The willingness to adopt artificial intelligence-driven Clinical Decision Support Systems among doctors at different hospitals in China: A fuzzy set qualitative comparative analysis of survey data

Zhongguang Yu, Ning Hu, Qiuyi Zhao, Xiang Hu, Cunbo Jia, Chunyu Zhang, Bing Liu, Yanping Li

Submitted to: Journal of Medical Internet Research
on: May 29, 2024

Table of Contents

The willingness to adopt artificial intelligence-driven Clinical Decision Support Systems among doctors at different hospitals in China: A fuzzy set qualitative comparative analysis of survey data

Zhongguang Yu[1*]; Ning Hu[2*]; Qiuyi Zhao[3]; Xiang Hu[4]; Cunbo Jia[5]; Chunyu Zhang[6]; Bing Liu[5]; Yanping Li[1]

[1]Economics and Management School Wuhan University Wuhan CN
[2]School of Management Beijing University of Chinese Medicine Beijing CN
[3]Dushu Lake Hospital Suzhou CN
[4]Business School Hubei University Wuhan CN
[5]Hospital Office China-Japan Friendship Hospital Beijing CN
[6]Department of Human Resources China-Japan Friendship Hospital Beijing CN
[*]these authors contributed equally

Corresponding Author:
Yanping Li
Economics and Management School
Wuhan University
Economics and Management School, Wuhan University?Luojia Hill, Wuhan
Wuhan
CN

Abstract

Background: Artificial intelligence (AI) driven Clinical Decision Support Systems (CDSS) play an important role in assisting doctors in diagnosis and treatment and in improving the efficiency and quality of medical services. However, not all doctors trust AI technology, and many remain sceptical and unwilling to adopt these systems.

Objective: Our study's aim is to explore in depth the factors influencing different doctors' intentions to adopt AI-CDSS, along with the causal relationships among these factors, to gain a better understanding to promote their clinical application and widespread implementation.

Methods: Based on the Unified Theory of Acceptance and Use of Technology (UTAUT) and Technology-Organisation-Environment (TOE) models, we propose and design a framework for doctors' willingness to adopt AI-CDSS. We conducted a nationwide questionnaire survey in China and fuzzy set qualitative comparative analysis (fsQCA) to explore the willingness of doctors in different types of medical institutions to adopt AI-CDSS along with the factors influencing their willingness.

Results: The survey was distributed to doctors from different medical institutions in China, categorised as tertiary hospital and primary/secondary hospital. We distributed 578 questionnaires and received 450 valid responses with good reliability and validity. The effective response rate was 77.85%. We analyse the influencing factors and pathways of willingness from three perspectives: the technology, the organisation, and the individual. Doctors in tertiary hospitals were found to have six pathways to AI-CDSS adoption willingness, categorised as technology, individual, and technology-individual dual-driven; doctors at primary/secondary hospital had three pathways to AI-CDSS adoption willingness, categorised as technology-individual dual-driven and organisation-individual dual-driven. There were both commonalities and differences in the pathways among the doctors at the different medical institutions in terms of the factors influencing AI-CDSS adoption. Among the commonalities, AI technology and individual doctor factors played a dominant role in the willingness to adopt, implying that all the doctors believed that AI-CDSS could provide efficient diagnostic and treatment support; thus, they were willing to accept and try these new technologies. Among the differences, conditions of convenience (namely, facility support and resources) had a greater impact on doctors at primary/secondary hospital. For these doctors, only sufficient support would encourage their active adoption of AI-CDSS.

Conclusions: From the perspective of the six configurations among the doctors at the tertiary hospitals and the three configurations among the doctors at primary/secondary hospital, performance expectancy and individual innovativeness were two indispensable and core conditions in the pathways to achieving a favourable intention to adopt AI-CDSS.

(JMIR Preprints 29/05/2024:62692)
DOI: https://doi.org/10.2196/preprints.62692

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 u**
   - 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**
   - Yes, but only make the title and abstract visible (see Important note, above). I understand that if I later pay to participate in <a href="http

Original Manuscript

Original Paper

The willingness to adopt artificial intelligence-driven Clinical Decision Support Systems among doctors at different hospitals in China: A fuzzy set qualitative comparative analysis of survey data

[1]Zhongguang Yu, PhD; [2]Ning Hu, MSc; [3]Qiuyi Zhao, MSc; [4]Xiang Hu, PhD; [5]Cunbo Jia, MSc; [6]Chunyu Zhang, PhD; [5]Bing Liu, MSc; [7]Yanping Li, PhD

[1]Respiratory Centre, China-Japan Friendship Hospital, Beijing, China
[2]School of Management, Beijing University of Chinese Medicine, Beijing, China
[3]Dushu Lake Hospital, Suzhou, China
[4]Hubei University Business School, Wuhan, China
[5]Hospital Office, China-Japan Friendship Hospital, Beijing, China
[6]Department of Human Resources, China-Japan Friendship Hospital, Beijing, China
[7]Economics and Management School, Wuhan University, Wuhan, China

Corresponding Author:
Yanping Li, PhD
Economics and Management School
Wuhan University
Luojia Hill
Wuhan, 430072
China
Email: ypli@whu.edu.cn

Abstract

Background: Artificial intelligence (AI) driven Clinical Decision Support Systems (CDSS) play an important role in assisting doctors in diagnosis and treatment and in improving the efficiency and quality of medical services. However, not all doctors trust AI technology, and many remain sceptical and unwilling to adopt these systems.
Objective: Our study's aim is to explore in depth the factors influencing different doctors' intentions to adopt AI-CDSS, along with the causal relationships among these factors, to gain a better understanding to promote their clinical application and widespread implementation.
Methods: Based on the Unified Theory of Acceptance and Use of Technology (UTAUT) and Technology-Organisation-Environment (TOE) models, we propose and design a framework for doctors' willingness to adopt AI-CDSS. We conducted a nationwide questionnaire survey in China and fuzzy set qualitative comparative analysis (fsQCA) to explore the willingness of doctors in different types of medical institutions to adopt AI-CDSS along with the factors influencing their willingness.
Results: The survey was distributed to doctors from different medical institutions in China, categorised as tertiary hospital and primary/secondary hospital. We distributed 578 questionnaires and received 450 valid responses with good reliability and validity. The effective response rate was 77.85%. We analyse the influencing factors and pathways of willingness from three perspectives: the technology, the organisation, and the individual. Doctors in tertiary hospitals were found to have six pathways to AI-CDSS adoption willingness, categorised as technology, individual, and technology-

individual dual-driven; doctors at primary/secondary hospital had three pathways to AI-CDSS adoption willingness, categorised as technology-individual dual-driven and organisation-individual dual-driven. There were both commonalities and differences in the pathways among the doctors at the different medical institutions in terms of the factors influencing AI-CDSS adoption. Among the commonalities, AI technology and individual doctor factors played a dominant role in the willingness to adopt, implying that all the doctors believed that AI-CDSS could provide efficient diagnostic and treatment support; thus, they were willing to accept and try these new technologies. Among the differences, conditions of convenience (namely, facility support and resources) had a greater impact on doctors at primary/secondary hospital. For these doctors, only sufficient support would encourage their active adoption of AI-CDSS.

Conclusions: From the perspective of the six configurations among the doctors at the tertiary hospitals and the three configurations among the doctors at primary/secondary hospital, performance expectancy and individual innovativeness were two indispensable and core conditions in the pathways to achieving a favourable intention to adopt AI-CDSS.

Trial Registration: 2022-KY-032

KEYWORDS

Artificial Intelligence; Clinical Decision Support Systems; Willingness, technology adoption; Fuzzy Set Qualitative Comparative Analysis; pathways

Introduction

AI-CDSS were first used in the 1980s [1] with the aim of strengthening medical decision making. AI-CDSS target clinical knowledge, patient information, and other health information to improve healthcare services [2]. These systems are designed to provide healthcare professionals, patients, and caregivers with an intelligent way to detect, manage, and improve patient health conditions, while providing key and essential information [3]. With the advancement of artificial intelligence (AI) technology, current AI-CDSS can generate specific assessments or recommendations through logical reasoning, automatically collecting and analysing patient characteristics from electronic medical records, providing decision support to healthcare providers [4], and even assessing data humans are unable to analyse or explain [5]. AI-CDSS are widely used in the medical field, for example, in clinical diagnoses, drug treatment, preventive measures, clinical decision making, and patient management. The application of AI-CDSS in healthcare is considered a key factor in improving the quality of healthcare decision making in the healthcare environment, with many AI-CDSS proven to enhance the performance of doctors [6]. For instance, scholars such as Hansen et al. [7] conducted research from the perspective of patient management, evaluating the application of AI-CDSS in the nursing field, and confirmed that certain systems were able to improve the accuracy and comprehensiveness of nursing treatment. Alsharqi et al. [8] and others have evaluated the application effects of AI-CDSS in the automatic image selection field of echocardiography, finding that AI-CDSS can effectively identify, distinguish, and explain images through machine learning models. Islam et al. [9] studied how AI-CDSS could help patients continuously observe different parameters for controlling insulin levels, automatically analysing the personal data of diabetic patients. The application of AI-CDSS in the field of anaesthesiology is also extensive. According to existing research results, AI-CDSS can improve the preoperative use of antibiotics and beta-blockers, reduce the use of inhaled anaesthetics, and assist in completing anaesthesia records and billing work [10-12].

AI-CDSS are mainly aimed at doctors, and their willingness to use these systems plays an important role in promoting their application. However, doctors' willingness to adopt these systems and their general views on AI are diverse. Some reflect positive attitudes towards adopting AI-CDSS, while others respond negatively to the new systems, mainly due to concerns about technology immaturity, data privacy and security, the lack of a human touch, and a distrust of new technologies. In a recent study, Wagner et al. [13] showed that only 54.9% of family doctors were willing to use AI for medical diagnosis. In an earlier study, O'Leary et al. [14] surveyed doctors, nurses, and physical therapists on the diagnostic capabilities of AI for rare diseases and found that 82% of the respondents (N=19) did indicate that the tool was useful. Park et al.[15] conducted a study of 156 American radiology students in 2020, with over 75% (117/156) believing that AI will play an important role in future medicine and 66% (103/156) believing that diagnostic radiology will be the profession most influenced by AI. Notably, almost half of the students (69/156, 44.2%) reported that AI had lowered their enthusiasm for radiology as a medical specialty. In the study by Scheetz et al.[16], surveying 632 researchers and students in three professions (ophthalmology, radiology or radiation oncology, and dermatology) in Australia and New Zealand, 71% (449/632) of the respondents believed that AI would improve the field of medicine, and 85.7% (542/632) believed that AI would affect healthcare manpower demand in the next decade. Oh et al. [17] conducted a recent survey in South Korea, showing that although most respondents believed that AI was effective in medical practice, only 5.9% (40/669) of the practising doctors reported being very familiar with the technology. A 2020 study by Sit et al. [18] on the attitudes of 484 UK medical students towards AI technology training found that they were not adequately prepared to work with AI. Many scholars express mixed views on the involvement of AI in healthcare, mainly due to concerns about humans being replaced by technology. In the study by Poon and Sung [19], doctors indicated scepticism about the application of AI technology in clinical practice, leading to slow progress in these applications owing to a lack of trust.

As the expectations for these systems remain high, investigating doctors' willingness to use them and gaining a better understanding of the influencing factors can have a significant impact on the comprehensive integration of AI-CDSS into clinical applications. Previous studies have identified various reasons for the limited application and acceptance of AI in clinical diagnosis and treatment. Sambasivan et al. [20] used structural equation modelling to explore the intention of doctors to use AI-CDSS in developing countries and found that the perceived threat to professional autonomy reduced their willingness to use these systems, whereas participation in AI-CDSS planning, design, and implementation increased their willingness to do so. Laka et al. [21] conducted a logistic regression analysis of the adoption intention of AI-CDSS and found that compared with doctors in large hospitals, doctors in local primary care facilities considered factors such as time constraints, threats to professional autonomy, and patient preferences as important barriers to using AI-CDSS.

Current research focuses mainly on examining the impact of individual factors or certain factors affecting the allocation of medical resources. Thus, the literature lacks in-depth analysis of the interactive mechanisms and synergistic effects of factors influencing doctors' intention to adopt AI-CDSS. There is also a lack of comprehensive analysis that combines the multiple factors influencing doctors' intentions to adopt AI-CDSS to look at their causal relationship. To explore the driving mechanisms of multiple conditional linkages on doctors' adoption intentions, our study focuses on doctors at different medical institutions in China. Using fsQCA, we clarify the synergistic effects of multiple factors influencing doctors' intention to adopt AI-CDSS, thereby providing theoretical support for promoting their application in the medical field.

Framework for AI-CDSS Adoption Intention

The integration of the unified theory of acceptance and use of technology (UTAUT) was proposed in 2003 by Venkatesh et al. [22] to explain the relevant factors influencing an individual's intention to accept or use new technology. The UTAUT consists of four key factors: performance expectancy, effort expectancy, social influence, and facilitating conditions, which influence behaviour through intention [23]. The UTAUT also considers the moderating effects of sex, age, experience, and voluntary use. The theory was established in the context of the organisational implementation of new technology, with the influencing factors having clear utilitarian characteristics. With the emergence of AI technology, an increasing number of scholars are using the UTAUT to study individual AI technology adoption issues. The technology-organisation-environment (TOE) model proposed by Tornatzky et al. [24] suggests that technological, organisational, and external environmental factors also have a certain impact on an organisation's adoption and implementation of new technology.

Technical factors influencing the adoption of AI-CDSS by doctors

Performance expectancy is one of the key constructs in the UTAUT model used to explain and predict individual technology acceptance behaviour [25]. In a hospital setting, it can capture the extent that doctors believe that using new technology will help improve their job performance [26]. Previous studies have shown that performance expectancy is crucial for doctor adoption and acceptance of AI-CDSS [27], similar to the perceived usefulness in the technology acceptance model (TAM). Compared with other technology application scenarios, doctors place more emphasis on the impact of technology on their job performance when adopting new technology. Currently, AI technology has the ability to assist in eliminating redundant work steps, providing decision support, and improving job performance [28-29]. However, there are also issues, such as communication barriers between doctors and AI technology, which impact work efficiency. The effectiveness of AI technology in the workplace has yet to be widely validated [30]. Therefore, performance expectancy still plays an important role in doctors' willingness to adopt AI technology.

Perceived risk refers to the degree of insecurity that doctors perceive when they are using technology to execute tasks and exchange data [31]. AI technology requires big data to achieve powerful learning, which means that AI technology may involve the inputting of data from various parties, such as individuals and vendors. When there is a risk of information leaks, doctors using AI technology may face legal, moral, and ethical issues. This can have a significant impact on their willingness to adopt AI technology.

Organisational factors influencing the adoption of AI-CDSS by doctors

Social influence refers to the influence doctors feel from their social environment regarding a specific behaviour. It is a key factor in the UTAUT model that affects individuals' willingness to adopt new technology [27]. In an organisational context, doctors are frequently influenced by colleagues and leaders; they enhance their sense of belonging by conforming to these groups. When faced with emerging technologies such as AI, there may not be enough information for an informed decision, making doctors more susceptible to peer influence., However, leaders also influence doctors' willingness to adopt AI technology [32] and have the power to authorise subordinates, determine job promotions, provide rewards, and administer punishments. Thus, doctors align with leaders to receive recognition.

Facilitating conditions, another UTAUT construct, refer to the extent that doctors perceive that the necessary infrastructure and resources in the organisation support their use of new technology [27]. Thus, this would also influence the doctors' willingness to adopt AI technology. The promotion of new technology requires organisations to provide various resources such as knowledge, funds, and technology. The simpler and more convenient the external support conditions are, the more likely doctors are to adopt AI technology. Research has shown that facilitating conditions positively influence an individual's willingness to adopt AI technology [33-34].

Individual Factors Influencing the Adoption of AI-CDSS by Doctors

Technology anxiety refers to an individual's emotional anxiety or fear of the performance of new technology; namely, when individuals believe that the technology may threaten their sense of self, they may experience technology anxiety, which reduces their willingness to adopt it [25]. The existing and potential capabilities of AI technology to replace human abilities are constantly increasing, causing individuals to experience stronger feelings of anxiety compared with other technologies. Therefore, our study includes technology anxiety as a factor in our framework.

Personal innovativeness reflects an individual’s willingness to try something new. Innovation diffusion theory suggests that owing to differences in innovation capabilities, individuals’ intentions and behaviours vary in this respect. Some scholars have proven that in consumer scenarios, individual innovativeness positively influences individuals’ intentions to adopt self-service technologies [35]. As AI technology is a disruptive innovation, individual innovativeness is needed to drive doctors towards a greater willingness to adopt it. Therefore, we assume that personal innovativeness significantly impacts doctors' willingness to adopt AI technology.

Study Model

Our study applies the UTAUT model for the basis of our research framework to analyse the factors influencing doctor adoption of AI-CDSS, adding other factors as well. Our model considers three perspectives: technology, organisations, and the individuals. The technical factors we include are performance expectancy and perceived risk; the organisational factors are social influence and facilitating conditions; and the individual factors are technology anxiety and personal innovativeness. We incorporate performance expectancy, social influence, and facilitating conditions from the UTAUT model; and based on the research of Chen et al. [34], personal innovativeness and perceived risk are introduced into the model and confirmed, along with key factors in the UTAUT model that significantly influence doctor acceptance of AI technology. Huang [36] demonstrated how technology anxiety reflected an individual’s emotional anxiety or fear regarding the performance of AI technology. When individuals perceived the technology as threatening their sense of self, they experienced technology anxiety, which reduced their willingness to adopt the technology. Therefore, we include technology anxiety in the model. Considering that AI technology often does not require users to learn how to operate it, as it possesses anthropomorphic characteristics that are different from nonintelligent technologies [6], we do not include effort expectancy. The factors ultimately in our analysis framework are performance expectancy, perceived risk, facilitating conditions, social influence, technology anxiety, and personal innovativeness.

Thus, we assume that doctor willingness to adopt AI technology will be influenced by these various factors. Although there are studies that have investigated the individual effects of these elements on doctors’ AI adoption intentions, providing a foundation for our understanding of the factors influencing the willingness to adopt AI technology, the research struggles to answer how these factors interact to influence willingness to adopt under multiple situational conditions. Additionally, the research has not identified the deep-rooted causal relationships that are affecting doctor willingness to adopt AI technology. To fill this gap in the literature, based on the UTAUT model and incorporating the TOE model, we explore the complex causal mechanisms of how environmental, technological, and individual factors influence doctors’ willingness to adopt AI technology from a configurational perspective, proposing a theoretical model (Figure 1).

Methods

We use fsQCA to explore the complex causal mechanisms influencing clinical doctors’ intention to adopt AI-CDSS, primarily for the following reasons. (1) Using this method uncovers the nonlinear relationships between various influencing factors and the doctors’ intention to adopt AI-CDSS. The fsQCA method also explores combinations of influencing factors instead of the factors individually [37]; (2) As our research question is ‘which factors can lead clinical doctors to a higher intention to adopt AI-CDSS’?, using this method can reveal multiple equivalent paths that influence the doctors’ intention to adopt AI-CDSS; and (3) Compared with other qualitative comparative analysis methods, fsQCA is more suitable for handling continuous variables.

Data Collection

We designed an online questionnaire and distributed it to doctors in China who had a certain amount of work experience. We distributed 578 questionnaires using the Wenjuanxing platform and received 450 valid responses, after removing invalid questionnaires. The questionnaire response rate was 77.85%. We present the basic participant demographic statistics in a table (Table 1).

According to the 'Hospital Classification Management Measures' issued by the National Health Department, hospitals in China are classified into three levels. Tertiary hospitals provide medical and health services across regions, provinces, cities, and nationwide. Secondary hospitals provide comprehensive medical and health services to multiple communities and undertake teaching and research tasks in regional hospitals. Primary hospitals are grassroots hospitals and health centres that provide preventive, medical, health, and rehabilitation services to their local communities [38]. In this study, we divide the hospitals into just two categories for simplicity: tertiary hospitals and other hospitals (secondary and primary hospitals). Among the respondents, there were 332 responses from clinical doctors working in tertiary medical institutions, and 118 responses from clinical doctors in the other (primary/secondary) medical institutions, as mentioned above.

Table 1. Basic respondent demographic statistics.

Category		Tertiary Hospitals		Primary/Secondary Hospitals	
		Frequency	Percentage (%)	Frequency	Percentage (%)
Gender	Male	171	51.51%	53	44.92%
	Female	161	48.49%	65	55.08%
Age	Under 25	27	8.13%	12	10.17%
	25 to 34	109	32.83%	31	26.27%
	35 to 44	142	42.77%	35	29.66%
	45 to 54	51	15.36%	34	28.81%
	Above 54	3	0.90%	6	5.08%
Education	Bachelor's degree	89	26.81%	85	72.03%
	Master's degree	176	53.01%	13	11.02%
	Doctoral degree	66	19.88%	1	0.85%
	Others	1	0.30%	19	16.10%
Major title	Resident physician	100	30.12%	46	38.98%
	Attending physician	113	34.04%	39	33.05%
	Associate chief physician	81	24.40%	19	16.10%
	Chief physician	38	11.45%	14	11.86%
Duration of employment	1 yr or less	28	8.43%	15	12.71%
	2 to 5 yrs	86	25.90%	25	21.19%
	6 to 10 yrs	71	21.39%	17	14.41%
	11 to 15 yrs	66	19.88%	23	19.49%

16 to 20 yrs	41	12.35%	5	4.24%
21 to 25 yrs	19	5.72%	11	9.32%
25 yrs or more	21	6.33%	22	18.64%

Variable *Measurement and Calibration*

To ensure the reliability and validity of our scales, we base ours on mature scales developed by scholars in the field of technology adoption and appropriately adjust these for our research question to create measurement items for our main variables. The main variables are performance expectancy, perceived risk, facilitating conditions, social influence, technology anxiety, individual innovativeness, and adoption intentions. The participant responses are on a five-point Likert scale that assesses the extent that they agreed with the content described in the items. We calculate the average score of the corresponding items within each scale to measure the variable. We use SPSS (version 25.0) to analyse the reliability and validity of the scales. All variables had a Cronbach α greater than 0.8, composite reliability (CR) greater than 0.8, KMO values greater than 0.7, and average variance extracted (AVE) greater than 0.5, indicating that the scales had good reliability and validity. To ensure the overall reliability of our results, we removed items with factor loadings less than 0.6; the conditions were still met after these items were deleted (Table 2).

Table 2. Reliability and validity analysis.

Variable	Item	Factor loading	Cronbach's α	KMO	CR	AVE
Performance Expectancy	1	0.913	0.831	0.797	0.916	0.611
	2	0.925				
	3	0.884				
	4	0.543				
Perceive Risk	1	0.567	0.879	0.848	0.934	0.568
	2	0.674				
	3	0.885				
	4	0.875				
	5	0.838				
Facilitating Conditions	1	0.775	0.857	0.821	0.929	0.640
	2	0.893				
	3	0.768				
	4	0.825				
Social Influence	1	0.842	0.883	0.811	0.940	0.864
	2	0.913				
	3	0.810				
	4	0.686				
Technology Anxiety	1	0.839	0.921	0.900	0.890	0.572
	2	0.833				
	3	0.859				
	4	0.620				
	5	0.723				
Personal Innovation	1	0.786	0.865	0.831	0.896	0.650
	2	0.824				
	3	0.912				

	4	0.880				
Adoption willingness	1	0.961				
	2	0.953	0.887	0.747	0.931	0.768
	3	0.946				

Note: PE, Performance Expectancy, PR, Perceived Risk, FC, Facilitating Conditions, SI, Social Influence, TA, Technology Anxiety, PI, Individual Innovativeness, and AW, adoption willingness.

To meet the Boolean logic requirements for qualitative comparative analysis, variables need to be transformed into sets, and cases assigned to the sets before conducting the fsQCA—a process known as data calibration. In this process, we need to establish calibration points for 'full membership', 'crossing point', and 'full non-membership'. We adopt a scholar's calibration method for the Likert scale questionnaire data, coding 'completely agrees (5)' as 'full membership', 'neutral (3)' as 'crossing point', and 'completely disagrees (1)' as 'full non-membership'. By setting these three thresholds, we convert the original data into the fuzzy scores ranging from zero to one using the calibrate (x, n1, n2, n3) function in the fsQCA software.

Results

Necessary Condition

According to the fsQCA method, before conducting the configuration analysis, the first step is to perform a necessity analysis on the individual condition variables, with the results reflected through consistency and coverage. Consistency represents the degree that the condition variables are a subset of the outcome variables. Identifying a necessary condition generally requires a consistency score higher than 0.9. Coverage represents the extent that the condition variables explain the outcome. This is only meaningful for conditions that pass the consistency test, with no acceptable threshold. The results of the necessity test for the individual conditions are shown in a table (Table 3).

Table 3. Necessary condition analysis.

Condition Variable	Tertiary Hospitals		Other Hospitals (primary/secondary)	
	Consistency	Coverage	Consistency	Coverage
Performance Expectancy	0.882	0.917	0.872	0.832
~Performance Expectancy	0.376	0.852	0.423	0.784
Perceive Risk	0.471	0.952	0.570	0.890
~Perceive Risk	0.775	0.853	0.722	0.763
Facilitating Conditions	0.653	0.955	0.757	0.924
~Facilitating Conditions	0.611	0.849	0.567	0.739
Social Influence	0.787	0.944	0.854	0.934
~ Social Influence	0.487	0.855	0.479	0.711
Technology Anxiety	0.707	0.939	0.661	0.908
~Technology Anxiety	0.555	0.854	0.658	0.766
Personal Innovation	*0.861*	*0.949*	*0.930*[b]	*0.933*
~ Personal Innovation	0.414	0.834	0.414	0.702

a"~" means that a factor does not appear or is "not."
b Italics denote that consistency exceeded 0.8.

In the table, we can see that the consistency of individual innovativeness in influencing doctor adoption intention of AI-CDSS at other medical institutions (primary and secondary) is higher than

0.9, and coverage is as high as 0.933. This indicates that individual innovativeness is a necessary condition influencing doctor adoption intention of AI-CDSS in these hospitals. The consistency of the other variables is less than 0.9, indicating that they are not sufficient to constitute the necessary conditions affecting doctor adoption intention of AI-CDSS, with these variables having relatively weak independent explanatory powers. Thus, we need to further analyse the combining effects of these condition variables and their impact on our outcome variable.

Adequacy Analysis of Configuration

As mentioned, we conducted fsQCA analysis separately for tertiary and the other hospitals (primary/secondary). According to the principles of fsQCA, we included six condition variables. We retained 85% of the case number to set the frequency threshold, with case number thresholds of five and two for tertiary hospitals and other hospitals (primary/secondary), respectively. The consistency threshold for each configuration was higher than 0.8, and the proportional reduction in inconsistency (PRI) threshold was greater than 0.75. A configuration with consistency below the threshold was assigned a value of 0 (Table 4).

Table 4. Truth table.

Level	Conditional variable						Number	Outcome Y	Raw consist.	PRI consist.	SYM consist
	A	B	C	D	E	F					
Doctors at Tertiary hospitals	1	1	1	1	1	1	32	1	0.997789	0.994404	0.994404
	1	1	0	1	1	1	7	1	0.997023	0.989236	0.989237
	1	0	1	1	1	1	38	1	0.995619	0.988805	0.988805
	1	1	1	1	0	1	5	1	0.996540	0.984514	0.987172
	1	0	0	1	1	1	22	1	0.994604	0.984282	0.984282
	1	0	1	1	0	1	44	1	0.992934	0.981120	0.981120
	1	0	0	0	1	1	19	1	0.992382	0.976033	0.978558
	1	0	0	1	0	1	10	1	0.990879	0.962754	0.963750
	1	0	0	0	1	0	8	1	0.988872	0.942290	0.942291
	0	0	1	1	0	1	5	1	0.988860	0.929057	0.932779
	1	0	0	0	0	1	13	1	0.982544	0.921498	0.931327
	1	0	0	1	0	0	8	1	0.984218	0.907492	0.907493
	0	0	0	0	1	1	8	1	0.981872	0.904679	0.909656
	0	0	0	1	0	1	6	1	0.985961	0.902044	0.902046

	1	0	1	1	0	0	10	1	0.971584	0.850015	0.866264
	0	0	0	0	0	1	10	1	0.973338	0.826399	0.828025
	1	0	0	0	0	0	11	1	0.964521	0.796661	0.797960
	0	0	0	0	0	0	24	0	0.895842	0.463338	0.467589
Doctors at Other hospitals (primary/secondary)	1	0	1	1	1	1	7	1	0.995976	0.986577	0.986577
	1	1	1	1	1	1	15	1	0.991665	0.977517	0.977518
	1	0	0	1	1	1	2	1	0.992201	0.963961	0.963961
	1	1	0	1	1	1	3	1	0.988830	0.953054	0.953054
	1	1	0	1	0	1	3	1	0.992045	0.952049	0.952050
	1	0	1	1	0	1	17	1	0.982767	0.947533	0.953350
	0	0	1	1	0	1	2	1	0.989427	0.927492	0.927492
	1	1	1	1	0	1	4	1	0.984086	0.922251	0.948591
	1	0	0	1	0	1	3	1	0.986501	0.920241	0.920242
	1	0	1	0	0	1	3	1	0.975536	0.830054	0.830053
	1	0	0	0	0	1	5	1	0.969439	0.797216	0.797216
	0	0	0	1	0	1	2	0	0.968835	0.732559	0.732558
	0	0	0	0	0	1	6	0	0.946550	0.654310	0.654310
	1	0	1	1	0	0	4	0	0.965158	0.631557	0.631558
	0	0	0	0	1	0	2	0	0.912641	0.349602	0.349602
	0	0	0	0	0	0	16	0	0.842963	0.315754	0.327492
	1	1	0	0	0	0	3	0	0.937445	0.308522	0.308522
	0	1	0	0	1	0	2	0	0.937238	0.290340	0.348758
	1	0	0	0	0	0	10	0	0.861165	0.251138	0.251138

After the standard analysis of the improved truth table, we found three types of solutions: complex, intermediate, and parsimonious. Among them, we obtained the intermediate solution through a counterfactual analysis, assuming that the emergence of individual innovativeness may increase doctor adoption intention of AI-CDSS, whereas the other individual conditions may contribute to doctor adoption intention of high AI-CDSS. We identify the core conditions for each configuration by comparing the nested relationships between the intermediate and parsimonious solutions. The conditions appearing in both the parsimonious and intermediate solutions are considered core conditions for that configuration, whereas those appearing only in the intermediate solution are considered marginal conditions (Table 5).

Table 5. Adoption intention of doctors in different medical institutions.

Conditions	Tertiary hospitals						Primary/Secondary hospitals		
	S1		S2		S3		N1	N2	
	S1a	S1b	S2a	S2b	S3a	S3b		N2a	N2b
Performance Expectancy	●	●			●	●	●	●	
Perceive Risk									
Facilitating Conditions					●				●
Social Influence		●		●	●	●	●		●
Technology Anxiety						●			
Personal Innovation			●	●	●	●	●	●	●
Consistency	0.963	0.970	0.964	0.985	0.992	0.994	0.972	0.961	0.983
Raw coverage	0.416	0.451	0.413	0.444	0.591	0.549	0.769	0.514	0.479
Unique coverage	0.018	0.015	0.017	0.011	0.022	0.040	0.279	0.023	0.017
Solution consistency	0.804						0.810		
Solution coverage	0.953						0.961		

Note: ● represents the presence of a core causal condition, ● represents the presence of a marginal causal condition, represents the absence of a marginal causal condition, and 'blank' indicates that the condition can or not exist in the configuration.

In the table, we can see that there are three pathways leading to positive doctor adoption intention of AI-CDSS in tertiary hospitals, as follows.

Doctors at Tertiary Hospitals Configuration

(1) Technology-driven

The core condition for both pathways, S1a and S1b, is performance expectancy, which plays a dominant role in the pathways. Meaning that these doctors believe that AI-CDSS is helpful in clinical work, can improve work efficiency, and enhance work quality. Pathway S1a indicates that under high performance expectancy, even with perceived technical risks for AI-CDSS and without organisational factors, such as convenience of AI use and social influence, the doctors have favourable adoption intentions for AI-CDSS. Pathway S2a indicates that under high performance expectancy, without technology anxiety but with perceived risks and social factors, such as influence from surrounding groups, the doctors still have favourable adoption intentions for AI-CDSS.

(2) Individual-driven

The core condition for pathways S1b and S2b is individual innovativeness, which plays a primary role in these pathways. Meaning that these doctors are willing to try new AI technology, as they typically favour innovativeness that enables continuous learning of new medical technologies and treatment methods. Pathway S1b shows that when doctors reflect strong individual innovativeness, without perceived risks, convenience factors, and social influence, they have positive adoption intentions for AI-CDSS. Pathway S2b indicates that when doctors have individual innovativeness without perceived risks and technology anxiety for AI-CDSS, but with a certain degree of social influence, they still tend to have positive adoption intentions for AI-CDSS.

(3) Technology-Individual dual driven

The core conditions for pathways S3a and S3b are performance expectancy and individual innovativeness, indicating that doctors with both high performance expectancy and high individual innovativeness develop strong adoption intentions. Pathway S3a demonstrates that doctors, with high performance expectancy and high individual innovativeness, need support from certain convenience factors as well as a certain degree of social influence to engender strong adoption intention for AI-CDSS. Pathway S3b shows that with high performance expectancy and high individual innovativeness, and some degree of technology anxiety and social influence, doctors still tend to have high adoption intentions for AI-CDSS.

Doctors at Other Hospitals (Primary and Secondary) Configuration

(1) Technology-Individual dual driven

As with the doctors at the tertiary hospitals, the core conditions for pathways N1 and N2a are performance expectancy and individual innovativeness, indicating that doctors with both high performance expectancy and high individual innovativeness have strong adoption intentions for AI-CDSS. Pathway N1 shows that doctors with high performance expectancy and high individual innovativeness, have strong adoption intentions when influenced by leaders, colleagues, and other people regarding the use of AI. Pathway N2a demonstrates that with high performance expectancy, high individual innovativeness, and no perceived risks or technology anxiety for AI technology, these doctors have strong adoption intentions.

(2) Organisation-Individual dual driven

The core conditions for pathway N2b are convenience factors and individual innovativeness, indicating that doctors who receive support from their workplace and from technology, and have high personal innovativeness, develop strong adoption intentions. In other words, with high convenience factors, personal innovation, and low social influence, even without perceived risks and technology anxiety, doctors have strong adoption intention for AI-CDSS.

Comparative Analysis

Comparing doctors at tertiary hospitals with those at the other (primary/ secondary) medical institutions, we can point out the similarities and differences. The pathways reflect what drives the doctors at these different medical institutions to stronger adoption intentions for AI-CDSS.

(1) Similarities

AI technology and personal factors play dominant roles in influencing the adoption of AI-CDSS by doctors at all the hospitals analysed. Not only are there single-dimensional factors that affect doctors' adoption intentions, but the combination of factors, as in the technology-individual dual model, reflects an impact on adoption. At the technological level, doctors believe that the application of AI-

CDSS in clinical diagnosis and treatment processes can provide efficient diagnostic support and improve the quality of clinical services. Although issues, such as overdiagnosis, may exist with AI-CDSS, the doctors considered the overall technology of AI-CDSS safe and reliable. At the individual level, the doctors demonstrated strong acceptance and openness to AI technology, showing no anxiety regarding the emergence of the new technology. Namely, they appeared willing to try the new AI technologies.

(2) Differences

Compared with doctors at tertiary hospitals, convenience factors had a greater impact on the adoption intention of doctors at other (primary/secondary) medical institutions. According to pathways S1a and S2a, a lack of convenience factors did not affect the strong adoption intentions of the doctors at the tertiary hospitals. Meaning, that even when the marginal condition of the convenience factor is missing, these doctors still have a positive adoption intention for AI-CDSS. In contrast, looking at pathway N2b, convenience factors are a necessary condition for doctors at the other (primary/secondary) medical institutions; namely, these doctors will only favour adoption of AI-CDSS when convenience factors are present. Thus, the convenience factors are the objective material factors influencing these doctors' willingness to adopt AI-CDSS. As tertiary hospitals generally are regional hospitals that have comprehensive hospital facilities and advanced information systems, such convenience factors are a given; thus, not a significant factor influencing the adoption of AI-CDSS among doctors at these facilities. Unlike tertiary hospitals, the other (primary/secondary) medical institutions are often county hospitals or primary healthcare institutions, some located in remote rural areas with fewer hardware and software resources to support their doctors. Therefore, the impact of convenience factors on the adoption intention of doctors at these medical institutions is greater. The survey results imply that only when there is sufficient external support for doctors at these primary and secondary institutions will they actively adopt AI-CDSS.

Robustness Test

To test the robustness of our results, we adjusted the consistency threshold from 0.8 to 0.85 and 0.72 [40]. There were no substantial changes observed in the configuration of the pathways or parameters. The results indicate that the adjusted structure remained consistent with the original structure and the pathways were the same as those before the adjustment. Therefore, the results remained robust.

Discussion

Principal Results

Our study constructs a theoretical framework based on the UTAUT and TOE models using configurational thinking and fsQCA to configure six conditional elements. We explore the multiple concurrent factors and causal complex mechanisms that influence the intention to adoption AI-CDSS among clinical doctors at different medical institutions in China from a technological, organisational, and individual perspective. Our results provide a theoretical basis for the further integration of AI-CDSS into clinical applications. The following are our key results.

(1) The paths driving high AI-CDSS adoption intention among clinical doctors in tertiary hospitals are categorised into six paths, summarised into three configurations: technology-driven, individual-driven, and technology-individual dual-driven. The paths driving high AI-CDSS adoption intention among clinical doctors at other (primary/secondary) medical institutions are categorised into three paths, summarised as technology-individual dual-driven and organisation-individual dual-driven.

(2) Comparing tertiary hospitals with other (primary/secondary) medical institutions, the paths driving doctors to a positive intention to adopt AI-CDSS have some commonalities and some

differences. In terms of commonalities, AI technology and individual factors play a dominant role in all the doctors' adoption intentions. The doctors indicated their beliefs that AI-CDSS can provide efficient diagnostic support and improve the quality of medical services. Doctors are also willing to try new technologies. In terms of differences, convenience factors had a greater impact on doctors at the other (primary/secondary) medical institutions. These doctors would actively adopt AI-CDSS only with sufficient external support.

Limitations

Our study explores the adoption intention of AI-CDSS and its influencing factors among doctors at different medical institutions in China. A key contribution of our study is the introduction of the TOE model based on UTAUT, which categorises variables and discusses factors influencing doctors' intentions from technological, organisational, and individual perspectives. By using fsQCA, we achieve the goal of configurational analysis, exploring different combinations of relationships among paths, and avoiding the limitations of traditional methods that analyse single factors. However, our study has some limitations. We did not ensure sample balance in the questionnaire collection, with a ratio of 3:1 between tertiary hospitals and other (primary/secondary) medical institutions. In the future, larger and more balanced samples should be used. We use fsQCA to explore the driving mechanism of doctors' adoption intention based on the interactive matching of multiple conditions, which cannot verify the impact of individual variables or a few factors on adoption intention. To address the limitations of the fsQCA method, future research could consider combining the use of structural equation modelling (SEM) to reveal a more complex model structure by considering the relationships between latent variables and correlations between multiple observed indicators, thus providing a more comprehensive data analysis and explanation.

Theoretical Contributions

Our study contributes to the literature in several ways. First, we build a comprehensive analytical framework for doctor adoption intention of AI-CDSS. This is based on the UTAUT and TOE models, combined with specific characteristics and application scenarios for AI technology, focusing on technical, organisational, and individual factors. Previous studies have focused mainly on the causal relationships between individual variables and the willingness to adopt AI technology. However, our study introduces multiple factors that can influence doctor adoption intention of AI-CDSS; namely: performance expectancy, perceived risks, convenience factors, social influence, technology anxiety, and individual innovativeness. Building on the UTAUT model, we incorporate additional factors, specifically individual innovativeness, technology anxiety, and perceived risks, into the analytical framework. As such, we are able to enrich the theoretical research regarding factors influencing doctor willingness to adopt AI technology.

Second, we explore the synergistic effects influencing doctors' adoption intentions for AI-CDSS from a configuration perspective, expanding the application of the UTAUT model in explaining causal complexity. Although the UTAUT model is widely used to explain individual adoption of new technologies within organisations, existing studies on AI adoption have largely overlooked the complexity of causal relationships. Owing to limitations in research methods, existing technology adoption models have been unable to test and explain the impact of multiple conditions on doctors' intentions to adopt AI-CDSS. In our study, we empirically investigate the synergistic effects of six specific factors related to technology, organisation, and individual aspects on doctors' intentions to adopt AI-CDSS from a configuration perspective. By addressing the aforementioned issues, we expand the application of the UTAUT model in explaining causal complexity.

Finally, we utilise the fsQCA method to analyse the configurations of doctors' intentions to adopt AI-CDSS at different medical institutions. Our results indicate that across different medical institutions, performance expectancy and individual innovativeness are the two important conditions for doctors to engender strong adoption intentions for AI-CDSS, whereas perceived risks hinder adoption. Social influence can either promote or hinder doctor intention to adopt AI-CDSS, and convenience factors have a greater impact on doctors' adoption intention at other (primary/secondary) medical institutions. In sum, our research extends the literature on doctors' intention to adopt AI-CDSS and provides theoretical support for future practical applications.

Practical Implications

From the perspective of the six configurations among the doctors at the tertiary hospitals and the three configurations among the doctors at the other (primary/secondary) medical institutions, performance expectancy and individual innovativeness are the two indispensable and core conditions in the pathways to achieving strong intention to adopt AI-CDSS powered by AI. Thus, AI product providers and healthcare managers should look closely at these factors when designing and implementing such systems. The organisational factor of convenience for doctors at other (primary/secondary) medical institutions also appeared to be a necessary condition influencing these doctors' adoption intention at these institutions. As such, we recommend the following measures for the AI-CDSS process.

Importance of performance expectancy in adoption

(1) For AI product providers, to improve the quality and applicability of AI products, the focus should be on designing AI-CDSS systems that meet the specific needs of different clinical doctors. This means involving these doctors in the design and development process of AI-CDSS to ensure that these systems address practical needs. In addition, to ensure that AI-CDSS comply with data privacy and security standards, security measures should be included to increase doctors' trust in the systems. The systems should also be evaluated regularly for effectiveness and impact and should be continuously improved based on feedback to ensure they are meeting user needs and expectations.

Importance of personal innovativeness

(2) healthcare institution managers should provide the appropriate training and support for doctors before introducing AI-CDSS. This can be done through various activities, such as videos and practical exercises, among others. Such training can help doctors become comfortable with using AI-CDSS and increase their effectiveness, boosting doctor confidence in the systems and willingness to adopt them. In addition, doctors should be actively encouraged to be innovative, cultivate innovation awareness, and improve their acceptance of new technology.

Importance of addressing technology anxiety

(3) Individual doctors need to actively participate in training to understand the basic functions and usage of AI-CDSS. Some doctors may be sceptical of AI-CDSS, fearing that these systems will replace their work or reduce work quality. Appropriate training can help change this negative mindset, encouraging doctors to recognise that these systems are meant to assist and enhance the efficiency and accuracy of clinical work, and not to replace doctors.

Conclusion

The above measures represent some specific steps that can be taken to improve AI-CDSS adoption and effectiveness. Through these and other steps, healthcare professionals' interest and willingness to use AI-CDSS can be increased, promoting the widespread application of these systems in clinical decision making.

Acknowledgements

We would like to thank the interviewees who participated in the study. This work was supported by

National Natural Science Fund for Young Scholars of China (72104255), Chinese Academy of Medical Sciences (CAMS) Innovation Fund for Medical Sciences (CIFMS; 2021-I2M-1-046).

Data Availability

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Authors' Contribution

ZY, NH and YL played a significant role in study design, recruitment, data coding, and paper writing. QZ was responsible for investigation, data collecting and editing. XH and CJ was responsible for the methodology and writing—review and editing. CZ and BL was responsible for the methodology, and writing—review and editing and supervision.

Conflicts of Interest

None declared.

Abbreviations

Artificial Intelligence (AI)
Clinical Decision Support Systems (CDSS)
Proportional reduction in inconsistency (PRI)
Symmetric consistency (SYM)
Technology-organization-environment (TOE)
Unified theory of acceptance and use of technology (UTAUT)

Reference

1. Sutton RT, Pincock D, Baumgart DC, Sadowski DC, Fedorak RN, Kroeker KI. An overview of clinical decision support systems: benefits risks and strategies for success. NPJ Digit. Med. 2020; 3: 17. doi: 10.1038/s41746-020-0221-y.
2. Osheroff JA, Teich J, Levick D, Saldana L, Velasco F, Sittig D, et al. Improving Outcomes with Clinical Decision Support: An Implementer's Guide. Second Edition; 2012; HIMSS Publishing. doi: 10.4324/9780367806125.
3. Shankar P, Anderson N. Advances in sharing multi-sourced health data on decision support science 2016–2017 IMIA Schattauer GmbH Adv. 2018;27;1: 16–24 doi:10.1055/s- 0038-1641215.
4. Lu Y, Melnick ER, Krumholz HM. Clinical decision support in cardiovascular medicine. BMJ. 2022 May 25;377:e059818. doi: 10.1136/bmj-2020-059818. PMID: 35613721.
5. Sutton RT, Pincock D, Baumgart DC, Sadowski DC, Fedorak RN, Kroeker KI. An overview of clinical decision support systems: benefits risks and strategies for success. NPJ Digit Med. 2020;3:17. doi: 10.1038/s41746-020-0221-y.
6. Ash JS, Sittig DF, Guappone AP, Dykstra RH, Richardson J, Wright A, Carpenter J, et al.Recommended practices for computerized clinical decision support and knowledge management in community settings: a qualitative study. BMC Med Inform Decis Mak 2012;12:6.
7. Hanson LC, Zimmerman S, Song MK, Lin FC, Rosemond C, Carey TS, et al. Effect of the goals of care intervention for advanced dementia: A randomized clinical trial. JAMA Intern Med. 2017;1771:24–31. doi:10.1001/jamainternmed. 2016.7031.

8. Alsharqi M, Upton R, Mumith A, Leeson P. Artificial intelligence: a new clinical support tool for stress echocardiography. Exp Rev Med Devices. 2018;15(8): 513-515 doi: 10.1080/17434440. 1497482.
9. Islam R, Sultana A, Tuhin MN, Saikat MS, Islam MR. Clinical Decision Support System for diabetic patients by predicting type 2 diabetes using machine learning algorithms. J Healthcare Eng. 2023 May 30:6992441. doi: 10.1155/2023/6992441.
10. Nair BG, Peterson GN, Newman SF, Wu WY, Kolios-Morris V, Schwid HA. Improving documentation of a β-blocker quality measure through an anesthesia information management system and real-time notification of documentation errors. Comm J Qual Patient Safety. 2012;386:283-288. doi:10.1016/s1553-725012;38036-7.
11. Nair BG, Peterson GN, Neradllek MB, Newman SF, Huang EY, Schwid HA. Reducing wastage of inhalation anesthetics using realtime decision support to notify of excessive fresh gas. Anesthesiology. 2013;1184:874-884. doi:10.1097/ALN.0b013e3182829de0.
12. Freundlich RE, Barnet C, Mathis MR, Shanks AM, Tremper KK, Kheterpal S. A randomized trial of automated electronic alerts demonstrating improved reimbursable anesthesia time documentation. J Clinic Anesth. 2013;252:110-114. doi:10.1016/i.jiclinane.2012.06.020.
13. Wagner G, Raymond L, Paré G. Understanding prospective physicians' intention to use artificial intelligence in their future medical practice: A configurational analysis. JMIR Med Ed. 2023; 9(10):2196/45631.
14. O'Leary P, Carroll N, Richardson I. The practitioner's perspective on clinical pathway support systems. Proceedings of the IEEE International Conference on Healthcare Informatics. 2014: 194–201.
15. Park CJ, Yi PH, Siegel EL. Medical student perspectives on the impact of artificial intelligence on the practice of medicine. Curr Probl Diagn Radiol. 2021;505:614–9. doi: 10.1067/j.cpradiol.2020.06.011.S0363-018820;30124-9.
16. Scheetz J, Rothschild P, McGuinness M, Hadoux X, Soyer HP, Janda M, et al. A survey of clinicians on the use of artificial intelligence in ophthalmology dermatology radiology and radiation oncology. Sci Rep. 2021 Mar 04;111:5193. doi: 10.1038/s41598-021-84698-5.10.1038/s41598-021-84698-5.
17. Oh S, Kim JH, Choi SW, Lee HJ, Hong J, Kwon SH. Physician confidence in artificial intelligence: an online mobile survey. J Med Internet Res. 2019 Mar 25;213:e12422. doi: 10.2196/12422. https://www.jmir.org/2019/3/e12422/ v21i3e12422
18. Sit C, Srinivasan R, Amlani A, Muthuswamy K, Azam A, Monzon L, et al. Attitudes and perceptions of UK medical students towards artificial intelligence and radiology: a multicentre survey. Insights Imag. 2020 Feb 05;111:14. doi: 10.1186/s13244-019-0830-7.
19. Poon AIF, Sung JJY. Opening the black box of AI-Medicine. J Gastroenterol Hepatol. 2021 Mar;363:581-584. doi: 10.1111/jgh.15384.
20. Sambasivan M, Esmaeilzadeh P, Kumar N, Nezakati H. Intention to adopt clinical decision support systems in a developing country: effect of physician's perceived professional autonomy involvement and belief: a cross-sectional study. BMC Med Inform Decis Mak. 2012; 12: 142. doi: 10.1186/1472-6947-12-142.
21. Laka M, Milazzo A, Merlin T. Factors that impact the adoption of clinical decision support systems CDSS for antibiotic management. Int J Environ Res Public Health. 2021:18. DOI:10.3390/ijerph18041901.
22. Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: Toward a unified view. J Manag Info Syst Q. 2003; 273: 425-478. DOI:10.2307/30036540.
23. Bendary N, Al-sahouly I. Exploring the extension of unified theory of acceptance and use of technology UTAUT2 factors effect on perceived usefulness and ease of use on mobile commerce in Egypt. JBRMR. 2018. doi: 10.24052/JBRMR/V12IS02/ETEOUTOAAUOTUFEOPUAEOUOMCIE.

24. Tornatzky LG, Klein KJ. Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings. IEEE Trans Engineer Manag.1982;EM-291:28-45. DOI: 10.1109/TEM.1982.6447463.
25. Menon D, Shilpa K. "Chatting with ChatGPT": Analyzing the factors influencing users' intention to use the open AI's ChatGPT using the UTAUT model. Heliyon. 2023 Oct 18;911:e20962. doi: 10.1016/j.heliyon.2023.e20962.
26. Venkatesh V, Thong JY, Xu X. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. MIS Q. 2012:157–178. doi: 10.2307/41410412.
27. Lambert SI, Madi M, Sopka S, Lenes A, Stange H, Buszello CP, et al. An integrative review on the acceptance of artificial intelligence among healthcare professionals in hospitals. NPJ Digit Med. 2023 Jun 10;61:111. doi: 10.1038/s41746-023-00852-5. Erratum in: NPJ Digit Med. 2023 Jul 11;61:125.
28. Kaplan A, Haenlein M. Siri Siri in my hand: Who's the fairest in the land? On the interpretations illustrations and implications of artificial intelligence J. Business Horizons 2019; 621: 15-25. doi:10.1016/J.BUSHOR.2018.08.004.
29. Xu P, Xu XY. Logical and analytical framework of enterprise management reform in the era of artificial intelligence. J Manag World. 2020. 361: 122-129+238.
30. Qiu Y, He Q. Research on the progress the impact of artificial intelligence on employment and the theoretical analysis framework in Chinese context. J Human Res Dev China. 2020; 3702:90-103.
31. Pillai R, Sivathanu B. Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organizations. Benchmarking: An Int J. 2020; 279: 2599-2629. doi:10.1108/bij-04-2020-0186.
32. Chatterjee S, Bhattacharjee KK. Adoption of artificial intelligence in higher education: A quantitative analysis using structural equation modelling. J Ed InfoTechnol. 2020; 255: 3443-3463. doi: 10.1007/s10639-020-10159-7.
33. Sohn K, Kwon O. Technology acceptance theories and factors influencing artificial intelligence-based intelligent products. Telematics and Informatics. 2020; 47: 101324. doi:10.1016/j.tele.2019.101324.
34. Chen LSL, Wu KIF. Antecedents of intention to use CUSS system: Moderating effects of self-efficacy. Service Bus. 2014; 84: 615-634. doi: 10.1007/s11628-013-0210-1.
35. Jian C, Rui L, Mi G, Zhiyan F, Fatao Y. Public acceptance of driverless buses in China: An empirical analysis based on an extended UTAUT model. Discrete Dynamics in Nature Soc. 2020: 1-13. doi:10.1155/2020/4318182.
36. Huang LM, Song CP, Li J. Mechanism of artificial intelligence anxiety of tourism employees on knowledge sharing—based on the technology acceptance model. Res Dev Market. 2020; 3611: 1192-1196+1258.
37. Vis B, Dul J. Analyzing relationships of necessity not just in kind but also in degree: Complementing fsQCA with NCA. Sociol Methods Res. 2018 Nov;474:872-899. doi: 10.1177/0049124115626179. Epub 2016 Feb 3. PMID: 30443090; PMCID: PMC6195096.
38. Du C. An empirical analysis of hierarchical hospital management system in China. Soc Sci Front. 2018;04:84-94.
39. Teufel A, Binder H. Clinical Decision Support Systems. Visc Med. 2021 Dec;376:491-498. doi: 10.1159/000519420.
40. White L, Lockett A, Currie G, Hayton J. Hybrid context management practices and organizational performance: a configurational approach. J Manag Stud. 2021; 58:718–48. doi: 10.1111/joms.12609.

Supplementary Files

Figures

Analysis framework of factors influencing Chinese doctors' AI-CDSS adoption intention.

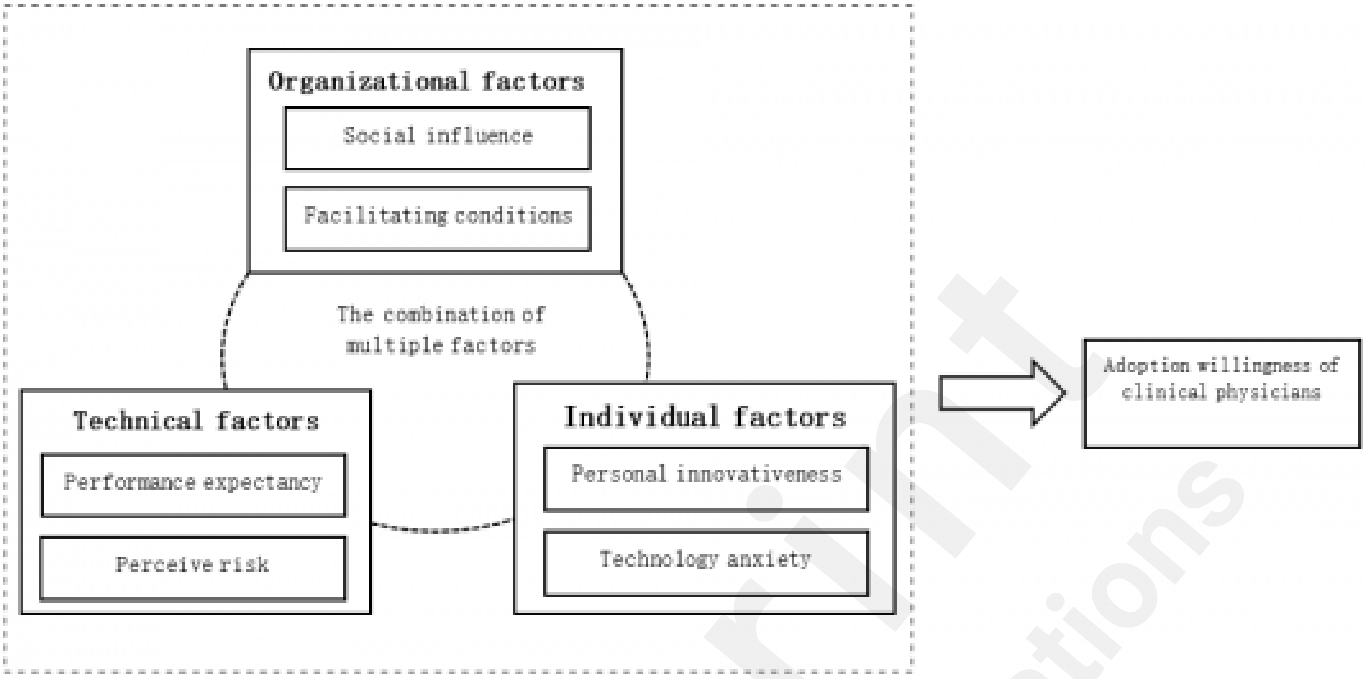

Figure 1. Analysis framework of factors influencing Chinese doctors' AI-CDSS adoption intention.