The Relevance of Trust in the Implementation of AI-Driven Clinical Decision Support Systems by Healthcare Professionals: An Extended UTAUT Model

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Abstract: **Background**. In the healthcare sector clinical decision support powered by artificial intelligence is rapidly expanding. It can help medical personnel make better-informed decisions while saving time. The opposition of healthcare professionals to AI initiatives in the healthcare industry might prove to be a significant barrier, due to the combination of optimism and fear related to the technology. Professionals in the sector may be apprehensive about AI due to job security worries and the general public's lack of faith in the technology. **Objective**. A primary objective of this study is to examine how trust influences healthcare professionals' willingness to use AI-driven CDSS, particularly at well-known tertiary hospitals in Delhi-NCR region India, as well as to expand the Unified theory of acceptance and use of technology (UTAUT) by including constructs such as perceived risk and self-efficacy. **Method**. The UTAUT model provided the basis for the construction of a new model, which was developed by integrating the variables of perceived risk and self-efficacy. The model had eight components which were assessed using 31 survey questions. Two hundred and twenty participants filled out the surveys for the study. **Results**. The findings indicate that there are significant relationships between (PE) and (AI), (EE) and(AI), (PR) and (AI) and (SE) and (AI). This study reveals that trust fully mediates the relationship between AI which means that fostering trust in AI technology is essential for the successful adoption and implementation of AI-CDSS technology. There was no significant relationship between social influence and adoption of AI-powered CDSS nor between intention to adopt and actual use. **Conclusion**. The result of this study shed light on the factors influencing healthcare professionals to adopt AI-CDSS. The outcomes of this study provide insight into how individuals' performance expectancy, effort expectancy, social influence, perceived risk, and self-efficacy determine whether they embrace AI-CDSS. This study highlights the importance of trust in the deployment of these technologies in the healthcare sector. Furthermore, it highlights the significance of addressing perceived risk and self-efficacy. Although social influence plays a crucial role in technology adoption its impact may be limited in the case of AI-CDSS deployment in India. This could be due to the complexities of AI-CDSS implementation, the requirement for training, or the fact that healthcare personnel are unaware of the benefits of AI-CDSS or have limited exposure to it.

Keywords: Trust, Healthcare professionals, Self-efficacy, AI-clinical decision support systems, UTAUT model

1. Introduction

The rapid growth of AI-driven systems has resulted in major extensions of clinical decision-making within the healthcare industry. The use of artificial intelligence, which entails the simulation of human cognitive capacities in machines is predicted to enable enhanced illness surveillance, identification, and diagnosis, as well as find novel therapeutic techniques to promote precision medicine(Fogel and Kvedar, 2018) (Hamet and Tremblay, 2017)(Mesko, 2017)(Rajkomar, Dean and Kohane, 2019). According to recent studies, dermatologists may not be as good at diagnosing skin cancer as artificial intelligence (AI) systems(Esteva et al., 2017). Furthermore, researchers predict that AI systems will beat medical specialists in surgical performance by 2050 (Grace et al., 2018). As a result, the healthcare industry stands to gain significantly from the forthcoming "AI revolution" (Jiang et al., 2017)(Murdoch and Detsky, 2013). Even though artificial intelligence has the potential to enhance healthcare quality, safety and efficiency, major obstacles need to be overcome to successfully integrate algorithmic systems throughout the first stages of clinical practice. As a result, it is frequently noticed that these systems have not been trained using data particular to the local environment and do not align with context-specific patterns of care (Fogel and Kvedar, 2018)(He et al., 2019)(Panch, Mattie and Celi, 2019).

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Clinical studies are mounting up that demonstrate artificial intelligence algorithms can detect medical imaging abnormalities at a rate that is either faster than or comparable to that of human experts. Furthermore, these AI models show precision on par with, if not better than, that of human specialists(Qin et al., 2019) (Ting et al., 2017). Artificial intelligence provides possible advantages by pointing up trends that human specialists can miss due to the complexity of the present decision-making procedures or the obscurity of the indications(Sutton et al., 2020). This is a huge problem in developing nations like India, where the population is growing quickly, and few modern diagnostic tools are available. AI has been extensively utilized in medical diagnostics since the introduction of the first clinical decision support system in the 1970s. Despite frequently utilising algorithms, these systems typically depend on an extensive set of preprogrammed rules (Sutton et al., 2020).

Clinical decision support systems Based on artificial intelligence, or AI-CDSS, have an intelligent component. (Salem et al., 2015). These systems represent a major shift in thinking when compared to traditional CDSS. The creation of innovative algorithms aims to assist healthcare practitioners by integrating raw medical data, papers, and expert knowledge into a cohesive collection. CDSS, which incorporates AI, can enhance several facets of healthcare, involving healthcare workers' efficiency, patients' satisfaction with their care, and patients' overall security (Richard et al., 2020). Despite significant progress and clear benefits, CDSS technology based on artificial intelligence has not been adopted at the anticipated rate (Shortliffe and Sepúlveda, 2018) (Shinners et al., 2020) (Kohli & Jha, 2018).

While the market for AI-CDDSS has grown rapidly in recent years, a review of the existing literature reveals that more investigation into this area is warranted(Shinners et al., 2020). There needs to be more thorough knowledge because the existing corpus of research on the adoption of AI-CDSS is narrow(Shinners et al., 2020). In addition, AI-CDDSS's unique qualities may mean that past research on similar technologies needs to provide more context for implementing the system. Some of these characteristics include autonomous decision-making, the capacity for learning and improvement, the ability to beat human experts in terms of accuracy, and the opacity of its techniques. These one-of-a-kind traits give birth to a plethora of new fears, including the possible infringement on professional autonomy, worry about being replaced, dependency on the system, worries surrounding patient safety, and the legal liability connected with misdiagnosis (Shortliffe and Sepúlveda, 2018) (Fan et al., 2020) (Hengstler, Enkel and Duelli, 2016).

1.1 Introduction to the UTAUT Model and its Constructs

The UTAUT model, which was put forth by (Venkatesh et al., 2003) is a well-known and widely applied model that has attracted a lot of interest in the field of technology adoption. This theory has been used extensively to predict and clarify individuals' behaviour patterns when embracing contemporary technology. According to UTAUT, facilitating conditions and behavioural intention are two main aspects that impact an individual's adopting behaviour. In turn , three elements determine behavioural intention: performance expectancy, effort expectancy and social influence. Performance expectancy (PE) is "the degree to which an individual believes that applying the technology will help him or her to attain gains in job performance" (Venkatesh et al., 2003). Effort Expectancy (EE) measures how easy the system is to use. Social influence includes how people think other people feel about a given technology influences their feelings about that technology. The final element is the enabling condition, which is a person’s conviction that there is organizational support available for using the system. however, this construct impacts actual use rather than directly influencing the desire to use addition, UTAUT has four moderating variables: age, experience, gender, age, and voluntariness.

1.2 Research Objectives

Trust plays a major role in people's decision to embrace AI-CDSS systems. understanding the relationship between adoption intention, trust and actual usage is crucial to understanding the reason propelling the broad adoption of AI-driven CDSS. Understanding the importance of trust in the utilisation of AI-CDSS can have a substantial impact on their implementation and effectiveness. The primary goals of this research are:

- To identify the elements that influence healthcare professionals to use AI-CDSS.
- Expanding our focus beyond technological aspects, we delve into the human dimension of AI by examining the importance of trust within the healthcare setting when practitioners elect to implement A-CDSS.
- Another objective is to investigate the impact of personal factors, including self-efficacy and perceived risk, on an individual's receptiveness to adopting novel AI-CDSS-related behaviours.

2. Literature Review

2.1 Clinical Decision Support System

CDSSs, or clinical decision support systems, are high-tech computer programs used by hospitals and other medical facilities. These systems leverage extensive datasets, medical expertise, and analytical engines to generate personalized assessments or recommendations for healthcare professionals. The main aim of CDSS is to accelerate the process of clinical decision-making by enabling effective interaction between humans and computers(Sim et al., 2001; Haynes and Wilczynski, 2010). Metzger et al. delineate a conceptual structure for CDSS that incorporates temporal(i.e., preceding, during or after the clinical decision) and activity level (passive or active notifications) components. With this method, CDSS can be differentiated based on how much they assist and involve the user(Perreault and Metzger, 1999). Osheroff et al. have enhanced clinical decision assistance by integrating knowledge bases, order sets and other forms of support, in addition to notification and reminders(Osheroff et al., 2014). Knowledge-based systems are distinguished from non-knowledge-based systems in a CDSS by a unique categorization paradigm that makes use of machine learning and other statistical pattern recognition(Teufel and Binder, 2021).

A knowledge based clinical decision support system uses a knowledge base and reasoning engine to combine previous information with real-time patient data which facilitates the formulation of diagnosis non knowledge-based CDSS utilises state-of-the-art artificial intelligence techniques such as deep learning and machine learning to analyse previous patient cases and identify trends in clinical data. Knowledge-based clinical decision support systems (CDSS) utilize conditional criteria and the experience of certified medical experts to determine a definite diagnosis. On the other hand, non-knowledge-based CDSS does not require the creation of rules or the involvement of subject matter experts.

AI-CDSS can improve the efficiency of healthcare professionals, leading to better healthcare quality and increased patient safety(Richard et al., 2020). These systems have been employed in diverse applications, such as the diagnosis of rare diseases (Faviez et al., 2020) Diagnostic or prognostic sepsis(Wulff et al., 2019), detection of fractures(Langerhuizen et al., 2019), detection of cancer(Yassin et al., 2018), pharmacotherapy(Rawson et al., 2017; Roumeliotis et al., 2019) healthcare management (Oluoch et al., 2012; Carter et al., 2019).

Non-knowledge-based clinical decision support systems have attracted scholarly attention recently in the field of medical diagnosis, although further research is necessary. these CDSSs exhibit a significant level of independence, do not rely on pre-existing data, and employ self-learning techniques to consistently enhance their effectiveness AI-CDSS can greatly reduce diagnostic errors by leveraging their complexity and accuracy. This makes them capable of replacing human expertise, especially considering the limited research in this area. Our analysis will focus on AI-CDSS, which aims to aid medical practitioners in the diagnostic process.

2.2 Relevance of Trust in the Adoption of CDSS Driven by AI

The significance of Trust in healthcare professionals' acceptance and utilization of AI-powered CDSS is widely acknowledged. Past research emphasizes the pivotal role of Trust in healthcare practitioners' inclination to embrace AI-based CDSS. Fan et al. proposed combining the UTAUT model with Trust Theory (AIMDSS) to investigate the potential of an AI medical diagnostic system(Fan et al., 2020) in which it was observed that EE and SI have no impact on BI to use AIMDSS. Trust plays a crucial role in determining whether or not a person intends to use AI-CDSS. (Tran et al., 2021) conducted an online cross-sectional survey and found that EE and SI were positively influenced by initial trust, while no association was found between PE and initial trust. (Hameed et al., 2023) found that PE, EE, and initial trust positively influence healthcare providers' behavioural intentions to use AI. According to the results, trust holds a considerable influence on the intentions of one’s behaviour. However, a significant research gap remains in comprehending the influence of Trust as an intermediary factor between the intention to adopt and the practical utilization of AI-CDSS.

In addition to these studies, there were studies where the mediation role of trust was examined but not between adoption intention and actual usage. For example, (Bedué and Fritzsche, 2022)conducted research where the mediating role of perceived benefits and perceived risk between trust and adoption intention was studied. Another study by (Thakkar and Bharathi, 2023) found that Initial trust fully mediates the relationship between effort expectancy and behavioural intention, while partially mediating the relationship between performance expectancy and behavioural intention.(Cheng, Li and Xu, 2022)surveyed radiologists and found that human-computer trust mediates the relationship between expectancy and adoption intention

Additional research has emphasized the prominence of Trust in promoting the widespread acceptance and utilization of CDSS powered by AI in the healthcare sector but does not provide a theoretical or empirical approach to assess AI-CDDSS adoption. For example, studies by (Bajwa et al., 2023)(Crigger et al., 2022)(Choudhury and Asan, 2022) One of the key factors highlighted is Trust. The outcomes of these studies underscore the significance of Trust as a crucial factor influencing healthcare professionals' engagement with the system. Table 1 provides a summary of the key studies, their publication years, main findings, and research gaps related to the study. While previous research has highlighted the significance of trust in the implementation of CDSS powered by AI still there is a notable gap in research concerning the role of trust as a mediator between the intention to adopt CDSS powered by AI and its actual usage behaviour, This can provide insight into the mechanisms that govern the adoption process and is crucial for developing strategies to boost their adoption and successful incorporation into clinical workflows.

Table 1: Insights from Past Studies: Trust as a Key Determinant in AI-CDSS Implementation

Authors	Year	Method of the study	Main findings	Research gap
(Fan et al., 2020)	2018	The study proposed an incorporation of the UTAUT and Trust Theory to study the adoption of AIMDSS	EE and SI have no significant impact on behavioural intention to use AIMDSS. Trust has a significant impact on the behavioural intention(BI) of using AIMDSS.	No mediation role of trust was studied.
(Tran et al., 2021)	2021	Online cross-sectional survey	EE and SI were positively associated with initial trust, while no association was found between PE and initial trust. Only SI was positively related to BI.	
(Hameed et al., 2023)	2023	Integrated survey among healthcare providers	PE, EE, and initial trust positively influence healthcare providers' BI to use AI. The results indicate that trust has a significant impact on BI.	
(Thakkar and Bharathi, 2023)	2023	Mixed-methods approach	Factors such as PE, EE, SI, initial trust, and resistance to change predict the intention to use intelligent clinical diagnostic decision support systems. Initial trust fully mediates the relationship between EE and BI, while partially mediating the relationship between PE and BI.	The mediation role of trust was checked but not between adoption intention and actual usage.
(Cheng, Li and Xu, 2022)	2022	Cross-sectional study of 343 dental healthcare workers.	PE and EE positively influence healthcare workers' adoption intention of AI-assisted diagnosis and treatment. SI and human-computer trust mediate the relationship between expectancy and adoption intention. Trust plays a mediation role between EE and adoption intention.	
(Bedué and Fritzsche, 2022)	2022	Semi-structured interviews.	Lack of trust is a hindrance to AI adoption. Among the factors that increase trust in AI are access to knowledge, understandability, transparency and explainability. The mediating role of perceived benefits and perceived risk between trust and adoption intention was studied.	
(Bajwa et al., 2023)	2023	A structured questionnaire was distributed to 1419 fertility professionals.	Fertility professionals have a positive view towards using AI in clinical practice. Barriers to AI adoption include insufficient experience, knowledge, and validation.	Does not provide a conceptual or empirical model to examine AI-CDDSS adoption.
(Crigger et al., 2022)	2022	Review literature on challenges	Trust is crucial for AI adoption in healthcare. Physicians' trust accelerates AI integration, ensuring responsible, evidence-based, unbiased, and equitable AI deployment to enhance patient care and meet quadruple aim goals.	
(Choudhury and Asan, 2022)	2022	Semi-structured survey	Various factors such as workload, trustworthiness, risk, and training impact the use of AI in healthcare. Lack of trust inhibits the use of AI in healthcare.	

3. Theoretical Framework

The present study adopts the UTAUT model as the theoretical framework, further expanding to incorporate perceived risk and self-efficacy constructs. The following predictor variables from UTAUT were included in the analysis: Performance expectancy, effort expectancy, and social influence. The purpose of this update is to make it easier for researchers to learn whether medical practitioners plan to embrace CDSS, which is powered by artificial intelligence. The significance of adoption intention as a predictive factor for technology acceptance must be considered. However, it is crucial to note that the mere intention to adopt technology only sometimes results in its actual usage. Research on AI-driven CDSS in the Indian healthcare setting might benefit from including actual usage as an outcome variable. This would provide a deeper comprehension of the elements influencing the effective implementation and ongoing use of such systems.

3.1 Incorporation of Additional Constructs

The word self-efficacy describes a person's conviction and assurance in their capacity to carry out the essential tasks to accomplish desired results. In the framework of artificial intelligence(AI), an individual’s self-efficacy is a key factor in assessing their ability to use and complete tasks related to such technology(Chao, 2019) several studies have investigated the role of self-efficacy in accepting and utilizing artificial intelligence-based technologies across multiple sectors. The impact that self-efficacy had on nursing students' behavioural intentions was one of the most intriguing conclusions of a recent study that examined how they used AI-based healthcare technologies. The study found that nursing students' willingness to accept and employ AI-based healthcare technologies is influenced by their sense of self-efficacy (Kwak et al., 2022). According to the study, AI self-efficacy fosters positive attitudes toward AI-based health technology and reduces anxiety (Kwak, Seo and Ahn, 2022). A thorough study of the digital revolution taking place in the healthcare sector revealed that end users' lack of self-efficacy is a major barrier to their adoption and continued usage of technological innovations. (Iyanna et al., 2022). Thus, it is critical to comprehend the role that self-efficacy plays in healthcare practitioners’ intentions to adopt AI-CDSS.

“Perceived risk” relates to an individual's subjective view of the potential negative outcomes or uncertainties involved with adopting and making use of AI-based technology. Previous studies have shed light on the role of individuals' perceptions of risk in determining their attitudes and intentions regarding the embracing of novel technology. From the perspective of AI technology adoption in healthcare, clinicians' perception of risks and safety associated with AI systems can have significant implications (Choudhury, 2022) (Stuck and Walker, 2019) researched to study the connection between people's perceptions of risk and their willingness to embrace and implement new technology developments. According to the findings of the study, one of the most significant factors in technology acceptance and adoption is perceived risk.

The proposed study's goal is to understand the perception of risk associated with using such a system. Healthcare professionals may have concerns about relying on machine learning algorithms to make clinical decisions, fearing potential errors or biases. Additionally, they may worry about the security and confidentiality of patient data when using AI-based systems. It is essential to understand the role that perceived risk plays in the process of adopting AI-based CDSS technology to devise tactics to promote its uptake effectively. By addressing and mitigating perceived risk, healthcare organizations can enhance professionals' confidence in using these systems and facilitate their adoption.

3.2 Development of Hypothesis

3.2.1 Performance expectancy

When it comes to healthcare information systems (IS), the adoption and use of innovative technology depend on doctors' and nurses' evaluations of the advantages it offers over conventional practices (Payne, Wharrad and Watts, 2012) (Aggelidis and Chatzoglou, 2009). Henceforth, it is posited that if the practitioner holds the belief that the utilization of AI-based Clinical Decision Support Systems (CDDSS) will enhance their job performance, encompassing heightened speed, accuracy, productivity, and diminished workload, they will be inclined to foster an intention to employ said systems. The following hypothesis is proposed in this study:

H1. PE has a significant impact on the healthcare professional’s intention to adopt AI-based CDDSS.

3.2.2 Effort expectancy

Perceived ease of use is an essential factor in promoting the adoption of CDSS(Esmaeilzadeh et al., 2015). According to existing literature, there is a prevailing belief that individuals are more inclined to use user-friendly and straightforward systems than those that are complex and convoluted (Pennington, Kelton and DeVries, 2006). It is expected that doctors' propensity to embrace and employ AI-based Clinical Decision Support Systems (CDDSS) in medical practice will be influenced by the doctor's impression of the system's simplicity and ease of use. The analysis and the observations above lead to the following hypothesis:

H2. EE has a significant impact on healthcare professionals' intention to use AI-based CDDSS.

3.2.3 Social influence

It has been observed that when doctors are thinking about incorporating new and creative methods into their practice, they often look to their colleagues for approval (Chang et al., 2012)(Payne, Wharrad and Watts, 2012). In addition, a recent study by (Lu et al., 2020) highlights the importance of social impact (SI) in encouraging physicians to adopt Health Information Technology (HIT). The current investigation hypothesizes that healthcare workers' professional and social connections may affect their adoption of AI-based Clinical Decision Support Systems (CDDSS). The effect above would exhibit a heightened degree of prominence within the framework of a collectivist society, specifically exemplified by India (Taufique and Vaithianathan, 2018)(Yang and Jolly, 2009)Therefore, it is proposed that the following hypothesis be put forth:

H3. SI has a significant impact on the medical practitioner's intention to use AI-based CDDSS.

3.2.4 Perceived risk

Perceived risk refers to how worried people are that using a new technology or changing an established procedure would have undesirable consequences for them (Choudhury, 2022). Concerns that medical practitioners may have about the possibility of mistakes or biases in an AI model are what the term "perceived risk" refers to in the context of AI-powered CDSS. These concerns have the potential to affect patient outcomes detrimentally. Perceived risk pertains to how individuals perceive that using a particular technology or system will lead to unfavourable outcomes (Choudhury, 2022). In the area of AI-powered CDSS, the concept of perceived risk refers to the apprehensions that healthcare professionals harbour over the probability of errors or biases that are inherent in the AI model. These concerns have the potential to affect patient outcomes detrimentally. In the realm of AI-CDSS, the presence of perceived risk stirs genuine concerns among healthcare practitioners, provoking a sense of unease regarding the AI model's effectiveness and reliability. The worries and reservations surrounding this technology play a pivotal role in influencing the readiness of medical professionals to embrace AI-CDSS. The fear of venturing into the unknown, often labelled as perceived risk, emerges as a formidable obstacle, significantly impeding healthcare professionals from wholeheartedly adopting AI-driven Clinical Decision Support Systems (CDSS). This challenge, as emphasized in earlier research, sheds light on the hesitancy ingrained in the healthcare community. A notable study (Stuck and Walker, 2019)delved into the intricate correlation between individuals' perceptions of risk and their receptiveness to embracing and implementing new technical developments. The outcomes of the current study underscore the crucial role that perceived risk plays in the decision-making process when it comes to embracing and integrating new technology. A recent research study carried out found that the adoption of e-health innovations is induced by a variety of factors, one of which is perceived risk. This investigation focuses on the technological barriers that may prevent people from embracing AI-driven CDSS. To fully comprehend the elements that influence healthcare professionals' perspectives on adopting AI-driven CDSS, it is necessary to consider adding perceived risk as a vital part of this research attempt. The following hypothesis is provided based on the data and reasoning shown above

H4. PR negatively affects healthcare professionals' intention of AI-based CDDSS.

3.2.5 Self-efficacy

Healthcare personnel's level of self-efficacy may affect how quickly they adopt AI-driven CDSS. A person's "self-efficacy" refers to their belief in their ability to perform a task successfully or make the right decision in a particular situation. In AI-driven CDSS, self-efficacy can be defined as healthcare professionals' confidence in using such systems to make appropriate clinical judgments. Self-efficacy strongly benefits behavioural intention to use information technology; according to research on IT acceptability in the public sector(Al-Haderi, 2013), actual usage behaviour was found to be significantly influenced by the incorporation of self-efficacy into the UTAUT paradigm in a study of mobile health services (Liu et al., 2022). Another study explored a self-efficacy-based value adoption model and suggested a new theoretical framework for accepting technological advances. Adoption intent was found to be positively affected by self-efficacy (Zhu, Sunanda and Ting‐Jie, 2010)This research emphasizes the importance of analysing healthcare workers' sense of self-efficacy in comprehending their propensity to use AI-CDSS. Individuals desiring to adopt AI-driven CDSS may be positively influenced by their self-efficacy when using technology. Based on the observations above and the analysis, the formulation of the following hypothesis is proposed:

H5. Self-efficacy has a significant impact on healthcare professionals' adoption intention of AI-CDSS

3.2.6 Adoption intention

CDSS driven by AI has been shown to have a strong correlation between adoption intent and actual adoption. Adoption intent has been demonstrated to be a significant factor in the uptake of AI-based CDSS in the healthcare sector by several studies. There are various obstacles to the responsible adoption of AI-based CDSS at both individual and societal levels, underscoring the importance of understanding the elements that drive adoption intention. Top influencing factors for CDSS adoption include considerations like the system's perceived usefulness. Moreover, studies indicate that doctors express a strong intention to utilize AI, and the explainability of AI is highly significant with a major impact on adoption. Consequently, the intent to adopt emerges as a critical factor in the actual implementation of AI-based CDSS in the healthcare setting.

H6. Adoption intention has a significant impact on the actual use behaviour of AI-CDSS.

3.2.7 Trust

According to Safa and Von Solms (2016), trust can be the belief that another person or thing is honest, dependable, good, and effective, or the desire to depend on another person or thing for security. In the context of AI-based CDSS, trust demonstrates that healthcare workers have faith in the recommendations, procedures, and conclusions made by AI-based CDSS (De Angelis et al., 2022)(Choung, David and Ross, 2023). Existing research provides strong evidence to support the idea that trust is a key factor in getting healthcare workers to accept and use AI-driven Clinical Decision Support Systems (CDSS) (Table 1). Incorporating trust theory into CDSS, as (Panicker & George, 2023) argues, may increase the system's uptake. Recent research by (Jones, Thornton and Wyatt, 2021) suggests that the degree to which medical professionals have faith in the healthcare system is predictive of how frequently they will use it in patient care. This finding underscores the significance of trust as a crucial factor influencing healthcare professionals' engagement with the system.

H7. Tthe relationship between the intention of using and the actual usage of AI-based CDSS is mediated by trust.

4. Methodology

The quantitative survey was conducted to empirically investigate the links between parameters found through the literature review. The motivations of healthcare professionals to adopt AI-based CDDSS were investigated by developing a research model (see Fig. 1). Hypotheses and data collection and analysis are described below.

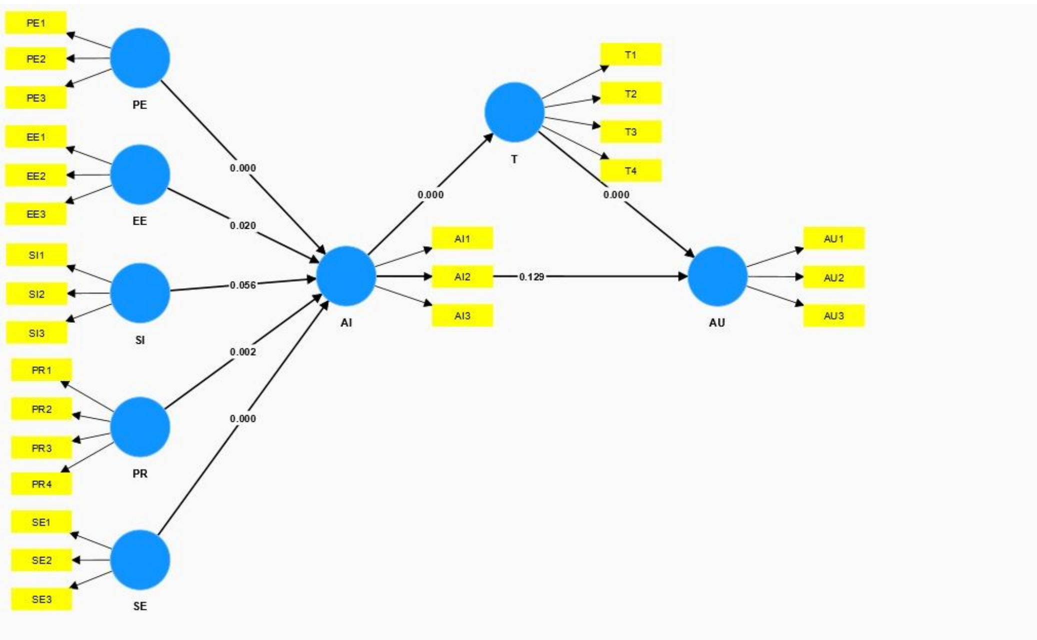

Figure 1: Research model

4.1 Measurement Instruments

To ensure the accuracy of all measurements, the items used to evaluate latent variables in the proposed model were obtained from previous research. The questionnaire consisted of 31 questions divided into two sections: basic information (age, gender, duration of practice, current role in the healthcare industry) and measurement scale. We incorporated eight constructs comprising 27 items. These survey questions were created by drawing from existing research statements and creating new ones (as presented in Table 2). Several adjustments were made to align the statements with the specific context of the AI-CDSS. The survey included inquiries related to participant demographics, including factors such as age, gender, and professional experience. Participants were then asked to evaluate these statements on a five-point Likert scale, with 1 representing strong disagreement and 5 representing strong agreement. The comprehensive items for each construct, as well as their origins, can be found in Table 2.

Table 2: Measurement instruments

Variable	Questions	Reference
Performance Expectancy	1. Using AI-based CDSS will enhance my diagnosis accuracy. 2. AI-based CDSS will increase my efficiency. 3. AI-based CDSS will help me make better treatment decisions.	(Venkatesh et al., 2003)(Fan et al., 2020)
Effort Expectancy	1. Using AI-based CDSS is simple and understandable. 2. it's easy to use AI-based CDSS. 3. Learning how to use AI-based CDSS is easy.	(Venkatesh et al., 2003)(Fan et al., 2020)
Self-Efficacy	1. I have full confidence in my capability to use AI-based CDSS. 2. I am capable of learning how to efficiently employ AI-based CDSS. 3. I am competent in using AI-based CDSS.	(Compeau and Higgins, 1995)(Wang and Wang, 2022)
Perceived Risk	1. Using AI-based CDSS may lead to medical errors. 2. Using AI-based CDSS may be risky for patients. 3. Using AI-based CDSS may compromise patient privacy. 4. Using AI-based CDSS may result in legal liability.	(Aytekin et al., 2021)(Hasan, Shams and Rahman, 2021)
Social Influence	1. Colleagues who I respect think I should use AI-based CDSS. 2. My supervisor thinks I should use AI-based CDSS 3. Peers who are close to me think I should use AI-based CDSS. 4. Colleagues who influence my decisions think I should use AI-based CDSS.	(Venkatesh et al., 2003)(Fan et al., 2020)
Trust	1. I trust that AI-based CDSS will provide accurate recommendations 2. I trust that AI-based CDSS will protect patient privacy. 3. I trust that AI-based CDSS will perform as expected. 4. I trust the competence of the developers of AI-based CDSS.	(McKnight and Chervany Norman, 2001)
Adoption Intention	1. I intend to use AI-based CDSS in my practice. 2. I plan to use AI-based CDSS in my practice. 3. I expect to incorporate AI-based CDSS in my work.	(Venkatesh et al., 2003)(Fan et al., 2020)

Variable	Questions	Reference
Actual Usage	1. I have used AI-based CDSS in my practice. 2. I currently utilize AI-based CDSS in my practice. 3. I utilize AI-based CDSS regularly in my practice.	(Maillet, Mathieu and Sicotte, 2015)

4.2 Participants and Sampling

This research study involved healthcare professionals including physicians, consultants, and technicians from Delhi-NCR regions of India, selected primarily to represent different backgrounds and healthcare settings. Purpose sampling was chosen to target individuals with specific knowledge and experience relevant to the adoption of AI-driven CDSS. Twenty respondents completed a pre-survey to improve the questionnaire's quality. A modified questionnaire was developed based on feedback to make sure the information was accurate and accessible. As our survey had twenty-seven items, the estimated number of participants was more than 270. A cross-sectional survey was conducted online using an anonymized Google Form between August 1, 2023, and December 25, 2023, resulting in three hundred twenty responses. The survey was circulated utilizing several social media platforms, including Facebook and WhatsApp.

4.3 Data Analysis

To verify the hypotheses, this study used a technique called partial least squares-structural equation modelling (PLS-SEM). This strategy is a great option for simulating the behaviour related to the adoption of new technologies because it has been recognized as a prediction-oriented approach (Hair et al., 2014)PLS-SEM is also appropriate for this study because it works well with small sample numbers, especially when non-normality is present (Hair et al., 2014)Considering the advice provided by(Hair et al., 2019), PLS-SEM was chosen to analyse this study. Smart pls 4 was used for the PLS-SEM.

5. Results

5.1 Demographic Result

Most of the respondents were male(71.86 %) and under the age of 40(32.5%). Out of all respondent's majority of them possessed work experience ranging between 5-10 years i.e.,35.93%. A significant percentage of respondents fell under the category of having experience of less than 5 years (34.37). Only 29.68% of the sample of Medical practitioners were having experience of more than 10 years. In terms of title, most of them 40.63%) were physicians, followed by consultants (35.93%) and technicians (23.44 %). The results are displayed in Table 3.

Table 3: Demographic result

Items	Categories	Frequency	percentage
Gender	Male	230	71.86%
	Female	90	28.14%
Age	Less than 30 years	96	30%
	31-40 years	104	32.5%
	41-50 years	74	23.13%
	More than 50 years	46	14.38%
Duration of practice	Less than 5 years	110	34.37%
	5-10 years	115	35.93%
	More than 10 years	95	29.68%
Current role in the healthcare industry	Physician	130	40.63%
	Consultant	115	35.93%
	Technicians	75	23.44%

5.2 Measurement Model

To assess the soundness and consistency of the measurement instrument, it is necessary to initially analyse the results of Partial Least Squares Structural Equation Modelling (PLS-SEM) through the measurement model. The evaluation followed the guidelines established by (Hair et al., 2019), as all the constructs were operationalized using reflective indicators. The reliability of the scale for all constructs was assessed by analysing the indicator loadings and calculating the composite reliability (CR), as presented in Table 4. For indicators, items with loadings above 0.708 are considered dependable because this shows that the construct accounts for more than 50% of the variance in the indicator (Hair et al., 2019). By analysing the CR, we were able to evaluate the instrument's consistency and reliability within itself. In this respect, statistical evidence showed that all CR values were greater than 0.7, meeting the criteria (Hair et al., 2019). This proves the instrument's construct reliability.

After that, we checked for construct validity by evaluating convergent and discriminant validity. The average variance extracted (AVE) served as the measure for determining convergent validity (Hair et al., 2019). Since all the AVEs in Table 4 are higher than the cutoff value of 0.50 advocated by the literature (Hair et al., 2019), it is safe to assume that the constructs have sufficient convergent validity. We evaluated the constructs' discriminant validity using the Fornell-Larcker criterion (Fornell and Larcker, 1981), as suggested by (Hair et al., 2019). Specifically, as shown in Table 5 (Hair et al., 2019), all latent constructs had squared root AVEs that were larger than their inter-correlation estimates with other similar constructs, indicating sufficient discriminant validity.

Table 4: Reliability and validity statistics

Latent variable	Mean	Standard deviation	Items	Outer loadings	CR	AVE	Cronbach's α
Adoption Intention	3.288	1.114	AI1	0.945	0.928	0.813	0.927
	3.324	1.099	AI2	0.947			
	3.365	1.115	AI3	0.909			
Actual usage behaviour	2.153	1.127	AU1	0.918	0.917	0.786	0.916
	2.053	1.102	AU2	0.942			
	2.047	1.177	AU3	0.916			
Effort expectancy	3.129	0.961	EE1	0.857	0.771	0.548	0.771
	3.306	0.888	EE2	0.819			
	3.312	0.896	EE3	0.805			
Performance expectancy	3.159	0.916	PE1	0.921	0.887	0.728	0.879
	3.329	0.993	PE2	0.948			
	3.271	0.957	PE3	0.820			
Perceived risk	3.224	1.083	PR1	0.829	0.875	0.664	0.876
	2.959	1.097	PR2	0.815			
	2.853	1.115	PR3	0.916			
	3.153	1.046	PR4	0.828			
Self-efficacy	3.065	0.965	SE1	0.919	0.803	0.596	0.790
	3.435	0.976	SE2	0.810			
	3.065	1.091	SE3	0.771			
social influence	2.88	1.18	SI1	0.830	0.870	0.695	0.870
	3.065	1.128	SI2	0.941			
	3.065	1.128	SI3	0.890			
Trust	3.053	1.002	T1	0.851	0.908	0.712	0.908
	2.982	1.176	T2	0.894			
	3.253	0.958	T3	0.869			
	3.171	1.068	T4	0.924			

Table 5: Discriminant validity (Fornell-Larcker criterion)

constructs	AI	AU	EE	PE	PR	SE	SI	T
AI	**0.934**							
AU	0.267	**0.926**						
EE	0.368	0.324	**0.827**					
PE	0.698	0.272	0.429	**0.898**				
PR	-0.255	0.174	-0.154	-0.073	**0.848**			
SE	0.449	0.279	0.693	0.373	0.015	**0.836**		
SI	0.430	0.318	0.647	0.433	-0.123	0.501	**0.888**	
T	0.561	0.362	0.765	0.552	-0.260	0.741	0.706	**0.885**

5.3 Common Method Bias

Research employing cross-sectional surveys may be susceptible to common method bias (CMB) (Podsakoff et al., 2003). Several ex-ante approaches were employed to mitigate potential method bias, as recommended by (Podsakoff et al., 2003)The questionnaire was intentionally anonymized to promote candid and unrestricted responses. Furthermore, during the survey development process, careful attention was given to the presentation of independent factors and dependent variables in a manner that did not adhere to a linear progression, as outlined by (Podsakoff et al., 2003). According to the methodology outlined by (Podsakoff et al., 2003), the third phase of the study involved the evaluation of measurement items by a panel comprising medical professionals and a doctorate holder specializing in the field of Information Systems (IS). The primary aim of this evaluation was to discover and rectify any ambiguous terms, errors, or inconsistencies within the measurement items, thereby mitigating the potential for method bias. To assess the presence of Cognitive Bias Modification (CMB), Harman's single-factor test, as described by(Chang, Van Witteloostuijn and Eden, 2010), was employed (as shown in Table 6). The primary determinant that surfaced explained 34.42% of the variance, falling short of the recommended threshold of 50%, as suggested by(Podsakoff et al., 2003), indicating the need for a more substantial conceptual model. The determination was made by conducting a comparison between the percentage of variance explained by the most significant factor and the established threshold.

Table 6: Harman's single-factor test

Component	Total	Initial Eigenvalues %of variance	Cumulative %	Extraction Total	The sum of the squared % of the variance	Loadings Cumulative %
1	9.979	34.412	34.412	9.979	34.412	34.412
2	4.737	16.336	50.747			
3	2.514	8.686	59.416			
4	2.03	6.999	66.415			
5	1.558	5.371	71.786			
6	1.175	4.053	75.838			
7	0.938	3.235	79.073			
8	0.872	3.008	82.082			
9	0.82	2.829	84.91			
10	0.581	2.002	86.912			
11	0.506	1.744	88.657			
12	0.433	1.493	90.15			
13	0.422	1.456	91.606			
14	0.352	1.215	92.821			
15	0.282	0.973	93.794			
16	0.273	0.941	94.736			
17	0.25	0.863	95.599			

Component	Total	Initial Eigenvalues %of variance	Cumulative %	Extraction Total	The sum of the squared % of the variance	Loadings Cumulative %
18	0.196	0.677	96.276			
19	0.186	0.64	96.917			
20	0.15	0.517	97.434			
21	0.134	0.462	97.896			
22	0.129	0.372	98.341			
23	0.108	0.304	98.713			
24	0.088	0.301	99.017			
25	0.087	0.22	99.318			
26	0.064	0.22	99.538			
27	0.055	0.189	99.727			
28	0.046	0.158	99.885			
29	0.033	0.115	100			

5.4 Structural model

The model fit was assessed by (Henseler, Ringle and Sarstedt, 2015) method, considering the Standard Root Mean Square Residual(SRMR). The value of SRMR was 0.077 which is well within the maximum permissible value of 0.08 (Hu and Bentler, 1998). The assessment of the structural model's overall explanatory power was conducted by the established assessment criteria. This evaluation involved examining R2, Q2, and path coefficient β-values. In the first round of our structural model evaluation, we assessed the variance inflation factor (VIF) to check for multicollinearity problems. The term "multicollinearity" describes a situation in which the variables being measured are highly correlated with one another. Because of this, SEM analysis outcomes may be skewed(Kock and Lynn, 2012). The Variance Inflation Factor (VIF) values for all the constructs in this model were found to be less than 5, indicating that multicollinearity problems are not present (Kock and Lynn, 2012) (Hair et al., 2019)For the VIF values, see Table 7.Stone–Giesser's Q2 value, along with the blindfolding process, was utilized to analyse and determine the predictive usefulness of the model(Hair et al., 2014). Table 8 shows that all Q2 values are significantly greater than zero, indicating that the model is highly predictive of the endogenous constructs (Hair et al., 2014)

The bootstrapping procedure, as outlined by(Hair et al., 2014), was implemented by generating 5,000 subsamples. The study aimed to assess the statistical significance and practical relevance of the path coefficients in the structural model. The objective of this inquiry was to ascertain the optimal structural model. Table 9 displays the outcomes derived from bootstrapping for the pathways within the proposed model. The presented table offers a concise overview of the path coefficient, t statistic, and significance value (p). The empirical results are illustrated in Figure 2.

The results indicate significant relationships between (PE) and (AI) ($t = 9.750$, $\beta = 0.598$, $p < 0.05$), (EE) and (AI) ($t = 2.055$, $\beta = 0.214$, $p < 0.05$), (PR) and (AI) ($t = 3.031$, $\beta = -0.239$, $p < 0.05$), and (SE) and (AI) ($t = 3.587$, $\beta = 0.311$, $p < 0.05$). Therefore, hypotheses H1, H2, H4, and H5 were found to be supported. Nevertheless, the statistical analysis conducted in this study revealed that the associations between SI and AI ($t = 1.607$, $\beta = 0.130$, $p > 0.05$) as well as AI and AU ($t = 1.132$, $\beta = 0.082$, $p > 0.05$) were found to be statistically insignificant. These findings do not provide support for hypotheses H3 and H6 in the present investigation.

Table 7: Collinearity statistics

Constructs	AI	AU	T
AI		1.460	1.000
AU			
EE	2.623		
PE	1.304		
PR	1.058		

Constructs	AI	AU	T
SE	2.022		
SI	1.825		
T		1.460	

Table 8: Predictive relevance

Construct	Q^2	R^2
AI	0.544	0.616
AU	0.401	0.546
T	0.424	0.522

Table 9: Results of Hypothesis testing

Hypothesis	Path	Path coefficient	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	F2	Remarks
H1	PE -> AI	0.598	0.062	9.750	0.000	0.698	supported
H2	EE -> AI	0.214	0.116	2.055	0.020	0.054	supported
H3	SI -> AI	0.130	0.081	1.607	0.056	0.023	not supported
H4	PR -> AI	-0.239	0.078	3.031	0.002	0.132	supported
H5	SE -> AI	0.311	0.091	3.587	0.000	0.131	supported
H6	AI -> AU	0.082	0.082	1.132	0.129	0.007	not supported

5.5 Mediation Analysis

We analysed the proposed model and performed a mediation analysis to determine how trust affects the main relationship in the model. The significance of the mediation was evaluated by performing a PLS-SEM analysis using the bootstrapping method. The analysis aimed to investigate the importance of both direct and indirect effects to determine the type of mediation involved—whether it can be classified as full, complementary, or competitive partial. To conduct a more comprehensive evaluation of mediation, the researchers computed the Variation Accounted For (VAF). According to (Hair et al., 2014)cases can be classified as partially mediated when the Variance Accounted For (VAF) falls within the range of 20% to 80%. VAFs below 20% suggest minimal mediation, while VAFs exceeding 20% indicate a more typical scenario of partial mediation. Table 10 displays the results of the mediation analysis. Overall, statistically significant effects related to mediator credibility were observed (Table 10). The significance of both direct and indirect impacts was then assessed. A substantial (p = 0.002) indirect influence was found between AI and AU, while the direct effect was not significant (p = 0.129). Thus, the connection between AI and AU is entirely mediated by trust.

Table 10: Analysis of Mediation of Trust between Adoption intention and actual usage.

Type of effect	Effect	Path coefficient	T statistics (|O/STDEV|)	P values	Remark
Total effect	AI -> AU	0.263	3.782	0.000	significant
Indirect effect	AI -> T -> AU	0.181	2.860	0.002	significant
Direct effect	AI -> AU	0.082	1.132	0.129	not significant
VAF	IE/TE	69%			
CONCLUSION	MODERATELY SIGNIFICANT (FULL MEDIATION)				

6. Discussions

The findings indicate that healthcare practitioners' inclination to adopt AI-CDSS is notably influenced by performance expectancy (PE)with path coefficients of 0.598 and a p-value of 0.000. If practitioners believe AI-based CDSS will enhance productivity, reduce workload, and improve diagnoses, they are more likely to embrace its use (PE), which agrees with the evidence presented in earlier studies by UTAUT (Wang et al., 2020) (Alsyouf et al., 2022) (Hossain, Quaresma and Rahman, 2019) (Fan et al., 2020). Further, the research reveals that healthcare professionals' inclination to adopt AI-CDSS is significantly influenced by effort expectancy (EE) with a path coefficient of 0.124 and p-value of 0.020. This implies that if healthcare practitioners believe that AI–CDSS is easy to use they can adopt it without much effort. this result aligns with the previous studies (Chatterjee and Bhattacharjee, 2020) (Chatterjee et al., 2023). Based on the results, there is no significant influence of social influence (SI) on healthcare professionals' inclinations to employ artificial intelligence (AI), indicated by a path coefficient of 0.130 and a p-value of 0.054. This aligns with previous studies that found social pressure does not significantly affect AI-CDSS uptake among medical professionals(Cheng, Li and Xu, 2022)(Aljarboa, Shah and Kerr, 2019; Aljarboa and Miah, 2023). This may be due to the complexity of AI-CDSS implementation, the need for training or if healthcare professionals are not aware of AI-CDSS benefits or limited exposure, social influence may have minimal role.

Furthermore, the findings suggest that healthcare professionals' adoption intention of AI-CDSS has an inverse relationship with perceived risk (path coefficients of -0.239 and p-value of 0.0000. Healthcare professionals may hesitate to adopt AI-CDSS if they perceive the risk associated with its implementation. Previous studies(Choudhury, 2022) (Cheng, Li and Xu, 2022)(Ben Arfi et al., 2021)(Tran et al., 2021) also highlight the impact of user expectations and risk perceptions on the uptake of AI-driven CDSS. Healthcare organizations should prioritize addressing professionals' concerns about AI-CDSS hazards and emphasize the benefits of increasing adoption and deployment in clinical practice. Table 11 shows the summarized findings of hypothesis testing.

Table 11: Summary of hypothesis findings

Hypothesis	Result
H1 PE -> AI	The results indicate significant relationships between Performance expectancy and Adoption intention with a p-value less than 0.000. Therefore, H1 was supported. Therefore, if practitioners believe AI-based CDSS will enhance productivity, reduce workload, and improve diagnoses, they are more likely to embrace its use.
H2 EE -> AI	The results indicate significant relationships between EE and adoption intention with a p-value of 0.020. Therefore, H2 was found to be supported.
H3 SI -> AI	There is no significant influence of social influence (SI) on healthcare professionals' inclinations to employ artificial intelligence (AI), as the p-value is 0.054(which is more than 0.005). Therefore, H3 was not supported. This aligns with previous studies that found social pressure does not significantly affect AI-CDSS uptake among medical professionals.
H4 PR -> AI	The findings suggest that healthcare professionals' adoption intention of AI-CDSS is influenced by concerns about the risks related to the technology. Healthcare organizations should prioritize addressing professionals' concerns about AI-CDSS hazards and emphasize the benefits of increasing adoption and deployment in clinical practice.
H5 SE -> AI	The research reveals that healthcare professionals' inclination to adopt AI-CDSS is significantly influenced by self-efficacy (SE). The path coefficient for self-efficacy is 0.311 with a p-value of less than 0.000, suggesting that professionals' confidence in using the technology influences adoption intentions
H6 AI -> AU	The direct influence of artificial intelligence (AI) on user acceptance (AU) was found to be insignificant. This may be because artificial intelligence is still in its infancy, and it may require further development to significantly influence healthcare professionals' actual adoption of AI-CDSS.
H7 AI -> T -> AU	The total effect of AI on AU is significant (with a path coefficient of 0.263, t statistics of 3.782 and p-value of 0.000). The indirect effect of AI on AU through trust is also significant with a p-value of 0.002. However, the direct effect of AI on AU without considering trust is not significant (with a p-value of 0.129). According to the findings, trust plays a significant role in relationships between AI and AU, and it fully mediates the relationship.

The research reveals that healthcare professionals' inclination to adopt AI-CDSS is significantly influenced by self-efficacy which means that professionals with high self-efficacy are more likely to adopt AI–CDSS as they trust their capabilities to master the necessary skills and overcome challenges. The path coefficient for self-efficacy is 0.311 with a p-value of less than 0.001, suggesting that professionals' confidence in using the technology influences adoption intentions. Consistent with prior research,(Kwak, Ahn and Seo, 2022)(Liu et al., 2022) (Zhu, Sunanda and Ting□Jie, 2010), self-efficacy significantly contribute to AI-driven CDSS acceptance and implementation. Healthcare organizations should provide education and training to increase familiarity with AI-CDSS, reducing the perceived effort required.

The direct influence of artificial intelligence (AI) on user acceptance (AU) was statistically irrelevant, with a path coefficient of 0.082 and a p-value of 0.129. This implies that Adoption intention alone cannot impact healthcare professionals’ actual adoption of AI-CDSS, which is in alignment with another study (George Saadé, Tan and Kira, 2008) (Jamieson et al., 2022). Several explanations for the study's failure to find a statistically significant link between AI and AU are suggested by the search results. Firstly, artificial intelligence is still in its infancy, and it may need further development to significantly influence healthcare professionals' actual adoption of AI-CDSS**.** In conclusion, we can say that Adoption intention may not itself lead to actual usage of AI-CDSS, but trust in AI systems serves as a crucial mediator. This study reveals that trust fully mediates the relationship between AI which means that fostering trust in AI technology is essential for the successful adoption and implementation of AI-CDSS technology.

6.1 Theoretical Implications

There are numerous theoretical implications in the current study. This discourse aims to elucidate plausible ramifications arising from the subject under consideration. The main goal is to make a substantial scholarly contribution to the further expansion of the UTAUT framework. Specifically, it seeks to expand the existing framework by incorporating supplementary constructs significantly influencing individuals' adoption intention. Two constructs of interest are perceived risk and self-efficacy. By incorporating these within the UTAUT model, a more comprehensive understanding can be obtained regarding the determinants impacting individuals' inclinations to embrace technological innovations.

This research will offer insights into factors influencing the viewpoints and choices of healthcare professionals regarding the utilization of AI-driven CDSS. The study will investigate whether and how beliefs about one's risk and ability to handle challenging situations affect these orientations and resolutions. In the healthcare industry, increasing acceptance among varied labour sectors is crucial. Healthcare organizations can optimize the adoption of novel practices, technologies, or interventions by customizing these strategies to offer to the distinct needs of various professional groups. Thirdly, the study can shed light on how addressing additional constructs (PR and SE) might help increase the implementation of CDSS driven by AI in healthcare settings. It is possible to highlight how AI-based CDSS might improve patient outcomes, and efforts can be made to make CDSS systems more open and flexible, as well as to educate medical professionals. Fourth, the research can shed light on how trust influences healthcare professionals' acceptance of AI-CDSS. This will facilitate the dissemination of more accurate information regarding the strategies implemented to enhance confidence in the utilization of CDSS driven by AI within healthcare environments. The present study can offer significant insights for policymakers aiming to facilitate the extensive implementation and effective assimilation of clinical AI-driven CDSS. Additionally, it can contribute to the advancement of our theoretical understanding regarding the determinants impacting healthcare professionals' utilization of these systems.

6.2 Practical Implications

According to this study, a broad range of stakeholders within the healthcare ecosystem can benefit from this study, including marketers and developers of AI-driven CDDSS, vendors, policymakers, and healthcare IT managers. These insights aim to enhance the integration process of CDDSS powered by AI and address any hesitation among healthcare professionals, thereby fostering smoother adoption within clinical settings. Primarily, Performance expectancy (PE) appeared as a strong predictor of adoption intentions. Marketers of AI-CDSS should personalize their communication and organize training sessions to highlight the benefits of using AI systems, including speed, precision, efficiency, and reduced workload. By enabling medical practitioners to experience firsthand the benefits of AI-CDSS in their daily tasks, PE can be enhanced, fostering user acceptance. Secondly, the study provides valuable insight that can assist healthcare administrators in developing effective approaches to uplift the use of AI-driven CDSS, considering the unique requirements of various healthcare practitioners in the healthcare industry. Nurses and other staff may prioritize the accuracy and trustworthiness of AI models, while physicians may be less concerned about job displacement. This study highlights the need to address perceived risks for the effective adoption of CDSS driven by AI in clinical settings.

To empower healthcare professionals in utilizing AI-based CDSS effectively, understanding the benefits and receiving proper training is crucial. This not only enhances patient outcomes but also influences the development of rules and standards for AI-driven CDSS in healthcare facilities. The proposed standards may include recommendations to reduce anxiety, boost confidence, and establish trust, fostering widespread use of these technologies.

A notable role of trust in the adoption of AI-CDSS demonstrates that developer must provide scientific evidence, such as regulatory certifications(e.g., FDA approvals), to prove that their products are credible, reliable, accurate, and safe in clinical settings. Essentially, prioritizing the cultivation of trust and building affiliations with esteemed medical institutions is essential for the adoption of CDSS powered by AI.

Moreover, there exists the chance to inspire policymakers to devise unique legislation structures targeting legal apprehensions linked to the incorporation of AI-powered CDSS. Our study seeks to promote the invention and implementation of efficient and favourably accepted AI-driven CDDSS customized to their intended beneficiaries.

6.3 Research Limitations and Future Research Directions

The first limitation is about the choice of target individual. We did not consider specific subspecialties in medicine. Thus, future studies can evaluate this model's validity with the AI-powered CDSS intended for doctors from other specific subspecialties. Also, the variations in expertise level among the targeted respondents (physicians, consultants, and technicians) may influence their perception towards the adoption of AI-BASED CDSS leading to biased responses. Secondly, it overlooked the important role that cultural factors play in determining adoption intention, despite recent studies demonstrating their importance(Dwivedi et al., 2016) (Zhang, Xia and Huang, 2022). Considering this, the findings must be replicated in different geographical areas (developed vs. developing countries).

Thirdly, Our study's reliance on a small sample size could impede the generalizability of our findings to the wider healthcare community. Fourthly, the data was geographically limited to India(Delhi-NCR region).Due to widespread adoption of AI-CDSS replication among different geographical context is imperative. Lastly The cross-sectional design used offers a snapshot of healthcare professionals' adoption intentions at a specific moment, lacking a continuous view. A longitudinal study, tracking changes over time, would be beneficial, to acquire more deeper understanding of aspects that contribute to the deployment of CDSS driven by AI.

In future investigations, employing a longitudinal methodology could be advantageous for tracking the implementation of AI-CDSS among healthcare practitioners over an extended period, facilitating the identification of factors influencing sustained utilization. Furthermore, the next research could utilize a qualitative method approach to obtain information regarding the utilization of AI-CDSS by medical professionals which would enable a more enhanced comprehension of factors influencing technology dissemination. Moreover, the potential influence of moderators on the relationships among key variables was not considered, despite numerous studies showing that age and gender both have moderating impacts on how people react to new technologies. This oversight may lead to different results. In subsequent studies, potential moderators, including gender, age, professional status, and other similar factors, should be taken into consideration.

7. Conclusions

This research aims to augment the previously validated UTAUT framework by incorporating the novel framework of the adoption of CDSS driven by AI and utilization among medical practitioners in India. The additional variables introduced include perceived risk, self-efficacy, and trust. Healthcare professionals' willingness to adopt AI-CDSS is mainly influenced by three factors which include PE, EE, and S. The adoption intention of AI-CDSS was significantly influenced by the perceived risk among healthcare professionals. Although Adoption intention did not significantly impact actual usage, the research confirmed that trust mediates relationship between AI and AU.

The use of AI-CDSS in the healthcare system could be substantially impacted by the findings of this study. Healthcare organizations should prioritize addressing healthcare professionals' perceptions of the potential advantages and hazards associated with AI-CDSS, along with fostering confidence in using the technology effectively for its adoption and implementation in clinical practice. Emphasizing the function of trust in healthcare professionals' adoption of AI-CDSS is crucial. Gaining patients' trust in AI-CDSS requires healthcare organizations to undertake essential actions, including educating and training healthcare personnel and ensuring the technology's dependability, accuracy, and security.

In summary, the study offers a new understanding of the variables impacting medical practitioners' intention to adopt AI-CDSS. The findings suggest that healthcare institutions should give top priority to addressing healthcare practitioners' confidence in AI-CDSS and their assessments of its advantages and risks to encourage the implementation and application of the technology in clinical settings. The study also demonstrates the relevance of trust in the use of AI-CDSS by medical practitioners. By concentrating on these areas, healthcare professionals may enhance the acceptance and implementation of AI-CDSS in clinical settings, leading to improved patient outcomes and satisfaction levels.

Ethical considerations: This research does not involve any experiments on human individuals and/or animals. Informed consent was obtained from all individuals involved in the study.

AI Statement: The author declares that no generative artificial intelligence has been used in the writing of this manuscript, nor in the creation of images, graphics, tables, or their corresponding captions

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