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Clinical perspectives on AI integration: assessing readiness and training needs among healthcare practitioners

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ABSTRACT
The rapid advancement of Artificial Intelligence (AI) is transforming healthcare, offering both opportunities and challenges. This study examines the perceptions of healthcare practitioners in Wales regarding AI's role in diagnostics. Through semi-structured interviews with 10 expert practitioners from various specializations, it uncovers diverse views shaped by experience and second-hand knowledge. While AI is recognized for enhancing diagnostic accuracy and administrative efficiency, concerns persist about the loss of human touch, data security, and biases. A key finding is the unanimous call for comprehensive AI training to bridge knowledge gaps and build confidence. Using an interpretivist qualitative approach, with purposive sampling and thematic analysis, the study highlights nuanced practitioner perspectives. The findings underscore the need for equitable AI resource distribution and tailored training to address geographical disparities. The study advocates for future research with larger, more diverse samples and follow-up evaluations to assess AI training's long-term impact on healthcare practice.

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Artificial intelligence; innovation; healthcare; clinician; information systems; UTAUT

Introduction

The rapid growth and development of Artificial Intelligence (AI) across various sectors have instigated a surge of research studies focusing on its implications, advantages, and potential drawbacks. One of the most significant areas undergoing such a transformation is the healthcare sector, which grapples with both the opportunities and challenges posed by the integration of AI technologies. Healthcare practitioners are positioned at the frontline of these advancements, dealing with life-or-death situations daily, amidst ever-growing pressures due to resource constraints and patient influx (Blessed et al., 2019). Their unique position underscores the importance of understanding their perceptions and hesitations regarding AI, which ultimately can influence its acceptance, utility, and efficiency in real-world clinical settings.

AI offers substantial benefits in healthcare by addressing human limitations such as cognitive retention, potentially reducing human error and ensuring efficient knowledge

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transfer (Kilov, 2021; Radević et al., 2023). With advancements in processing power, AI can assimilate multiple datasets, providing healthcare practitioners with a comprehensive knowledge base to facilitate more precise, tailored treatment plans. This fusion of human intellect and AI is seen as crucial for achieving key healthcare objectives (Maddox et al., 2019).

AI also reduces unnecessary alarms and lightens the workload for healthcare providers, minimising resource usage, hospital strain, and time spent on unnecessary procedures. This allows practitioners to focus on critical tasks, ultimately improving healthcare delivery (Kitsios et al., 2023). By managing the influx of biomedical data, AI enhances efficiency in clinical environments (Khan et al., 2020). An example is CURATE.AI, which optimises chemotherapy doses using patient data, demonstrating success in lowering doses and improving patient outcomes compared to standard care (Blasiak et al., 2022). These advances underscore AI's potential to augment decision-making and overall healthcare efficiency

However, alongside these optimistic views, there are reservations. Sceptics point to AI's diagnostic limitations (Oh et al., 2019), particularly its inability to account for the nuanced understanding and intuition that physicians develop through years of experience. For instance, physicians may feel that their professional autonomy is compromised when AI systems are required for consultation before making decisions, potentially imposing ethical obligations. This challenge is further compounded when physicians must explain or clarify diagnoses generated by AI systems that they neither fully understand nor agree with (Witkowski et al., 2024)., AI may struggle with rare or complex cases where sufficient training data is lacking, leading to diagnostic inaccuracies and further scepticism about its widespread adoption (Hallowell et al., 2022).

In addition to the diagnostic challenges, there are broader potential governance issues, and concerns about AI's ability to reflect human empathy and provide comprehensive explanations for its diagnostic conclusions (Lysaght et al., 2019). These concerns highlight the risks associated with AI's reliance on potentially biased datasets (Zou & Schiebinger, 2021), which can lead to inaccurate or non-inclusive solutions, as evidenced by systems like MYCIN (Giles & Smith, 2021). Furthermore, the looming question of responsibility, in cases of AI-driven misdiagnoses, further exacerbates hesitations (Verdicchio & Perin, 2022).

While an extensive body of literature discusses the capabilities and shortcomings of AI, there is a gap concerning the perceptions and experiences of those at the coalface of these changes – the healthcare practitioners (Al Kuwaiti et al., 2023; Alowais et al., 2023; Aung et al., 2021; Kitsios et al., 2023; Ueda et al., 2024). Their perspectives play a crucial role in shaping the integration of AI into healthcare, influencing patient care, practitioner responsibilities, and overall healthcare outcomes.

The motivations for this study are thus multi-fold: Firstly, addressing the existing knowledge gap is crucial. In 2019, the SHAIP (Shinners Artificial Intelligence Perception) questionnaire was developed through an Australian e-Delphi study involving 252 healthcare professionals. Unlike other tools, it exclusively addresses healthcare professionals' perceptions of AI. The findings highlighted low ratings in both 'comfort' and 'perceived capability' for AI applications in health, emphasising the need for a better understanding in this complex healthcare domain. The literature suggests a lack of clarity among healthcare professionals and organisations about AI, hindering their ability to form positive or negative perceptions (Shinners et al., 2022). Despite the abundant literature on AI in healthcare, there's a noticeable absence of in-depth studies focusing on healthcare practitioners' views, the primary stakeholders who will interface with AI systems (Khan et al., 2020).

Secondly, delving into the fundamental reasons shaping practitioners' perceptions of AI is vital. Medical professionals, including doctors and nurses, exhibit reluctance towards Health Information Technology (HIT). The primary perceived concerns for physicians and nurses involve the potential loss of professional autonomy. Additionally, five factors influencing these apprehensions are recognised: knowledge in the field, support from management, user engagement, system performance, and social influences (Alohali et al., 2020). Consequently, through direct engagement with healthcare professionals, this research seeks to reveal the underlying sentiments regarding AI incorporation, transitioning from general perspectives to precise, actionable understandings.

Promotion of AI-practitioner synergy is another critical motivation. Preconceived uncertainties and anxieties arising from misinformation have been present amongst healthcare practitioners for an extended period. Ambiguity persists regarding the advantages and drawbacks of AI. Moreover, threats of a changing work environment add to their resistance (Buck et al., 2022). Therefore, addressing these sentiments and educating healthcare practitioners about AI can potentially encourage an AI-practitioner partnership, ensuring the best possible patient care outcomes.

Understanding healthcare professionals' perceptions of AI is crucial, as their acceptance and willingness to engage with this technology will ultimately shape its successful implementation in healthcare. As previous studies have shown, there are various barriers and enablers to AI adoption, ranging from concerns about professional autonomy to the perceived complexity of AI systems. In this context, it is important to identify the factors that influence these perceptions to help guide effective AI integration.

To guide the exploration of these perceptions and the factors influencing the adoption of AI in healthcare, this study will view the results through the lens of the Unified Theory of Acceptance and Use of Technology (UTAUT2) (Venkatesh et al., 2012). UTAUT2 provides a comprehensive framework for understanding technology acceptance by evaluating key constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions. This framework is particularly relevant in healthcare, where the successful adoption of AI depends not only on the technology's capabilities but also on how well it aligns with practitioners' workflows, expectations, and support structures (Barchielli et al., 2021; Shiferaw et al., 2021).

Recent technological developments have aimed to implement various usage of AI systems, ranging from diagnostics to surgery. This research focuses on the use of AI in diagnostics; more specifically, it focuses on the use of AI through these Clinical Decision Support Systems (CDSS), such as electronic Modified Early Warning Scorecard (eMEWS), to improve patient care and decision-making processes. By assessing healthcare practitioners' current viewpoints on AI, systems can be put in place to aid in addressing the fears, doubts, and uncertainties they have expressed towards the implementation of AI. Consequently, this would allow for conversations surrounding their willingness and readiness to work alongside AI to be explored further.

From 2007 to 2014, researchers conducted a study to assess the advantages of employing e-health systems in the Canadian healthcare sector. This study focused on the practical utilisation of the clinical decision support system (CDSS). The results showed 63.8% of healthcare providers utilised a CDSS at work, marking a six-fold increase since 2007. Further results showed that in 2014, younger physicians across all age groups demonstrated a higher adoption rate of CDSS in their practices (Razmak et al., 2018). An electronic Modified Early Warning Scorecard (eMEWS) prototype was created to serve as a computerised CDSS, aiding healthcare professionals in decision-making activities (Zarabzadeh et al., 2013). Following this study, recommendations were proposed to enhance technological infrastructure and bridge gaps related to age, gender, and speciality (Razmak et al., 2018).

The advent of AI within the healthcare sector has generated extensive academic discourse over the past few years. On one hand, the potential of AI to streamline operations, augment diagnosis, and facilitate efficient knowledge transfer is celebrated (Blessed et al., 2019; Kumar et al., 2023; Maddox et al., 2019). Conversely, concerns emerge around its diagnostic benefits, with some contending its value lies chiefly in administrative task automation (Oh et al., 2019). Additionally, issues like potential biases, lack of explainability, and governance gaps further punctuate the debate (Gillies & Smith, 2022; Oh et al., 2019; Zou & Schiebinger, 2021). Amidst this vast landscape of AI potentialities and challenges, the perceptions of healthcare practitioners – those on the frontline of care delivery – remain insufficiently explored. As healthcare undergoes this transformative phase, understanding their viewpoints becomes paramount, forming the crux of this study.

The following sections of this paper will delve into the methodology employed to capture the nuanced perspectives of healthcare practitioners, detailing the sampling techniques and data collection processes used to ensure comprehensive insights. The results section will present the key findings, highlighting themes and sub-themes identified through thematic analysis. This will be followed by a discussion that contextualises these findings through UTAUT2 addressing both the potential and challenges of AI integration in healthcare. Finally, the conclusion will summarise the study's contributions and propose practical implications and recommendations for future research and policy development.

Methodology

To gain authentic insights into practitioners' perceptions, we employed a flexible research philosophy that allowed participants to freely express their opinions in a comfortable environment during the field study (Bowen et al., 2009). Therefore, the study utilised an interpretivist approach, focusing on understanding the perceptions of healthcare practitioners in Wales regarding the use of AI in their field.

Purposive sampling was utilised in this study, as a mechanism to ensure participants can offer deep, contextual insights, aligned with the research objectives (Zickar & Keith, 2023). This technique is especially valuable in healthcare, where the diversity of expertise and experience across various roles makes it crucial to select participants who can provide nuanced, context-rich insights into the complexities of the field (Petersson et al., 2022). Purposive sampling enabled a deep understanding from participants who shared specific characteristics or experiences (Baltes & Ralph, 2022), in this case, those connected within a church community. The selection from the church community not only facilitates access but also draws on the shared experiences and trust built over 4 years, likely enhancing the candour and richness of responses. Moreover, their rich, contextual insights align with the research's aims. Inclusion criteria for interviewees focused on geographic location, preferably in Wales, and demographic characteristics, mainly age, gender and ethnicity. Exclusion criteria focused on ethical considerations where participants were able to give informed consent.

Wales was chosen for this study due to its approach to AI adoption in healthcare. Unlike England, which has seen rapid integration of AI technologies supported by initiatives like the NHS AI Lab, Wales has focused more on piloting and testing AI solutions. This slower adoption provides a distinct context where healthcare professionals may have different experiences and perceptions compared to those in England. By selecting Welsh participants, the study aimed to capture insights from a healthcare system still in the early experimental stages of AI implementation, allowing for a deeper understanding of potential challenges and benefits before full integration.

Data was collected over 2 months (June–July 2023) using open-ended questions during semi-structured interviews. These interviews, influenced by the guidelines, were strategically conducted both in person and through digital platforms like Microsoft Teams to accommodate participant preferences and logistical considerations (Zickar & Keith, 2023).

To ensure a holistic understanding, the interview questions were designed to capture a wide range of insights, including practitioners' roles, training, and exposure to AI. Thematic analysis was deployed to identify recurring themes and patterns which could offer insights into shared and divergent perceptions among participants whilst providing flexibility and adaptability (Braun & Clarke, 2006; Timonen et al., 2018; Zickar & Keith, 2023). This method enabled the extraction of shared experiences and unique perspectives from the data.

Informed consent was obtained from all participants, and their anonymity was maintained using coded names. By balancing methodological rigour with ethical considerations and participant inclusivity, the research design provided a comprehensive framework that aligned with the study's objectives.

Participants

The study involved semi-structured interviews, ranging from 35 to 60 minutes, with 10 expert healthcare practitioners from different regions in Wales. Participants comprised a Dermatologist, an ENT specialist registrar, two General Practitioners, a Gynaecologist, a Neurologist, and a Cardiologist. These professionals were selected to offer a wide-ranging perspective on the use and implications of AI in diverse medical specialities. Their distinct roles and specialisations ensured a comprehensive understanding of healthcare professionals' viewpoints on AI integration across various branches of medicine. Table 1 provides additional information of the chosen interview participants.

Table 1. Interviewee profile.

Code	Job Title/specialism	Years of Experience	City	Interview style	Interview duration (Minutes)
BB1	Dermatologist	3	Tenby	In person	35
SD2	ENT specialist registerer	9	Swansea	In person	45
LC3	General practitioner	4	Cardiff	Via Teams	60
PR4	Gynaecologist	2	Bangor	Via Teams	40
EC5	Neurologist	17	Neath	In person	50
EF6	General practitioner	1	Bridgend	In person	40
TM7	Cardiologist	12	Wrexham	Via Teams	30
JP8	General Practitioner	5	Swansea	Via Teams	30
PF9	General Practitioner	10	Swansea	In person	25
SJ10	Surgeon	15	Cardiff	Via Teams	35

Data collection

The data collection method employed in this study utilised semi-structured interviews with 10 healthcare practitioners situated across Wales. To ensure accuracy and authenticity, the interviews were digitally captured and later transcribed verbatim. This qualitative approach facilitated an in-depth exploration of practitioners' perceptions regarding the role of AI in healthcare. The interviews provided flexibility, allowing participants to freely express their perspectives within a structured format. To maintain the privacy and confidentiality of the participants, all data collected were anonymised. The choice of semi-structured interviews combined with digital capture and subsequent anonymisation ensured both the reliability and ethical integrity of the gathered data. Table 2 shows the questions posed to participants.

Table 2. Interview questions.

(1) Describe your role as a healthcare practitioner.
(2) What is your perception of AI?
(3) Describe the ways you are aware AI is used in hospitals.
(4) At university did any modules include explanations or use cases of how a healthcare practitioner can work alongside AI?
(5) At the hospitals you have previously worked at, was AI applied in any capacity?
(6) Have you received training on how to work alongside AI?
(7) Would you be willing to be trained on how to work alongside AI?
(8) At what stage of your journey to becoming a healthcare practitioner would you have wanted to be exposed to AI?

Data analysis

The data analysis for this study employed the UTAUT2 framework as a theoretical lens. By examining the transcribed interviews, the core constructs of UTAUT2—such as performance expectancy, effort expectancy, social influence, and facilitating conditions – were used to identify and analyse patterns in healthcare practitioners' perceptions of AI in healthcare (Figure 1). While gender and age were not collected, and although years of experience were recorded, the limited number of interviews did not allow for in-depth analysis through comparisons of experience with participants' views. This approach still enabled a structured understanding of the factors influencing AI adoption, highlighting both unconscious biases and evolving attitudes among the participants.

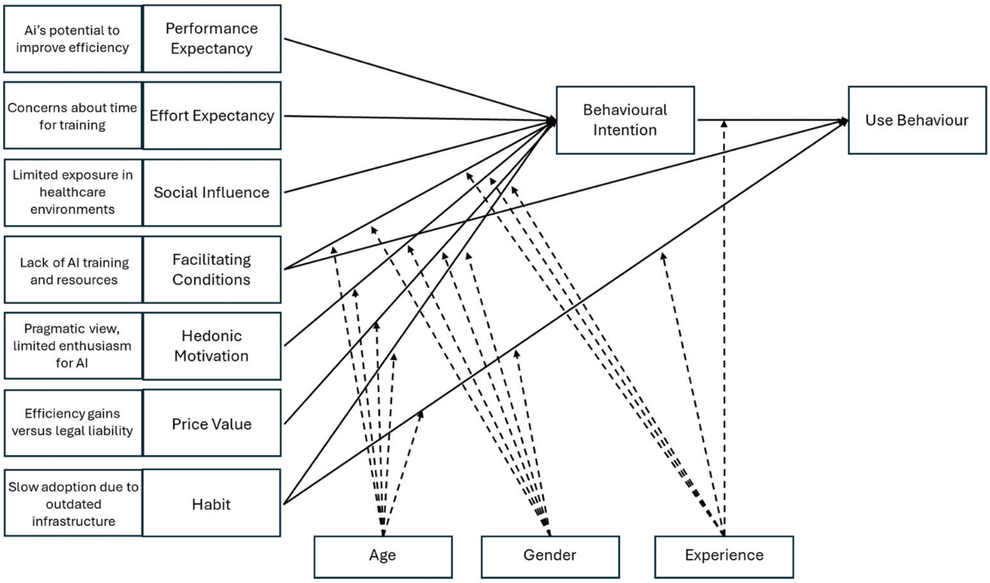

Figure 1. UTAUT2 model where solid lines represent the factors identified in the thematic analysis and dotted lines indicate factors of the model not considered in the analysis. Examples from the thematic analysis are aligned with corresponding UTAUT2 constructs.

Results

Performance expectancy

Participants' perceptions of AI's potential to improve healthcare performance were varied. Many, despite lacking direct experience with AI, recognised its potential to enhance efficiency and clinical outcomes. For example, PR4 mentioned, 'AI could assist in clerical work, speeding up patient information input', aligning with the performance expectancy construct of UTAUT2—AI's ability to improve job performance. Similarly, EC5 reflected, 'By implementing AI in hospitals, the intention is to empower me to provide better care options to my patients', indicating a belief in AI's capacity to improve clinical effectiveness. However, concerns about AI's impact on the human aspects of care were raised. SD2 warned, 'I think we stand the risk of dehumanising patient care', reflecting a common fear that AI, while improving efficiency, could diminish the personal connection between healthcare providers and patients. Additionally, the absence of firsthand experience often led to scepticism about AI's real-world benefits. PF9 remarked, 'People make AI out to be some utopian dream that's going to solve all our needs', highlighting both optimism and doubt. This suggests that while performance expectancy for AI is high in theory, its perceived practicality is limited by lack of exposure.

Effort expectancy

Participants expressed concerns about how difficult it might be to work with AI systems, which corresponds to effort expectancy in UTAUT2. For instance, BB1 noted, 'I understand that in more routine cases, AI would save me a lot of time. My worry would be that I do not have the time to complete the training if it is not as flexible and cannot work with my current schedule'. This reflects a common concern about balancing the potential time-saving benefits of AI with the time investment required for training. Similarly, EC5 said, 'At this age, I don't know if I will be able to pick up on how to work with AI, but I am willing to give it a shot if it makes routine work easier'. Both statements capture the dual nature of effort expectancy – the fear of the complexity of learning AI but the willingness to try if it simplifies tasks. SD2, despite being 'not technically inclined', was also open to training, provided it didn't impose continuous burdens: 'I would prefer that the training could be completed during chosen intervals because continuous training would put pressure on me'. These responses emphasise the importance of reducing perceived difficulty and offering flexible training programmes to support AI adoption for healthcare professionals.

Social influence

The impact of social influence, where the opinions of peers and supervisors affect the acceptance of technology, was less explicitly addressed in the interviews but can be inferred. Most participants, such as SD1, discussed AI based on external sources like media or hearsay, saying, 'It feels more futuristic than real'. This reliance on second-hand information rather than the guidance of colleagues suggests a gap in peer or institutional encouragement, which could be critical in shaping healthcare professionals' perceptions of AI. The lack of exposure to AI within healthcare settings was a recurring theme. EF6 noted, 'At the hospitals where I worked, I did not witness Human-AI interaction'. This absence of AI exposure in professional environments could contribute to lower social influence towards AI adoption.

Facilitating conditions

The availability of resources and institutional support for AI adoption, key elements of facilitating conditions, was a significant concern for participants. Many had not received any formal training on AI. EF6 stated, 'Modules taught at university did not mention anything regarding the use of AI in hospitals', highlighting the absence of facilitating conditions during educational training. Similarly, several participants, including PR4, noted that their hospitals had not applied AI in any capacity, further underscoring the lack of support structures. Despite this, participants were generally open to receiving training, as seen in TM7's pragmatic response: 'If working alongside AI makes my work easier, why would I not want to learn more?' This illustrates the potential to strengthen facilitating conditions through adequate training and institutional support.

Hedonic motivation

Hedonic motivation, or the enjoyment and satisfaction derived from using new technology, was not a dominant theme in the participants' responses. Most viewed AI pragmatically, focusing on its potential to improve efficiency rather than deriving pleasure from its use. LC3 reflected this practical stance, stating, 'Things are always changing in medicine, and we all need to be open to change. If there are changes that can help us practice better, we should know about it to help our patients'. This highlights an openness to technological advancements for the sake of improved patient care, rather than personal enjoyment.

Conversely, some participants expressed scepticism about AI's ability to replicate the human elements of healthcare, which further suggests that hedonic motivation was not a significant factor. SD2 remarked, 'Medicine is an art and science; I do not believe AI can do it alone', emphasising the irreplaceable value of human judgement and intuition. Similarly, PR4 commented, 'No matter how advanced it is, I do not think AI has the ability to mimic human characteristics such as empathy, compassion, and intuition'. These sentiments indicate that while participants recognised AI's potential benefits, they did not anticipate deriving satisfaction or enjoyment from its use, especially if it threatened the humanistic aspects of their profession.

However, TM7's comment, 'If working alongside AI makes my work easier, why would I not want to learn more', suggests a willingness to engage with AI for practical benefits. This reflects a utilitarian motivation rather than hedonic pleasure. Overall, the responses indicate that enjoyment or excitement about using AI was not a primary driver for these healthcare professionals; instead, their focus was on how AI could practically support their work without compromising the essential human elements of care.

Price value

Although the price value in the traditional UTAUT2 sense (cost-benefit analysis) wasn't explicitly addressed in terms of financial costs, participants did consider the 'cost' in terms of time and effort. BB1, for instance, expressed being overwhelmed by the current workload but was willing to try AI if it could make their job easier: 'If something can make my life easier, I would be open to trying'. This indicates a perceived value in AI's potential to reduce the time spent on routine tasks, aligning with the concept of price value in terms of effort versus benefit.

Similarly, EC5 expressed a willingness to engage with AI despite concerns about their ability to learn it: 'At this age, I do not know if I will be able to pick up on how to work with AI but, I am willing to give it my best shot if it makes routine work easier'. This demonstrates the perceived benefit of AI in reducing routine burdens, even if there are concerns about the effort required to learn and adopt the technology.

However, BB1 also raised concerns about potential legal implications, reflecting a different aspect of price value related to risk: 'If the AI cannot be completely transparent about how it came up with a diagnosis, who is liable if it presents an inappropriate treatment plan?' This introduces the notion that the perceived value of AI must also account for legal risks and liabilities, not just time and effort. For healthcare professionals, the price value of AI extends beyond the immediate benefits of efficiency and includes the potential costs related to accountability and trust in AI's decision-making processes.

Habit

While habit – the automatic use of technology – was not explicitly mentioned, the lack of exposure to AI suggests that it has not yet become integrated into the daily routines of healthcare professionals. As JP8 noted, certain specialities like dermatology and radiology may be more amenable to AI integration, suggesting that in these fields, AI could become more habitual as it is gradually introduced into specific workflows.

BB1 provided a practical example of how AI could become part of the routine in high-pressure situations: 'When I am on ward cover, if there is an issue with the patient, then I suppose having the patient's information easily accessible using AI systems might reduce any delay in treatment rather than trying to look through records to understand the patient's condition'. This illustrates how AI could be routinely relied upon to quickly access critical patient data, potentially improving response times in urgent situations.

However, some participants highlighted how far behind their institutions are in adopting even basic digital solutions. EF6 remarked, 'We are very behind because we do not even yet have digital prescribing'. This indicates that in some healthcare settings, the lack of foundational digital infrastructure is a major barrier to AI becoming a habitual part of day-to-day practice.

Discussion

The results of this study aim to provide a deeper understanding of healthcare practitioners' perspectives on integrating AI into their professional practices. Drawing from a diverse pool of specialities, including Dermatology, ENT, General Practice, Gynaecology, Neurology, and Cardiology, the study revealed a complex mix of opinions, aspirations, and concerns. Geographical location played a significant role in shaping these perspectives. Practitioners based in metropolitan areas, who benefit from advanced technological infrastructure and progressive training environments, generally expressed a more favourable outlook towards AI. They envisioned AI as a tool that could enhance diagnostic precision, streamline administrative tasks, and improve patient care quality. In contrast, practitioners in smaller cities expressed more caution, highlighting deficiencies in training infrastructure and challenges in keeping pace with the rapid evolution of AI technologies.

This geographic divide underscores the importance of facilitating conditions, a key construct in the UTAUT2 model. Similarly, Huang (2024) found that facilitating conditions significantly influenced patient acceptance of AI in healthcare. This emphasises the role of resource availability in both patient and clinician adoption of new technologies. In this study, for healthcare professionals, particularly in smaller cities, the lack of resources and institutional support posed significant barriers to the effective integration of AI. This suggests that healthcare organisations need to ensure equitable access to AI training programmes and resources across different regions to bridge this gap. Schretzlmaier et al. (2023) expanded further on the UTAUT2 model and found that perceived disease threat and trust significantly influence technology acceptance, factors that are likely to be relevant for clinicians as they consider the potential risks and benefits of AI systems in patient care.

Across all participants, there was a unanimous call for comprehensive AI training programmes tailored to their specific needs. This highlights the importance of effort expectancy within the UTAUT2 framework. Many practitioners noted that their willingness to adopt AI depends on the perceived difficulty of integrating it into their existing workflows. Flexible, accessible training programmes that accommodate the demands of healthcare professionals' busy schedules could alleviate these concerns and help them build confidence in using AI (Schomakers et al., 2022). Alsahli et al. (2023) also underscored the importance of trust and perceived ease of use, emphasising that clinicians' confidence in AI's performance can make adoption more seamless. Owusu Kwateng et al. (2022) stress the importance of information quality as a moderator in the adoption of telemedicine, suggesting that providing high-quality, reliable information about AI systems could significantly impact clinicians' perceptions and acceptance.

Interestingly, while hedonic motivation played a significant role in a health technology (mHealth app) adoption among patients and general users (Schomakers et al., 2022), it was not a dominant factor for clinicians in this study. Clinicians in this research expressed practical, performance-based expectations rather than seeking enjoyment from using AI. This suggests that the utilitarian value of AI tools in improving clinical efficiency and patient care is more important to healthcare practitioners than any inherent satisfaction or pleasure in using the technology. This is consistent with findings from Owusu Kwateng et al. (2022), who also reported that performance expectancy plays a more critical role than hedonic motivation in influencing healthcare professionals' behavioural intention to adopt new technologies like telemedicine.

While practitioners acknowledged AI's potential to enhance job performance – especially in routine tasks – concerns remained about the impact of AI on the human aspects of care. Many participants expressed apprehension that AI, while improving efficiency, could never replicate the empathy, intuition, and compassion that are central to the patient–caregiver relationship. This ties into performance expectancy in UTAUT2. Although AI is expected to enhance efficiency, its introduction must be framed in a way that complements rather than replaces the human elements of healthcare delivery. Lambert et al. (2023) similarly highlighted concerns about AI replacing the human touch in healthcare, echoing the need for solutions that augment, rather than replace, human care.

Ethical concerns also featured prominently in the participants' responses, particularly regarding biases in AI algorithms and the risks of automating life-altering decisions. These apprehensions reflect social influence, another UTAUT2 construct, as the wider societal and professional discourse surrounding AI plays a significant role in shaping how healthcare practitioners perceive its integration. Practitioners' attitudes towards AI are influenced not only by their colleagues and institutional leaders but also by the broader ethical debates that arise within the public sphere. Addressing these concerns will require the development of robust ethical guidelines and governance frameworks to ensure that AI systems are transparent, accountable, and free from bias. Huang et al. (2024) also noted that stakeholder engagement is crucial in addressing these ethical concerns, suggesting that a more collaborative approach between policymakers and practitioners could ease the concerns of clinicians. Schretzlmaier et al. (2023) further emphasised the importance of trust in technology adoption, suggesting that without trust, clinicians may hesitate to adopt AI systems, especially for high-stakes clinical decision-making.

The findings of this study carry significant implications for both healthcare professionals and policymakers, as they hold the highest power of influence on the Power-Interest Matrix (Figure 2). The analysis highlights the disparity in AI readiness and acceptance between metropolitan and smaller city practitioners, underscoring the urgent need for equitable distribution of AI resources and training. Bridging these geographical gaps in AI exposure and education is essential for a seamless transition to an AI-integrated healthcare landscape. Policymakers and institutional leaders, identified as high-power

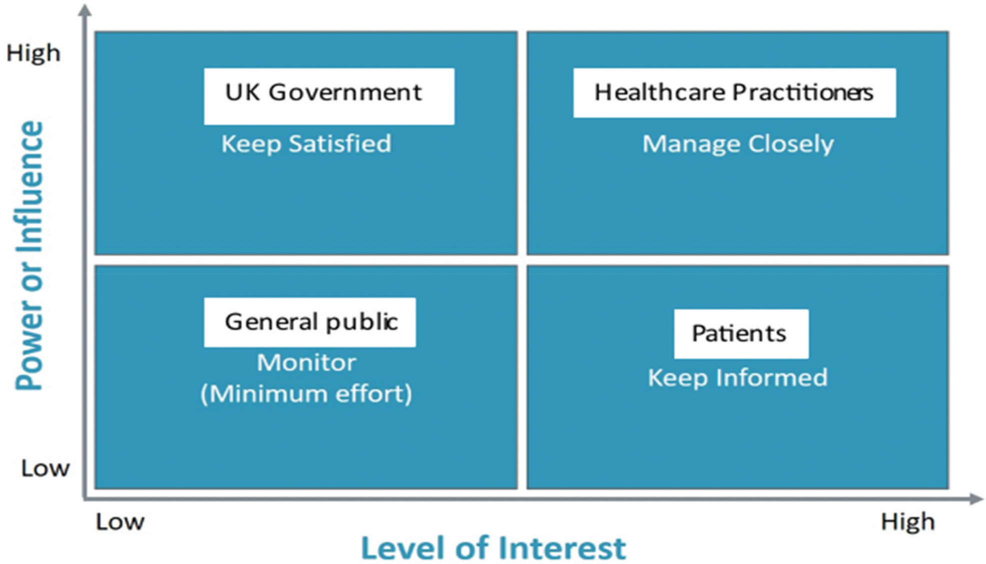

Figure 2. Power interest matrix.

stakeholders, must play a central role in ensuring that healthcare professionals across diverse regions have access to the necessary training and infrastructure to adopt AI effectively.

A key takeaway from the study is the pressing need for healthcare organisations and educational institutions to design specialised AI training programs. These programs must be tailored to the varying needs of healthcare professionals based on their roles, experience, and geographical location. As Lambert et al. (2023) argues, the potential of AI in healthcare will only be fully realised if clinicians are adequately trained and supported throughout the adoption process. This highlights the ongoing need for targeted training initiatives, particularly for those in underrepresented areas, to foster greater AI adoption.

Despite its contributions, this study also has several limitations. The small sample size, which primarily included participants from larger cities, may have introduced selection bias, limiting the generalisability of the findings to other regions or rural settings. Additionally, the qualitative nature of the study, while providing rich and detailed insights, makes it difficult to capture broader trends across the healthcare profession. Key demographic data, such as age, gender, and specific past experience with AI – important moderators in the UTAUT2 model – were not collected. These demographic factors likely play a significant role in shaping attitudes towards AI adoption, and their absence limits the ability to fully understand the different experiences and viewpoints within the participant group.

Future research should aim to address these limitations by expanding the sample size and incorporating quantitative methods to examine how demographic variables, such as age, gender, and experience, influence AI adoption. In addition, longitudinal studies could provide valuable insights into how healthcare professionals' perceptions of AI evolve, particularly after receiving targeted training or after the implementation of AI systems in their workplaces. Using quantitative modelling techniques, such as structural equation modelling within the UTAUT2 framework, future research could validate the constructs identified in this study and provide further insights into the interaction of factors influencing AI adoption. Schretzlmaier et al. (2023) also advocate for the use of mixed-methods approaches, combining qualitative and quantitative insights, to better understand the complex factors influencing technology adoption in healthcare.

By building on these insights, future research can help refine strategies for overcoming resistance to AI and ensuring its successful integration into healthcare. These findings also suggest broader implications for policymakers and educators, as addressing the barriers to AI adoption will require coordinated efforts to provide the necessary training, support, and governance to ensure that AI enhances healthcare delivery without compromising its humanistic elements.

Conclusion

This study offers a comprehensive exploration of healthcare practitioners' perceptions of AI, highlighting both its potential benefits and challenges. It emphasises the importance of addressing concerns related to AI integration in healthcare, such as patient-practitioner relationships, the efficiency of consultations, and a general hesitation towards adopting new technologies due to a lack of experience. While this study is one piece of a larger puzzle, it lays the groundwork for future research and provides insights for policymakers and educators to navigate the complexities of AI in healthcare.

However, several limitations must be considered. The small sample size and demographic imbalances, with most participants residing in larger cities, may have introduced selection bias, potentially skewing the study's findings. Moreover, the qualitative nature of the study presented challenges in data visualisation, and ethical considerations, such as maintaining participant anonymity, limited the ability to provide detailed context. Addressing these issues in future research will be essential to providing a more accurate representation of healthcare practitioners' views.

Looking ahead, expanding the sample size and employing snowball sampling techniques could help reduce bias and increase participant diversity, leading to more generalisable findings. Additionally, conducting similar studies in different contexts, locations, or cultures would enrich the diversity of perspectives. Comparative research could also assess the reasons behind healthcare practitioners' attitudes towards AI, helping organisations and health boards allocate resources and develop support systems for AI education and integration. Practical applications could include trial training programs for healthcare practitioners. Further research using UTAUT2 as a theoretical framework could incorporate quantitative approaches and modelling to assess the key factors influencing healthcare practitioners' adoption of AI providing valuable guidance for the successful integration of AI in healthcare and offering policymakers and educators a roadmap for overcoming adoption barriers.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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