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Assessing the Influence of Task and Technology Characteristics on AI-Based Medical Decision Support: Mediating Role of Task-Technology Fit and Moderating Influence of Personal Innovativeness in IT

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Abstract

Purpose: AI-based decision-support systems are expanding in Malaysian healthcare, yet doctors' utilisation remains inconsistent due to concerns about reliability, workflow alignment, and task complexity. This study examines how task and technology characteristics influence Task-Technology Fit (TTF) and, subsequently, AI-based medical decision-making (AIIM). It also tests the mediating role of TTF and the moderating effect of Personal Innovativeness in IT (PIIT). **Design/methodology/approach:** A cross-sectional online survey was conducted with 197 medical doctors in Malaysia who had experience using AI-based tools. Validated 7-point Likert scales measured Task Characteristics (TAC), Technology Characteristics (TEC), TTF, PIIT, and AIIM. Purposive sampling was used, and hypotheses were tested via PLS-SEM. **Findings:** TAC positively influences TTF ($\beta = 0.380$, $p = 0.001$), contrary to the hypothesised negative path, while TEC positively influences TTF ($\beta = 0.610$, $p = 0.000$). TTF significantly enhances AIIM ($\beta = 0.296$, $p = 0.000$). Mediation analysis shows a positive indirect effect of TAC on AIIM through TTF ($\beta = 0.281$, $p = 0.000$), whereas TEC shows a positive and significant indirect effect ($\beta = 0.673$, $p = 0.000$), confirming TTF's mediating role. PIIT significantly strengthens the TTF–AIIM relationship ($\beta = 0.132$, $t = 3.143$, $p = 0.000$). **Research limitations:** This study used purposive sampling and focused only on doctors in Selangor, limiting generalisability. Future studies should include broader and multi-state samples. Control variables such as decision type, doctor level, and clinical experience were not included; accounting for these factors may better isolate the influences of TAC, TEC, TTF, and PIIT on AIIM. **Implications:** The study advances TTF theory by showing that task and technology characteristics shape AI-based medical decision making, with TTF acting as a mediator and PIIT strengthening this relationship. Practically, healthcare institutions and AI developers should prioritise AI tools that integrate smoothly with existing Malaysian clinical systems (e.g., MySejahtera Health Records, Teleprimary Care, EMRs) to improve adoption. Doctors with lower PIIT may benefit from structured training, peer support, and low-risk AI "sandbox" environments. Socially, effective AI use can improve patient safety, diagnostic accuracy, workflow efficiency, and job satisfaction, contributing to a more sustainable healthcare workforce and greater public trust in AI. **Originality/value:** This study is among the first in Malaysia to examine how TAC and TEC jointly influence AIIM through TTF. It establishes TTF as a mediator and PIIT as a key individual level moderator. The study also reframes the traditional TTF outcome of "performance impacts" into a domain specific measure, AIIM, capturing accuracy, efficiency, confidence, diagnostic reasoning, and error reduction. This provides new theoretical insights and practical guidance for strengthening AI adoption in clinical settings.

Keywords: Task-Technology Fit, Task Characteristics, Technology Characteristics, Personal Innovativeness in IT, AI-Based Medical Decision-Making

Introduction

AI-based decision-support systems have increasingly been integrated into clinical practice in Malaysia, offering the promise of enhanced diagnostic accuracy, improved patient outcomes, and optimised workflows (Elhaddad & Hamam, 2024). The AI market in Malaysia is projected to reach US$1.06 billion by 2025, with an annual growth rate of 27.63% expected from 2025 to 2030, reflecting growing interest and investment in AI technologies across various sectors, including healthcare (Statista, 2025).

Despite these advancements, the effective utilisation of AI in medical decision-making remains inconsistent, particularly among medical doctors (Khosravi et al., 2024). Concerns about the reliability, trustworthiness, and integration of AI tools into clinical workflows contribute to this hesitation (Nair et al., 2024). The complexity of clinical tasks often requires nuanced judgment, which AI systems may not fully accommodate. This can lead to a mismatch between task demands and technological capabilities (Mennella et al., 2024; Masawi et al., 2025). This issue is closely related to the concept of Task-Technology Fit (TTF), the degree to which AI-based systems align with the specific demands of clinical decision-making (Abdekhoda & Dehnad, 2024). When misalignment occurs, AI tools may contribute to cognitive overload or provide generalised recommendations that ignore patient-specific nuances. While previous research has explored task and technology characteristics in general, there is limited literature on their influence on AI-based medical decision-making through the lens of TTF (Przegalinska et al., 2024; Alhendawi, 2022; Wang & Lin, 2019; Saifi et al., 2025). Furthermore, individual differences, particularly Personal Innovativeness in IT (PIIT), may influence how doctors perceive and engage with AI-based tools, yet this aspect remains underexplored in the context of medical decision-making (Ratta et al., 2025; Phaik et al., 2024; Seebacher et al., 2023).

In response to these challenges, this study aims to investigate how task and technology characteristics affect TTF, and how TTF subsequently influences AI-based medical decision-making among medical doctors. The study also examines the mediating role of TTF and the moderating influence of PIIT.

Literature Review

AI-based medical decision-making refers to the application of artificial intelligence technologies, such as machine learning, deep learning, and natural language processing, to assist healthcare professionals in diagnosing diseases, recommending treatments, and predicting patient outcomes (Aljohani & Alanazi, 2025). AI has increasingly become a transformative tool in modern medicine, offering enhanced accuracy, efficiency, and scalability in clinical decision-making processes. Studies have demonstrated that AI can analyse vast amounts of medical data with greater speed and precision than human practitioners, leading to improved diagnostic accuracy and personalised treatment plans (Bajwa et al., 2021; Varnosfaderani & Forouzanfar, 2024). For example, Bi et al. (2019) and Singh et al. (2024) found that AI-assisted radiology systems significantly improved the early detection of malignant tumours, reducing diagnostic errors and enhancing patient prognosis. Similarly, Elhaddad and Hamam (2024) highlighted that AI-driven clinical decision support systems (CDSS) provide real-time recommendations based on patient history, laboratory results, and clinical guidelines, thereby optimising treatment plans and reducing the risk of medical errors.

Existing literature emphasises that the success of AI-based healthcare technologies depends on how well they align with clinical workflows and the expertise of medical professionals (Esmaeilzadeh, 2024; Rahman et al., 2024; Elhaddad & Hamam, 2024). However, no prior studies have explicitly examined AI-based medical decision-making through the Task-Technology Fit (TTF) lens, creating a significant gap in the literature. The TTF model suggests that the effectiveness of a technology depends on how well it aligns with task requirements and user capabilities (Goodhue & Thompson, 1995). In the context of AI-based medical decision-making, this means that AI systems should not only provide accurate predictions but must also fit the cognitive and workflow demands of doctors. By integrating TTF into this study, the researcher bridges this gap by examining how task complexity and AI capabilities jointly influence medical decision-making.

While TTF highlights the importance of aligning AI functionalities with clinical needs, individual differences in technology adoption must also be considered (Al-Emran et al., 2024). Research in technology acceptance suggests that healthcare professionals exhibit varying levels of openness toward AI-driven decision support, which may influence their willingness to adopt and utilise AI-based tools (Ratta et al., 2025; Masawi et al., 2025). Some practitioners may readily experiment with AI applications and integrate them into their workflows, whereas others may remain hesitant despite the demonstrated benefits. This variation suggests that user traits could shape how AI adoption unfolds in medical practice. Specifically, the concept of Personal Innovativeness in IT (PIIT) provides a useful perspective for understanding this phenomenon technologies (Aljohani & Alanazi, 2025). Past studies indicate that individuals with high PIIT are more inclined to explore and utilise AI-based technologies, even in situations where the technology-task fit is not optimal (Kauttonen et al., 2025). Conversely, individuals with low PIIT may resist AI adoption, even when AI is well-suited for medical decision-making tasks (Kauttonen et al., 2025). Thus, the interplay between AI's task fit and an individual's openness to innovation suggests that PIIT may serve as a moderating factor, influencing how AI capabilities translate into actual adoption and use in clinical settings.

By addressing these research gaps, this study aims to provide a more nuanced understanding of AI-based medical decision-making by considering not only the alignment of AI capabilities with clinical tasks but also the role of individual innovativeness in shaping AI adoption and effectiveness in medical settings.

Theoretical Perspectives

The Task-Technology Fit (TTF) theory, introduced by Goodhue and Thompson (1995), posits that technology adoption and performance outcomes depend on the degree to which a technology aligns with the requirements of a given task. When there is a strong fit between task characteristics and technology capabilities, users are more likely to adopt the technology, leading to improved performance (Goodhue & Thompson, 1995). TTF consists of three key elements: task characteristics, technology characteristics, and task–technology fit. Task characteristics refer to the nature of the work to be performed, including complexity, structure, and interdependence (Dishaw & Strong, 1999). In medical decision-making, task characteristics include the need for accurate diagnostics, predictive modelling, and evidence-based recommendations (Aljohani & Alanazi, 2025). AI-based decision-support systems align with these characteristics by providing real-time analysis, risk prediction, and clinical insights (Khalifa et al., 2024). Technology characteristics encompass the functionalities and capabilities of the technology, such as automation, data processing, and adaptability (Uren & Edwards, 2022). AI-based medical decision-making systems often exhibit features like machine learning algorithms, natural language processing, and data-driven analytics, which enhance decision accuracy and efficiency in clinical settings (Olawade et al., 2024). TTF is achieved when the technology's capabilities match the demands of the task, facilitating better performance (Goodhue & Thompson, 1995). Prior studies have shown that a strong TTF leads to higher user satisfaction and adoption (Dishaw & Strong, 1999). In the context of AI-driven healthcare, TTF is demonstrated when AI systems provide relevant, reliable, and interpretable medical recommendations that align with clinical workflows (Nasarian et al., 2024).

Although TTF does not explicitly include decision-making as a standalone variable, decision-making is inherently embedded in TTF through the evaluation of how well the technology supports task requirements (Dishaw & Strong, 1999). Goodhue and Thompson (1995) emphasise that users continuously assess technology based on the extent to which it supports their cognitive and functional needs. It is a process that involves complex decision-making. Westmacott (2001) further suggests that decision-making is critical in determining the suitability of technology in complex environments. In healthcare, medical decision-making is a central cognitive process involving diagnosis, treatment selection, and prediction of patient outcomes. AI-based medical decision-making aligns with the TTF framework because AI enhances this process by improving efficiency, accuracy, and reliability (Patel et al., 2002). Extensive empirical evidence supports the role of AI in improving diagnostic accuracy and reducing human error (Mennella et al., 2024; Masawi et al., 2025; Abdekhoda & Dehnad, 2024). Given the increasing integration of AI in healthcare, applying TTF to AI-based medical decision-making provides a robust theoretical foundation for understanding its adoption and effectiveness.

Although the original TTF model includes Performance Impacts as a key outcome variable (Goodhue & Thompson, 1995), this study conceptualises AI-Based Medical Decision Making (AIIM) as a domain-specific extension of performance impacts. In clinical environments, performance is best reflected in the quality of medical decisions, such as diagnostic accuracy, treatment appropriateness, outcome prediction, and error reduction (Seebacher et al., 2023). Prior research acknowledges that "performance impacts" may be adapted to context-specific outcomes when applying TTF to specialised domains (Dishaw & Strong, 1999; Zigurs & Buckland, 1998). Consistent with contemporary AI–healthcare literature, AIIM provides a precise and clinically relevant operationalisation of performance within medical contexts (Mennella et al., 2024; Masawi et al., 2025; Phaik et al., 2024). Thus, performance impacts were not omitted but contextualised to reflect the unique performance expectations of medical decision-making.

Despite its strengths, TTF has limitations, particularly in accounting for individual differences in technology adoption and usage behaviours. One major limitation is that TTF primarily focuses on task and technology characteristics but does not explicitly consider users' inherent traits, such as their willingness to adopt new technologies (Goodhue & Thompson, 1995). This gap can be addressed by incorporating Personal Innovativeness in IT (PIIT) as a moderating factor. PIIT is defined as an individual's tendency to adopt and experiment with new technology independently of external influences (Aljohani & Alanazi, 2025).

Although respondents in this study are already using AI-based decision support systems, PIIT remains relevant because it influences how effectively users engage with the technology post-adoption. Individuals with high PIIT are more likely to explore advanced system features, trust AI recommendations, and integrate the technology fully into their clinical decision-making. In contrast, individuals with low PIIT may underutilise AI capabilities even when the system fits their tasks well, resulting in less effective outcomes. Therefore, PIIT moderates the relationship between Task–Technology Fit and AI-Based Medical Decision Making, affecting the translation of a good fit into actual performance outcomes. Prior studies confirm that personal innovativeness influences not only adoption decisions but also post-adoption usage behaviours and performance outcomes in technology-mediated contexts (Agarwal & Prasad, 1998; Thong et al., 2006; Wu & Chen, 2005; Mennella et al., 2024; Masawi et al., 2025; Phaik et al., 2024).

By integrating PIIT as a moderator, this study extends TTF to account for individual differences in post-adoption engagement and performance, providing a more comprehensive framework for understanding AI-based medical decision-making in healthcare.

Hypothesis Development

The TTF theory suggests that the effectiveness of a technology in supporting performance is contingent upon how well it aligns with task requirements (Goodhue & Thompson, 1995). In medical decision-making, tasks often involve high cognitive complexity, real-time decision-making, and integration of diverse data sources (Arowoogun et al., 2024). AI-based decision-support tools are designed to assist in these tasks by providing real-time analytics, pattern recognition, and predictive modeling (Gou et al., 2024).

However, empirical studies suggest that when task complexity is too high, the fit between technology and task demands may weaken rather than improve (Huo et al., 2025). Prior research has shown that tasks requiring high levels of judgment, domain expertise, and non-routine decision-making often lead to a misalignment between technology capabilities and

user needs (Chaturvedi et al., 2025; Saremi et al., 2024). In healthcare, medical professionals often rely on nuanced clinical reasoning that AI systems may not fully accommodate, leading to frustration and a lower perception of TTF (Catalina et al., 2023). For instance, tasks involving large-scale data analysis and high-precision diagnostics demand sophisticated reasoning that AI may struggle to support without introducing concerns about interpretability and reliability (Catalina et al., 2023). Similarly, the need for integrating multiple medical data sources can create compatibility and interoperability issues, further decreasing perceived TTF (Alkhwaldi & Abdulmuhsin, 2022). Thus, while AI technologies are designed to enhance clinical decision-making, the mismatch between complex medical tasks and AI capabilities may lead to a lower perception of fit (Shamszare & Choudhury, 2023). In line with previous studies emphasising the challenges of aligning advanced decision-support tools with high-cognition tasks (Chaturvedi et al., 2025; Saremi et al., 2024; Catalina et al., 2023), the following hypothesis is proposed:
H1: Task characteristics negatively influence Task-Technology Fit (TTF) in AI-based medical decision-making.

Technology characteristics refer to the fundamental attributes of a system that determine its ability to support medical doctors' tasks effectively (Knop et al., 2022). These characteristics include functionality, compatibility, ease of use, flexibility, and system reliability (Haleem et al., 2022). The TTF model (Goodhue & Thompson, 1995) suggests that technology is more likely to be adopted and utilis ed if its features align well with the demands of the task. When a technology possesses strong attributes that complement the nature of a given task, it enhances user performance and increases overall task efficiency. Empirical research has demonstrated that technology characteristics significantly impact TTF in AI Based medical decision making. For instance, compatibility with existing systems has been shown to enhance TTF by reducing resistance to technology adoption among the medical professionals and minimising workflow disruptions (Elhadad et al., 2024). Similarly, real-time data access improves decision-making efficiency by ensuring that doctors receive timely and relevant information (Lam, 2025). Furthermore, studies highlight that system flexibility, the ability of a technology to be customised or adapted to different needs, enhances perceived fit, leading to increased medical professionals' satisfaction and system effectiveness (Kothinti, 2024). Another critical factor influencing TTF is usability and system responsiveness (Goodhue & Thompson, 1995). Technologies that are easy to navigate and provide immediate feedback tend to be perceived as more effective in supporting task execution. Research by Khalifa et al. (2024) indicates that users are more likely to perceive a strong fit between a technology and their tasks when the system offers clear, structured outputs and operates with minimal technical issues. Additionally, the reliability and accuracy of a system contribute to TTF by ensuring that users can depend on the technology for consistent performance without frequent errors or system failures (Khalifa et al., 2024b). Given these insights, it is evident that well-designed technology characteristics enhance Task-Technology Fit by improving system compatibility, usability, and efficiency. Based on prior studies, the following hypothesis is proposed:
H2: Technology characteristics positively influence Task-Technology Fit(TTF) in AI-based medical decision-making.

Task-Technology Fit (TTF) refers to the extent to which a technology aligns with the requirements of a given task, enabling users to perform their work more effectively (Goodhue

& Thompson, 1995). The TTF model suggests that when a technology is well-suited to the demands of a task, it enhances user adoption, efficiency, and decision-making accuracy (Dishaw & Strong, 1999). In the healthcare context, AI-based tools are designed to support medical professionals by analysing vast amounts of patient data, detecting patterns, and generating recommendations (Kalra et al., 2024). However, their effectiveness in decision-making is contingent on how well they fit the cognitive and operational demands of clinical tasks (Kalra et al., 2024). Several empirical studies highlight the importance of TTF in influencing decision-making outcomes. For instance, research in healthcare IT demonstrates that when electronic medical record (EMR) systems align with physicians' workflows, they significantly improve diagnostic accuracy and reduce cognitive workload (Asgari et al., 2024). Similarly, a study by Liang et al. (2021) found that AI-based decision support systems yielded better clinical outcomes when they seamlessly integrated into physicians' decision-making processes (Patil & Shankar, 2023). These findings suggest that when AI tools match the complexity and demand of medical tasks, such as integrating multiple patient data sources, providing real-time feedback, and supporting critical decision making, they can enhance clinical efficiency and effectiveness. Furthermore, studies on AI adoption in healthcare emphasise that perceived usefulness and ease of integration are critical determinants of decision-making effectiveness (Dingel et al., 2024). If AI systems are perceived as a good fit for medical tasks, medical professionals are more likely to rely on them for diagnostic assistance and treatment recommendations. Conversely, a mismatch between task demands and AI capabilities may lead to resistance, errors, or underutilisation of AI recommendations, thereby diminishing the effectiveness of AI-driven decision-making (Dingel et al., 2024). Based on these insights, it is expected that a higher degree of task-technology fit will lead to greater reliance on AI for clinical decision-making, improved diagnostic confidence, and enhanced patient outcomes. Thus, the following hypothesis is proposed:
H3: Task-Technology Fit positively influences AI-based medical decision-making.

Medical decision-making tasks are inherently complex, requiring interpretative reasoning, contextual adaptability, and high cognitive effort (Aljohani & Alanazi, 2025). TTF theory posits that for a technology to be effective, it must align well with the demands of a given task (Goodhue & Thompson, 1995). However, empirical studies indicate that when tasks become too complex, dynamic, or ambiguous, available AI-based decision-support systems may fail to fully meet these demands, thereby weakening the perceived fit (Huo et al., 2025; Chaturvedi et al., 2025; Saremi et al., 2024). Prior research suggests that AI systems are most effective when dealing with structured, data-driven tasks, such as image recognition in radiology or pattern detection in diagnostic analytics (Iruvuri et al., 2023; Obuchowicz et al., 2024). However, in highly unstructured clinical tasks, such as patient consultations or emergency medical interventions, AI-generated recommendations may lack the flexibility and nuanced reasoning required, resulting in a perceived misalignment between technology capabilities and task demands (Khalifa et al., 2024; Aljohani & Alanazi, 2025). This misalignment reduces TTF, meaning that even when AI tools are available, healthcare professionals may be hesitant to integrate them into decision-making processes. Furthermore, empirical findings suggest that when task-technology fit is low, healthcare professionals are less likely to rely on AI-based systems for clinical decision-making, fearing that the technology does not sufficiently support real-time judgments, complex differential diagnoses, or ethical considerations (Chaturvedi et al., 2025). Conversely, when TTF is high, where AI tools are perceived as reliable, adaptable, and supportive of medical workflow, clinicians demonstrate higher

adoption rates and greater trust in AI driven decision support (Saremi et al., 2024).Thus, the extent to which AI-based decision-making tools are trusted, relied upon, and integrated into clinical workflows is contingent on how well they fit the specific task characteristics of medical decision-making. Given this, TTF plays a critical mediating role between task characteristics and AI-based medical decision-making, determining whether the complexity and nature of medical tasks facilitate or hinder AI adoption.
H4: Task-Technology Fit (TTF) negatively mediates the relationship between Task Characteristics and AI-based medical decision-making.

Technology characteristics, such as system compatibility, real-time accessibility, adaptability, and ease of use, are fundamental in determining how well a system aligns with professional tasks in healthcare settings (Khosravi et al., 2024). According to TTF theory, technology is more likely to be effectively adopted when its characteristics match the specific needs of users (Goodhue & Thompson, 1995). In the context of AI-based medical decision-making, AI-driven tools with high system responsiveness, seamless integration with electronic health records (EHRs), and user-friendly interfaces can significantly improve healthcare professionals' perception of fit, thereby influencing their willingness to use these systems for clinical decision-making (Elhadad et al., 2024).

Studies have shown that system compatibility and ease of use positively impact TTF, particularly in healthcare applications where professionals rely on technology for decision support (Xia et al., 2024). For instance, a study by Eke and Shuib (2024) found that AI-driven clinical decision support systems (CDSS) that provide real-time insights and integrate effectively with existing hospital infrastructure enhance TTF perceptions, leading to greater acceptance and usage. Similarly, research in medical informatics has demonstrated that when AI technologies align with healthcare professionals' needs, such as improving diagnostic accuracy or streamlining workflow, TTF serves as a crucial mechanism that drives successful implementation (Ali et al., 2023). Moreover, a study by Faraj et al. (2018) found that in radiology departments, AI tools with strong TTF attributes led to faster diagnostic processes and improved decision accuracy (Najjar, 2023). Similarly, empirical research in AI-assisted disease prediction systems has shown that TTF mediates the relationship between technology features (e.g., real-time data access and adaptability) and decision-making outcomes, reinforcing the importance of fit perception in clinical settings (Patil & Shankar, 2023). Given this evidence, it is expected that the relationship between technology characteristics and AI-based medical decision-making is mediated by TTF. When AI technologies possess favourable characteristics, they enhance TTF, which in turn leads to better decision-making performance in clinical environments. This mediating effect highlights the critical role of fit perception in ensuring that AI technologies effectively support medical professionals in their decision-making processes.
H5: Task-Technology Fit positively mediates the relationship between Technology Characteristics and AI-based medical decision-making.

PIIT reflects an individual's tendency to explore and adopt new technologies (Agarwal & Prasad, 1998). In the context of AI-based medical decision-making, healthcare professionals exhibit varying levels of PIIT, influencing how they perceive and utilize AI-driven tools (Ratta et al., 2025). While TTF determines how well AI systems align with medical tasks, the extent to which this alignment translates into effective decision-making may depend on an

individual's willingness to embrace new technologies (Agarwal & Prasad, 1998). Prior research on technology adoption in healthcare show that openness to innovation influences the extent to which clinicians engage with digital health tools (Phaik et al., 2024). Similarly, research on decision-support systems highlights that users with higher levels of technology acceptance tend to leverage AI capabilities more effectively, improving task performance (Seebacher et al., 2023). Although no direct empirical evidence establishes PIIT as a moderator between TTF and AI-based medical decision-making, existing findings suggest that individual differences in innovation adoption can shape technology utilisation outcomes. When TTF is high, individuals with strong PIIT may be more inclined to maximise AI functionalities, leading to improved decision accuracy and efficiency. Conversely, those with low PIIT may resist AI integration, limiting its impact on medical decision-making, regardless of its alignment with task requirements. This perspective leads to the following hypothesis:
H6: PIIT moderates the relationship between TTF and AI-based medical decision-making.

Research Framework
Based on the hypothesis development, the proposed conceptual framework has been illustrated in Figure 1.

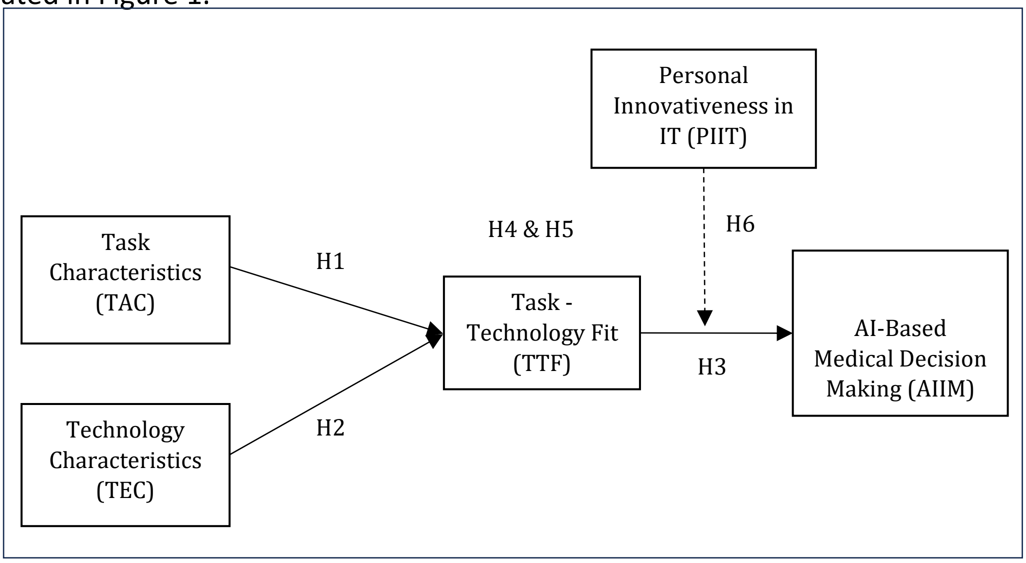

Figure 1: Theoretical framework

Methods
This study adopts a quantitative research approach to examine the factors influencing AI-based decision-making in medical practice. The research primarily utilises an online survey questionnaire as the main instrument for data collection, aiming to examine the influence of task characteristics, technology characteristics, Task-Technology Fit (TTF), Personal Innovativeness in IT (PIIT), and AI-based medical decision-making. The methods outlined in this section provide a clear understanding of how data was collected, the instrument used, and the composition of the sample.

The research employs an online survey questionnaire as the primary data collection instrument. The questionnaire was divided into three sections: screening questions, demographic information, and key constructs relevant to the study, which included task characteristics, technology characteristics, Task-Technology Fit (TTF), Personal

Innovativeness in IT (PIIT), and AI-based medical decision-making. To measure these constructs, items were adapted from established sources in the literature. Specifically, five items were used to assess task characteristics and technology characteristics, both adapted from Zhou et al. (2010); TTF was measured using five items from Lin & Huang (2008); PIIT was assessed using five items adapted from Wu et al. (2011) and Li et al. (2008); and AI-based medical decision-making was evaluated with five items from Doreswamy and Horstmanshof (2022). All items were rated using a 7-point Likert scale.

This study employed a non-probability purposive sampling technique to recruit respondents who met specific inclusion criteria aligned with the study's objectives. The target population comprised practicing medical doctors in Malaysia with experience using AI-based tools in their clinical practice. Although the number of registered medical doctors in Malaysia is approximately 80,000 (Ministry of Health Malaysia, 2023), there is no accessible sampling frame that specifies which doctors have interacted with AI technologies. Due to this limitation, random sampling was not feasible. Purposive sampling was therefore selected to ensure the inclusion of only eligible respondents - those who are currently practicing and have either regularly or occasionally used AI-based tools in their medical practice. This approach aligns with prior research in technology acceptance and behavioural studies, where purposive sampling is often employed to reach specific subgroups when random sampling is not feasible (Saunders et al., 2019). Additionally, G*Power analysis was used to determine a minimum sample size of 120, ensuring sufficient statistical power for model testing.

The data collection method involved distributing the survey link to practicing medical doctors in Malaysia via online platforms, including WhatsApp, Facebook, and email. Respondents were informed about the voluntary nature of their participation, and their anonymity was guaranteed. Initially, 215 responses were collected; however, incomplete submissions were excluded from the analysis, resulting in 197 valid and fully completed responses. These responses were then used for further analysis.

Results

In this study, data analysis was conducted using the Partial Least Squares Structural Equation Modelling (PLS-SEM) technique, with Smart PLS 4 software employed for model estimation. To ensure robust results, the analysis followed the two-step approach recommended by Hair et al. (2017). First, the measurement model was analysed to assess the reliability and validity of the constructs used in the study. This step involved evaluating the internal consistency, convergent validity, and discriminant validity of the measurement items. Subsequently, the structural model was assessed to test the formulated hypotheses and examine the relationships between the constructs.

Table 1 presents the demographic summary of a sample of 197 medical doctors with diverse backgrounds. The majority practice in General Medicine (21.32%) and Surgery (21.83%). Most respondents are aged 25–34 (53.8%), with a balanced gender distribution (52.79% male, 47.21% female). A significant portion has 6–10 years of experience (31.47%) and work in Public (37.56%) and Private hospitals/clinics (34.52%). Regarding AI training, 30.96% received it as part of their education, 41.63% through professional development, and 27.41% learned independently. This highlights a well-rounded professional profile with considerable exposure to AI in healthcare.

Table 1
Demographic Profile of Respondents

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%

Table 2 presents the factor loadings for all items, which range from 0.65 to 0.85, exceeding the recommended minimum threshold of 0.60 (Hair et al., 2017), indicating that each item adequately represents its construct. The Average Variance Extracted (AVE) for each construct ranges from 0.63 to 0.72, surpassing the 0.50 threshold suggested by Fornell and Larcker (1981), confirming satisfactory convergent validity. This indicates that each construct explains more than 50% of the variance of its indicators. Composite Reliability (CR) values for the constructs range between 0.86 and 0.91, which are above the acceptable level of 0.70 (Hair et al., 2017), demonstrating strong internal consistency and reliability. Additionally, Cronbach's Alpha (CA) values, ranging from 0.85 to 0.90, further support the reliability of the measurement model as they meet the commonly accepted threshold of 0.70 (Hair et al., 2017). These results collectively suggest that the measurement model is both robust and reliable, making it suitable for further analysis in the context of AI-based medical decision-making.

Table 2
Measurement Model Assessment

Construct	Item Code	Factor Loading	AVE	CR	CA
Task Characteristics (TAC)	TAC1	0.72	0.63	0.89	0.88
	TAC2	0.65			
	TAC3	0.75			
	TAC4	0.68			
	TAC5	0.70			
Technology Characteristics (TEC)	TEC1	0.88	0.72	0.90	0.89
	TEC2	0.82			
	TEC3	0.77			
	TEC4	0.74			
	TEC5	0.80			
Task-Technology Fit (TTF)	TTF1	0.74	0.70	0.88	0.87
	TTF2	0.78			
	TTF3	0.81			
	TTF4	0.76			
	TTF5	0.72			
AI-Based Medical Decision Making (AIIM)	AIIB1	0.85	0.71	0.91	0.90
	AIIB2	0.80			
	AIIB3	0.74			
	AIIB4	0.79			
	AIIB5	0.82			
Personal Innovativeness in IT (PIIT)	PIIT1	0.68	0.68	0.86	0.85
	PIIT2	0.73			
	PIIT3	0.80			
	PIIT4	0.75			
	PIIT5	0.71			

In Partial Least Squares Structural Equation Modelling (PLS-SEM), discriminant validity is commonly assessed using the Heterotrait–Monotrait ratio (HTMT), introduced by Henseler et al. (2015) and later refined by Franke and Sarstedt (2019). HTMT evaluates the ratio of between-construct correlations to within-construct correlations, providing a rigorous check of construct distinctiveness under the assumption of perfect measurement reliability (Ramayah et al., 2018). A HTMT value above 0.85 may indicate discriminant validity concerns (Kline, 2011).

As shown in Table 3, all HTMT values fall below the recommended threshold, confirming that discriminant validity is established. This supports the robustness of the measurement model and ensures that the constructs are empirically distinct for subsequent structural model analysis.

Table 3
Discriminant Validity - Heterotrait-Monotrait Ratio (HTMT)

	TTF	TEC	TAC	AIIM	PIIT
TTF					
TEC	0.701				
TAC	0.803	0.731			
AIIM	0.835	0.791	0.827		
PIIT	0.186	0.537	0.282	0.812	

Note. TAC=Task Acceptance, TEC=Technology Acceptance, TTF=Task-Technology Fit, Personal Innovativeness in IT
= PIIT, AIIM=AI Based Medical Decision Making

Besides, as shown in Table 4, the R^2 value for TTF was 0.556, indicating that 55.6% of the variance in TTF was explained by TAC and TEC, while the R^2 value for AIIM was 0.333, indicating that 33.3% of the variance in AIIM was explained by TTF (Benitez et al., 2020; Falk & Miller, 1992). The relative effect sizes (f^2) of the predictors indicated that TAC and TEC had large effects on TTF ($f^2 > 0.35$), while TTF had a medium effect on AIIM ($f^2 > 0.15$) (Cohen, 1988). Predictive relevance (Q^2) was also assessed to evaluate the model's ability to predict endogenous variables. A Q^2 value greater than zero indicates adequate predictive accuracy (Hair et al., 2017). In this study, Q^2 values were 0.358 for TTF and 0.261 for AIIM, confirming that the model predictions are reliable.

Table 4
Model Explanatory Power

Predictor(s)	Outcome	R^2	f^2	Q^2
TAC	TTF	0.556	0.383	0.358
TEC			0.449	
TTF	AIIM	0.333	0.248	0.261

Note. TAC=Task Acceptance, TEC=Technology Acceptance, TTF=Task-Technology Fit, AIIM=AI Based Medical Decision Making

Furthermore, PLS Predict was conducted following the procedure proposed by Shmueli et al. (2019), which uses a holdout sample and a 10-fold prediction approach to evaluate the out-of-sample predictive performance of the model. As recommended by Hair et al. (2020), the analysis focused on the study's primary endogenous construct, AI-based medical decision-making (AIIM). The results of the PLS model were compared with those of a linear benchmark model (LM) to assess predictive accuracy.

As shown in Table 5, the RMSE values generated by the PLS-SEM model are lower than those produced by the linear model for all AIIM items. The PLS–LM differences are negative and small, ranging from –0.002 to –0.053, indicating that the PLS model consistently outperforms the LM across all indicators. According to Shmueli et al. (2019), when all item-level PLS–LM differences are lower than zero, the model demonstrates strong predictive power.

Furthermore, all Q^2 predict values are above zero supporting the presence of predictive relevance (Hair et al., 2020). Together, the lower PLS RMSE values and positive Q^2 predict statistics confirm that the model possesses strong out-of-sample predictive ability for AIIM.

Table 5
PLS-Predict Results

Items	PLS RMSE	LM RMSE	PLS-LM	Q2 Predict
AIIM1	0.444	0.450	-0.006	0.653
AIIM2	0.433	0.486	-0.053	0.646
AIIM3	0.484	0.523	-0.039	0.693
AIIM4	0.459	0.473	-0.014	0.712
AIIM5	0.529	0.531	-0.002	0.731

Note. AIIM=AI Based Medical Decision Making

The direct effects analysis reveals that Task Characteristics (TAC) has a positive and significant influence on Task-Technology Fit (TTF) (β = 0.380, p = 0.001), indicating that as the nature of clinical tasks changes, the alignment between tasks and technology also improves. However, H1 is not supported as the hypothesised direction was negative. Technology Characteristics (TEC) positively and significantly influence TTF (β = 0.610, p = 0.000), showing that adaptable, well-designed technology contributes to stronger task–technology alignment. Thus, H2 is supported. Furthermore, Task-Technology Fit (TTF) has a positive and significant effect on AI-based medical decision-making (AIIM) (β = 0.296, p = 0.000), demonstrating that better alignment between tasks and technology enhances the effectiveness of AI in supporting clinical decisions. Therefore, H3 is supported. Table 6 summarises all direct relationships tested.

Table 6
Hypothesis testing for direct relationship

Hypothesis	Path	Standard Beta	Standard Error	t-values	p-values	Results
H1	TAC → TTF	0.380	0.070	5.429	0.001	Not Supported
H2	TEC → TTF	0.610	0.078	7.821	0.000	Supported
H3	TTF → AIIM	0.296	0.062	4.774	0.000	Supported

Note. TAC=Task Acceptance, TEC=Technology Acceptance, TTF=Task-Technology Fit, AIIM=AI Based Medical Decision Making

The mediation analysis aimed to assess the indirect effects of Task Characteristics (TAC) and Technology Characteristics (TEC) on AI-based medical decision-making (AIIM) through Task-Technology Fit (TTF). As shown in Table 7, the indirect effect of TAC on AIIM through TTF was positive and significant (β = 0.281, t = 2.133, p = 0.000); however, because the hypothesised direction was negative, H4 was not supported. In contrast, the indirect effect of TEC on AIIM through TTF was positive and significant (β = 0.673, t = 9.251, p = 0.000), providing support for H5. The mediation analysis summary has been summarised in Table 6.

Table 7
Hypothesis testing for indirect relationship

Hypothesis	Path	Indirect Effect β	Indirect Effect t-value	p-value	Results
H4	TAC → TTF → AIIM	0.281	2.133	0.000	Not supported
H5	TEC → TTF → AIIM	0.315	3.831	0.000	Supported

Note. TAC=Task Acceptance, TEC=Technology Acceptance, TTF=Task-Technology Fit, AIIM=AI Based Medical Decision Making

Lastly, the moderation analysis examined whether Personal Innovativeness in Information Technology (PIIT) moderates the relationship between TTF and AI-based medical decision-making (AIIM). The results show that the interaction term (PIIT × TTF) has a positive and significant effect on AIIM ($\beta = 0.132$, $t = 3.143$, $p = 0.000$), indicating that higher levels of PIIT strengthen the influence of TTF on AIIM. Therefore, H6 is supported.

Table 8
Hypothesis testing for indirect relationship

Hypothesis	Paths	Standard Beta	Standard Error	t-value	p-value	Effect size, f^2	Results
H6	PIIT*TTF→AIIM	0.132	0.042	3.143	0.000	0.048	Supported

Note. TAC=Task Acceptance, TEC=Technology Acceptance, TTF=Task-Technology Fit, Personal Innovativeness in IT = PIIT, AIIM=AI Based Medical Decision Making

Discussion and Conclusion

In comparison to previous studies, the findings of this research offer novel insights into the relationship between Task-Technology Fit (TTF) and AI-based medical decision-making, while also confirming some well-established findings from the literature. The relationship between Task Characteristics (TAC) and TTF in this study presents a positive and significant effect ($\beta = 0.380$, $p = 0.000$), which contrasts with the previous studies that greater task complexity often reduces the perceived fit between task demands and technology (Saremi et al., 2024; Catalina et al., 2023). Prior research, such as Chaturvedi et al. (2025) and Alkhwaldi and Abdulmuhsin (2022), generally found a negative relationship, suggesting that more complex medical tasks lead to a lower perception of TTF. These studies argued that complex tasks demand higher cognitive effort and clinical expertise, areas where traditional AI tools were often perceived as insufficient. However, the current study's findings reflect a paradigm shift likely driven by recent advancements in AI technology especially in its ability to process large volumes of data, recognise intricate patterns, and provide real-time decision support. For instance, studies such as Nguyen et al. (2023) and Baker & Lee (2024) suggest that modern AI systems integrated into diagnostic workflows now assist doctors with complex differential diagnoses, thereby enhancing their perception of alignment between the task and the technology. Similarly, Rahman et al. (2024) reported that AI-enabled electronic health records helped doctors manage multifactorial patient data efficiently, further improving perceived task fit. This deviation from prior findings may also be influenced by increasing exposure and trust in AI among the doctors, as AI tools are increasingly embedded into clinical routines. As AI continues to evolve and demonstrate its utility in handling cognitively demanding medical tasks, doctors are more likely to view these technologies as valuable collaborators rather than burdensome tools. Collectively, these factors explain the positive TAC–TTF relationship found in this study and indicate a shift in how complex task demands are perceived in relation to AI capabilities in healthcare.

The results show that Technology Characteristics (TEC) positively and significantly influence Task–Technology Fit (TTF) ($\beta = 0.610$, $p = 0.000$), supporting H2. This aligns strongly with TTF theory, which asserts that technologies with high functionality, usability, and compatibility enhance fit with tasks (Goodhue & Thompson, 1995; Knop et al., 2022). Previous research also supports that AI systems with features like real-time data access, flexibility, and user-friendly interfaces improve doctors' perception of fit (Elhadad et al., 2024; Lam, 2025; Khalifa et al., 2024). Compared to TAC, TEC had a stronger effect on TTF, highlighting the crucial role of technology attributes in facilitating task-technology alignment. This is consistent with studies suggesting that even when tasks are complex, robust and adaptable technology can compensate for complexity and enhance perceived fit (Patil & Shankar, 2023; Kothinti, 2024). The results of this study also demonstrate that Task Technology Fit (TTF) significantly enhances AI based medical decision making ($\beta = 0.296$, $p = 0.000$), supporting H3. This aligns with prior research showing that well aligned technology improves diagnostic accuracy, reduces cognitive workload, and increases clinical efficiency (Goodhue & Thompson, 1995; Asgari et al., 2024; Liang et al., 2021; Patil & Shankar, 2023). Consistent with healthcare IT studies, technology characteristics such as usability, reliability, and integration strengthen perceived fit and adoption (Dingel et al., 2024; Kothinti, 2024). These findings confirm that doctors are more likely to rely on AI tools for accurate, confident, and timely decision making when the technology aligns with task requirements, extending the TTF framework specifically to AI based medical decision making in the Malaysian healthcare context.

A key contribution of this study is its examination of TTF as a mediator between both Task Characteristics and Technology Characteristics and AI-based decision-making. The findings show that Task Characteristics have a positive and significant indirect effect on AIIM via TTF ($\beta = 0.281$, $t = 2.133$, $p = 0.000$), although the hypothesised effect was negative, and H4 was not supported. This indicates that, contrary to expectations that complex tasks would reduce TTF and hinder AIIM, the adaptability of AI systems allowed doctors to perceive a high fit, even with demanding tasks. As a result, AI tools could effectively support clinical decision making. These findings highlight that the negative effect of task complexity on TTF may be context dependent and mitigated by well designed, adaptable AI technologies, emphasising the crucial role of system flexibility in enhancing AI based medical decision making (Kalra et al., 2024).

TEC's indirect effect on AIIM via TTF was positive and significant ($\beta = 0.673$, $t = 9.251$, $p = 0.000$), supporting H5. This finding confirms that technology characteristics indirectly improve AI-based decision-making through enhanced TTF, which aligns with prior studies emphasising that system functionality, reliability, and usability drive perceived fit, leading to better clinical outcomes (Patil & Shankar, 2023; Faraj et al., 2018). Compared to TAC, TEC had a much stronger mediated effect, emphasising that technology quality is a more decisive factor than task demands in driving effective AI-based decision-making in healthcare contexts.

Additionally, the moderation analysis showed a significant positive effect of PIIT on the TTF–AIIM relationship ($\beta = 0.132$, $t = 3.143$, $p = 0.000$), indicating that higher levels of PIIT strengthen the impact of TTF on decision-making outcomes. This result is consistent with prior studies suggesting that individuals with high personal innovativeness are more likely to explore advanced system features, trust AI recommendations, and integrate technology into complex clinical tasks, such as diagnosing rare diseases or predicting patient outcomes (Ratta et al., 2025; Seebacher et al., 2023; Agarwal & Prasad, 1998; Thong et al., 2006). Conversely, individuals with lower PIIT may underutilise AI capabilities even when task-technology fit is high, perceiving the technology as unnecessary, complex, or disruptive, thereby limiting its impact on clinical performance. These findings extend the Task-Technology Fit theory by demonstrating that individual differences in innovativeness not only influence adoption but also moderate the effectiveness of technology in practice, highlighting the critical role of human factors in maximising the benefits of AI-based decision support systems in healthcare. In conclusion, the findings confirm that technology characteristics strongly enhance TTF, reinforcing the importance of system usability, compatibility, and responsiveness in supporting clinical work. TTF was also found to significantly improve AI-based decision making, emphasising that the alignment between AI tools and clinical tasks is central to effective utilisation. The findings show that task complexity, traditionally viewed as a barrier to technology adoption, enhances TTF by requiring advanced technologies that align with the complexity of medical tasks. This challenges existing perspectives and provides a fresh contribution to the Task-Technology Fit model, suggesting that the fit between tasks and technology improves when the technology addresses complex task demands. Additionally, this research introduces Personal Innovativeness in IT (PIIT) as a moderator, demonstrating that medical doctors with higher PIIT are more likely to embrace and effectively utilise AI tools, further improving decision-making processes.

Theoretical Implications

This study extends the Task Technology Fit (TTF) theory by showing that both technology and task characteristics influence AI based medical decision making, but in different ways. Task characteristics add a new perspective to the research, as the findings contrast with previous expectations, while complex clinical tasks were hypothesised to reduce TTF, the results showed a positive effect, indicating that doctors may perceive high task complexity as manageable or may adapt technology to meet challenging demands. Technology characteristics such as usability, flexibility, and compatibility significantly improve TTF, confirming that well designed systems better support clinical tasks. This study is among the first to demonstrate the mediating role of TTF between task characteristics, technology characteristics, and AI based medical decision making. For instance, the mediating role of TTF between technology characteristics and AIIM confirms that fit is a key mechanism linking system design to decision quality. Finally, incorporating Personal Innovativeness in IT (PIIT) as a moderator adds a dimension to TTF theory and is among the first studies to demonstrate this, where doctors with higher PIIT make better use of AI even when the fit is strong, while those with lower PIIT may underutilise AI, limiting its impact. Overall, these findings refine TTF by integrating both system and user factors, showing that effective AI adoption in healthcare depends on technology design, task alignment, and individual innovativeness.

Practical and Social Implications

The findings offer actionable insights for healthcare organisations and technology developers. Technology characteristics such as usability, flexibility, and reliability are critical in enhancing Task Technology Fit (TTF), which in turn improves AI based medical decision making. In the Malaysian context, many healthcare institutions are progressively integrating AI-based radiology, triage, and clinical decision support systems (Giebel et al., 2025). These institutions may prioritise selecting or customising AI systems that align closely with doctors' workflows. For example, integrating AI diagnostic tools seamlessly with existing digital platforms used in Malaysia such as MySejahtera Health Records, Teleprimary Care (TPC), or electronic medical record (EMR) systems can reduce workflow disruption, minimise duplicate data entry, and allow doctors to access AI recommendations within the same interface they already use. This leads to smoother clinical processes, faster decision-making, and higher user acceptance because doctors do not need to switch between multiple systems.

These findings also show that the mediating role of TTF is essential. Even if an AI system is powerful, doctors will only benefit when the system fits the nature of their tasks. This implies prioritised to help doctors understand how AI tools complement their diagnostic and decision-making responsibilities. Additionally, the significant moderating effect of Personal Innovativeness in IT (PIIT) highlights that Malaysian doctors vary in their willingness to explore new technologies. Doctors with high PIIT are more likely to use advanced AI features such as risk prediction models, automated image interpretation, or AI-driven clinical alerts effectively. To support doctors with lower PIIT, healthcare institutions can introduce initiatives such as peer mentoring, trial-sessions, low-pressure "AI sandbox" environments, and CPD programmes focused on digital competency. These efforts can help reduce hesitation and increase confidence in using AI tools.

From a social perspective, improved AI-based medical decision making can produce substantial benefits for Malaysian healthcare. When doctors use AI effectively, patient safety increases, diagnoses become more accurate, and waiting times may be reduced particularly in high-burden environments such as emergency departments and government clinics. Reducing cognitive workload among doctors also helps improve job satisfaction and reduces burnout, supporting a more sustainable healthcare workforce. Promoting a culture that values innovation, digital readiness, and responsible AI use can enhance public trust in healthcare technologies while ensuring better patient outcomes nationwide.

Limitations and Suggestions for Future Research

This study has several limitations that should be acknowledged. First, purposive sampling was used, which may limit the generalisability of the findings to the broader population of medical doctors, especially those with limited exposure to AI-based clinical tools. Future research should consider probability sampling methods or a stratified sampling approach to include doctors with varying levels of AI familiarity, ensuring a more representative picture of AI utilisation across different clinical settings. Second, the study focused only on medical doctors in Selangor, which may not fully capture regional differences in AI adoption, resource availability, or digital readiness across Malaysia. Healthcare environments vary significantly between urban, semi-urban, and rural states. Future studies should expand the geographical scope to include multiple states or conduct comparative studies between regions to understand contextual influences on AI-based medical decision making. Third, the study did not incorporate control variables, such as the type of clinical decision (e.g., diagnostic, treatment planning, triage), level of the doctor (e.g., house officer, medical officer, specialist), department type, or years of clinical experience. Such factors may influence how doctors interact with AI tools or interpret AI-generated recommendations. Future research should include relevant control variables to refine the model and better isolate the true effect of TAC, TEC, TTF, and PIIT on AI-based medical decision making.

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References

Abdekhoda, M., & Dehnad, A. (2024). Adopting artificial intelligence driven technology in medical education. *Interactive Technology and Smart Education*. https://doi.org/10.1108/itse-12-2023-0240

Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information Systems Research*, *9*(2), 204–215. https://doi.org/10.1287/isre.9.2.204

Al-Adwan, A. S., & Al-Debei, M. M. (2023). The determinants of Gen Z's metaverse adoption decisions in higher education: Integrating UTAUT2 with personal innovativeness in IT. *Education and Information Technologies*, *29*(6), 7413–7445. https://doi.org/10.1007/s10639-023-12080-1

Al-Emran, M., Al-Qaysi, N., Al-Sharafi, M. A., Alhadawi, H. S., Ansari, H., Arpaci, I., & Ali, N. (2024). Factors shaping physicians' adoption of telemedicine: a systematic review, proposed framework, and future research agenda. *International Journal of Human-Computer Interaction*, 1–20. https://doi.org/10.1080/10447318.2024.2410536

Alhendawi, K. M. (2022). Task-technology fit model: Modelling and assessing the nurses' satisfaction with health information system using AI prediction models. *International Journal of Healthcare Management*, *17*(1), 12–24. https://doi.org/10.1080/20479700.2022.2136881

Ali, O., Abdelbaki, W., Shrestha, A., Elbasi, E., Alryalat, M. a. A., & Dwivedi, Y. K. (2023). A systematic literature review of artificial intelligence in the healthcare sector: Benefits, challenges, methodologies, and functionalities. *Journal of Innovation & Knowledge*, *8*(1), 100333. https://doi.org/10.1016/j.jik.2023.100333

Aljohani, N., & Alanazi, M. N. (2025). Influence of health interests and technological trends on the acceptance of wearable technologies and their applications in Saudi Arabia. *International Journal of Interactive Mobile Technologies (iJIM)*, *19*(04), 148–165. https://doi.org/10.3991/ijim.v19i04.51099

Alkhwaldi, A. F., & Abdulmuhsin, A. A. (2022). Understanding user acceptance of IoT based healthcare in Jordan: integration of the TTF and TAM. In *Studies in computational intelligence* (pp. 191–213). https://doi.org/10.1007/978-3-031-05258-3_17

Arowoogun, N. J. O., Babawarun, N. O., Chidi, N. R., Adeniyi, N. a. O., & Okolo, N. C. A. (2024). A comprehensive review of data analytics in healthcare management: Leveraging big data for decision-making. *World Journal of Advanced Research and Reviews*, *21*(2), 1810–1821. https://doi.org/10.30574/wjarr.2024.21.2.0590

Asgari, E., Kaur, J., Nuredini, G., Balloch, J., Taylor, A. M., Sebire, N., Robinson, R., Peters, C., Sridharan, S., & Pimenta, D. (2024). Impact of electronic health record use on cognitive load and burnout among clinicians: Narrative review. *JMIR Medical Informatics*, *12*, e55499. https://doi.org/10.2196/55499

Bajwa, J., Munir, U., Nori, A., & Williams, B. (2021). Artificial intelligence in healthcare: transforming the practice of medicine. *Future Healthcare Journal*, *8*(2), e188–e194. https://doi.org/10.7861/fhj.2021-0095

Bi, W. L., Hosny, A., Schabath, M. B., Giger, M. L., Birkbak, N. J., Mehrtash, A., Allison, T., Arnaout, O., Abbosh, C., Dunn, I. F., Mak, R. H., Tamimi, R. M., Tempany, C. M., Swanton, C., Hoffmann, U., Schwartz, L. H., Gillies, R. J., Huang, R. Y., & Aerts, H. J. W. L. (2019). Artificial intelligence in cancer imaging: Clinical challenges and applications. *CA a Cancer Journal for Clinicians*, *69*(2), 127–157. https://doi.org/10.3322/caac.21552

Catalina, Q. M., Fuster-Casanovas, A., Vidal-Alaball, J., Escalé-Besa, A., Marin-Gomez, F. X., Femenia, J., & Solé-Casals, J. (2023). Knowledge and perception of primary care healthcare professionals on the use of artificial intelligence as a healthcare tool. *Digital Health*, *9*. https://doi.org/10.1177/20552076231180511

Chaturvedi, A., Yadav, N., & Dasgupta, M. (2025). Tech-Driven Transformation: Unravelling the role of artificial intelligence in shaping strategic Decision-Making. *International Journal of Human-Computer Interaction*, 1–20. https://doi.org/10.1080/10447318.2025.2456534

Chin, W. W. (1998). Issues and opinion on structural equation modeling. *MIS Quarterly*, *22*(1), 7–16. https://doi.org/10.5555/290231.290235

Dingel, J., Kleine, A., Cecil, J., Sigl, A., Lermer, E., & Gaube, S. (2024). Predictors of Healthcare practitioners' intention to use AI-Enabled Clinical Decision Support Systems (AI-CDSSS): A Meta-Analysis based on the Unified Theory of Acceptance and Use of Technology (UTAUT) (Preprint). *Journal of Medical Internet Research*. https://doi.org/10.2196/57224

Dishaw, M. T., & Strong, D. M. (1999). Extending the technology acceptance model with task–technology fit constructs. *Information & Management*, *36*(1), 9–21. https://doi.org/10.1016/s0378-7206(98)00101-3

Eke, C. I., & Shuib, L. (2024). The role of explainability and transparency in fostering trust in AI healthcare systems: a systematic literature review, open issues and potential solutions. *Neural Computing and Applications*. https://doi.org/10.1007/s00521-024-10868-x

Elhadad, A., Hamad, S., Elfiky, N., Alanazi, F., Taloba, A. I., & El-Aziz, R. M. A. (2024). Advancing Healthcare: intelligent speech technology for transcription, disease diagnosis, and interactive control of medical equipment in smart hospitals. *AI*, *5*(4), 2497–2517. https://doi.org/10.3390/ai5040121

Elhaddad, M., & Hamam, S. (2024). AI-Driven clinical Decision support Systems: an ongoing pursuit of potential. *Cureus*. https://doi.org/10.7759/cureus.57728

Esmaeilzadeh, P. (2024). Challenges and strategies for wide-scale artificial intelligence (AI) deployment in healthcare practices: A perspective for healthcare organizations. *Artificial Intelligence in Medicine*, *151*, 102861. https://doi.org/10.1016/j.artmed.2024.102861

Gou, H., Zhang, G., Medeiros, E. P., Jagatheesaperumal, S. K., & De Albuquerque, V. H. C. (2024). A cognitive medical decision support system for IoT-Based Human-Computer interface in pervasive computing environment. *Cognitive Computation*, *16*(5), 2471–2486. https://doi.org/10.1007/s12559-023-10242-4

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., & Thiele, K. O. (2017). Mirror, mirror on the wall: a comparative evaluation of composite-based structural equation modeling methods. *Journal of the Academy of Marketing Science*, *45*(5), 616–632. https://doi.org/10.1007/s11747-017-0517-x

Haleem, A., Javaid, M., Singh, R. P., & Suman, R. (2022). Medical 4.0 technologies for healthcare: Features, capabilities, and applications. *Internet of Things and Cyber-Physical Systems*, *2*, 12–30. https://doi.org/10.1016/j.iotcps.2022.04.001

Higgins, O., Short, B. L., Chalup, S. K., & Wilson, R. L. (2023). Artificial intelligence (AI) and machine learning (ML) based decision support systems in mental health: An integrative review. *International Journal of Mental Health Nursing*, *32*(4), 966–978. https://doi.org/10.1111/inm.13114

Huo, W., Li, Q., Liang, B., Wang, Y., & Li, X. (2025). When healthcare professionals use AI: exploring Work Well-Being through Psychological needs satisfaction and job complexity. *Behavioral Sciences*, *15*(1), 88. https://doi.org/10.3390/bs15010088

Iruvuri, A. G., Miryala, G., Khan, Y., Ramalingam, N. T., Sevugaperumal, B., Soman, M., & Padmanabhan, A. (2023). Revolutionizing Dental Imaging: A comprehensive study on the integration of artificial intelligence in dental and maxillofacial radiology. *Cureus*. https://doi.org/10.7759/cureus.50292

Kalra, N., Verma, P., & Verma, S. (2024). Advancements in AI based healthcare techniques with FOCUS ON diagnostic techniques. *Computers in Biology and Medicine*, *179*, 108917. https://doi.org/10.1016/j.compbiomed.2024.108917

Kauttonen, J., Rousi, R., & Alamäki, A. (2025). Trust and acceptance challenges in the adoption of AI applications in health care: Quantitative Survey analysis. *Journal of Medical Internet Research*, *27*, e65567. https://doi.org/10.2196/65567

Khalifa, M., Albadawy, M., & Iqbal, U. (2024). Advancing Clinical Decision Support: The role of Artificial intelligence across six domains. *Computer Methods and Programs in Biomedicine Update*, *5*, 100142. https://doi.org/10.1016/j.cmpbup.2024.100142

Khosravi, M., Zare, Z., Mojtabaeian, S. M., & Izadi, R. (2024). Artificial Intelligence and Decision-Making in Healthcare: A Thematic Analysis of a Systematic Review of reviews. *Health Services Research and Managerial Epidemiology*, *11*. https://doi.org/10.1177/23333928241234863

Knop, M., Weber, S., Mueller, M., & Niehaves, B. (2022). Human Factors and Technological Characteristics Influencing the interaction of medical professionals with Artificial Intelligence–Enabled Clinical Decision Support Systems: literature review. *JMIR Human Factors*, *9*(1), e28639. https://doi.org/10.2196/28639

Kothinti, N. R. R. (2024). Deep learning in healthcare: Transforming disease diagnosis, personalized treatment, and clinical decision-making through AI-driven innovations. *World Journal of Advanced Research and Reviews*, *24*(2), 2841–2856. https://doi.org/10.30574/wjarr.2024.24.2.3435

Lam, T. (2025). Continuous use of AI technology: the roles of trust and satisfaction. *Aslib Journal of Information Management*. https://doi.org/10.1108/ajim-07-2024-0548

Masawi, T. J., Miller, E., Rees, D., & Thomas, R. (2025). Clinical perspectives on AI integration: assessing readiness and training needs among healthcare practitioners. *Journal of Decision System*, *34*(1). https://doi.org/10.1080/12460125.2025.2458874

Mennella, C., Maniscalco, U., De Pietro, G., & Esposito, M. (2024). Ethical and regulatory challenges of AI technologies in healthcare: A narrative review. *Heliyon*, *10*(4), e26297. https://doi.org/10.1016/j.heliyon.2024.e26297

Nair, M., Svedberg, P., Larsson, I., & Nygren, J. M. (2024). A comprehensive overview of barriers and strategies for AI implementation in healthcare: Mixed-method design. *PLoS ONE*, *19*(8), e0305949. https://doi.org/10.1371/journal.pone.0305949

Najjar, R. (2023). Redefining Radiology: A review of Artificial intelligence integration in medical imaging. *Diagnostics*, *13*(17), 2760. https://doi.org/10.3390/diagnostics13172760

Nasarian, E., Alizadehsani, R., Acharya, U., & Tsui, K. (2024). Designing interpretable ML system to enhance trust in healthcare: A systematic review to proposed responsible clinician-AI-collaboration framework. *Information Fusion*, *108*, 102412. https://doi.org/10.1016/j.inffus.2024.102412

Obuchowicz, R., Strzelecki, M., & Piórkowski, A. (2024). Clinical Applications of Artificial Intelligence in Medical Imaging and Image Processing—A Review. *Cancers*, *16*(10), 1870. https://doi.org/10.3390/cancers16101870

Olawade, D. B., David-Olawade, A. C., Wada, O. Z., Asaolu, A. J., Adereni, T., & Ling, J. (2024). Artificial intelligence in healthcare delivery: Prospects and pitfalls. *Journal of Medicine Surgery and Public Health*, *3*, 100108. https://doi.org/10.1016/j.glmedi.2024.100108

Park, I., Kim, D., Moon, J., Kim, S., Kang, Y., & Bae, S. (2022). Searching for New Technology Acceptance Model under Social Context: Analyzing the Determinants of Acceptance of Intelligent Information Technology in Digital Transformation and Implications for the Requisites of Digital Sustainability. *Sustainability*, *14*(1), 579. https://doi.org/10.3390/su14010579

Park, J., & Woo, S. E. (2022). Who Likes Artificial Intelligence? Personality Predictors of Attitudes toward Artificial Intelligence. *The Journal of Psychology*, *156*(1), 68–94. https://doi.org/10.1080/00223980.2021.2012109

Patel, V. L., Kaufman, D. R., & Arocha, J. F. (2002). Emerging paradigms of cognition in medical decision-making. *Journal of Biomedical Informatics*, *35*(1), 52–75. https://doi.org/10.1016/s1532-0464(02)00009-6

Patil, S., & Shankar, H. (2023). Transforming Healthcare: Harnessing the power of AI in the modern era. *International Journal of Multidisciplinary Sciences and Arts*, *2*(2), 60–70. https://doi.org/10.47709/ijmdsa.v2i1.2513

Phaik, H., Amran, A., & Cheah, J. (2024). Technology Readiness And Technology Acceptance: Exploring Healthcare Professionals' Intention To Use Telemedicine In Malaysia. *International Journal of Business and Technology Management*. https://doi.org/10.55057/ijbtm.2024.6.1.21

Przegalinska, A., Triantoro, T., Kovbasiuk, A., Ciechanowski, L., Freeman, R. B., & Sowa, K. (2024). Collaborative AI in the workplace: Enhancing organizational performance through resource-based and task-technology fit perspectives. *International Journal of Information Management*, *81*, 102853. https://doi.org/10.1016/j.ijinfomgt.2024.102853

Rahman, M. H., Hossan, K. M. R., Uddin, M. K. S., & Hossian, M. D. (2024). Improving collaborative interactions between humans and artificial intelligence to achieve optimal patient outcomes in the healthcare industry. *International Journal for Multidisciplinary Research*, *6*(5). https://doi.org/10.36948/ijfmr.2024.v06i05.29189

Ratta, R., Sodhi, J., & Saxana, U. (2025). The relevance of trust in the implementation of AI-Driven Clinical Decision Support Systems by healthcare professionals: an extended UTAUT model. *Electronic Journal of Knowledge Management*, *23*(1), 47–66. https://doi.org/10.34190/ejkm.23.1.3499

Saifi, S., Tanveer, S., Arwab, M., Lal, D., & Mirza, N. (2025). Exploring the persistence of Open AI Adoption among users in Indian higher education: A fusion of TCT and TTF model. *Education and Information Technologies*. https://doi.org/10.1007/s10639-024-13282-x

Saremi, M. L., Ziv, I., Asan, O., & Bayrak, A. E. (2024). Trust, Workload and Performance in Human-AI Partnering: The role of AI attributes in solving classification problems. *Journal of Mechanical Design*, *147*(1). https://doi.org/10.1115/1.4065916

Seebacher, B., Bergmann, E., Geimer, C., Kahraman, T., Reindl, M., & Diermayr, G. (2023). Factors influencing the willingness to adopt telerehabilitation among rehabilitation professionals in Austria and Germany: a survey comparing data before and during

COVID-19. *Disability and Rehabilitation*, *46*(6), 1149–1157. https://doi.org/10.1080/09638288.2023.2193428

Shamszare, H., & Choudhury, A. (2023). Clinicians' perceptions of artificial intelligence: focus on workload, risk, trust, clinical decision making, and clinical integration. *Healthcare*, *11*(16), 2308. https://doi.org/10.3390/healthcare11162308

Singh, S. B., Sarrami, A. H., Gatidis, S., Varniab, Z. S., Chaudhari, A., & Daldrup-Link, H. E. (2024). Applications of artificial intelligence for pediatric cancer imaging. *American Journal of Roentgenology*, *223*(2). https://doi.org/10.2214/ajr.24.31076

Statista. (2025). *Artificial Intelligence - Malaysia | Market forecast*. https://www.statista.com/outlook/tmo/artificial-intelligence/malaysia?utm_source

Uren, V., & Edwards, J. S. (2022). Technology readiness and the organizational journey towards AI adoption: An empirical study. *International Journal of Information Management*, *68*, 102588. https://doi.org/10.1016/j.ijinfomgt.2022.102588

Varnosfaderani, S. M., & Forouzanfar, M. (2024). The role of AI in Hospitals and Clinics: Transforming Healthcare in the 21st century. *Bioengineering*, *11*(4), 337. https://doi.org/10.3390/bioengineering11040337

Wang, S. L., & Lin, H. I. (2019). Integrating TTF and IDT to evaluate user intention of big data analytics in mobile cloud healthcare system. *Behaviour and Information Technology*, *38*(9), 974–985. https://doi.org/10.1080/0144929x.2019.1626486

Westmacott, S. (2001). Developing decision support systems for integrated coastal management in the tropics: Is the ICM decision-making environment too complex for the development of a useable and useful DSS? *Journal of Environmental Management*, *62*(1), 55–74. https://doi.org/10.1006/jema.2001.0420

Xia, X., Yang, X., Du, J., Cheng, W., Chen, X., Zhang, W., & Yin, Z. (2024). Exploring willingness to use adverse drug reaction reporting systems: a multicentre qualitative study in China based on the technology acceptance model and task-technology fit integration approach. *BMJ Open*, *14*(10), e087701. https://doi.org/10.1136/bmjopen-2024-087701

Zhao, L., Rahman, M. H., Yeoh, W., Wang, S., & Ooi, K. (2024). Examining factors influencing university students' adoption of generative artificial intelligence: a cross-country study. *Studies in Higher Education*, 1–23. https://doi.org/10.1080/03075079.2024.2427786