

Investigating Clinicians' Intentions and Influencing Factors for Using Intelligence-enabled Clinical Decision Support Systems in Healthcare Systems – Cross-sectional Survey

Rui Zheng, Xiao Jiang, Li Shen, Mengting Ji, Tianrui He, Xingyi Li, Guangjun Yu

Submitted to: Journal of Medical Internet Research
on: May 30, 2024

Disclaimer: © The authors. All rights reserved. This is a privileged document currently under peer-review/community review. Authors have provided JMIR Publications with an exclusive license to publish this preprint on its website for review purposes only. While the final peer-reviewed paper may be licensed under a CC BY license on publication, at this stage authors and publisher expressly prohibit redistribution of this draft paper other than for review purposes.

Table of Contents

Original Manuscript..... 5

Supplementary Files..... 25

 Figures 26

 Figure 1..... 27

 Figure 2..... 28

 Multimedia Appendixes 29

 Multimedia Appendix 1..... 30

Investigating Clinicians' Intentions and Influencing Factors for Using Intelligence-enabled Clinical Decision Support Systems in Healthcare Systems?Cross-sectional Survey

Rui Zheng^{1*}; Xiao Jiang^{1*}; Li Shen^{2*}; Mengting Ji³; Tianrui He¹; Xingyi Li⁴; Guangjun Yu⁵

¹School of Public Health, Shanghai Jiao Tong University School of Medicine Shanghai CN

²Clinical Research Center, Shanghai Sixth People's Hospital Affiliated to Shanghai Jiao Tong University School of Medicine Shanghai CN

³Renji Hospital, Shanghai Jiao Tong University School of Medicine Shanghai CN

⁴Shanghai Chest Hospital, School of Medicine?Shanghai Jiao Tong University Shanghai CN

⁵Shanghai Children's Hospital Shanghai CN

*these authors contributed equally

Corresponding Author:

Guangjun Yu

Shanghai Children's Hospital

No 355 Luding Road Shanghai

Shanghai

CN

Abstract

Background: Intelligence-enabled clinical decision support systems (CDSS) are sophisticated software systems designed to assist healthcare providers in making clinical decisions by leveraging various forms of intelligence. Research studies have shown that CDSS utilization rates have not met expectations. Clinicians' intentions and their attitudes determine the use and promotion of CDSS in clinical practice.

Objective: The aim of this study was to enhance the successful utilization of CDSS by analyzing the pivotal factors that influence clinicians' intention to adopt it and by putting forward targeted management recommendations.

Methods: This study proposed a research model grounded in the Task-Technology Fit (TTF) model and the Technology Acceptance Model (TAM), which was then tested through a cross-sectional survey. The measurement instrument comprised demographic characteristics, multi-item scales, and an open-ended query regarding areas where clinicians perceived the system required improvement. We leveraged structural equation modeling to assess the direct and indirect effects of "Task-Technology Fit" and "Perceived Ease of Use" on clinicians' intention to use the CDSS when mediated by "Performance Expectation" and "Perceived Risk". We collated and analyzed the responses to the open-ended question.

Results: We collected a total of 247 questionnaires. The model explained 65.8% of the variance in use intention. Performance expectations ($\beta=0.228$; $P<0.001$) and perceived risk ($\beta=-0.579$; $P<0.001$) were both significant predictors of use intention. Task-technology fit ($\beta=-0.281$; $P<0.001$) and perceived ease of use ($\beta=-0.377$; $P<0.001$) negatively affected perceived risk. Perceived risk ($\beta=-0.308$; $P<0.001$) negatively affected performance expectations. Task-technology fit positively affected perceived ease of use ($\beta=0.692$; $P<0.001$) and performance expectations ($\beta=0.508$; $P<0.001$). Task characteristics ($\beta=0.168$; $P<0.001$) and technology characteristics ($\beta=0.749$; $P<0.001$) positively affected Task-technology fit. Contrary to expectations, perceived ease of use ($\beta=0.108$; $P=0.073$) did not have a significant impact on use intention. From the open-ended question, three main themes emerged regarding clinician's perceived deficiencies in CDSS: system security risks, personalized interaction, seamless integration.

Conclusions: Perceived risk and performance expectations were direct determinants of clinicians' adoption of CDSS, significantly influenced by task-technology fit and perceived ease of use. In the future, increasing transparency within CDSS, fostering trust between clinicians and technology should be prioritized. Furthermore, focusing on personalized interactions and ensuring seamless integration into clinical workflows are crucial steps moving forward.

(JMIR Preprints 30/05/2024:62732)

DOI: <https://doi.org/10.2196/preprints.62732>

Preprint Settings

1) Would you like to publish your submitted manuscript as preprint?

✓ **Please make my preprint PDF available to anyone at any time (recommended).**

Please make my preprint PDF available only to logged-in users; I understand that my title and abstract will remain visible to all users.

Only make the preprint title and abstract visible.

No, I do not wish to publish my submitted manuscript as a preprint.

2) If accepted for publication in a JMIR journal, would you like the PDF to be visible to the public?

✓ **Yes, please make my accepted manuscript PDF available to anyone at any time (Recommended).**

Yes, but please make my accepted manuscript PDF available only to logged-in users; I understand that the title and abstract will remain visible to all users.

Yes, but only make the title and abstract visible (see Important note, above). I understand that if I later pay to participate in [http://www.jmir.org/](#)

Original Manuscript

Original Paper

Investigating Clinicians' Intentions and Influencing Factors for Using Intelligence-enabled Clinical Decision Support Systems in Healthcare Systems—Cross-sectional Survey

Rui Zheng¹, MPH; Xiao Jiang¹, MPH; Li Shen², PhD; Mengting Ji³, PhD; Tianrui He¹, PhD; Xingyi Li⁴, MPH; Guangjun Yu⁵, PhD

¹School of Public Health, Shanghai Jiao Tong University School of Medicine, Shanghai, China

²Clinical Research Center, Shanghai Sixth People's Hospital Affiliated to Shanghai Jiao Tong University School of Medicine, Shanghai, China

³Renji Hospital, Shanghai Jiao Tong University School of Medicine, Shanghai, China

⁴Shanghai Chest Hospital, Shanghai, China

⁵Shanghai Children's Hospital, Shanghai Jiao Tong University School of Medicine, Shanghai, China

Corresponding Author:

Guangjun Yu, PhD

Shanghai Children's Hospital

Shanghai Jiao Tong University School of Medicine

No 355 Luding Road

Shanghai, 200062

China

Phone: 86 18917762998

Email: gjyu@shchildren.com.cn

Abstract

Background: Intelligence-enabled clinical decision support systems (CDSS) are sophisticated software systems designed to assist healthcare providers in making clinical decisions by leveraging various forms of intelligence. Research studies have shown that CDSS utilization rates have not met expectations. Clinicians' intentions and their attitudes determine the use and promotion of CDSS in clinical practice.

Objective: The aim of this study was to enhance the successful utilization of CDSS by analyzing the pivotal factors that influence clinicians' intention to adopt it and by putting forward targeted management recommendations.

Methods: This study proposed a research model grounded in the Task-Technology Fit (TTF) model and the Technology Acceptance Model (TAM), which was then tested through a cross-sectional survey. The measurement instrument comprised demographic characteristics, multi-item scales, and an open-ended query regarding areas where clinicians perceived the system required improvement. We leveraged structural equation modeling to assess the direct and indirect effects of "Task-Technology Fit" and "Perceived Ease of Use" on clinicians' intention to use the CDSS when mediated by "Performance Expectation" and "Perceived Risk". We collated and analyzed the responses to the open-ended question.

Results: We collected a total of 247 questionnaires. The model explained 65.8% of the variance in use intention. Performance expectations ($\beta=0.228$; $P<0.001$) and perceived risk ($\beta=-0.579$; $P<0.001$) were both significant predictors of use intention. Task-technology fit ($\beta=-0.281$; $P<0.001$) and perceived ease of use ($\beta=-0.377$; $P<0.001$) negatively affected perceived risk. Perceived risk ($\beta=-0.308$; $P<0.001$) negatively affected performance expectations. Task-technology fit positively affected perceived ease of use ($\beta=0.692$; $P<0.001$) and performance expectations ($\beta=0.508$; $P<0.001$). Task characteristics ($\beta=0.168$; $P<0.001$) and technology characteristics ($\beta=0.749$; $P<0.001$) positively affected Task-technology fit. Contrary to expectations, perceived ease of use ($\beta=0.108$; $P=0.073$) did not have a significant impact on use intention. From the open-ended question, three main themes emerged regarding clinician's perceived deficiencies in CDSS: system security risks, personalized interaction, seamless integration.

Conclusions: Perceived risk and performance expectations were direct determinants of clinicians' adoption of CDSS, significantly influenced by task-technology fit and perceived ease of use. In the future, increasing transparency within CDSS, fostering trust between clinicians and technology should be prioritized. Furthermore, focusing on personalized interactions and ensuring seamless integration into clinical workflows are crucial steps moving forward.

Keyword: Artificial intelligence; Clinical decision support systems; Task-Technology fit; Technology acceptance model; Perceived risk; Performance expectations; Intention to use

Introduction

Background

Clinical diagnosis indeed stands out as one of the most complex cognitive tasks humans undertake, requiring a combination of knowledge, critical thinking, pattern recognition, and decision-making skills. There are, roughly, only 200 symptoms but over 10,000 diseases, and each disease may present in different ways depending on the patient. Standard textbooks of medicine cover fewer than 1000 of these, and often describe only classic presentations. A survey report shows that most subjects experience at least one misdiagnosis in their lifetime, and the incidence of diagnostic error in primary care practice is roughly 10%. Even a modest 5% enhancement in diagnostic accuracy could halve the detrimental impact of diagnostic errors, thought to be the most serious safety concern globally^[1].

In recent years, with the rapid development of artificial intelligence technology, the integration and practical application of artificial intelligence (AI) in healthcare have provided a promising direction for addressing the aforementioned issues. AI-enabled clinical decision support systems (CDSS) have become a core concept in leveraging technology to support the healthcare field^[2]. CDSS are the results of combining traditional decision support system and AI. They are designed to aid clinicians

by converting the raw medical-related data, documents, and expert practice into a set of sophisticated algorithms, applying numerical, logical and intelligent techniques such as machine learning and natural language processing, enabling clinicians to find appropriate solutions to medical problems and make clinical decisions^[3].

Previous studies have suggested that CDSS hold promise in enhancing clinicians' performance, promoting patient safety, and improving the overall quality of healthcare^{[4][5][6][7]}. However, the potential of CDSS in medicine remains underutilized^[8]. Shanghai as a leader in digital transformation, various tertiary hospitals are starting to deploy CDSS. Despite this, hospitals' investment in CDSS do not always achieve the desired results, and there may even be the negative correlation between inputs and outputs^[9]. CDSS was deployed in a tertiary hospital in Shanghai for 12 months, resulting in a lower expected utilization rate (43% for the tertiary hospital), due to clinicians' distrust of the system and its poor integration into clinicians' workflows^[2]. Clinicians, as end users of the system, their perceptions will ultimately influence the development of CDSS^[10]. Therefore, it is crucial to understand the key factors that influence clinicians' intent to use CDSS, yet limited studies are available^[11].

Therefore, we have 3 aims. First, we attempt to identify factors influencing clinicians' intent to use via a theoretical model. Second, we empirically examine the applicability of the model in the context of implementing CDSS. Third, we propose corresponding managerial implications based on the results.

Theory and related work

In recent years, a significant amount of theory-based research has been conducted to explore information systems usage behavior. A number of studies exploring the use of CDSS from the perspective of human factors have applied a variety of theoretical models, including but not limited to technology acceptance model (TAM)^{[12][13][14]}, stating that clinicians' interactions with CDSS are influenced by their overarching perceptions of technology. These perceptions encompass their attitudes, beliefs, and experiences with various technological tools and systems, which collectively shape their acceptance and utilization of CDSS. TAM elucidates how perceived ease of use and perceived usefulness act as intermediary factors between system characteristics and its utilization^[11]. There are additional studies that consider the specificity of information technology in the healthcare field and utilize the Task-Technology Fit (TTF) framework to assess the level of support provided by information technology to clinicians' work^{[15][16]}. The TTF framework evaluates how well the characteristics of technology and the requirements of tasks align to enhance user performance. By analyzing both technology and task characters, the model aims to identify areas where adjustments or

improvements can be made to better meet user needs and optimize performance^[17]. The TTF framework has undergone empirical validation across diverse settings, encompassing healthcare domains such as hospital information systems and electronic health records ^{[15][18]}.

Absolutely, each model exhibits unique advantages. The TAM primarily focuses on exploring user behavior and trends, emphasizing users' perceptions of the technology's ease of use and perceived usefulness. Nevertheless, the TAM may not comprehensively take into account specific task requirements. Conversely, the TTF model heavily emphasizes assessing the congruence between technology and task characteristics, focusing on how well the technology aligns with the task's demands. It offers valuable insights into how effectively the technology facilitates users to accomplish their tasks efficiently and effectively.

Several studies have integrated the TTF model with the TAM, demonstrating synergistic effects between the two. This integration highlights the importance of both user perceptions and task-technology alignment, thus providing a more comprehensive understanding of user behavior and system effectiveness than either model alone^{[19][20][21][22]}. By integrating TAM and TTF model, researchers can harness the strengths of both, offering a more comprehensive understanding of user acceptance and system performance. Previous research has substantiated the substantial influence of the task-technology fit on perceived ease of use. This validation underscores the critical role of aligning technology with task requirements in shaping users' perceptions of how easy the system is to use and how beneficial it is for their tasks^[23]. Therefore, the TTF model can serve as a precursor factor influencing perceived ease of use. Based on this rationale, this study has selected the core variable of "Perceived Ease of Use" from the TAM.

Given the complexity and constant evolution of AI, it has yet to become a cornerstone of the healthcare system or medical education. The lingering uncertainty regarding the safety and potential risks posed by AI to patients remains a pivotal factor influencing clinicians' intention to adopt the technology^{[11][24][25]}. At the same time, the significant impact of task-technology fit and perceived ease of use on perceived risk also has been verified^{[26][27]}. Therefore, this study further incorporates the variable of "Perceived Risk" into the research framework., aiming to deepen comprehension of clinicians' tendency to adopt CDSS.

Drawing upon the theoretical underpinnings and existing research findings, we herein introduce a theoretical model (Figure 1) along with the corresponding hypotheses, as outlined below: (1) task characteristics positively affects task-technology fit (hypothesis 1),(2) technology characteristics positively affects task-technology fit (hypothesis 2),(3) task-technology fit positively affects performance expectations (hypothesis 3), (4) task-technology fit negatively affect perceived risk

(hypothesis 4), (5) task-technology fit positively affects perceived ease of use (hypothesis 5), (6) perceived ease of use negatively affect perceived risk (hypothesis 6), (7) perceived risk negatively affect performance expectations (hypothesis 7), (8) performance expectations positively affects intention to use (hypothesis 8), (9) perceived ease of use positively affects intention to use (hypothesis 9), (10) perceived risk negatively affect negatively affect intention to use (hypothesis 10).

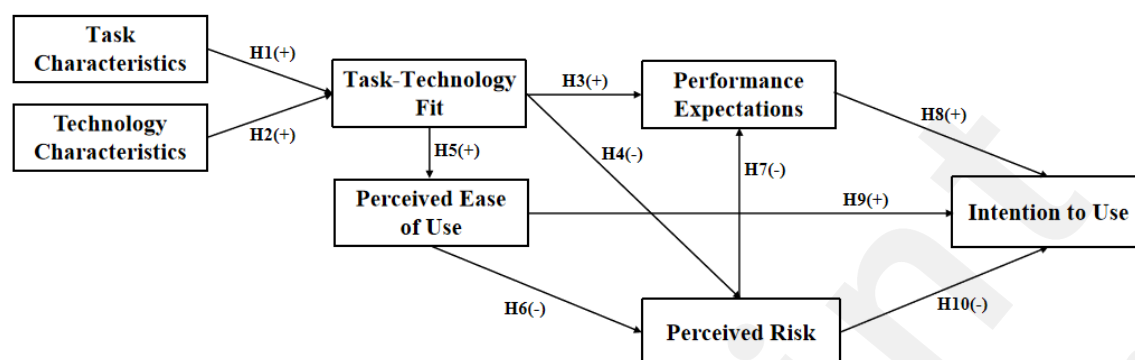


Figure 1. conceptual model. H: hypothesis; +: positive effect; -: negative effect.

Methods

Study Design and Setting

We conducted the study in three tertiary hospitals (Shanghai Children's Hospital, Ren Ji Hospital, and Shanghai Sixth People's Hospital) in Shanghai. The study involved administering a questionnaire survey to 247 clinicians across the inpatient and outpatient departments of three hospitals mentioned. The study spanned a duration of 4 months, from December 2023 to March 2024.

Sample Size and Sampling

Saunders contend that the minimum sample size is contingent on the maximum number of arrows directed towards the latent variable^[28]. While establishing the suitable sample size is crucial in Structural Equation Modeling (SEM), consensus within the literature on the ideal sample size remains lacking. Evidence suggests that even simple SEM models can yield meaningful results with small sample sizes. However, as a general guideline, a minimum sample size of N= 100~150 is often recommended for conducting SEM analyses^[29]. Simple random sampling was employed for this study, with a total of 247 clinicians participating and completing the study. This sample size is sufficient to yield statistically significant results.

Measurement instrument

The questionnaire comprised three sections: demographic characteristics, multiple-item scales, and an optional open-ended question: "What deficiencies do you identify in the CDSS?" The seven constructs within the model were evaluated using multi-item scales adapted from Davis^[30], Wells^[31], Goodhue^[32], and Venkatesh^[33], with modifications made to the original items to align with the context

of this research, which primarily focuses on clinicians' attitudes to CDSS use. The items were scored using 5-point Likert scales. Table 1 presents the origins and definitions of the constructs.

Appendix 1 contains the items corresponding to each construct along with their respective sources. We conducted a pretest involving 63 clinicians, and the results indicated that the questionnaire demonstrated good reliability and validity.

Table 1. Definitions of construct.

Construct	Operational definition	Reference
Task Characteristics	Those that might move a user to rely more heavily on certain aspects of the information	Goodhue ^[34]
Technology Characteristics	The characteristics of using CDSS during clinicians' operation	Goodhue ^[34]
Task-Technology Fit	The degree to which a clinician believes that using CDSS would enhance his or her job performance	Wells ^[31]
Performance Expectations	the performance related consequence of the behavior specifically performance expectation deal with job related outcomes	Venkatesh ^[33]
Perceived Ease of Use	The degree to which clinicians believe that using CDSS would be free from effort	Davis ^[30]
Perceived Risk	An assumption of risk on the part of clinicians in the use of CDSS	Stone ^[31]
Intention to Use	Clinicians' intention to use CDSS	Venkatesh ^[33]

Data collection/ recruitment

We specifically included clinicians with varying levels of seniority and educational backgrounds in our research. We distributed an email to clinicians affiliated with the hospital through list servers. The email outlined the objectives of the study, gave an overview of CDSS, and contained a link to the online survey. Interested clinicians voluntarily participated after providing their consent. A total of 247 clinicians participated in the study, and all 247 questionnaires collected were audited to be valid. In addition, we randomly selected 48 clinicians and administered an open-ended survey to garner their insights on the shortcomings and potential improvements of the CDSS.

Statistical analysis

Frequencies and percentages were used to describe the characteristics of the clinicians. Analyses were carried out using SPSS version 25.0. After conducting the descriptive statistics, the next step in the research process was to validate the model and test the hypotheses using a partial least squares structural equation modeling (PLS-SEM) analysis. This analysis was conducted in Smart PLS4. PLS-SEM is a variance-based approach that doesn't assume multivariate normality, making it robust for analyzing data with non-normal distributions and small sample sizes.

The implementation of the method involves a two-step process^[35]. The first step involves using the PLS algorithm to evaluate the reliability and validity of the measurement model. In the second step, we assessed the fit of the structural model and tested hypotheses using bootstrapping.

The open-ended questions were analyzed via thematic analysis, analyzing the number of themes and the frequency of occurrence of each theme.

Ethics Approval

This study was approved by the Ethics Committee of Shanghai Children's Hospital (approval number: 2021R077-E01). All clinicians voluntarily and anonymously participated in this study, having provided their informed consent.

Results

Demographic Information

The study involved the participation of 247 clinicians, and all valid questionnaires were collected. In Table 2, the demographic information of the clinicians is presented. A total of 129(52.2%) men and 118(47.8%) women participated in the study, with ages ranging between 25 and 55 years. Individuals aged 25-40 constitute the majority, comprising 62.8% (155 individuals). Regarding professional titles, resident physicians (66 individuals, 26.7%) and attending physicians (60 individuals, 24.3%) are the predominant groups.

Table 2. Participant characteristics.

Participant characteristics	Participants (N=247), n (%)
Gender	
Men	129(52.2)
Women	118(47.8)
Age(years)	
≤24	47(19.0)
25-40	155(62.8)
≥41	45(18.2)
Professional position	
Resident physician	66(26.7)
Attending physician	60(24.3)
Deputy chief physician	38(15.4)
Chief physician	8(3.2)
Others	75(30.4)
Working experience(years)	
<1	40(16.2)
1-10	102(41.3)

11-20	71(28.7)
≥21	34(13.8)
System usage time(years)	
<1	106(42.8)
1-3	56(22.7)
4-5	32(13.0)
≥6	53(21.5)

Intention to Use CDSS Dimensional Scores

The average scores of the dimension items in this study are as follows: clinicians' task characteristics (4.45 ± 0.87), technological characteristics (3.97 ± 0.80), task-technology fit (4.20 ± 0.74), performance expectancy (4.14 ± 0.78), perceived ease of use (4.03 ± 0.92), perceived risk (1.80 ± 0.85), and intention to use (3.88 ± 1.28).

Measurement Model Assessment

We typically assessed the reliability of each latent construct (e.g., factors, variables) using measures like composite reliability or Cronbach's α ^[36]. Furthermore, we assessed the convergent validity by examining the loadings of the indicators on their respective constructs and the average variance extracted (AVE)^[37]. The outcomes of this analysis are summarized in Table 3. The results presented in Table 3 reveal that all Cronbach's α and composite reliability values exceeded 0.7, indicating solid internal consistency and reliability for each construct. Moreover, the AVE for each construct surpassed 0.5, signifying adequate convergent validity. Additionally, the factor loadings for each item were above 0.7, suggesting that each item reliably measures its respective construct. Collectively, these findings demonstrate robust reliability and convergent validity for the measurement model.

Table3. Construct reliability and convergent validity

Constructs and items	CR ^a	AVE ^b	Cronbach α	Factor loading
TAC ^c	0.965	0.933	0.930	
TAC1				0.974
TAC2				0.958
TEC ^d	0.961	0.924	0.918	
TEC1				0.963
TEC2				0.960
TTF ^e	0.939	0.886	0.871	
TTF1				0.947
TTF2				0.935
PEOU ^f	0.940	0.797	0.915	
PEOU1				0.890
PEOU2				0.854
PEOU3				0.936
PEOU4				0.890
PE ^g	0.928	0.812	0.884	

PE1				0.913
PE2				0.915
PE3				0.875
PR ^h	0.939	0.836	0.902	
PR1				0.888
PR2				0.915
PR3				0.939
ITU ⁱ	0.960	0.923	0.916	
ITU1				0.961
ITU2				0.961

^a CR: Composite Score

^b AVE: Average Variance Extracted

^c TAC: Task Characteristics

^d TEC: Technology Characteristics

^e TTF: Task-Technology Fit

^f PEOU: Perceived Ease of Use

^g PE: Performance Expectations

^h PR: Perceived Risk

ⁱ ITU: Intention to Use

Moreover, discriminant validity is evaluated to ensure that the constructs in the measurement model are distinct from each other. Discriminant validity is a concept in research and statistics that assesses the extent to which different measures or constructs truly represent distinct concepts or variables. This analysis helps confirm that the measures intended to represent different constructs do not overlap substantially. By examining the correlations between constructs and comparing them to the square root of the average variance extracted (AVE) for each construct, we can determine whether the measures exhibit adequate discriminant validity. The outcomes of this analysis are summarized in Table 4. As evidenced in Table 4, the outcomes confirm that discriminant validity has been achieved. This is evident by ensuring that the square root of the average variance extracted (AVE) for each construct exceeds the correlations between that construct and other constructs. Importantly, this criterion was met for all constructs included in the analysis. Consequently, the measurement model successfully demonstrates discriminant validity, indicating that the constructs are distinct from each other as intended ^[37]. Based on the comprehensive assessment of the measurement model, which included evaluating construct reliability, convergent validity, and discriminant validity. As a result, we can proceed with confidence to test the research hypotheses using this robust measurement model.

Table4.Discriminant validity

	Task Characteristic s	Technolog y Characteri stics	Task- Technolo gy Fit	Performa nce Expectati ons	Perceiv ed Ease of Use	Percei ved Risk	Intention to Use
Task							
Characteristi cs	0.966	—	—	—	—	—	—
Technology							
Characteristi cs	0.103	0.962	—	—	—	—	—
Task- Technology							
Fit	0.245	0.767	0.941	—	—	—	—
Performance							
Expectation s	0.084	0.678	0.675	0.901	—	—	—
Perceived							
Ease of Use	0.076	0.667	0.692	0.689	0.893	—	—
Perceived							
Risk	-0.054	-0.394	-0.542	-0.583	-0.571	0.914	—
Intention to Use	0.039	0.370	0.468	0.640	0.595	-0.774	0.961

Structure Model Assessment

In our research, all Variance Inflation Factors (VIF) were below the predefined cutoff value of 5. Therefore, we concluded that no multicollinearity was present in our dataset^[38]. The assessment of the research model involved evaluating the path coefficients (β) and coefficients of determination (R^2). Table 5 presents the path coefficients along with their significance levels, hypothesis outcomes, and R^2 values. Additionally, Figure 2 provides a visual representation of the research model, illustrating the relationships between the variables and highlighting the significant paths identified through the analysis. These results offer insights into the strength and direction of the relationships between the variables within the model, as well as the extent to which they explain the variance in the dependent variables. The coefficient of determination, or R^2 , represents the proportion of variance in the endogenous latent variable (in this case, "intention to use") that is accounted for by the predictors included in the model. In our analysis, the entire model explained 65.8% of the variance in "intention to use." This level of explained variance is considered substantial, indicating that a significant portion of the variability in the intention to use can be attributed to the predictors

included in the model. The path coefficients (β) indicate the strength and direction of the direct effects of independent variables on dependent variables in the structural model. In our analysis, hypotheses based on the TTF (hypotheses 1, 2, 3, 8) were all supported, suggesting significant relationships between the TTF constructs and the specified dependent variables. Similarly, hypotheses related to the newly integrated constructs, perceived ease of use and perceived risk (hypotheses 4, 5, 6, 7, 10), were also supported, indicating significant direct effects between these constructs and the specified dependent variables. However, hypothesis 9, presumably involving a relationship between one of the newly integrated constructs and a dependent variable, was not supported by the data.

Table 5 Hypothesis test result

Hypothesis	Path	path coefficients (β)	P value	Outcome
Hypothesis1	task characteristics→task-technology fit	0.168	<0.001	Supported
Hypothesis2	technology characteristics→task-technology fit	0.749	<0.001	Supported
Hypothesis3	task-technology fit→performance expectations	0.508	<0.001	Supported
Hypothesis4	task-technology fit→perceived risk	-0.281	<0.001	Supported
Hypothesis5	task-technology fit→perceived ease of use	0.692	<0.001	Supported
Hypothesis6	perceived ease of use→perceived risk	-0.377	<0.001	Supported
Hypothesis7	perceived risk→performance expectations	-0.308	<0.001	Supported
Hypothesis8	performance expectations→intention to use	0.228	<0.001	Supported
Hypothesis9	perceived ease of use→intention to use	0.108	0.073	Rejected
Hypothesis10	perceived risk→intention to use	-0.579	<0.001	Supported

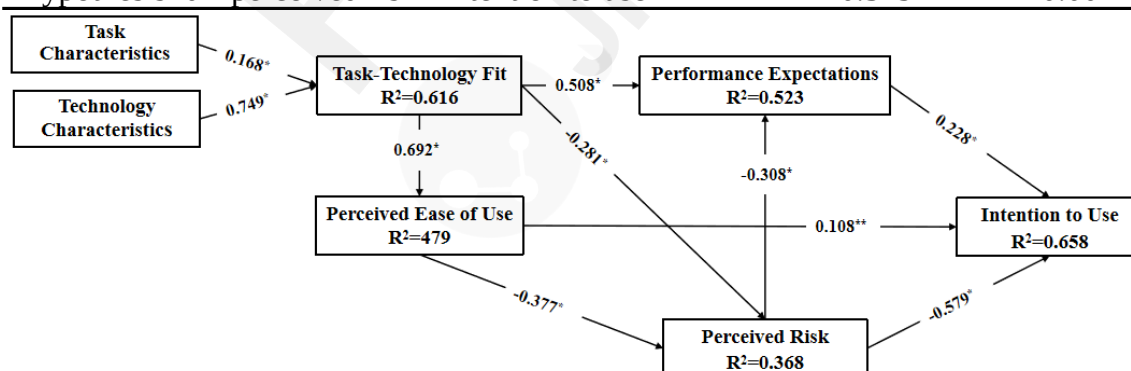


Figure 2 Result of the structure model. * $P < 0.001$; ** $P > 0.05$

Qualitative data analysis

From the 48 responses regarding clinicians' expectations that CDSS failed to meet, three themes emerged. The first theme, mentioned 28 times, revolves around reducing system security risks.

Clinicians expect CDSS not only to offer accurate predictions but also to provide transparent explanations for its decisions. This transparency is crucial for fostering trust among healthcare professionals, ensuring regulatory compliance, and safeguarding patient safety. The second theme, mentioned 10 times, pertains to personalized interactions. Clinicians expressed a desire for CDSS to move beyond standardized interactions and instead offer personalized conversations. They sought tailored content and forms of interaction that would better meet their individual needs and preferences. The third theme, mentioned 10 times, relates to effective utilization. Clinicians emphasized the importance of efficiently utilizing CDSS within their busy clinical workflows. Given that time is a scarce resource in healthcare settings, clinicians expect CDSS to be designed in a way that seamlessly integrates into their workflows and enhances efficiency rather than adding burdensome tasks.

Discussion

Principal Results and Comparison with Prior Work

As CDSS gains widespread adoption in healthcare, significant questions arise concerning how it shapes performance expectations and perceived risks, as well as clinicians' willingness to adopt and seamlessly integrate this technology into their clinical workflows. This study marks a pioneering effort in combining the perceived risk theory with the TTF framework, examining how perceived ease of use and the task-technology fit influence clinicians' perceived risk and performance expectations, thereby impacting clinicians' willingness to adopt AI systems in their practice.

In our study, clinicians' willingness to adopt CDSS varied from moderate to moderately high. We pinpointed several crucial factors that significantly influence their intention to utilize this technology. Notably, we discovered that perceived risk has a negative impact on clinicians' intention to use CDSS, with a significant portion of them exhibiting a low level of perceived risk associated with the system. Indeed, perceived risk arises from the system's lack of transparency. The absence of transparency in a CDSS refers to a deficiency in clarity or openness in how the system makes decisions or generates recommendations. This opacity can foster uncertainty among clinicians regarding the rationale behind the system's outputs, thereby undermining their trust and confidence in its reliability, hindering their ability to effectively integrate the CDSS into clinical decision-making processes^[39]. This finding is consistent with prior research on users' adoption of mobile service systems, indicating that higher perceived risks associated with new technology usage correspond to lower levels of willingness to use it^[40]. Additionally, we observed that the perceived risk served as a pivotal mediating factor in the interplay between task-technology fit and clinicians' intention to utilize CDSS. This is due to clinicians' consideration of the system's potential risks and

uncertainties when evaluating task-technology fit. When clinicians perceive a low fit between tasks and technology, they may be apprehensive that the system may not adequately support their work demands, subsequently enhancing their perception of risk associated with using the system, ultimately diminishing their usage behavior^[41].

We also found that clinicians' performance expectations for CDSS were at a high level. Our findings indicate a significant positive influence of performance expectations on clinicians' intention to use CDSS. This suggests that clinicians are more likely to adopt the technology if they believe it enhances their productivity and contributes to better clinical outcomes for their patients. This is consistent with the findings of a 2021 study that explored the impact of performance expectations on the adoption of AI^[42]. At present, the primary factor affecting clinicians' performance expectations of CDSS is the system's inability to effectively integrate into their daily workflows. The main reason is that clinicians have already established a relatively smooth workflow in their daily practice. They are accustomed to using tools and processes that may differ from CDSS. If the CDSS cannot seamlessly integrate with clinicians' existing workflow, they may perceive its use as adding to their workload, reducing efficiency, or even causing workflow interruptions. Therefore, clinicians may doubt the CDSS's effectiveness, fearing it will disrupt their workflow instead of enhancing efficiency and accuracy^{[43][44]}.

It's intriguing that in this particular study, perceived ease of use emerged as insignificant within the context of CDSS. This suggests that other factors might have played a more dominant role in influencing clinicians' intentions to use these systems. However, the clinicians' intention to use CDSS is indirectly influenced by their perceived ease of use, mediated through the variable of perceived risk. It's not uncommon to find studies within the realm of information system usage where the relationship between perceived ease of use and usage intention is deemed insignificant^[45]^[46]. This result underscores that even if a system is user-friendly, if it fails to deliver tangible benefits in terms of patient care or diagnostic accuracy, clinicians may not be motivated to use it.

Through qualitative data analysis, we have pinpointed three key areas where clinicians perceive shortcomings in CDSS: a lack of transparency, limited personalized interactions, and inadequate integration with clinical workflows. This revelation provides hospital administrators and system developers with valuable insights into the underlying reasons for the low utilization rates of CDSS. When clinicians encounter CDSS with opaque algorithms, their perceived risk increases. Additionally, the absence of personalized interactions and seamless integration into workflows diminishes clinicians' performance expectations, thereby leading to reluctance in continued CDSS usage.

Managerial and Public Health Implications

Drawing upon the unique characteristics and requirements of clinical tasks, CDSS is tailored and optimized to harmonize with clinicians' operational routines and bolster their decision-making processes. Concurrently, a real-time feedback loop should be embedded within CDSS to systematically gather clinicians' ongoing usage feedback and recommendations. This feedback loop facilitates a deep understanding of clinicians' satisfaction levels and identifies areas for potential improvement. All of the above measures help to ensure that the CDSS remains tightly synchronized with the changing tasks and needs of clinicians.

The lack of transparency, interpret-ability, regulatory and ethical compliance, as well as accountability issues surrounding AI's participation in medical decision-making, poses a series of challenges in the healthcare industry, which has sparked the demand for Explainable Artificial Intelligence (XAI) in the medical field. XAI not only provides accurate predictions but also offers transparent explanations for their decisions, which is crucial for building trust with clinicians, validating generated insights, ensuring regulatory compliance, and patient safety^[47]. In the future, various methods can be relied upon during system design to achieve model interpret-ability, including post-hock explain-ability techniques (such as feature importance analysis and SHAP values), rule-based methods, visual explanations and heat-maps, case-based reasoning, and natural language explanations. These methods can help clinicians understand the algorithms behind the models, establish trust in the system, and reduce their perceived risks.

Although this study did not prove that perceived ease of use can directly increase clinicians' willingness to use CDSS, a pleasant system interface, simple and easy operation process, and easy-to-understand information prompts can effectively reduce clinicians' perceived risk, increase clinicians' performance expectations, and thus indirectly affect clinicians' use of the system. Therefore, providing comprehensive user support, including detailed user manuals, online help documents, and video tutorials, ensures that clinicians can easily obtain the necessary help during use, ultimately improving its effectiveness and utilization in clinical decision-making.

Contribution

The contribution of this study is the identification of several key factors that influence clinicians' use of CDSS. There remains a notable gap, with only a limited number of studies integrating both TAM and TTF model to comprehensively understand CDSS adoption factors^{[48][49]}. Our study captures the perception of clinicians and degree of technical fit with the task. This study offers a dual contribution. Theoretically, it identifies pivotal factors influencing clinicians' readiness to embrace CDSS and verifies the model's applicability and utility via a cross-sectional survey. Practically,

leveraging the study's findings, it furnishes tailored managerial recommendations to foster the implementation and efficacy of CDSS, thus bridging the gap between theory and practice in healthcare settings.

Limitations

There are some limitations of this study that must be acknowledged. One limitation of the study is the reliance on intention to use as a final variable. While willingness to use can predict usage behavior, it's important to note that it's not synonymous with actual usage behavior. The study may not fully capture the complex dynamics that affect CDSS utilization in real-world clinical settings. Another limitation of the study is its focus on hospitals with a high degree of CDSS development. The study's findings may be influenced by contextual factors specific to the hospitals included in the sample, such as organizational culture, leadership support, or existing IT infrastructure. Extrapolating the results to hospitals with different contextual factors should be done cautiously. Lastly, the cross-sectional nature of the study may restrict the ability to establish causality between the identified factors and clinicians' willingness to use CDSS. Longitudinal studies tracking changes in attitudes and behaviors over time would provide stronger evidence of causal relationships.

Conclusions

In conclusion, this study set out to uncover the critical factors shaping clinicians' intentions to utilize CDSS. Performance expectations and perceived risk emerged as significant predictors of usage intention. Task-technology fit and perceived ease of use can significantly influence users' perceived risk and performance expectations. Therefore, CDSS developers must emphasize the advantages of AI technology, align technology objectives with organizational missions (task-technology fit), prioritize user-friendly design to reduce effort expectancy (perceived ease of use), articulate the system's capabilities clearly (performance expectancy), and mitigate risk perceptions by refining the overall design. In the future, management policies should encourage the active involvement of clinicians and all stakeholders in the decision-making process concerning CDSS. This participatory approach ensures that diverse perspectives are considered, leading to greater acceptance and buy-in from healthcare professionals. Furthermore, establishing clear accountability and responsibility frameworks can foster trust and confidence among users, guiding the use of AI technology. By implementing these measures, organizations can mitigate risk perception, enhance performance, and ultimately increase clinicians' intention to integrate CDSS into their daily practice.

Acknowledgments

This study was supported by the General Program of the National Natural Science Foundation (grant 72074146) and the Major Research Plan Project of the National Natural Science Foundation (grant

72293585). We confirm that this paper has been read and approved by all named authors. RZ conceived and designed this study. LS, XL and MJ provided technical support. RZ, XJ and TH acquired and analyzed the data. GY supervised this study. RZ drafted this paper. All authors critically revised this paper.

RZ, XJ, and LS contributed equally to this work and should be considered joint first authors.

Conflicts of Interest

None declared.

Abbreviations

CDSS: Clinical Decision Support System

TTF: Task-Technology Fit

TAM: Technology Acceptance Model

AI: Artificial Intelligence

PLS-SEM: Partial Least Squares Structural Equation Model

AVE: Average Variance Extracted

Multimedia Appendix 1

Operationalization of the research variables.

References

- [1] Graber ML. Reaching 95%: decision support tools are the surest way to improve diagnosis now. BMJ Publishing Group Ltd; 2022: 415-418. [doi: 10.1136/bmjqs-2021-014033]
- [2] Syrowatka A, Krömker D, Meguerditchian AN, et al. Features of computer-based decision aids: systematic review, thematic synthesis, and meta-analyses. J Med Internet Res; 2016; 18(1): e20. [doi: 10.2196/jmir.4982]
- [3] Huang S, Liang Y, Li J, et al. Applications of clinical decision support systems in diabetes care: scoping review. J Med Internet Res; 2023; 25: e51024. [doi: 10.2196/51024]
- [4] Magrabi F, Ammenwerth E, McNair JB, et al. Artificial intelligence in clinical decision support: challenges for evaluating AI and practical implications. Yearbook of medical informatics; 2019; 28(01): 128-134. [doi: 10.1055/s-0039-1677903]
- [5] Vasey B, Ursprung S, Beddoe B, et al. Association of clinician diagnostic performance with machine learning-based decision support systems: a systematic review. JAMA network open; 2021; 4(3): e211276. [doi: 10.1001/jamanetworkopen.2021.1276]
- [6] Bates DW, Levine D, Syrowatka A, et al. The potential of artificial intelligence to improve patient safety: a scoping review. NPJ digital medicine; 2021; 4(1): 54-62. [doi: 10.1038/s41746-021-00423-6]
- [7] Reverberi C, Rigon T, Solari A, et al. Experimental evidence of effective human-AI collaboration in medical decision-making. Scientific reports; 2022; 12(1): 14952-14957. [doi: 10.1038/s41598-022-18751-2]
- [8] Davenport T, Kalakota R. The potential for artificial intelligence in healthcare. Future healthcare journal; 2019; 6(2): 94-99. [doi: 10.7861/futurehosp.6-2-94]
- [9] Haghighparast-Bidgoli H, Hull-Bailey T, Nkhoma D, et al. Development and pilot

- implementation of Neotree, a digital quality improvement tool designed to improve newborn care and survival in 3 hospitals in Malawi and Zimbabwe: cost analysis study. *JMIR Mhealth Uhealth*; 2023; 11: e50467. [doi: 10.2196/50467]
- [10] Khairat S, Marc D, Crosby W, et al. Reasons for physicians not adopting clinical decision support systems: critical analysis. *JMIR Med Inform*; 2018; 6(2): e24. [doi: 10.2196/medinform.8912]
- [11] Choudhury A. Factors influencing clinicians' willingness to use an AI-based clinical decision support system. *Frontiers in Digital Health*; 2022; 4: 920662. [doi: 10.3389/fdgth.2022.920662]
- [12] Hossain A, Quaresma R, Rahman H. Investigating factors influencing the physicians' adoption of electronic health record (EHR) in healthcare system of Bangladesh: an empirical study. *International Journal of Information Management*; 2019; 44: 76-87. [doi: 10.1016/j.ijinfomgt.2018.09.016]
- [13] Venkatesh V, Thong JY, Xu X. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly*; 2012: 157-78. [doi: 10.2307/41410412]
- [14] Laka M, Milazzo A, Merlin T. Factors that impact the adoption of clinical decision support systems (CDSS) for antibiotic management. *International journal of environmental research and public health*; 2021; 18(4): 1901-1910. [doi: 10.3390/ijerph18041901]
- [15] Cheng YM. Quality antecedents and performance outcome of cloud-based hospital information system continuance intention. *Journal of Enterprise Information Management*; 2020; 33(3): 654-83. [doi: 10.1108/JEIM-04-2019-0107]
- [16] O'Connor Y, Andreev P, O'Reilly P. MHealth and perceived quality of care delivery: a conceptual model and validation. *BMC medical informatics and decision making*; 2020; 20: 1-13. [doi: 10.1186/s12911-020-1049-8]
- [17] Rahi S, Khan MM, Alghizzawi M. Extension of technology continuance theory (TCT) with task technology fit (TTF) in the context of Internet banking user continuance intention. *International Journal of Quality & Reliability Management*; 2021; 38(4): 986-1004. [doi: 10.1108/IJQRM-03-2020-0074]
- [18] Wills MJ, El-Gayar OF, Deokar A. Evaluating the impact of EHR on clinical reasoning performance: a TTF perspective. 2012.
- [19] Awa H, Ukoha K. Studying enterprise systems' acceptance using integrated unified theory of acceptance and use of technology (UTAUT). *Journal of Sustainability Science and Management*; 2020; 15(5): 98-126. [doi: 10.3390/su142114506]
- [20] Afshan S, Sharif A. Acceptance of mobile banking framework in Pakistan. *Telematics and Informatics*; 2016; 33(2): 370-87. [doi: 10.1016/j.tele.2015.09.005]
- [21] Usoro A, Shoyelu S, Kuofie M. Task-technology fit and technology acceptance models applicability to e-tourism. *Journal of Economic Development, Management, IT, Finance, and Marketing*; 2010; 2(1): 1-7.
- [22] Oliveira T, Faria M, Thomas MA, et al. Extending the understanding of mobile banking adoption: when UTAUT meets TTF and ITM. *International journal of information management*; 2014; 34(5): 689-703. [doi: 10.1016/j.ijinfomgt.2014.06.004]
- [23] Alqatan S, Noor NMM, Man M, et al. A theoretical discussion of factors affecting the acceptance of m-commerce among SMTEs by integrating TTF with TAM. *International Journal of Business Information Systems*; 2017; 26(1): 66-111. [doi: 10.1504/ijbis.2017.10006282]
- [24] Bansal G, Gefen D. The impact of personal dispositions on information sensitivity, privacy concern and trust in disclosing health information online. *Decision support systems*; 2010; 49(2): 138-50. [doi: 10.1016/j.dss.2010.01.010]
- [25] Parikh RB, Obermeyer Z, Navathe AS. Regulation of predictive analytics in medicine.

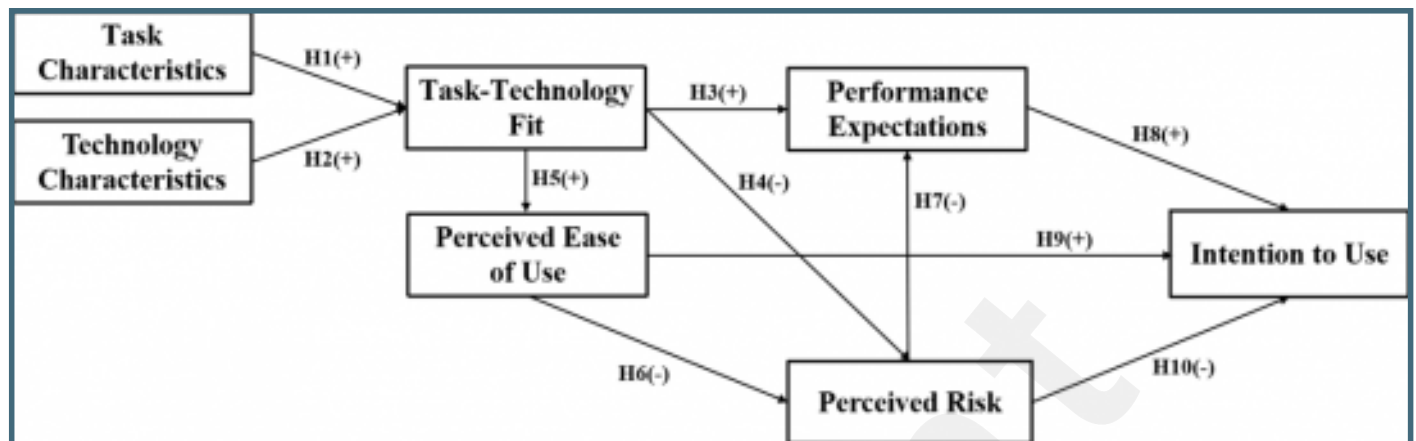
- Science; 2019; 363(6429): 810-812. [doi: 10.1126/science.aaw0029]
- [26] Chang HH, Fu CS, Jain HT. Modifying UTAUT and innovation diffusion theory to reveal online shopping behavior: Familiarity and perceived risk as mediators. *Information Development*; 2016; 32(5): 1757-1773. [doi: 10.1177/0266666915623317]
- [27] Ahlan A, Ahmad B. An overview of patient acceptance of health information technology in developing countries: A review and conceptual model. *International Journal of Information Systems and Project Management*; 2015; 3(1): 29-48.
- [28] Marcoulides GA, Saunders C. Editor's comments: PLS: a silver bullet? *MIS quarterly*; 2006; 4: 3-6. [doi: 10.2307/25148727]
- [29] Hoyle RH. The structural equation modeling approach: Basic concepts and fundamental issues. 1995.
- [30] Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*; 1989: 319-40. [doi: 10.2307/249008]
- [31] Stone RN, Grønhaug K. Perceived risk: Further considerations for the marketing discipline. *European Journal of marketing*; 1993; 27(3): 39-50. [doi: 10.1108/03090569310026637]
- [32] Goodhue DL. Development and measurement validity of a task-technology fit instrument for user evaluations of information system. *Decision sciences*; 1998; 29(1): 105-38. [doi: 10.1111/j.1540-5915.1998.tb01346.x]
- [33] Venkatesh V, Morris MG, Davis GB, et al. User acceptance of information technology: Toward a unified view. *MIS quarterly*; 2003: 425-478. [doi: 10.2307/30036540]
- [34] Goodhue DL, Thompson RL. Task-technology fit and individual performance. *MIS quarterly*; 1995; 7: 213-236. [doi: 10.2307/249689]
- [35] Li X, Xie S, Ye Z, et al. Investigating Patients' Continuance Intention Toward Conversational Agents in Outpatient Departments: Cross-sectional Field Survey. *J Med Internet Res*; 2022; 24(11): e40681. [doi: 10.2196/40681]
- [36] Souza ACD, Alexandre NMC, Guirardello EDB. Psychometric properties in instruments evaluation of reliability and validity. *Epidemiologia e servicos de saude*; 2017; 26: 649-659. [doi: 10.5123/s1679-49742017000300022]
- [37] Chin WW. How to write up and report PLS analyses. *Handbook of partial least squares: Concepts, methods and applications*. Springer; 2009; 11: 655-90.
- [38] Li X, Du J, Long H. Mechanism for Green Development Behavior and Performance of Industrial Enterprises (GDBP-IE) Using Partial Least Squares Structural Equation Modeling (PLS-SEM). *Int J Environ Res Public Health*; 2020; 17(22). [doi: 10.3390/ijerph17228450]
- [39] Shulha M, Hovdebo J, D'Souza V, et al. Integrating Explainable Machine Learning in Clinical Decision Support Systems: Study Involving a Modified Design Thinking Approach. *JMIR Form Res*; 2024; 8: e50475. [doi: 10.2196/50475]
- [40] Hanafizadeh P, Behboudi M, Koshksaray AA, et al. Mobile-banking adoption by Iranian bank clients. *Telematics and informatics*; 2014; 31(1): 62-78. [doi: 10.1016/j.tele.2012.11.001]
- [41] Ulapane N, Forkan ARM, Jayaraman PP, et al. Using Task Technology Fit Theory to Guide the Codesign of Mobile Clinical Decision Support Systems. 2023.
- [42] Gansser OA, Reich CS. A new acceptance model for artificial intelligence with extensions to UTAUT2: An empirical study in three segments of application. *Technology in Society*; 2021; 65: 101535. [doi: 10.1016/j.techsoc.2021.101535]
- [43] Olakotan OO, Mohd Yusof M. The appropriateness of clinical decision support systems alerts in supporting clinical workflows: a systematic review. *Health informatics journal*; 2021; 27(2): 14604582211007536. [doi: 10.1177/14604582211007536]
- [44] Olakotan OO, Yusof MM. Evaluating the alert appropriateness of clinical decision support systems in supporting clinical workflow. *Journal of biomedical informatics*; 2020; 106: 103453. [doi: 10.1016/j.jbi.2020.103453]

- [45] Kao HY, Yang YC, Wu YJ. When does Da Vinci robotic surgical systems come into play? *Frontiers in public health*; 2022; 10: 828542. [doi: 10.3389/fpubh.2022.828542]
- [46] Sun S-L, Hwang H-G, Dutta B, et al. Exploring critical factors influencing nurses' intention to use tablet PC in Patients' care using an integrated theoretical model. *Libyan Journal of Medicine*; 2019; 14(1): 1648963. [doi: 10.1080/19932820.2019.1648963]
- [47] Ammar N, Shaban-Nejad A. Explainable Artificial Intelligence Recommendation System by Leveraging the Semantics of Adverse Childhood Experiences: Proof-of-Concept Prototype Development. *JMIR Med Inform*; 2020; 8(11): e18752. [doi: 10.2196/18752]
- [48] Abouzahra M, Guenter D, Tan J. Exploring physicians' continuous use of clinical decision support systems. *European Journal of Information Systems*; 2024; 33(2): 123-44. [doi: 10.1080/0960085x.2022.2119172]
- [49] Dalvi-Esfahani M, Mosharaf-Dehkordi M, Leong LW, et al. Exploring the drivers of XAI-enhanced clinical decision support systems adoption: Insights from a stimulus-organism-response perspective. *Technological Forecasting and Social Change*; 2023; 195: 122768. [doi: 10.1016/j.techfore.2023.122768]

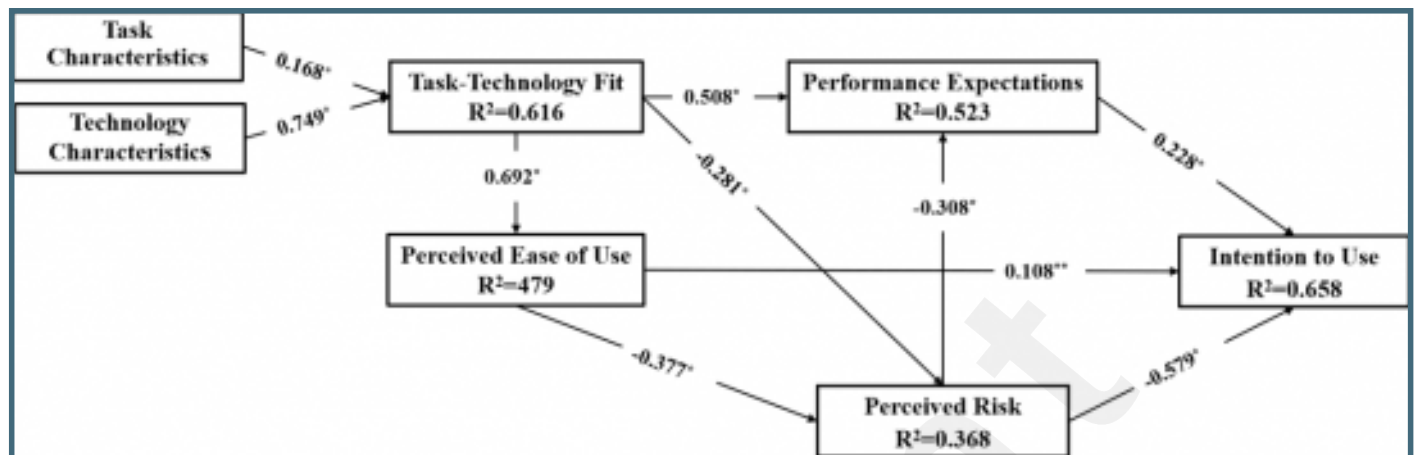
Supplementary Files

Figures

Conceptual Model.



Result of the structure model.



Multimedia Appendixes

Operationalization of the research variables.

URL: <http://asset.jmir.pub/assets/48a3bdab7f1608d57442745f43368ed7.docx>

