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Responsible AI for perceived improvement in efficiency: The mediating roles of mindfulness and emotion regulation

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ABSTRACT

Purpose: There is little information about how healthcare professionals' psychological aspects, such as mindfulness and emotion regulation, affect the adoption and effectiveness of artificial intelligence (AI) systems in healthcare. To address this gap, this study investigates whether responsible AI (RAI) can be associated to perceived improvements in efficiency (PIE) in the UAE healthcare system and whether this influence is mediated by mindfulness and adaptive emotion regulation (ER).

Design/methodology/approach: Drawing from anthropomorphism and commitment–consistency theory, a conceptual model of how RAI and psychological factors impact PIE was built and validated. Partial least squares-structural equation modeling was adopted for multiple linear regression analysis of survey data collected from 300 healthcare professionals in the UAE.

Findings: Direct, positive relationships are observed between RAI, mindfulness, and PIE. Additionally, adaptive emotion regulation mediates the relationships of RAI with PIE and mindfulness. Furthermore, compared to ER, mindfulness is a far more powerful mediator.

Practical implications: The findings suggest that managers should develop strategies that create a conducive environment for both technological and human resource development. Additionally, management should promote ongoing professional development that integrates AI tools with soft skills training to enhance healthcare professionals' emotional resilience and adaptability.

Originality/value: This article is one of the early studies offering empirical insights on the intersection of RAI, psychological aspects of healthcare professionals, and perceived improvement in efficiency. The research contributes to the emerging intersection of technological advancement with psychological wellness. Moreover, the dual-theory approach is novel and relevant in AI technology and organizational outcome research.

1. Introduction

Artificial intelligence (AI) is rapidly becoming an inescapable innovation that organizations must integrate to remain competitive and future ready. AI is predicted to increase global GDP by $15.7 trillion by 2030. In the healthcare industry, AI, together with open innovation that facilitates the integration of external knowledge sources, have the potential to become a transformative force by advancing scientific research, enhancing diagnosis and treatment recommendations, improving patient involvement and adherence, expediting drug development and delivery, reducing costs, and promoting health equity (Zhang and Wang, 2021). As the healthcare landscape evolves, AI integration is essential for managing the challenges faced by professionals and ensuring a sustainable healthcare environment. AI can help healthcare providers investigate medical concerns more quickly and precisely (Dignum, 2019). Additionally, healthcare professionals can use interactive agents to respond to inquiries and provide medical services, telemedicine, and customized medication (Gupta et al., 2022).

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Thus, AI creates efficiency from digitally created data (Borges et al., 2021). Furthermore, the productivity gains of AI can be harnessed through open data initiatives that promote transparency and ethical considerations in AI development (Ali et al., 2024). Such practices can bolster healthcare providers' confidence in their ability to respond competently to patients, a crucial factor not only for effective emotion regulation (Askey-Jones, 2018) but also for quality of patient-centric care. However, *empirical research on the specific mechanisms through which AI facilitates improvements in operational efficiency is scarce*.

Addressing this research gap is important, as the rapid adoption of AI applications in the healthcare sector is poised to profoundly influence scientific advancement and societal outcomes, while also creating new business opportunities (Tani et al., 2025). However, alongside these transformative benefits, AI technologies introduce significant ethical and governance challenges (World Economic Forum, 2023). Persistent concerns related to data privacy, user trust, transparency of information flow, ethical accountability, data security, system performance, broader societal risks, and financial implications must therefore be carefully examined and addressed (Shetty et al., 2025). Given these concerns, this paper focuses on responsible AI (RAI), a framework for effectively building trust and handling significant challenges in healthcare applications (Luxton, 2014). Responsible AI (RAI) aims to reduce bias and promote fairness by ensuring that AI systems produce interpretable and explainable outcomes, in line with established frameworks for trustworthy AI—such as the OECD AI Principles, the World Health Organization (WHO) ethical guidance on AI for health, and the FUTURE-AI consensus framework—which emphasize transparency, robustness, security, and accountability in healthcare applications (World Health Organization, 2024; Kim and Kim, 2025; Lekadir et al., 2025; Al Zaabi et al., 2025). In healthcare settings, RAI facilitates the aggregation of large clinical datasets required for clinical decision-making, which in turn aids customized patient care and increased productivity (Hasan et al., 2025). Open innovation is particularly relevant to RAI implementation in healthcare because responsible AI development inherently requires transparency, external collaboration, and knowledge sharing across organizational boundaries (Shetty et al., 2025). When used as a tool by healthcare professionals, RAI can establish trust and minimize privacy issues by harnessing technological and analytical capabilities, including risk mitigation, data, and machine learning algorithms (Chatterjee, 2020).

The relationship between RAI and perceived improvements in efficiency in healthcare is both direct and indirect, depending on the context and application of AI technologies. AI directly enhances patient-centric performance through improved clinical decision-making and personalized care (Russell et al., 2023). Although RAI can enhance efficiency, it may indirectly reduce the quality of the patient–provider relationship if not implemented thoughtfully. This risk highlights the importance of healthcare professionals' mindfulness practices and emotion regulation in preserving empathy and compassion in patient care (Askey-Jones, 2018). Healthcare organizations that embrace open innovation principles, such as sharing anonymized datasets for algorithm training, collaborating with external AI developers, and engaging in transparent communication about AI capabilities, can create environments where healthcare professionals can develop informed, mindful approaches to AI adoption. Therefore, we argue that the relationship between AI and operational efficiency is complex and multifaceted. Accordingly, the main objective of this study is to address the following research question: *How does RAI implementation lead to perceived improvements in efficiency in healthcare, and what intervening variables mediate this relationship?*

To understand how healthcare professionals employ RAI in patient care, this study focuses on the healthcare sector in the United Arab Emirates (UAE). We choose the UAE as our empirical setting because it is a leader in regulations and guidelines for the responsible use of AI in healthcare (Alhashmi et al., 2019). The UAE is regarded as a top destination for medical tourists and constantly promotes the usage of AI in healthcare. The Ministry of Health and Prevention (MOHAP) recommends the use of AI to interpret X-rays, streamline patient admissions, and monitor prescriptions (Solaiman et al., 2024). Among Arab nations, the UAE received the highest ranking for technological advancement using AI for innovation, implementation and investment (Almuraqab et al., 2024). In addition, the UAE government has suggested a new set of rules and regulations pertaining to AI in healthcare. However, there is a paucity of empirical research on the application of RAI in the UAE for the inclusive promotion of emotion control and mindfulness practices among healthcare professionals, which ultimately help improve operational performance.

Figure 1 presents the proposed conceptual model integrating RAI, mindfulness, emotion regulation, and perceived improvement in efficiency. This model contributes to the literature on AI, healthcare, and psychological well-being. The theoretical underpinnings are based on anthropomorphism and commitment–consistency theory. This multidisciplinary dual-theory approach is innovative and relevant in AI research, particularly given the global push toward sustainable development goals (SDGs) for ensuring healthy lives and promoting well-being (SDG3) and providing more accessible healthcare at affordable costs (SDG13). To test the model, multiple regression analysis of survey data collected from 300 professionals in the UAE healthcare industry is performed by partial least squares-structural equation modeling (PLS-SEM). By addressing the ethical and practical aspects of AI in healthcare, as well as the psychological constructs of mindfulness and emotion regulation, this study contributes to the literature on the ethical deployment of AI technologies in healthcare settings and provides actionable insights for improving patient care practices. Fostering the resilience and emotional intelligence of healthcare professionals will ultimately enhance the overall patient experience. Anthropomorphism and commitment-consistency theories explain how individuals respond to RAI, but these psychological mechanisms do not operate in isolation. They unfold within broader organizational and innovation contexts. Research on open innovation indicates that the way AI is developed and introduced matters considerably for user perceptions and engagement. When development processes are transparent and collaborative, outcomes differ markedly from those associated with opaque, top-down implementation. RAI inherently reflects open innovation principles given its emphasis on transparency, explainability, and stakeholder engagement. The psychological mechanisms examined in this study are therefore expected to be activated when healthcare professionals interact with responsibly-developed AI systems grounded in open innovation values.

The remainder of this study is organized as follows. Section two presents an overview of the literature, while section three develops the hypotheses. Sections four and five describe the methodology and findings. Finally, section six provides a discussion, conclusions, implications, and directions for future research.

2. Literature review

This study takes a multidisciplinary approach and draws on theoretical underpinnings from anthropomorphism theory (Epley et al., 2007; Van Pinxteren et al., 2019), and commitment–consistency theory (Adam et al., 2021). Anthropomorphism theory, which involves

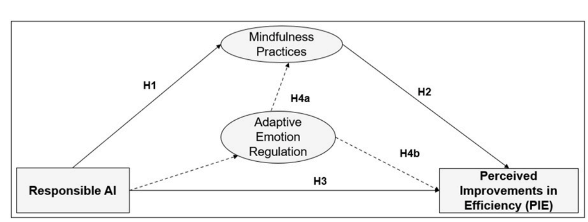

Fig. 1. Conceptual Model.

attributing human-like features (e.g., agency, intention, emotion, social presence) to non-human entities, can play a significant role in using responsible AI (RAI) in healthcare to enhance operational performance (Li et al., 2023, Lin et al., 2017). Prior research has shown that equipping nonhuman agents with anthropomorphic cues (e.g., visual, auditory, or mental) makes them appear more human. This can increase clinician's acceptance of new technologies, trust in the non-human agent, and even perceive their interactions with the agent as more meaningful (Ochmann et al., 2024). Additionally, RAI systems deploy anthropomorphic elements to improve user interactions by leveraging the data analytics tools to simplify complex information to more understandable and actionable insights for healthcare practitioners (Côrte-Real et al., 2020). Furthermore, anthropomorphism supports customized medical consultations for patients through the attributes of empathy and social presence, improves patient recovery efficiency, allows virtual assistants to organize patient appointments, and enables continuous monitoring of patient wellness (Zhang et al., 2023; Troshani et al., 2021).

Commitment - consistency theory applies to technology usage and implementation in healthcare settings (Alslaity and Tran, 2021; Orji and Moffatt, 2018). Once healthcare professionals commit to a course of action (e.g., adopting or trusting an AI system), they experience psychological pressure to maintain consistency, even in the face of contradictory evidence (Adam et al., 2021; Goh et al., 2011). Therefore, clinicians' initial commitment to AI use is positively associated with continued reliance on AI recommendations. When AI is framed as evidence-based or best practice, clinicians may integrate AI use into their professional identity, increasing consistent reliance (Paré et al., 2020). Moreover, individuals who are motivated to perform consistently with their commitments can improve their mindfulness practices, allowing them to be vigilant and adaptive in their routines and patient interactions, resulting in operational performance (Goh et al., 2011). This can futher assist in reducing mental health problems while using conversational agents and repetitive follow-ups in healthcare settings (Gupta et al., 2022).

2.1. Responsible AI

In today's world, data is viewed as the new oil, while artificial intelligence (AI) is the machinery for responsibly extracting its value (Krishna, 2024). As organizations embrace digital transformation, a strategic focus on open innovation becomes crucial in effectively integrating AI technologies (Zhang and Wang, 2021). Together, vast data and AI generate an ecosystem that can support social and economic dimensions (AlDhaheri et al., 2025; Varsha et al., 2021). RAI involves taking human responsibility for designing intelligent systems based on fundamental principles and values that ensure human flourishing and well-being in a sustainable world (Dhaigude and Kamath, 2025; Dignum, 2019). A proposed framework for RAI comprises six critical attributes: fairness, transparency, trustworthiness, accountability, privacy, and empathy in the healthcare setting (Siala and Wang, 2022). Thus, RAI is a multifaceted concept for exploring standards for AI prototypes that provide equality, accountability, and privacy in practical applications (Arrieta et al., 2020). In a nutshell, RAI promotes trust, which is the most crucial component for academics, practitioners, and people.

2.2. Adaptive emotion regulation

Emotion regulation encompasses intrinsic and extrinsic methods for monitoring, assessing and modifying individual reactions to situations (Thompson, 1991). Integrating AI with emotion regulation would enable both the recognition of patient emotions like anger, misery, happiness, disgust, and neutrality and the incorporation of "nurse bots" to monitor a patient's overall welfare (Ahuja, 2024). Emotion regulation can be further divided into emotion self-regulation and emotion dysregulation. Emotion self-regulation is the ability to improve, adjust, or monitor one's perspectives, feelings, actions, and words (Whelan et al., 2022). AI can contribute to improved emotional self-regulation among healthcare professionals by reducing cognitive overload, enhancing decision-making confidence, providing training opportunities, and promoting self-awareness (Morrow et al., 2023). Conversely, emotion dysregulation is a mental health syndrome in which individuals find it difficult to monitor their emotions and act on their feelings (Cleveland Clinic, 2023).

2.3. Mindfulness practices

Research indicates that mindfulness practices such as meditation decrease depression, anxiety and loneliness (Kabat-Zinn, 2003) and can be implemented by healthcare experts to monitor patient wellness. Healthcare professionals who engage in mindfulness exhibit improved empathy, active listening, and communication skills, which are all essential for effective patient–provider interactions. A systematic review by Lomas et al. (2019) found that mindfulness practices among healthcare providers foster a greater sense of presence and attention during patient encounters, leading to more satisfying and productive clinical interactions. Moreover, healthcare professionals often face high levels of stress, burnout, and compassion fatigue due to the demanding nature of their work. Mindfulness practices, such as meditation and mindfulness-based stress reduction (MBSR), have been shown to significantly reduce stress and improve overall psychological well-being among healthcare workers (Burton et al., 2017). Finally, mindfulness practices can also positively affect team dynamics among healthcare professionals. A systematic review by Wolever et al. (2012) emphasized the role of collective mindfulness in reducing conflicts and enhancing teamwork in clinical settings, which can lead to improved patient outcomes.

2.4. Perceived improvements in efficiency

The quality of patient-centric care is a key aspect of operational efficiency in healthcare delivery and requires the alignment of healthcare services with patients' preferences, needs, and values. Health technologies play an important role in the advancement of patient-centered care. These technologies empower healthcare professionals to take an active role in care management, potentially improving health outcomes (Kulal et al., 2024). Therefore, measuring the effectiveness of patient-centered initiatives is critical for assessing productivity in healthcare settings (Ali et al., 2024; Quazi et al., 2024).

3. Hypothesis development

3.1. Responsible AI and mindfulness practices

The way the technology and healthcare workers interact is increasingly shaping practices surrounding mindfulness, and employee well-being (Wang et al., 2023). Responsible AI (RAI) emphasizes explainability, transparency, and accountability in healthcare systems, and it supports clinicians' present-moment awareness and reflective judgment, which is the core aspects of mindfulness (Song and Lin, 2023). Moreover, trust, fairness, and ethical compliance are central to RAI. For example, trustworthy AI reduces cognitive stress and performance anxiety, freeing up attentional capacity for mindful awareness rather than defensive monitoring (Song et al., 2024). Drawing on anthropomorphism theory, RAI may foster clinician mindfulness by calibrating human-like attributions of agency, morality, and social presence, thereby encouraging reflective engagement rather than automatic reliance on AI systems. RAI principles (fairness, accountability) reduce ethical ambiguity and moral anxiety, helps clinicians to maintain emotional balance and present-moment awareness, rather than becoming preoccupied with ethical doubt (Ochmann et al., 2024; Côrte-Real et al., 2020). According to commitment–consistency theory, healthcare professionals converse with AI systems to maintain commitment in certain instances, even if they face challenges like ethical problems or patient care quality (Adam et al., 2021). RAI developed through transparent, collaborative (open innovation) processes, creates conditions conducive to positive psychological and operational outcomes (Vössing et al., 2022). In sum, commitment–consistency theory supports informed commitment that encourages conscious awareness and reflective engagement, aligning with mindfulness principles. Thus, our first hypothesis is as follows:

H1. . Responsible AI positively impacts the mindfulness practices of healthcare professionals.

3.2. Mindfulness Practices and Perceived Improvement in Efficiency

For healthcare professionals, mindfulness and acceptance require continuous focused attention and high awareness. Through their interactions with patients, healthcare professionals develop an empathetic environment to optimize personalized healthcare services (Zhang et al., 2023). Social presence is the key anthropomorphic attribute that plays a crucial role in healthcare by enhancing trust and reliance on AI and robotic technologies (Pelau et al., 2021). Deploying human-like attributes in interactive agents and AI-enabled interfaces can create familiarity and emotional acceptance, which encourage patients to become more actively involved in managing their overall health (Christoforakos et al., 2021). Commitment–consistency theory similarly implies that mindfulness in healthcare professionals can create dynamic patient adherence to medical advice (Wang et al., 2022). Commitment strengthens the ability of clinicians to care for a patient's wellness and sentiments in healthcare settings (Nadarzynski et al., 2019). This, in turn, encourages patients to commit to the treatment prescribed by healthcare professionals, resulting in perceived improvements in efficiency (Khattab et al., 2021). Accordingly, our second hypothesis is as follows:

H2. . The mindfulness practices of healthcare professionals are linked to perceived improvements in efficiency.

3.3. Responsible AI and Perceived Improvement in Efficiency

The deployment of RAI for improved efficiency and productivity has gained popularity in the healthcare sector in recent years (Sivarajah et al., 2023). Agency is the anthropomorphism attribute that explains how human dependence on AI enhances healthcare interactions. By positioning AI as a competent and autonomous agent, agency fosters trust, improves communication, and ultimately increases patient satisfaction in AI-supported healthcare environments. (Hoseini, 2023). These outcomes reflect the use of user-centered methods that enhance user acceptance and offer seamless engagement with AI-driven chatbots to address patient concerns (Nadarzynski et al., 2019). In addition, commitment–consistency theory affirms that individuals are inspired to support their commitments, which shape their health behaviors (Meyer et al., 2004). AI systems help patients actively engage with their health diagnoses, encouraging them to stick to their treatment plans (Tursunbayeva and Renkema, 2022). For instance, gamified AI tools support patient engagement in their health, which can reinforce their commitment to a speedy recovery (Ouanes, 2024). Furthermore, AI can deliver customized care to create more patient-centric settings that promote conformity with treatment and foster recovery, resulting into improved operational efficiency (Quazi et al., 2024). Accordingly,

H3. : Responsible AI is positively linked to perceived improvement in efficiency.

3.4. Mediating role of adaptive emotion regulation

Adaptive emotion regulation is a core feature that allows healthcare professionals like physicians and caretakers to provide quality treatment to patients (Weilenmann et al., 2018). This form of emotion regulation comprises both conscious and non-conscious potential to control or decrease multiple features of emotional response (Gross, 2015). In his seminal work, Gross (1998) argued that managers who equipped with emotion regulation skills can better handle stressful or emotionally charged work environments. The ability to effectively manage one's emotional responses can lead to a decrease in workplace stressors, allowing for enhanced focus and present moment awareness—fundamental aspects of mindfulness practice. Ayoko (2023) states that managers who regulate their emotions effectively can create a supportive environment that encourages mindfulness among their team members. This further implies that effective emotion regulation practices empower healthcare professionals to cultivate mindfulness, thus bolstering their resilience against stress and enhancing their caregiving abilities (Perilli et al., 2022). For example, emotion regulation training inherent in cognitive behavior therapy (CBT) often includes practical exercises that promote mindfulness of healthcare professionals while engaging with technology in the clinical environment (Söğütlü et al., 2021). By enhancing social presence, anthropomorphized AI creates supportive, interactive environments that help healthcare professionals regulate emotions, reduce cognitive and emotional strain, and develop mindfulness (Schanke et al., 2021). Furthermore, clinical trials of AI integration have shown that healthcare professionals can leverage AI technologies to monitor their mindfulness, through understanding their emotional responses (Petersson et al., 2022). Also, the deployment of chatbot applications in MSBR tools enables healthcare professionals to improve their adaptive emotion regulation capacity and enhance their overall psychological well-being through mindfulness (Kriakous et al., 2021). Accordingly, the following hypothesis is proposed:

H4a. : Adaptive emotion regulation mediates the relationship between responsible AI and mindfulness practices.

Studies have demonstrated that the emotional self-regulation skills of healthcare professionals can ameliorate the complexities of deploying AI in treatment to foster patient recovery (Balti and Karoui Zouaoui, 2024). Drawing in commitment-consistency theory, commitment can steer the adaptive emotional regulation to promote trust between the healthcare professionals and AI systems to attain better health outcomes (Moin et al., 2024). Individuals using adaptive regulation remain engaged even when AI outputs are uncertain or imperfect. This emotional stability translates into smoother workflows and higher perceived efficiency (Corti et al., 2023). Additionally, healthcare employees equipped with emotional intelligence and leadership skills are well-positioned to integrate AI tools in their practices effectively. This incorporation can improve patient satisfaction and overall treatment (Balti and Karoui Zouaoui, 2024). Moreover, by leveraging anthropomorphism, healthcare professionals feel comfortable in their interactions with technology, promoting a positive emotional state and encouraging effective communication (Benlian et al., 2019). Accordingly, we propose that:

H4b. : Adaptive emotion regulation mediates the relationship between responsible AI and perceived improvement in efficiency.

4. Research method

4.1. Research design

A quantitative, cross-sectional survey design is used to empirically test the proposed relationships among RAI, mindfulness practices, adaptive emotion regulation, and perceived improvement in efficiency. The study follows a positivist paradigm and seeks to test a theoretically grounded model of directional associations through hypothesis-driven modelling using structural equation modelling (SEM). The theoretical basis draws from the literature on ethical AI adoption, the role of mindfulness in clinical performance, and emotion regulation theories.

4.2. Research context and sample

Data was collected from clinical healthcare professionals from both public and private firms in the UAE who are actively using AI-enabled tools in patient care. This context was chosen due to the UAE's strategic investments in AI technologies in healthcare (Shaikh and Vivek, 2025). We sent out a survey invitation by email to 800 healthcare professionals, and 300 of them responded, resulting in a 37.5 % response rate. According to a study by Berghout et al. (2015), healthcare professionals can act as evaluators, capturing important metrics related to quality of care and efficiency, making their assessments more meaningful. A purposive sampling technique was employed to select professionals with relevant exposure and experience with AI in clinical workflows, as well as managerial decision-making abilities. The target population was physicians, nurses, clinical specialists, and medical technologists working in both public and private firms in the UAE. Calculations using G*Power software indicated that a minimum of 200 responses were necessary to detect medium effect sizes ($f^2 = 0.15$) at 80 % power with a significance level of 0.05 for the model's structural paths. The inclusion criteria were job roles requiring interaction with AI-based diagnostic, monitoring, or decision-support systems; administrative staff or those not exposed to AI use were excluded. Ethics clearance was obtained from Abu Dhabi University (CB– 0000073), and participant anonymity and informed consent were ensured.

4.3. Operationalization of constructs

Each construct was measured using multiple items on 5-point Likert scales (1 = strongly disagree, 5 = strongly agree) developed from existing validated instruments and adapted to the AI-healthcare context (refer Table 1).

RAI is defined as the degree to which healthcare professionals perceive AI technologies as ethical, fair, secure, transparent, and autonomy supportive. Six items reflecting the dimensions of ethical impact, fairness, trust in data security, transparency in design and communication, and autonomy support were adapted from the study by Wang et al. (2023) (e.g., "The AI has enough security measures to protect patients' personal information").

Mindfulness Practices (MP) refers to present-moment awareness and non-judgmental attention to internal and external stimuli in the context of AI use (Brown and Ryan, 2003). Five items adapted from study by Feldman et al. (2007) captured attentional control, reflective awareness, and cognitive presence (e.g., "I am able to focus on the present moment when using AI tools in patient interactions").

Adaptive Emotion Regulation (ER) is defined as the ability to manage emotional responses effectively in response to AI-related clinical challenges. Five items adapted from Emotion Regulation Questionnaire (ERQ) developed by Gross (2015) reflect reappraisal, suppression, and emotional clarity regarding AI interaction (e.g., "I manage my emotional responses to AI systems by changing the way I think about the technology's role in my work").

Perceived improvements in efficiency (PIE) refers to the extent to which clinicians deliver personalized, responsive, and ethically grounded care using AI systems. Indicators (five items adapted from Tortorella et al. (2022) reflected perceived improvements in care quality, patient engagement, and outcome alignment (e.g., "The implementation of AI tools has significantly optimized the time taken for patient admission to discharge, leading to perceived operational efficiency in our hospital").

The items were then evaluated using an exploratory factor analysis (EFA) to ensure their content validity and contextual adaptations for scale development in the UAE's healthcare industry. Since the dimensionality of constructs may differ when translating an instrument/item into a new population or context (Hurley et al., 1997), EFA is suitable for identifying factors before testing a conceptual model (Fabrigar et al., 1999).

Table 1
Item description of independent and dependent variables.

No.	Item description	Author(s)
Responsible AI		
1	I feel that actions of AI have a positive impact on healthcare practitioners and patients. (Beneficence)	Wang et al. (2023)
2	AI has enough security measures to protect patients' personal information. (Non-Maleficence)	
3	AI technology makes me feel that my work-related decisions reflect what I really want. (Autonomy)	
4	The process by which AI facilitated decisions was fair. (Justice)	
5	The communication about AI technology in my hospital is transparent. (Explainability)	
6	The relevant information about AI technology is shared among all healthcare practitioners in my hospital. (Explainability)	
Improved Operational Efficiency		
1	In my experience, the use of AI technologies has effectively reduced the rate of patient readmissions for the same condition within 30 days after discharge.	Tortorella et al. (2022)
2	I believe that AI-assisted care has contributed to a noticeable decrease in adverse events occurring among patients during their hospital stays	
3	The implementation of AI tools has significantly optimized the time taken for patient admission to discharge, leading to improved operational efficiency in our hospital.	
4	In my opinion, AI technologies have improved communication and responsiveness within hospital services, positively impacting patient satisfaction and operational workflow.	
5	I believe that the hospital effectively utilizes AI to enhance operational efficiency, leading to a reduction in incidents such as new infections or postoperative complications.	
Adaptive Emotion Regulation		
1	I manage my emotional responses to AI systems by changing the way I think about the technology's role in my work. (Reappraisal)	Gross (2015)
2	When I want to feel less negative emotion regarding AI decisions, I reframe my thoughts about AI's capabilities and limitations. (Reappraisal)	
3	When I want to feel more positive about using AI, I focus on the benefits it brings to my workflow and patient care. (Reappraisal)	
4	When I encounter challenges with AI systems, I consciously think about the situation in a way that helps me maintain a constructive attitude towards technology. (Suppression)	
5	When I experience negative emotions related to AI (such as fear or skepticism), I refrain from voicing them to my colleagues. (Suppression)	
Mindfullness		
1	I am mindful of the potential future implications of AI in healthcare. (Attention)	Feldman et al. (2007)
2	I can accept the limitations of AI technologies in certain medical situations. (Present Focus)	
3	It's easy for me to keep track of my thoughts and feelings about AI's effectiveness in my work. (Awareness)	
4	I am able to focus on the present moment when using AI tools in patient interactions. (Acceptance)	
5	I am able to pay close attention to the ethical considerations of AI applications for a long period of time. (Acceptance)	

4.4. Data collection procedure

Data was collected through an online survey platform distributed via hospital networks and professional associations. The instrument was first pilot tested with 30 healthcare professionals to ensure linguistic clarity, contextual fit, and item comprehension. Minor revisions were made prior to full deployment. To ensure content validity, a panel of five experts in medical technology, AI ethics, and clinical operations reviewed all measurement items. Internal consistency was assessed through Cronbach's alpha and composite reliability (CR).

4.5. Data analysis approach

Partial least squares-structural equation modelling (PLS-SEM) is suitable for predictive modelling and exploratory theory testing and was conducted using WarpPLS 8.0. The measurement model was evaluated for internal consistency using Cronbach's Alpha and CR (threshold > 0.70), with convergent validity established through average variance extracted (AVE, > 0.50) and discriminant validity via the Fornell-Larcker criterion. Full collinearity variance inflation factor (VIF) values were checked to ensure that multicollinearity remained below 5. Jarque-Bera and robust Jarque-Bera tests were applied to assess normality. Structural model assessment included examining path coefficients, t-values, R^2 and Q^2. No other higher order formative constructs were used in this study. These results were used to evaluate the proposed hypotheses by confirming the strength, direction, and significance of each structural path. The significance and strength of structural paths were used to test each hypothesis, confirming relational directionality and model fit. The observed effect sizes (f^2) ranged from 0.21 to 0.64. According to Cohen's guidelines, an f^2 of 0.02 is considered small, 0.15 is medium, and 0.35 is large. Hence, the predictors in this model contributed medium to large explanatory power to their respective dependent constructs. These values further reinforced the practical importance of the tested relationships, beyond their statistical significance. Additionally, f^2 effect sizes and mediation tests for H4a and H4b were conducted to assess indirect effects and explanatory power.

4.6. Reliability and validity controls

To minimize common method bias, procedural controls included anonymous participation, counterbalancing of question order, and neutral phrasing. Furthermore, Harman's one-factor common method bias (CMA) test confirms that the study does not display a common method bias issue (Fuller et al., 2016), as the single component explains less than 50 % of the variance. No common latent factor test was applied, as the study employs established constructs and multiple preventive measures at the design stage. Statistical assessment involved computing full collinearity VIF values, which were all below the conservative threshold of 2.5. Bootstrapping with 500 resamples and residual diagnostics ensured the robustness of the estimates. The model demonstrated strong internal consistency (CR > 0.80), convergent validity (AVE > 0.50), and discriminant validity. The explained variance for endogenous variables (R^2) and their predictive relevance (Q^2) all exceeded 0.60. Normality was confirmed using both Jarque-Bera and robust Jarque-Bera tests.

5. Results

5.1. Descriptive analysis

Descriptive statistics are reported in Table 2. According to the data collected, 54.3 % of the healthcare professionals were females, with majority of them aged 30–50. Regarding work experience, 74 % of them had more than five years. The respondents were from various job roles, including para-medical staff and nurse (52 %), doctor (20 %), administrators (12 %) and medical IT staff (10 %). The distribution of participation across various job roles might influence how AI is used. Education levels were high as expected, with 34 % of the respondents holding a master's degree, 46 % with a bachelor's degree, and 9.3 % holding a PhD. The high educational levels of the participants indicate that the sample consists of highly skilled professionals capable of making sound decisions. Finally, more than half of the professionals (52.3 %) were employed in firms with 250–500 employees, while 26 % worked with less than 250 employees.

Table 2
Descriptive statistics.

Demographic Profile of respondents		**Pilot Study**	**Main Study**	**Main Study (%)**
Gender	Male	13	137	45.7
	Female	17	163	54.3
Age	20–30 years	8	36	12.0
	30–40 years	17	89	29.7
	40–50 years	3	103	34.3
	Over 50 years	2	72	24.0
Job Role	Administrator	5	36	12.0
	Doctor	4	60	20.0
	Medical IT Staff	5	30	10.0
	Nurse	6	72	24.0
	Para-medical Staff	9	84	28.0
	Others	1	18	6.0
Work Experience	Less than 5 years	4	78	26.0
	5–10 years	7	54	18.0
	11–15 years	13	72	24.0
	Over 15 years	6	96	32.0
Level of Education	High school/ Diploma	7	32	10.7
	Bachelor's degree	11	138	46.0
	Master's degree	9	102	34.0
	Doctorate	3	28	9.30
Number of employees in the Organization	Below 250	7	78	26.0
	250–500	16	157	52.3
	500–1000	5	37	12.3
	More than 1000	2	28	9.4

Table 3 reports the means, standard deviations and Pearson product-moment correlations for the constructs.

5.2. Measurement model assessment

The measurement model was evaluated using established reliability and validity criteria. All constructs met acceptable reliability thresholds, with Dijkstra's rho values ranging between 0.788 for ER and 0.956 for PIE (see Table 4). CR values ranged from 0.854 (ER) to 0.966 (PIE), with Cronbach's alpha consistently above 0.78. Convergent validity was confirmed through AVE values exceeding 0.60 for RAI, MP, and PIE, while ER marginally satisfied the threshold at 0.539, which remained acceptable due to high CR. All indicator loadings were statistically significant ($p < 0.001$), with the majority exceeding 0.70. Cross-loadings remained below the respective primary loadings, indicating indicator specificity.

Discriminant validity was established using the Fornell–Larcker (1981) criterion. The square root of AVE (diagonal values) for each construct exceeded the corresponding inter-construct correlations (off-diagonal values), as shown in Table 5.

Heterotrait-monotrait (HTMT) ratios further confirmed discriminant validity, with all values falling well below the conservative 0.85 threshold. Specifically, the HTMT range was between 0.70 and 0.83 for RAI with other constructs, 0.70 and 0.80 for MP, 0.74 and 0.89 for ER, and 0.70 and 0.83 for PIE. Full collinearity VIF values ranged between 2.3 and 2.9, indicating no significant multicollinearity concerns.

5.3. Combined loadings and cross-loadings

To further verify indicator reliability and construct specificity, combined loadings and cross-loadings were examined. All primary loadings remained well above 0.70 for their respective constructs and were statistically significant at $p < 0.001$. Cross-loadings with non-target constructs remained low, indicating adequate discriminant validity at the item level. Standard errors (SEs) for loadings were consistently low, below 0.053, supporting the stability of the measurement indicators. The detailed results for both loadings and cross-loadings are

Table 3
Means, standard deviations and Pearson correlations.

	Variables	Mean	SD	1	2	3	4	5
1	Responsible AI	3.26	0.77					
2	Mindfulness Practices	2.26	0.74	0.728**				
3	Adaptive Emotion Regulation	2.49	0.78	0.739**	0.635**			
4	Perceived Improvement in Ffficiency	2.25	0.81	0.763**	0.668**	0.726**		
5	Firm age[a]	1.19	0.39	-0.024	-0.023	-0.010	-0.020	
6	Firm size[a]	4.73	2.58	-0.120*	-0.111	-0.061	-0.053	0.341**

Note: [a]Log10, BG- Business Group, n = 300, Two-tailed tests. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table 4
Summary of Measurement Model Results.

Variable	Composite reliability (cr)	Cronbach's alpha	Ave	Dijkstra's rho_a	Plsc loadings range
Responsible ai (rai)	0.904	0.872	0.610	0.873	0.715 – 0.761
Mindfulness practices (mp)	0.952	0.937	0.798	0.937	0.834 – 0.893
Emotion regulation (er)	0.854	0.785	0.539	0.788	0.598 – 0.778
Perceived improvement in efficiency (PIE)	0.966	0.955	0.849	0.956	0.890 – 0.926

Table 5
Fornell–Larcker Criterion.

Variable	**RAI**	**MP**	**ER**	**PIE**
RAI	0.781	0.729	0.740	0.764
MP	0.729	0.893	0.636	0.668
ER	0.740	0.636	0.734	0.726
PIE	0.764	0.668	0.726	0.921

presented in Table 6.

5.4. Structural model assessment

The structural model explained a substantial proportion of the variance in the endogenous constructs. Specifically, the model accounted for 55.3 % of the variance in MP ($R^2 = 0.553$; $Q^2 = 0.553$), 55.7 % in ER ($R^2 = 0.557$; $Q^2 = 0.558$), and 67.0 % in PIE ($R^2 = 0.670$; $Q^2 = 0.670$). These results indicated moderate explanatory and predictive power for all dependent variables.

All direct relationships were statistically significant at $p < 0.001$ (Table 7). The strongest observed direct effect was from RAI to ER ($\beta = 0.747$), followed by RAI to MP ($\beta = 0.570$) and RAI to PIE ($\beta = 0.412$). Positive and significant relationships were also found between MP and ER ($\beta = 0.216$), MP and PIE ($\beta = 0.183$), and ER and PIE ($\beta = 0.312$). These relationships indicated that RAI has both direct and indirect influences on PIE, with MP and ER acting as intermediary pathways.

Table 6
Combined Loadings and Cross-Loadings.

Indicator	RAI	MP	ER	PIE	SE	P-value
RAI_1	0.806	-0.023	0.101	-0.055	0.051	< 0.001
RAI_2	0.748	-0.076	-0.138	0.073	0.051	< 0.001
RAI_3	0.797	0.060	0.098	-0.074	0.051	< 0.001
RAI_4	0.748	-0.032	0.006	0.146	0.051	< 0.001
RAI_5	0.800	-0.013	-0.045	0.037	0.051	< 0.001
RAI_6	0.783	0.077	-0.039	-0.117	0.051	< 0.001
MP_1	-0.098	0.891	0.097	-0.051	0.050	< 0.001
MP_2	-0.072	0.894	-0.046	0.042	0.050	< 0.001
MP_3	0.027	0.898	-0.059	0.011	0.050	< 0.001
MP_4	0.119	0.895	-0.004	-0.045	0.050	< 0.001
MP_5	0.014	0.888	0.013	0.043	0.050	< 0.001
ER_1	-0.149	-0.075	0.778	0.117	0.051	< 0.001
ER_2	0.308	-0.130	0.690	-0.101	0.052	< 0.001
ER_3	0.032	-0.024	0.771	-0.044	0.051	< 0.001
ER_4	0.015	0.066	0.751	0.017	0.051	< 0.001
ER_5	-0.213	0.168	0.674	0.007	0.052	< 0.001
PIE_1	-0.085	0.049	0.072	0.923	0.050	< 0.001
PIE_2	-0.026	0.034	-0.028	0.918	0.050	< 0.001
PIE_3	0.086	-0.048	-0.001	0.922	0.050	< 0.001
PIE_4	0.107	-0.050	-0.065	0.918	0.050	< 0.001
PIE_5	-0.083	0.015	0.021	0.926	0.050	< 0.001

Notes: loadings are unrotated and cross-loadings are oblique-rotated. SE and p-values correspond to loadings. P-values < 0.05 indicate significance for reflective indicators.

Table 7
Direct Effects Summary.

Relationship	Effect size (f^2)	P-value	Significant (yes/no)
RAI → MP	0.416	< 0.001	Yes
RAI → ER	0.557	< 0.001	Yes
RAI → PIE	0.319	< 0.001	Yes
ER → MP	0.665	< 0.001	Yes
MP → PIE	0.124	< 0.001	Yes
ER → PIE	0.228	< 0.001	Yes

5.5. Indicator weights

To assess the relative contribution of each indicator within its respective construct, indicator weights were examined (Table 8). All indicators demonstrated statistically significant weights ($p < 0.001$), satisfying the recommended threshold for reflective measurement models. The results indicated that the individual indicators contributed meaningfully to their latent constructs. For RAI, indicator weights ranged from 0.198 to 0.223, with standard errors (SE) consistently at 0.056 and VIF values remaining below 2.0, confirming the absence of multicollinearity. The MP indicators had slightly higher weights, ranging between 0.217 and 0.232, with VIF values between 3.0 and 3.4, within acceptable thresholds for reflective constructs. For ER, indicator weights ranged from 0.249 to 0.290, with SE below 0.056 and VIF values consistently below 1.7, supporting indicator reliability. The PIE indicators exhibited the highest VIF values, ranging from 4.2 to 4.6, reflecting greater inter-item association, but all indicator weights remained statistically significant and within acceptable interpretative limits. The table below summarizes the indicator weights, standard errors, p-values, VIFs, weight-loading sign (WLS), and individual effect sizes (ES) for all constructs.

5.6. Mediation effects

The mediation analysis provided further insights into the indirect relationships among the constructs (Table 9). RAI exhibited a statistically significant indirect effect on MP, with an indirect coefficient of 0.161 ($p < 0.001$). Additionally, RAI demonstrated a significant indirect

Table 8
Indicator Weights Summary.

Indicator	RAI	MP	ER	PIE	SE	P-value	VIF	WLS	ES
RAI_1	0.221	0.000	0.000	0.000	0.056	< 0.001	1.990	1	0.178
RAI_2	0.198	0.000	0.000	0.000	0.056	< 0.001	1.724	1	0.148
RAI_3	0.223	0.000	0.000	0.000	0.056	< 0.001	1.915	1	0.177
RAI_4	0.211	0.000	0.000	0.000	0.056	< 0.001	1.671	1	0.158
RAI_5	0.218	0.000	0.000	0.000	0.056	< 0.001	1.988	1	0.174
RAI_6	0.209	0.000	0.000	0.000	0.056	< 0.001	1.874	1	0.164
MP_1	0.000	0.217	0.000	0.000	0.056	< 0.001	3.232	1	0.193
MP_2	0.000	0.217	0.000	0.000	0.056	< 0.001	3.293	1	0.194
MP_3	0.000	0.223	0.000	0.000	0.056	< 0.001	3.421	1	0.200
MP_4	0.000	0.231	0.000	0.000	0.056	< 0.001	3.234	1	0.207
MP_5	0.000	0.232	0.000	0.000	0.056	< 0.001	3.094	1	0.206
ER_1	0.000	0.000	0.276	0.000	0.055	< 0.001	1.647	1	0.215
ER_2	0.000	0.000	0.262	0.000	0.055	< 0.001	1.373	1	0.181
ER_3	0.000	0.000	0.283	0.000	0.055	< 0.001	1.599	1	0.218
ER_4	0.000	0.000	0.290	0.000	0.055	< 0.001	1.493	1	0.218
ER_5	0.000	0.000	0.249	0.000	0.056	< 0.001	1.345	1	0.168
PIE_1	0.000	0.000	0.000	0.220	0.056	< 0.001	4.520	1	0.203
PIE_2	0.000	0.000	0.000	0.214	0.056	< 0.001	4.226	1	0.196
PIE_3	0.000	0.000	0.000	0.221	0.056	< 0.001	4.468	1	0.204
PIE_4	0.000	0.000	0.000	0.217	0.056	< 0.001	4.214	1	0.199
PIE_5	0.000	0.000	0.000	0.214	0.056	< 0.001	4.626	1	0.198

Notes: p-values < 0.05 and VIF < 2.5 are desirable for reflective indicators. WLS indicates the weight-loading sign (+1 for consistent signs). Es represents the individual indicator effect size.

Table 9
Indirect Effects Summary.

Outcome	Indirect effect from RAI	Indirect effect from MP	Indirect effect from ER
MP	0.161	—	—
PIE	0.337	—	0.039

effect on PIE, with a total indirect coefficient of 0.337 ($p < 0.001$), confirming its influence through mediating pathways. ER also played a mediating role, with a smaller but significant indirect effect on PIE, estimated at 0.039 ($p < 0.001$). These results suggested that both MP and ER mediated the relationship between RAI and PIE, strengthening the indirect pathways alongside the direct effects. In reflecting on the magnitude and the significance of these indirect pathways, while RAI does indirectly impact PIE, MP is far more important and an influential mediator. This suggests that while RAI strongly shapes users ER capabilities, the emotional processes translate only modestly into PIE outcomes.

Overall, the significant direct and indirect effects confirmed the hypothesized model structure, indicating the importance of both mindfulness and emotion regulation mechanisms in linking RAI to improved patient-centric outcomes.

5.7. Interpretation of results

The results confirmed statistically significant direct and indirect relationships between the variables under investigation. The structural model explained 55.3 % of the variance in MP, 55.7 % in ER, and 67.0 % in PIE, indicating adequate explanatory capacity. The direct paths from RAI to MP, ER, and PIE were significant, with the strongest coefficient observed between RAI and ER ($\beta = 0.747$). This further implies that in healthcare settings, RAI and PIE have a close statistical relationship, and changes in one variable are highly associated with changes in the other. Additionally, both MP and ER contributed positively to PIE outcomes, supporting the proposed pathways.

The mediation analysis indicated significant indirect effects of RAI on PIE through MP and ER, with coefficients of 0.337 and 0.039, respectively. This implies that the effect of RAI does not reach PIE directly; instead, it first impacts MP and ER, which subsequently affect PIE. Overall, these results suggest that the influence of RAI on PIE operates both directly and indirectly through the mediating constructs. All hypothesized effects were significant at $p < 0.001$, with effect sizes (f^2) ranging from 0.124 to 0.557, supporting the relevance of these pathways. While this indicates strong explanatory power, it also underscores the importance of interpreting effect sizes alongside statistical significance.

Model fit indices, including Q^2 values exceeding 0.55, provided evidence of predictive relevance. Collectively, the empirical results are consistent with the hypothesized model, providing statistical support for the theorized relationships without any evidence of multicollinearity or indicator inconsistency.

6. Discussion and conclusion

The paper addresses a vital gap in understanding the effects of responsible AI (RAI) and its applications on healthcare professionals, specifically in terms of emotion control and mindfulness practices that promote quality of patient care and perceived operational efficiency. Responsible AI principles are integrated with an open innovation approach, where professionals can share insights on both technology and ethics, creating a culture where innovative solutions are developed responsibly (Kaur and Nagina, 2024). The findings indicate that perceived operational efficiency improves when healthcare professionals create empathetic and mindful attitudes aligned with ethical principles. When professionals attribute human-like qualities to AI and systems, their behaviors align more closely with desired ethical and performance outcomes, consistent with anthropomorphism theory (Song and Lin, 2023; Li et al., 2023; Van Pinxteren et al., 2019). In addition, commitment–consistency theory proposes that continuous engagement of healthcare professionals with AI systems to improve patient care adds value to productivity in healthcare (Adam et al., 2021). While our results show positive impacts of RAI, it's important to note that improper implementation of RAI could result in issues such as misaligned resource allocation, data errors, automation bias, accountability concerns, and diminished operational performance (Bürger et al., 2024).

Furthermore, the mindfulness practices of healthcare professionals have a significant effect on quality of care leading to perceived improvements in efficiency (PIE). Mindfulness helps healthcare professionals create compassionate ecosystems that offer customized healthcare services to patients (Zhang et al., 2023). Mindfulness enhances healthcare performance by encouraging healthcare professionals to engage with medical technologies in a more attentive and human-centered manner, fostering anthropomorphic perceptions that increase trust and effective use. This mindful human–technology interaction supports improved patient recovery outcomes (Khattab et al., 2021). Based on their interactions with RAI, patients can raise specific concerns to be addressed by healthcare professionals with an empathetic attitude to improve healthcare delivery (Nadarzynski et al., 2019).

Adaptive emotion regulation further mediates the relationships of RAI with PIE and mindfulness. The combination of RAI uses, and emotion regulation positively influences the mindfulness of healthcare professionals, resulting in mental wellness and workplace contentment (Bhattacharjee et al., 2024). Moreover, adaptive emotion regulation mediates the effects of RAI on faster patient recovery resulting into operational efficiency from a statistical significance perspective, even though the magnitude is relatively small, implying its secondary role and that mindfulness is far more an influential mediator. This could potentially be a result of the impact of mindful practices directly impacting work performance through focus, empathy, and individual motivation. Contrary to this emotional regulation (ER) supports mindfulness as evidenced by the smaller magnitude, though statistically significant. The substantially stronger indirect effect through mindfulness compared to ER also suggests that not all psychological mechanisms operate with equal influence on operational outcomes.

The overall findings provide a path for creating dynamic healthcare ecosystems in which healthcare professionals use RAI to develop unique treatment and wellness prototypes to ensure perceived improvement in efficiency. These findings can be viewed through the lens of open innovation dynamics at both macro and micro levels. At the macro level, RAI implementation in UAE healthcare reflects broader trends toward collaborative AI development among technology providers, regulators, and healthcare organizations (Zhang and Wang, 2021; West and Bogers, 2014). This ecosystem approach means healthcare professionals work with AI systems shaped by external input and transparency requirements. At the micro level, the mediating role of emotion regulation aligns with bounded rationality perspectives in open innovation research (Laursen and Salter, 2006). Healthcare professionals cannot fully grasp complex AI algorithms, so they develop adaptive emotional and cognitive responses to engage with these technologies practically (Yun et al., 2022). The positive link between RAI and mindfulness indicates that transparent, responsibly-developed AI lightens the cognitive load on professionals, enabling more deliberate interaction with technology.

6.1. Contribution

This study makes a compelling threefold contribution. *First*, this article is one of the early studies offering a conceptual framework linking RAI, mindfulness, emotion regulation, and perceived improvement in efficiency. In so doing, the study contributes to the literature on the ethical deployment of AI technologies in healthcare settings. By addressing the ethical and practical aspects of AI in healthcare, alongside the psychological constructs of mindfulness and emotion regulation, the study aims to enrich the existing body of knowledge and provide actionable insights for enhancing patient care practices within the healthcare system. *Second*, the study integrates anthropomorphism and commitment–consistency theory with AI technologies to suggest that RAI improves not only efficiency and innovation but also the holistic well-being of healthcare professionals. This dual theory approach is innovative and relevant in AI and business performance research. *Finally*, the empirical contribution fills a methodological void by strengthening the evidentiary base for developing strategies that promote mindfulness and emotion regulation among health professionals, resulting in perceived improvements in efficiency in the UAE healthcare system.

6.2. Managerial and policy implications

This study's managerial implications include the necessity for integrated training programs, the development of collaborative cultures, the prioritizing of ethical issues, and the establishment of ongoing evaluation frameworks. The healthcare organizations should prioritize training programs that cover both technical skills in AI applications and emotional wellness strategies, such as mindfulness and emotion regulation. Given the strong link between mindfulness and perceived efficiency, hospital management might benefit from investing in mindfulness-based training or stress-reduction initiatives alongside AI implementation efforts. In the meanwhile, making sure the AI systems are responsible (fair, transparent) and can support staff's emotional well-being. Moreover, developing a collaborative and open communication culture between AI systems and healthcare professionals can improve the acceptance and efficacy of AI technologies in clinical settings (Lai et al., 2020). Another critical implication is to ensure that ethical considerations are prioritized in the implementation of AI in healthcare. Abuadas and Albikawi (2025) argue that clear guidelines regarding informed consent, patient data privacy, and AI's role in clinician decision-making are vital for RAI applications. Last, managers can develop criteria and evaluations to assess AI's performance while also monitoring changes in healthcare delivery and provider well-being (Hilling et al., 2025). These steps may ensure that AI systems remain aligned with corporate goals of improving patient-centric care while also supporting healthcare professionals' mental well-being. By addressing these areas, healthcare professionals can facilitate the responsible and synergistic deployment of AI technologies, ultimately enhance operational efficiency in an evolving healthcare landscape. From an open innovation perspective, these findings suggest that healthcare organizations should attend to both external collaboration strategies and internal human resource development. Open innovation scholarship emphasizes that successful technology integration requires alignment between external knowledge sources and internal absorptive capacity (Cohen and Levinthal, 1990). Our results indicate that absorptive capacity in healthcare AI contexts involves not only technical skills but also psychological readiness, including mindfulness practices and emotion regulation capabilities.

6.3. Limitations and direction for future research

Like most studies, this study has limitations. *First*, because the research was conducted in the UAE, relationships may not extend to other settings, such as developing/developed countries; studies in these contexts are needed. *Second*, an explanatory research design was used. Future research could consider a robust mixed-methods research design that combines quantitative data (surveys measuring emotion regulation and mindfulness skills among healthcare providers) with qualitative case studies (interviews with professionals and patients interacting with AI tools). Such an approach would provide holistic insights into the mediating effects of mindfulness and emotion regulation on perceived improvements in efficiency and/or patient-centric performance. Third, future researchers may perform a comparative analysis of the findings in different cultural settings by adding potential moderating variables (like personality traits, individual-level differences, and organizational-level factors) and psychological covariates (such as burnout, perceived stress, and overall job satisfaction). For instance, personality traits like openness to experience and conscientiousness influence how healthcare professionals perceive ethical aspects of AI (e.g., transparency, fairness), allocate attention and awareness (mindfulness), and control their emotional responses to the uncertainty, moral tension, and workload that AI systems provide (Gross, 2015). Individual-level differences such as anxiety and avoidance (as attachment dimensions) interact with perceived emotion regulation (Domic-Siede et al., 2025a, 2025b). The psychological benefits of RAI may be increased in organizations with strong ethical cultures (Su and Hahn, 2022). Fourth, this study is limited by its small sample size. Future studies may use a larger sample to allow for generalization. *Finally*, longitudinal studies are recommended to understand the long-term effects of AI integration on operational efficiency/performance and the development of mindfulness and emotion regulation among healthcare practitioners. Such studies could reveal trends over time, providing deeper insights into the causal relationships between these variables.

In conclusion, the study investigates RAI – perceived improvements in efficiency relationship in the UAE healthcare sector by exploring whether emotion regulation mediates to improve healthcare professionals' mindfulness and operational efficiency. The findings carry important implications for the United Nations Sustainable Development Goals (SDGs) in healthcare. SDG 3, which focuses on Good Health and Well-being, benefits when healthcare professionals can use AI effectively without sacrificing the psychological wellness needed for compassionate patient care. SDG 8, centered on Decent Work and Economic Growth, gains ground when AI implementation supports rather than erodes professional autonomy and job satisfaction. The study's findings about the mediating roles of psychological constructs suggest a broader lesson: achieving these goals demands attention to human factors alongside technological implementation. Whether AI adoption proves sustainable and beneficial depends not just on the technology itself but on how well organizations support the people using it.

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Ethical Statement

This study was conducted in full compliance with established ethical standards for research involving human participants. All procedures followed the principles outlined in the Declaration of Helsinki.

Prior to data collection, the research protocol—including study objectives, instruments, data handling procedures, and participant recruitment methods—was reviewed and approved by the appropriate Institutional Review Board (IRB)/Ethics Committee.

Participation in the study was entirely voluntary. All participants were provided with a clear and comprehensive explanation of the study's purpose, procedures, expected duration, and potential risks and benefits. Informed consent was obtained before participation, and respondents were explicitly informed of their right to decline participation or withdraw from the study at any time. To protect participant privacy, no personally identifiable information was collected. Data were used solely for research purposes and analyzed in aggregate form. Moreover, the study adheres to principles of scientific integrity and responsible research conduct. Data were analyzed objectively, and findings are reported accurately and transparently.

CRediT authorship contribution statement

Amit Kumar: Methodology, Funding acquisition, Conceptualization. **P.S Varsha:** Visualization, Project administration, Formal analysis, Data curation. **Mahesh Joshi:** Writing – review & editing, Supervision, Resources, Project administration, Methodology. **Georges Samara:** Writing – original draft, Validation, Supervision, Investigation. **Arun Narayanasamy:** Writing – original draft, Visualization, Resources, Methodology, Investigation. **Saneesh Edacherian:** Writing – review & editing, Validation, Resources, Methodology.

Declaration of Generative AI and AI-assisted technologies in the writing process

I acknowledge that AI tools or technologies are not used to prepare this manuscript.

Declaration of Competing Interest

There is no conflict of interest.

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