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Understanding Trust as a Mediating Mechanism in AI-Based Medical Tools and Clinical Decision Processes

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Abstract

The growing integration of artificial intelligence (AI) in healthcare has transformed clinical decision-making. Nevertheless, doctors' engagement with AI-based tools remains hindered, particularly due to trust-related concerns. The purpose of this study is to examine the factors influencing doctors' engagement with AI-based medical tools, with a focus on the mediating role of trust within the Unified Theory of Acceptance and Use of Technology (UTAUT). Data were collected from 197 doctors in Selangor and Kuala Lumpur through a structured survey and analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) with SmartPLS 4 software. The findings reveal that performance expectancy, effort expectancy, social influence, and facilitating conditions significantly influence trust in AI tools, which in turn strongly predict AI-based clinical decision-making. Mediation analysis confirms that trust fully mediates the relationships between UTAUT constructs and AI engagement. Hence, trust is a critical mechanism linking user perceptions to behavioural outcomes in clinical contexts. The findings implied the need for transparent AI systems, targeted training and institutional support. Healthcare institutions should focus on clear governance to strengthen trust and facilitate effective human-AI integration.

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1.0 Introduction

Artificial Intelligence (AI) has emerged as an essential element transforming healthcare systems globally. AI usage promises to enhance diagnostic precision, optimise treatment strategies, and strengthen evidence-based decision-making (Sharon et al., 2025). Recently, the initiatives spearheaded by the Ministry of Health, along with regulatory frameworks established by the Malaysian Medical Council, have underscored the urgent need to integrate AI-driven clinical tools to bolster healthcare delivery and improve patient outcomes (Ministry of Health, 2025). Nonetheless, the contemporary AI applications in clinical environments face the challenge of achieving consistent effectiveness, revealing that the mere presence of technology may not equate to meaningful implementation (Shanthi & Seow, 2026). As doctors remain legally and ethically responsible for patient care, this raises significant issues regarding risk, accountability, and the interpretability of AI algorithms (Wong et al., 2024). Further, the realisation of potential benefits in using AI depends on healthcare professionals' willingness to integrate AI tools into their decision-making processes (Phang et al., 2024; Tun et al., 2025). Consequently, the dilemma has shifted from simple technology adoption to one centred on trust and practical applicability, compelling doctors to assess whether AI-generated insights are robust and transparent enough to inform their clinical decisions.

The adoption of AI in clinical decision-making within the Malaysian healthcare system faced several key challenges. For instance, the extent of AI adoption varies with clinicians' assessment of the practicality of these technologies in their daily practice. In particular, concerns about the transparency and reliability of algorithmic outputs are directly related to performance expectations (Cheruku, 2025; Mut et al., 2024). Furthermore, the complexity of integrating AI into routine workflows indicates that additional training opportunities are needed to reduce uncertainty and encourage confident use. The existing digital infrastructure entails clear legal and regulatory guidance to determine whether sufficient technical support is in place for effective implementation. Hence, there is a crucial knowledge gap regarding the extent to which the discussion above shapes doctors' trust, which in turn influences their AI-based clinical decision-making, especially in environments characterised by risk, uncertainty, and professional accountability.

2.0 Underpinning Theory

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a well-known framework to examine technology adoption through four key constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). Performance expectancy refers to the extent to which an individual believes that using a particular technology will enhance job performance or improve work outcomes. In healthcare settings, this reflects the degree to which doctors perceive that AI-based tools can support more accurate, efficient, or timely clinical decisions. Effort expectancy describes the perceived ease of using a technology. In the context of this study, it concerns whether intuitive and manageable AI tools fit within doctors' existing clinical workflows. Social influence captures the extent to which doctors perceive encouragement from senior doctors or institutional expectations regarding AI adoption. Facilitating conditions refer to the extent to which doctors believe that access to training, technical support, reliable digital systems, and institutional readiness enable them to use AI-based tools effectively.

This study adopts the UTAUT framework to guide research on AI-supported clinical decision-making. It assumes that medical doctors are more likely to trust AI-based tools when they perceive them as useful for improving performance, easy to operate, and supported by peers and institutional systems. Prior studies grounded in UTAUT have primarily examined behavioural intention toward AI adoption (Ratta et al., 2025; Kim, 2024; Yu et al., 2024; Zheng et al., 2025; Moor et al., 2020). There is research that focused on initial acceptance, technical skills, or general usage intention (Giebel et al., 2025; Masawi et al., 2025; Ratta et al., 2025; Jacob et al., 2025). The empirical evidence remains limited regarding how performance expectancy, effort expectancy, social influence, and facilitating conditions influence medical professionals' trust in AI-based tools, and whether such trust translates into informed, AI-supported clinical decision-making in real-world practice settings (Phang et al., 2024; Tun et al., 2025; Wong et al., 2024).

The study aims to examine the influence of performance expectancy, effort expectancy, social influence, and facilitating conditions on medical doctors' trust in AI-based tools, the effect of trust on AI-based clinical decision-making, and the mediating role of trust in the relationships between these UTAUT constructs and clinical decision-making. The UTAUT framework could provide insights into doctors' initial acceptance, continued use, and integration of AI technologies in clinical practice over time. Findings from this study provide empirical insights into the determinants of AI-supported clinical decision-making among medical doctors in Malaysia, thereby informing institutional strategies and policy frameworks for the effective integration of AI technologies into routine clinical practice.

2.1 Literature Review

As AI technologies continue to revolutionise healthcare delivery, research on AI-supported clinical decision making has become crucial (Sezgin, 2023). Medical professionals are increasingly using AI-based medical solutions to help with diagnosis, therapy selection, workflow optimisation, and predictive analytics (Kalra et al., 2024; Alowais et al., 2023; Dwivedi, 2019). Although numerous studies highlight the potential of these tools to improve clinical decision-making, there is still a dearth of empirical research, especially in Malaysia, that looks at the frequency, patterns, and long-term reliance on recommendations generated by AI (Kothinti, 2024; Oyeniyi & Oluwaseyi, 2024; Knop et al., 2022). As AI adoption increasingly hinges on implementation difficulty rather than feasibility, understanding long-term engagement is essential for successful AI integration into real-world clinical decision-making (Kim, 2024; Allen et al., 2024; Ghassemi et al., 2020; Siau & Wang, 2020).

Despite increasing recognition that trust is essential for effective and durable AI-supported clinical practice, there is a significant gap in research regarding trust as a mediating factor between UTAUT constructs and clinical decision-making (Kerstan et al., 2024; Shevtsova et al., 2024; Wang & Wang, 2024; Cai et al., 2022). Current studies treat trust as a direct predictor of technology use (Eke & Shuib, 2024; Tonekaboni et al., 2019; Ghassemi et al., 2020), with limited examination of how trust shapes the relationship between UTAUT dimensions and actual clinical decision-making behaviour. Long-term use of AI is not solely assured by perceived usefulness or ease of use, particularly when confidence in the system's recommendations is low (Kim, 2024; Baser & Erkul, 2024). The original UTAUT model incorporates moderators such as gender, age, experience, and voluntariness of use (Venkatesh et al., 2003); these were not included in the present study. In clinical settings where AI-based tools are mandatory and usage is guided by standardised professional training, demographic and voluntariness factors contribute minimally to variability in technology adoption, rendering their inclusion less relevant (Wang & Wang, 2024; Dingel et al., 2024).

The degree to which doctors anticipate that utilising AI-based tools will enhance their clinical judgment, diagnostic precision, or treatment planning is known as performance expectancy (Choudhury & Shamszare, 2024). Adoption is regularly predicted by high performance expectations, but scepticism endures when AI tools are opaque or difficult to use (Dingel et al., 2024; Kim, 2024; Daniel et al., 2024; Choudhury & Shamszare, 2024). Perceived ease of use is captured by effort expectancy; even highly functional technologies are less likely to be used if they are perceived as difficult or time-consuming (Wang & Wang, 2024). Doctors' trust in and reliance on AI-generated recommendations can be shaped by social influence from co-workers, senior consultants, or institutional leadership (Wong et al., 2024; Emon & Khan, 2025; Man et al., 2025). The organisational, technical, and infrastructure support offered, such as training, access to dependable AI systems, IT support, and workflow integration, are referred to as facilitating conditions (Ratta et al., 2025). Sufficient facilitating conditions reduce barriers to adoption and promote the integration of AI into clinical practice (Ratta et al., 2025; Wang & Wang, 2024).

Although medical doctors are central users of diagnostic and clinical decision-support technologies, they have not been extensively examined in the existing literature. It is interesting to note that a large portion of the current research on AI adoption involves a variety of healthcare professionals, including nurses, technicians, and administrative staff (Cadamuro et al., 2025; Jacob et al., 2025; Giebel et al., 2025). This wide inclusion may limit the extent to which findings accurately reflect the specific perspectives and experiences of medical doctors. This underrepresentation is especially apparent in Malaysia, where empirical research on AI-supported clinical decision-making is still limited (Mohamed, 2025; Ratta et al., 2025). Furthermore, incorporating trust is essential for understanding the transition from UTAUT constructs to clinical behaviour, as it ensures that AI-generated recommendations are integrated into patient care decisions. Collectively, these UTAUT constructs affect confidence in AI, a crucial mediator in the adoption process (Shevtsova et al., 2024). Low trust in AI tools' dependability or transparency can restrict their influence on clinical decision-making, even when they are seen as helpful, simple to use, socially acceptable, and well-supported (Kerstan et al., 2024; Shevtsova et al., 2024; Wang & Wang, 2024; Cai et al., 2022).

2.2 Hypothesis Development

2.2.1 Performance Expectancy and Trust in AI-Based Medical Tools

Doctors' adoption and continued use of AI-based medical tools are significantly influenced by their performance expectations, which reflect their perceptions that AI improves productivity, efficiency, and decision quality (Chaibi et al., 2025; Kim, 2024). Doctors' confidence in the system, or trust, tends to rise when they believe AI tools routinely enhance diagnostic accuracy, facilitate prompt interventions, or expedite decision-making. For example, by enhancing clinical judgment, reducing administrative burden, and generating reliable results, tools such as Buoy Health, Augmedix, and DeepScribe foster trust (Dinesh et al., 2025; McKenna, 2025). Similarly, sepsis prediction systems build confidence by demonstrating observable clinical benefits, including prompt therapies and reduced mortality, which bolster doctors' confidence in the tool's efficacy (Mutawa, 2025). On the other hand, inconsistent or unclear AI outputs reduce performance expectations and erode confidence in the system's dependability (Cheruku, 2025). The following hypothesis is derived from these insights. These insights lead to the following hypothesis.

Hypothesis 1 (H1): Performance Expectancy positively influences trust in AI-based medical tools.

2.2.2 Effort Expectancy and Trust in AI-Based Medical Tools

The perceived ease of using AI-based technologies, or effort expectancy, significantly affects doctors' adoption and trust in these technologies (Kim, 2024; Ratta et al., 2025). Because doctors can rely on the technology without struggling to understand or operate it, systems that are simple to use, intuitive, and require little cognitive effort promote confidence (Dingel et al., 2024). For instance, when interfaces were simple and required less training, radiologists and cardiologists expressed greater trust (Atoum, 2024; Rahman, 2024). In a similar vein, dermatologists and general practitioners accepted outputs such as heatmaps and electronic health record warnings when they were visually straightforward and easy to understand, reducing the likelihood of misunderstanding (Ayesha & Ahamed, 2024; Berry et al., 2025; Chanda et al., 2024; Helenason et al., 2024). Because they could effectively incorporate AI recommendations into critical clinical decisions, emergency doctors were more likely to trust technologies that provided quick answers in under two minutes and allowed overrides (Stewart et al., 2023; Yi et al., 2025). On the other hand, complicated or cluttered designs required more mental work and decreased confidence in the system's dependability (Liu et al., 2025). These insights lead to the following hypothesis.

Hypothesis 2 (H2): Effort Expectancy positively influences doctors' trust in AI-based medical tools.

2.2.3 Social Influence and Trust in AI-Based Medical Tools

Doctors' trust in AI is shaped by social influences, especially in hierarchical hospitals, where professional norms, mentorship, and peer behaviour dictate practice (Gani et al., 2024; Rosenbacke et al., 2024). Doctors are reassured that AI systems are trustworthy for clinical application when senior consultants or seasoned colleagues endorse them (Chen & Lee, 2024; Ayorinde et al., 2024). Additionally, when junior doctors or registrars witness their colleagues actively utilising AI solutions like Cardiologs, this behaviour fosters adoption within the team by reinforcing trust through social proof. Credibility is also increased by institutional cues, such as professors endorsing Aidoc or incorporating AI into standards like Sepsis Watch (Ismatullaev & Kim, 2024; Cao, 2024). By publicly confirming the system's efficiency, recognition through seminars or awards enhances trust (Howe et al., 2024; Joseph & Lalchand, 2024). Systematically, normative pressure is created to align AI use with ethical and professional standards through medical association endorsements, such as nephrology boards' endorsement of dialysis risk prediction technologies (Chuang et al., 2025). Thus, social impact shapes both participation and the cognitive-emotional foundation of confidence in AI at the interpersonal, institutional, and professional levels.

Hypothesis 3 (H3): Social Influence positively affects doctors' trust in AI-based medical tools.

2.2.4 Facilitating Conditions and Trust in AI-Based Medical Tools

According to Jeilani and Hussein (2025), Rahimi et al. (2024), and Ratta et al. (2025), facilitating conditions include organisational, educational, and infrastructural supports that facilitate the successful adoption of AI-based tools. These include resources, training, institutional endorsement, and policies that actively lower barriers and signal reliability, thereby fostering doctors' trust. Because these factors ensure consistent, predictable tool outputs, doctors are more likely to trust AI in settings with integrated platforms, high-performance computing resources, and reliable data access (Idowu & William, 2025; Najjar, 2024). Furthermore, by proving that the system is in line with clinical reasoning and patient-specific requirements, systematic training and comprehension of AI logic and limitations can boost confidence among cancer doctors utilising IBM Watson for cancer (Pandav et al., 2025; Almadani et al., 2025). Responsible use is further reinforced by practical assistance, explicit privacy, liability, and override procedures, which increase confidence that AI recommendations are secure and useful (Kyambade & Namatovu, 2025; Mwogosi, 2025; Chuang et al., 2025). Overall, well-crafted enabling conditions establish a controlled socio-technical environment that fosters trust, lowers barriers, and empowers doctors to comfortably interact with AI in clinical practice.

Hypothesis 4 (H4): Facilitating Conditions positively influence doctors' trust in AI-based medical tools.

2.2.5 Trust in AI-Based Medical Tools and AI-Based Clinical Decision Making

Doctors' use of AI relies heavily on trust, reflecting their confidence in the precision, reliability, and ethical integrity of AI-based medical tools (Kim, 2024). Doctors evaluate the consistency, transparency, and alignment of AI outputs with clinical reasoning across repeated contacts, thereby fostering trust (Choudhury et al., 2025; Dingel et al., 2024). To reduce errors and ethical risks, clinicians are more likely to meaningfully employ AI in diagnostics, risk prediction, and treatment planning when trust is high. This includes evaluating outputs, validating ideas, and integrating recommendations into clinical workflows (Lin et al., 2025). On the other hand, positive experiences encourage adoption and enable well-informed clinical judgment, whereas low trust restricts participation or leads to tool abandonment (Liu et al., 2025; Dingel et al., 2024).

Hypothesis 5 (H5): Trust in AI-based medical tools positively influences AI-based clinical decision-making.

2.2.6 Trust as a Mediator Between UTAUT Constructs and AI-Based Clinical Decision Making

Although few studies have explicitly tested trust as a mediator between UTAUT constructs and clinical decision-making, prior research provides strong supporting evidence that performance expectancy, effort expectancy, social influence, and facilitating conditions shape trust, and that trust, in turn, predicts adoption or engagement with AI-based tools (Shevtsova et al., 2024; Kim, 2024). This suggests a potential mediating role of trust, which the present study empirically examines. The idea that AI improves productivity, efficiency, and decision quality is reflected in performance expectations (Venkatesh et al., 2003; Chaibi et al., 2025). Trust and participation in clinical decision-making are supported by accurate, transparent, and trustworthy AI outputs, such as kidney damage monitoring or cardiac arrest prediction (Aravazhi et al., 2025; Kaushik et al., 2024; Reddy, 2024). Therefore, it is anticipated that performance expectancy will indirectly impact therapeutic decision-making through trust.

Hypothesis 6 (H6): Trust in AI mediates the relationship between Performance Expectancy and AI-based clinical decision-making.

The perceived ease of use of AI-based medical tools, which represent little cognitive and operational effort, is reflected in effort expectancy (Kim, 2024; Ratta et al., 2025). Through understanding outcomes rather than navigating complex interfaces, doctors are more likely to build trust in AI outputs when systems are simple, easy to use, and require less training (Dingel et al., 2024). For instance, radiologists and cardiologists expressed more confidence in imaging and ECG instruments with straightforward user interfaces and clear instructions (Atoum, 2024; Rahman, 2024). On the other hand, even if a system is accurate, excessive complexity undermines trust and prevents adoption (Liu et al., 2025). Therefore, doctors' trust in AI is increased by ease of use, making it easier to incorporate AI into clinical decision-making.

Hypothesis 7 (H7): Trust in AI mediates the relationship between Effort Expectancy and AI-based clinical decision-making.

The impact of peers, supervisors, and professional norms on doctors' use of AI-based tools is reflected in social influence (Rosenbacke et al., 2024). There is still little empirical data on how it directly affects confidence in AI for clinical decision-making. However, studies on the adoption of healthcare technology show that recommendations from institutional leaders, supervisors, or senior colleagues can validate new systems and influence users' opinions of their dependability and credibility (Quoi, 2025; Kaushik et al., 2024). Peer behaviour and mentor guidance give implicit social cues in hierarchical medical settings, strengthening trust in AI recommendations. Similarly, integrating AI tools into clinical protocols through professional associations and hospital regulations can enhance trust and align adoption with established ethical and professional standards (Ismatullaev & Kim, 2024; Cao, 2024). Taken as a whole, these elements suggest that social influence may promote trust, which in turn propels genuine AI-based clinical decision-making rather than nominal or passive awareness.

Hypothesis 8 (H8): Trust in AI mediates the relationship between Social Influence and AI-based clinical decision-making.

Organisational, technological, and educational assistance, such as IT infrastructure, policy frameworks, and training, are examples of facilitating conditions (Jeilani & Hussein, 2025). Technology adoption research shows that sufficient support, resources, and institutional backing can increase user confidence in new systems, despite the paucity of previous empirical studies that directly link facilitating conditions to trust in AI for clinical decision-making (Ratta et al., 2025; Kim, 2024). When doctors receive organised training, have access to trustworthy platforms, experience smooth workflow integration, and work under explicit institutional policies that address privacy, ethical compliance, and operational safeguards, they are more likely to trust and interact with AI in clinical settings (Idowu & William, 2025). These facilitating conditions reduce ambiguity, strengthen confidence in the system's dependability, and provide a controlled setting in which AI outputs can be successfully and securely integrated into clinical decision-making. Facilitating settings are therefore anticipated to promote trust, which mediates their impact on doctors' AI-based clinical decision-making.

Hypothesis 9 (H9): Trust in AI mediates the relationship between Facilitating Conditions and AI-based clinical decision-making.

2.3 Proposed Conceptual Framework

With trust in AI as the primary mediator, the research methodology demonstrates how performance expectancy, effort expectancy, social impact, and facilitating factors influence AI-based clinical decision-making. The perceived advantages and usefulness of AI-based solutions are related to performance expectancy and effort expectancy. Peer conduct, mentorship, and institutional support are examples of social influence, whereas organisational, technical, and educational assistance are examples of facilitating conditions. These elements are anticipated to promote trust, which in turn propels AI-based clinical decision-making, emphasising that favourable opinions and encouraging surroundings are insufficient without doctors' confidence in the AI system.

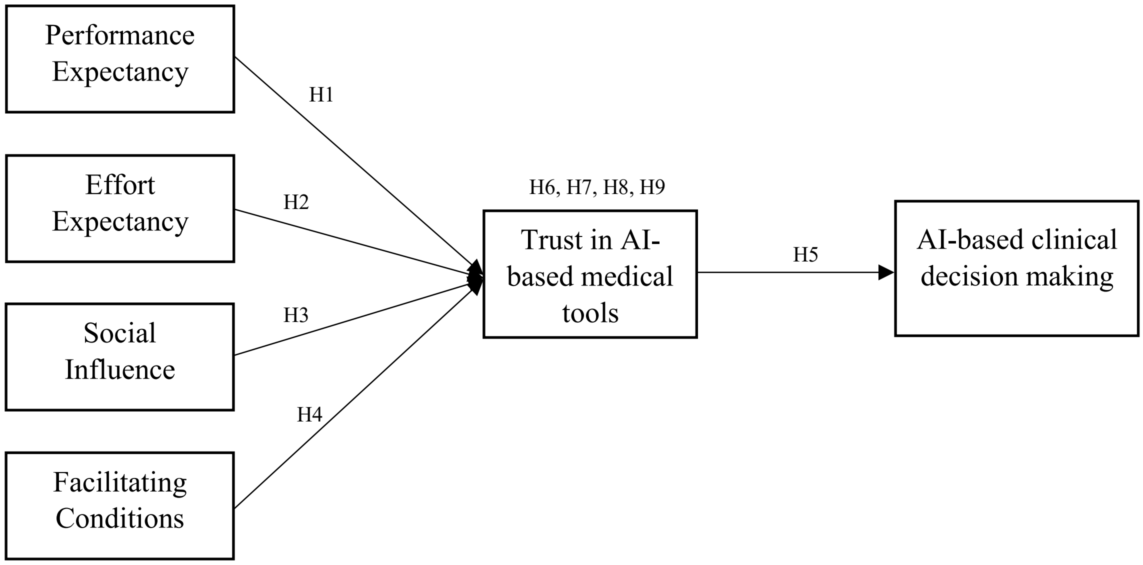

Figure 1: Conceptual Framework

3.0 Method

3.1 Research Design

This study uses a quantitative, cross-sectional research approach to investigate how Malaysian medical doctors' trust in AI and, consequently, AI-based clinical decision-making are influenced by performance expectancy, effort expectancy, social influence, and facilitating factors. To gather perceptual and behavioural data appropriate for structural equation modelling, a survey-based method was used.

3.2 Population, Sampling and Inclusion Criteria

The target population comprised practising medical doctors in Selangor and Kuala Lumpur. These areas were chosen for their high concentration of medical facilities, sophisticated digital infrastructure, and increased use of AI-based clinical solutions (Cao, 2024). To ensure that only pertinent respondents were included, a purposive sampling strategy was used. In order to be eligible, participants had to fulfil three requirements: (1) be a registered and practising doctor in Malaysia; (2) be employed in a clinical context, and (3) have previously used or interacted with AI-based clinical tools. This guaranteed that respondents had enough expertise and experience to offer insightful comments (Hair et al., 2019). Using G*Power, a minimum sample size of 85 respondents was required, assuming a medium effect size ($f^2 = 0.15$), statistical power of 0.80, significance level of 0.05, and four predictors (Kang, 2021). However, because larger samples increase statistical power, lower standard errors, and improve generalisability in structural equation modelling (SEM) involving multiple latent constructs, the study aimed for 300 participants (Kline, 2015; Hair et al., 2019; Hair et al., 2022; Memon et al., 2020).

3.3 Data Collection Method

An online survey disseminated via hospital digital networks, professional medical groups, and clinical communities was used to collect data between January and March of 2026. An introduction detailing the study's goals, confidentiality guarantees, and voluntary participation was included in the survey. A response rate of 91.6% was obtained during data collection, yielding 215 responses, of which 197 were complete and usable. Due to the absence of crucial information required for structural equation modelling, incomplete responses were excluded, potentially compromising the analysis's robustness. The final sample exceeded the suggested PLS-SEM thresholds while remaining below the original target, ensuring accurate parameter estimation and adequate statistical power for hypothesis testing (Hair et al., 2019; Becker et al., 2012; Reinartz et al., 2009).

3.4 Research Instrument and Pilot Testing

Measurement scales for each study construct, demographic questions, and screening questions made up the research instrument. Five questions, adapted from previous research, were used to measure performance expectancy, effort expectancy, social influence, and facilitating factors (Venkatesh et al., 2003; Aftab et al., 2025; Zheng et al., 2025; Chuang et al., 2025; Dwivedi et al., 2019). Five items each, modified from Madsen and Gregor (2000), Wang and Wang (2024), and Doreswamy and Horstmanshof (2022), were used to gauge trust in AI and AI-based clinical decision-making. Every item used a five-point Likert scale, with 1 denoting "strongly disagree" and 5 denoting "strongly agree." Medical informatics specialists evaluated the instrument to ensure content validity, and their suggestions were incorporated to enhance its phrasing, clarity, and contextual relevance. After that, a pilot study was conducted with 15 active doctors to evaluate usability, clarity, and reliability. This sample size is in line with recommendations for pilot testing survey instruments, which call for 10 to 30 participants (Isaac & Michael, 1995; Hill, 1998). After the pilot study, a few minor adjustments were made to maximise understanding and guarantee that the questionnaire was appropriate for widespread use in the primary study.

3.5 Data Analysis Technique

Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to analyse the data using SmartPLS. PLS-SEM was selected because the study is prediction-oriented, with predetermined hypotheses investigating how performance expectancy, effort expectancy, social influence, and facilitating conditions influence trust and, consequently, AI-based clinical decision-making. Because of the intricacy of the research model which includes numerous path linkages, mediating variables, and reflecting constructs, PLS-SEM provides a better fit than covariance-based SEM. Additionally, PLS-SEM works well with smaller to moderate sample sizes and does not require rigorous normality assumptions (Hair et al., 2022). Two steps were taken in the analysis. Initially, the measuring model was evaluated for discriminant validity (heterotrait-monotrait ratio), convergent validity (average variance extracted), and internal consistency reliability (Cronbach's alpha and composite reliability). Second, to determine the importance of direct and mediated effects, the structural model was assessed using path coefficients, coefficient of determination (R^2), predictive relevance (Q^2), and bootstrapping techniques. The indirect influence of trust in the connections between UTAUT components and AI-based clinical decision-making was investigated using mediation analysis.

3.6 Common Method Bias

Harman's single-factor test was used to evaluate common technique bias. According to the findings, common technique bias is not a major concern because the first factor explained 45.493% of the total variance, which is less than the 50% criterion (Podsakoff et al., 2003). Further evidence that common technique bias is unlikely to affect the results came from a comprehensive collinearity examination, which revealed that all variance inflation factor (VIF) values were below 3.3 (Kock, 2015).

4.0 Results

Data were analysed using PLS-SEM with SmartPLS 4. Following Hair et al. (2017), the measurement model was first assessed for reliability and validity, then the structural model was evaluated to test hypotheses and examine relationships among constructs.

4.1 Descriptive Analysis

The demographics of 197 doctors from various specialities are shown in Table 1. Surgery (21.83%) and General Medicine (21.32%) were the largest groups. With an almost equal gender split (52.79% male, 47.21% female), more than half (53.8%) were between the ages of 25 and 34. The majority worked in public (37.56%) or private healthcare facilities (34.52%) and had six to ten years of professional experience (31.47%). Formal education (30.96%), professional development programs (41.63%), or self-directed learning (27.41%) were the methods used to get AI-related expertise. The sample is representative of a varied cohort that has significant experience with AI in clinical settings.

Table 1: Demographic Profile

Category	Demography Information	Frequency	Percentage
Primary Field of Medical Practice	General Medicine	42	21.32%
	Surgery	43	21.83%
	Paediatrics	33	16.75%
	Radiology	38	19.29%
	Pathology	33	16.75%
	Other (e.g., Dermatology, Psychiatry, etc.)	8	4.06%
Age Group	Under 25	-	-
	25 – 34	106	53.8%
	35 – 44	56	28.43%
	45 – 54	22	11.17%
	55 – 64	10	5.08%
	65 or older	3	1.52%
Gender	Male	104	52.79%
	Female	93	47.21%
Years of Medical Practice	Less than 1 year	6	3.05%
	1 – 5 years	60	30.46%
	6 – 10 years	62	31.47%
	11 – 15 years	40	20.30%
	More than 15 years	29	14.72%
Type of Healthcare Institution	Public hospital/clinic	74	37.56%
	Private hospital/ clinic	68	34.52%
	Academic / Research institution	33	16.75%
	Telemedicine or digital healthcare service	14	7.11%
	Other (e.g., private practice, etc.)	8	4.06%
Formal Training in AI	Yes, as part of my medical education (e.g., university coursework, residency training)	61	30.96%
	Yes, through professional development during medical practice (e.g., workshops, conferences, certifications)	82	41.63%
	No, I have learned it independently (e.g., self-study, online courses)	54	27.41%

4.2 Measurement model

The measuring model's convergent validity, internal consistency, and indicator reliability were evaluated. According to Hair et al. (2017), outside loadings exceeded 0.60 and varied from 0.62 to 0.92, showing sufficient reliability. Constructs explained the majority of variance, as indicated by AVE values of 0.70 to 0.82 exceeding 0.50 (Fornell &

Larcker, 1981). High internal consistency was confirmed by CR (0.83 to 0.94) and CA (0.79 to 0.91) (Hair et al., 2017). The model's dependability and convergent validity for AI-based clinical decision-making analysis are supported by these findings.

Table 2: Measurement Model Assessment

Construct	Item Code	Factor Loading	AVE	CR	CA
Performance Expectancy (PE)	PE1	0.78	0.75	0.86	0.90
	PE2	0.62			
	PE3	0.81			
	PE4	0.73			
	PE5	0.70			
Effort Expectancy (EE)	EE1	0.84	0.70	0.88	0.85
	EE2	0.80			
	EE3	0.70			
	EE4	0.72			
	EE5	0.88			
Social Influence (SI)	SI1	0.78	0.78	0.83	0.79
	SI2	0.69			
	SI3	0.81			
	SI4	0.73			
	SI5	0.74			
Facilitating Conditions (FC)	FC1	0.80	0.73	0.94	0.91
	FC2	0.88			
	FC3	0.75			
	FC4	0.71			
	FC5	0.78			
Trust in AI-based medical tools (TR)	TR1	0.85	0.71	0.91	0.90
	TR2	0.80			
	TR3	0.74			
	TR4	0.79			
	TR5	0.82			
AI-based clinical decision making (AI-CDM)	AI-CDM	0.88	0.82	0.88	0.89
	AI-CDM	0.81			
	AI-CDM	0.85			
	AI-CDM	0.92			
	AI-CDM	0.80			

Table 3: Heterotrait-Monotrait (HTMT)

	PE	EE	SI	FC	TR	AI-CDM
PE						
EE	0.707					
SI	0.69	0.589				
FC	0.747	0.745	0.691			

	PE	EE	SI	FC	TR	AI-CDM
TR	0.079	0.159	0.059	0.054		
AI-CDM	0.156	0.215	0.102	0.113	0.726	

As suggested by Henseler et al. (2015) and Franke and Sarstedt (2019), discriminant validity was evaluated using the Heterotrait-Monotrait (HTMT) ratio. According to Ramayah et al. (2018), HTMT assesses the ratio of correlations between constructs to within-construct correlations; values less than 0.85 indicate sufficient discriminant validity (Kline, 2011). All HTMT values ranged from 0.054 to 0.747, as Table 3 illustrates, indicating that the measurement model is reliable and the constructs are empirically distinct.

4.3 Structural Model

Every hypothesised direct relationship (H1–H5) was statistically significant and supported. Trust (TR) was most influenced by facilitating conditions (FC → TR; $\beta = 0.715$, $t = 10.50$, $p < 0.05$, $f^2 = 0.625$), effort expectancy (EE → TR; $\beta = 0.701$, $t = 9.00$, $p < 0.05$, $f^2 = 0.523$), and performance expectancy (PE → TR; $\beta = 0.68$, $t = 9.71$, $p < 0.05$, $f^2 = 0.412$). AI-based clinical decision-making was significantly predicted by trust (TR → AI-CDM; $\beta = 0.685$, $t = 11.00$, $p < 0.05$, $f^2 = 0.481$) (Cohen, 1988; Ajzen, 1991; Davis, 1989; Venkatesh et al., 2003). All confidence intervals excluded zero, and all variance inflation factors (VIF = 1.89 to 2.48) were less than 5, indicating the absence of multicollinearity (Hair et al., 2011, 2017; Diamantopoulos & Siguaw, 2006; Ramayah et al., 2018). H6 to H9 were supported by the mediation analysis, which showed that trust (TR) strongly mediated the effects of all antecedents on AI-based clinical decision-making (AI-CDM). Through TR, performance expectancy (PE), effort expectancy (EE → TR → AI-CDM; $\beta = 0.573$, $t = 8.889$, $p < 0.05$, 95% CI [0.449, 0.697]), and facilitating conditions (FC → TR → AI-CDM; $\beta = 0.591$, $t = 11.504$, $p < 0.05$, 95% CI [0.491, 0.691], all had medium to large effect sizes. A lesser but beneficial indirect effect was also produced by social influence (SI) (SI → TR → AI-CDM; $\beta = 0.23$, $t = 4.102$, $p < 0.05$, 95% CI [0.121, 0.341]).

Table 4: Hypothesis Testing for Direct Relationship

Hypothesis	Path	Standard Beta	Standard Error	Confidence Interval	t-values	p-values	f²	VIF	Results
H1	PE→ TR	0.680	0.070	[0.543, 0.817]	9.714	0.001	0.412	2.100	Supported
H2	EE→ TR	0.701	0.078	[0.548, 0.854]	9.000	0.000	0.523	2.340	Supported
H3	SI → TR	0.301	0.062	[0.179, 0.423]	4.855	0.000	0.112	1.990	Supported
H4	FC→TR	0.715	0.068	[0.582, 0.848]	10.500	0.000	0.625	2.480	Supported
H5	TR→AI-CDM	0.685	0.062	[0.564, 0.806]	11.000	0.000	0.481	1.890	Supported

Note. PE = Performance Expectancy. EE = Effort Expectancy. SI = Social Influence. FC = Facilitating Conditions. TR = Trust in AI-based medical tools. AI CDM = AI-based clinical decision making

Table 5: Hypothesis Testing for Indirect Relationship

Hypothesis	Path	Indirect Effect β	Indirect Effect t-value	Standard Error	p-value	Confidence Interval	Results
H6	PE → TR → AI-CDM	0.523	8.724	0.060	0.000	[0.405, 0.641]	Supported
H7	EE → TR → AI-CDM	0.573	8.889	0.064	0.000	[0.447, 0.699]	Supported
H8	SI → TR → AI-CDM	0.23	4.102	0.056	0.000	[0.120, 0.340]	Supported
H9	FC → TR → AI-CDM	0.591	11.504	0.051	0.000	[0.490, 0.692]	Supported

Note. PE = Performance Expectancy. EE = Effort Expectancy. SI = Social Influence. FC = Facilitating Conditions. TR = Trust in AI-based medical tools. AI CDM = AI-based clinical decision making

Following Hair et al. (2017, 2020) and Shmueli et al. (2019), the model's predictive significance was assessed in the last stage using both the blindfolding process and PLS-Predict. The model's predictive usefulness is demonstrated by the blindfolding results, which show that Q^2 values for trust in AI (TR; $Q^2 = 0.388$) and AI-based clinical decision-making (AI-CDM; $Q^2 = 0.412$) are larger than zero. PLS-Predict produced case-level predictions for both constructs using a 10-fold holdout sample method. The linear model (TR = 0.343, AI-CDM = 0.335) had higher RMSE values than the PLS-SEM model (TR = 0.313, AI-CDM = 0.299), suggesting medium-to-high predictive power for TR and high predictive power for AI-CDM. All of these results show that the model has significant predictive power for the endogenous constructs in addition to fitting the data.

Table 6: PLS Predict Assessment

Construct	RMSE (PLS-SEM)	RMSE (LM)	Q^2 predict
Trust in AI (TR)	0.313	0.343	0.388
AI-based Clinical Decision Making (AI-CDM)	0.299	0.335	0.412

5.0 Discussion

This study examined the factors influencing doctors' trust in AI-based medical tools and how that trust affects AI-based clinical decision-making (AI-CDM). Doctors are more likely to trust AI systems that are thought to improve clinical efficiency, decision accuracy, and workflow performance, according to performance expectancy (PE), which strongly predicted trust. This result shows that perceived utility remains a major factor in building trust, consistent with the findings of Chaibi et al. (2025) and Kim (2024). Interestingly, compared with some earlier studies, the effect of PE appears slightly stronger in Malaysia. This could be due to doctors' dependence on observable performance gains while using new technologies in developing AI healthcare settings.

Effort expectancy (EE) also had a beneficial influence on trust, indicating that doctors are more inclined to depend on AI outputs when interfaces are easy to use, intuitive, and require little cognitive effort. This is consistent with the findings of Dingel et al. (2024) and Atoum (2024), who highlighted the significance of interface design in adoption. The focus on usability may be especially important in Malaysia, where AI integration is still in its infancy, to lessen opposition and promote adoption among doctors with different levels of digital literacy.

Peer behaviour, mentor endorsement, and institutional advice all boost confidence in AI technologies, according to social influence (SI), which had a moderately positive influence on trust. The effect size of SI in this study highlights the importance of hierarchical and collaborative structures in Malaysian hospitals, where doctors frequently rely on authority and peer endorsement to validate emerging technologies, consistent with Chuang et al. (2024) and Rosenbacke et al. (2024). The greatest influence on trust was shown by facilitating conditions (FC), underscoring the importance of organisational support, technical infrastructure, training initiatives, and policy frameworks. This research suggests that doctors may rely heavily on institutional and structural support to build confidence in AI tools within Malaysian healthcare, where AI adoption remains in its infancy. Although FC's prominence is consistent with that of Jeilani and Hussein (2025) and Ratta et al. (2025), the study's remarkably high influence may reflect the particular difficulties of integrating AI across hospitals with varying levels of resources, technological maturity, and regulatory control.

AI-CDM was significantly predicted by trust in AI, demonstrating its crucial role in converting opinions about its utility, usability, social cues, and organisational support into clinical engagement. Additionally, mediation analysis showed that trust significantly mediates the effects of PE, EE, SI, and FC on AI-CDM. In situations where AI is developing, and doctor confidence needs to be actively promoted, these highlight trust as a crucial psychological mechanism that connects technological, social, and organisational factors with practical clinical decision-making (Yu et al., 2024; Payne et al., 2024; Piedmont et al., 2024; Dingel et al., 2024; Goyal et al., 2025).

6.0 Implications

6.1 Theoretical Implication

This study offers several theoretical contributions by broadening the application of the Unified Theory of Acceptance and Use of Technology (UTAUT) beyond its conventional emphasis on intention and usage behaviour. The findings show that social influence, performance expectancy, effort expectancy, and facilitating conditions all significantly affect trust in AI, which, in turn, influences AI-based clinical decision-making. The mediating role of trust within the UTAUT paradigm, along with the factors influencing doctors' use of AI-based medical technologies, indicates that efforts to promote AI use should go beyond technical deployment. The study enriches the growing body of AI healthcare research by integrating trust into an established acceptance model, offering more comprehensive insights for understanding technology use in clinical contexts. Future scholars should further refine and extend UTAUT by incorporating trust and other context-specific factors when examining advanced technologies in complex professional settings.

6.2 Practical Implications

The mediation findings provide a sophisticated perspective on AI adoption in Malaysian healthcare by empirically demonstrating that trust is the primary mechanism through which these antecedents translate into clinical engagement. This shows that positive perceptions by medical professionals are insufficient in high-stakes clinical settings without trust. Healthcare organisations should emphasise the clinical benefits of AI tools to strengthen perceived usefulness, while ensuring that systems are intuitive and adequately supported by training to reduce complexity. In addition, encouragement from senior clinicians and alignment with professional norms can help cultivate a supportive environment for adoption. Familiarity with AI tools can be improved through structured training that includes hands-on workshops and practical simulations. Reliability and accountability can be improved by transparent algorithms and lucid explanations of AI decision-making, while strong organisational support, such as technological infrastructure, specialised help desks, and AI champions, can bolster doctors' trust. This highlights the need for developers and healthcare providers to prioritise consistency and system credibility. Strengthening these aspects can enhance confidence in AI tools and support meaningful integration into clinical practice, contributing to safer and more informed decision-making.

7.0 Limitations, Future Research, and Conclusion

The reliance on purposive sampling and the concentration on Selangor and Kuala Lumpur constitute limitations of this study. Future scholars are encouraged to broaden the geographical coverage to better represent diverse healthcare contexts. In addition, similar studies can employ longitudinal approaches to capture changes in trust and AI utilisation over time. Further research can explore how institutional settings and cultural influences shape AI adoption in medical practice. Overall, this study emphasises the importance of trust as a fundamental factor in the effective integration of AI within healthcare settings. Drawing on the UTAUT framework, the results provide empirical support for the proposed hypothesis development, indicating that the examined determinants significantly influence doctors' trust in AI-based tools. Trust has been shown to be an important driver of clinical decision-making involving AI support. By integrating theoretical insights with practical considerations, the findings suggest that policymakers, healthcare leaders, and technology developers can play a key role in strengthening clinicians' confidence in AI systems, ultimately contributing to safer and more effective clinical practice.

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