, can drive iterative improvement.

### 2.7 Research Gaps

The first gap is that of context specificity. While social influence has been determined as a key variable affecting the process of adoption among Chinese oncologists (Zhai et al., 2021), it has been insignificant among Dutch oncologists (Cornelissen et al., 2022). This inconsistency suggests the need for studying contextual aspects to determine which variables function in certain contexts.

The second gap concerns inadequate attention paid to the stage of transitioning from intention to integration. It has been noted that most studies concentrate on intentions rather than the continuity of use (Prakash and Das, 2021; Kim et al., 2024). The process of transitioning from intention to implementation is critical for those technologies that require gradual skill acquisition.

Thirdly, the organisational and implementation dimensions of AI adoption need further theoretical exploration. Whereas there is sufficient literature on the acceptability dimensions for individuals, there are not enough studies on the organisational processes by which individual acceptability is leveraged to facilitate organisational adoption through implementation processes, adaptive implementation, and training programs (Kokol et al., 2022; Nair et al., 2024).

## 3. Methodology

A sequential exploratory mixed-methods research design is used in this study, whereby the qualitative phase precedes the quantitative generalisation phase (Creswell & Clark, 2017). The initial qualitative phase utilizes semi-structured interviews to capture the unique cultural nuances of the Saudi context. These qualitative insights will then inform a quantitative survey designed to empirically validate the interaction of these factors and assess the effectiveness of Agile management practices in facilitating organisational integration.

### 3.1 Qualitative Phase

Seventeen semi-structured interviews were conducted with healthcare professionals across major Saudi cities, recruited through purposive expert sampling supplemented by snowball referrals. Participants were selected based on direct clinical experience with either AI-assisted robotic surgery (surgeons) or Clinical Decision Support Systems (physicians, radiologists, and nurses), ensuring diversity of role and specialisation. The protocol covered thematic areas aligned with UTAUT2 constructs including performance expectancy, effort expectancy, social influence, facilitating conditions alongside the additional constructs such as trust proposed by this study, and was pilot tested with two clinicians prior to data collection.

### 3.2 Data Analysis

Reflexive thematic analysis (Braun and Clarke, 2006) was applied through six inductive coding stages using NVivo. Saturation was monitored iteratively: new conceptual categories ceased to emerge by interview 15, with interviews 16 and 17 serving to confirm and enrich existing themes, distinguishing code from meaning saturation. Trustworthiness was ensured through member-checking, whereby Arabic transcripts were returned to participants for verification (Birt et al., 2016), and English translations were independently reviewed by two bilingual colleagues.

### 3.3 Quantitative Phase

Qualitative findings will inform a survey instrument deployed across Saudi health institutions, with each theme operationalised as a latent construct using validated scales where available and new items for constructs specific to the Saudi clinical context. The instrument will undergo cultural validation by Saudi healthcare experts, cognitive interviews to identify comprehension issues, and pilot testing (n=15–20) to assess psychometric properties. Common method bias will be assessed using Harman's single factor test and controlled via a common latent factor approach. Moderating variable’s professional role, years of experience, and institutional type were selected based on qualitative evidence that adoption trajectories vary across these dimensions. The target sample of 200–300 respondents was determined through power analysis (GPower: minimum 176), parameter-to-case ratios (Jackson, 2003), and Monte Carlo simulation, accounting for 15–20% non-response (Kline, 2016). Data will be analysed using PLS-SEM (Hair et al., 2019).

## 4. Initial Conceptual Thinking and Proposed Framework

The proposed framework integrates insights from the literature and early interview data into a theory-based model that goes beyond traditional adoption theories, differentiating between individual adoption and clinical integration as related but distinct outcomes. Each process requires different forms of organisational support and encounters different obstacles, examined here across three interrelated dimensions. Among individual-level variables are performance expectancy, effort expectancy, and trust, which foster initial willingness to use AI-based technology. Trust, for instance, is an outcome of a series of experiences ranging from initial scepticism to trusting use of the AI-based decision-making process. First, there is doubt followed by hesitant reliance on perceived system performance, until trust finally leads to use in making clinical decisions (Stevens and Stetson, 2023).

At the organisational level, organisational readiness, leadership support, training quality, and flexibility in adapting workflows are critical to whether an individual’s positive attitude translates into the effective use of clinical technology. Theoretically, these variables operate through a socio-technical logic where individual intent is moderated by the organisational environment. High-quality training and leadership communication act as vital catalysts that transform a practitioner’s initial positive attitude into sustained clinical usage. This relationship is inherently iterative; as practitioners achieve integration, their frontline experiences feed back into organisational policy, allowing for the continuous, data-driven refinement of workflows and safety governance.

The Adaptive Clinical Integration Framework (ACIF), presented in Figure 1, is structured around three propositions: P1 holds that individual-level factors mediated by Trust generate Behavioural Intention toward organisational enablers; P2 posits that organisational-level factors drive Sustained Use; and P3 captures the iterative feedback loop through which Sustained Use informs continuous Organisational refinement. This differs from static "Go-Live" models by treating implementation as a non-static, Agile co-evolution between technology and the clinical workforce over time. The qualitative data further indicate that additional Agile-aligned constructs, yet to be formally operationalised, play a meaningful role in facilitating this co-evolution. The complete development and empirical validation of the proposed theoretical framework will be outlined in separate manuscripts.

Figure 1 illustrates the proposed Adaptive Clinical Integration framework, linking individual acceptance constructs with organizational level.

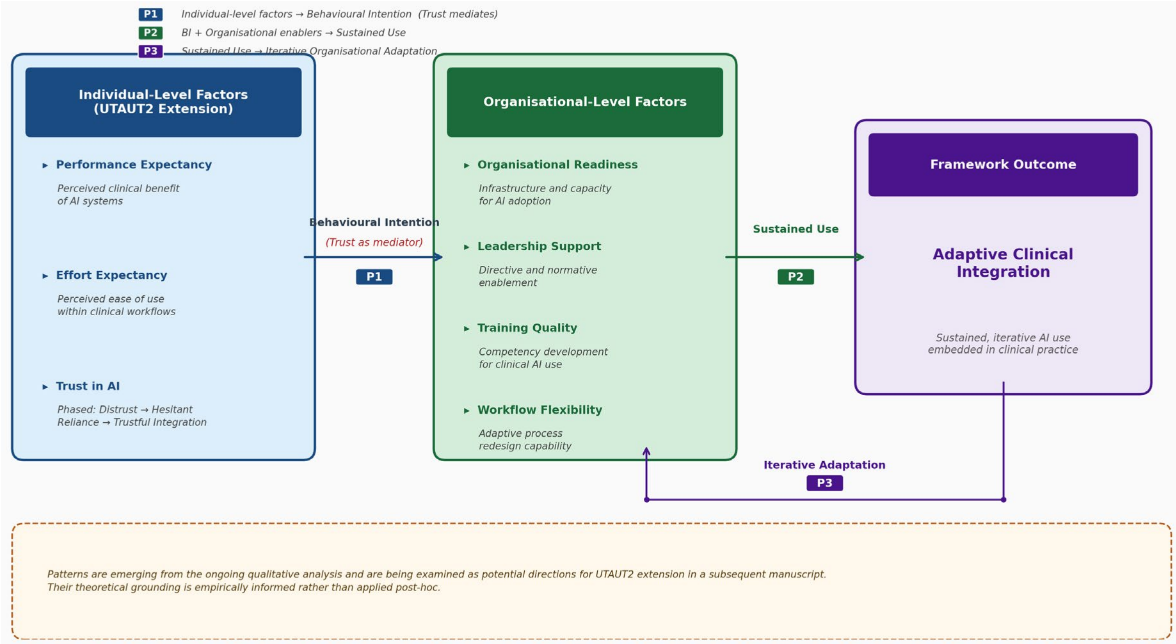


**Figure 1: Initial Conceptual Thinking**

## 5. Study Progress and Preliminary Insights

At the time of writing, data collection for the qualitative phase is almost done. Semi-structured interviews have been conducted with participants from hospitals and healthcare institutions across several major regions of Saudi Arabia.

The process of data analysis has started already. Some trends have been identified. Firstly, trust toward AI systems appears to emerge in distinct phases from distrust to cautious use and eventual trustful integration; as one participant noted, "I trust it at a high rate, maybe about 85%. But I still review every alert or suggestion before applying it" (P17). Secondly, issues with workflow integration appear to pose larger obstacles compared to problems of technology; as P04 described, "It took a while at the beginning, but it didn't last long; it was between one and two months." A third pattern concerns organisational support as a moderating factor; P10 captured the gap between institutional encouragement and actual provision: "The hospital encourages but does not adequately provide the necessary resources for education and training." These are summarised in Table 3 below.

**Table 3: Preliminary Themes from Early Interview**

| Emerging Theme | Illustrative Insight | Theoretical Relevance |
|---|---|---|
| Trust Development Phases | Trust evolves through distinct stages from skepticism to confident integration | Extends static trust models to dynamic processes |
| Workflow Integration Priority | Workflow concerns outweigh technical capability worries | Aligns with Task-Technology Fit (TTF) and implementation science |
| Organisational Support Moderation | Training and leadership quality influence the acceptance-sustained use link | Extends UTAUT facilitating conditions |

These are early observations rather than final conclusions. Thematic analysis is still in progress, and the final conceptual framework will be refined based on it.

## 6. Expected Contributions and Areas for Development

### 6.1 Theoretical Contribution

The contribution of this study to the technology acceptance literature can be viewed in three ways. First, by focusing on long-term clinical use rather than mere acceptance, this research fills the gap in understanding how AI is integrated into daily medical practice over time. Second, by including professional identity and autonomy as key concepts, this study builds on previous models to address the specific realities of clinical practice with autonomous systems. Third, by presenting adaptive clinical integration as an organisation-level concept that connects individual acceptance and implementation outcomes, the theoretical framework ties technology acceptance research to implementation science in a way that meets the challenges of autonomous AI in healthcare.

### 6.2 Practical Contribution

This study supports healthcare organisations and policymakers in Saudi Arabia in developing evidence-based strategies for a positive, sustained AI implementation process, in alignment with Vision 2030 objectives.

### 6.3 Methodological Contribution

This design is effective for exploring complex adoption questions in relatively unstudied regions. By creating surveys informed by insights from qualitative research, the current study ensures that future surveys can measure constructs and their relationships pertinent to Saudi Arabian health care practitioners.

## 7. Conclusion

This paper has presented the rationale, theoretical foundation, and methodology for a mixed-methods study on AI adoption among Saudi healthcare providers, motivated by several unresolved issues in the field. These issues include the neglect of the adoption process for medical professionals, lack of understanding concerning how adoption turns into sustainable usage, and a lack of studies in the Gulf region.

**Feedback Sought**

Feedback is welcomed on two areas: (1) the coherence of Agile principles as the implementation mechanism bridging individual acceptance and organisational integration, particularly how specific Agile practices are identified and linked to adoption constructs through the qualitative data in RQ3; and (2) the planned transition from qualitative themes to survey instrument development, particularly how identified themes will shape the survey questions and overall instrument structure.

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**Ethics Declaration:** Ethics clearance for the study was received from the Manchester Metropolitan University's Research Ethics Committee prior to data collection. Informed consent was obtained from the subjects before conducting the interview session. Data confidentiality is maintained by securing and anonymising the information collected from the respondents. The study adheres to the guidelines set forth in the Declaration of Helsinki.

**AI Declaration:** The author confirms that no AI tools were used in drafting, analysing, or preparing this manuscript. All content reflects the original work of the research.

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