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Healthcare professionals satisfaction and AI-based clinical decision support system in public sector hospitals during health crises: a cross-sectional study

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Abstract
The entire world's focus has shifted to a digital health management system after the COVID-19 pandemic and crisis management through information systems that provide potential health support and minimize the effects of similar healthcare emergencies. Artificial intelligence (AI) can create alternative techniques such as Clinical Decision Support System (CDSS), which can aid complex scenarios such as large volumes of data, information accuracy, patient turnover, and health management regimes. CDSS uses an AI-based health information system that is helpful, fast, effective, and offers advanced techniques in emergencies and pandemics such as COVID-19. Therefore, it is essential to analyze mechanisms that can influence the degree of health care professionals (HCP) satisfaction and intention to adopt CDSS. Based on DeLone and McLean's information system success model (D&M and ISSM), the researchers recruited 237 on-duty HCP from three major hospitals in Wuhan, China, in 2021. Data is collected through an online survey questionnaire with the consent of the hospital administration. The empirical findings show the strong influence of IS qualities (system, information, and service quality) and user satisfaction. These findings support the foundation for CDSS adoption in developing countries.

Keywords Clinical decision support system · Healthcare professionals · DeLone and McLean model · Information system service qualities · User satisfaction

1 Introduction

The flood of patients into hospitals put a strain on healthcare professionals; due to the sudden and rapid outbreak of COVID-19 in China, Wuhan Hongshan Stadium was transformed into an intelligent hospital to accommodate more patients [1, 2]. These global health crises and similar healthcare emergencies which may arise in the future have triggered a search for the healthcare industry and technologies to identify and control pandemics like COVID-19 [3]. Due to limited healthcare facilities, it was hard to locate and track the record of Covid patients [4]. The dramatic rise in the number of COVID-19 patients created grave concern about the satisfaction of HCP in the health sector [5]. Therefore, a centralized decision-based system becomes mandatory to support the safety of HCP and patients. The Clinical Decision Support System (CDSS) implementation is at an early stage, and the developing countries' adoption rate has been prolonged [6]. This study aims to identify the factors that influence CDSS adoption in the public sector hospitals.

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World Wide Web (WWW) is the application that allows access to the Internet of Things (IoT). Having 16 billion devices, the IoT is expected to be the biggest category of connected devices [7]. By using IoT advancements, HCP can observe patients in real-time and more efficiently manage their own health conditions through sensor-based health information systems (HIS) [8]. In an IoT device, the DSS communicates through intranets and the internet, analyzes data to generate reports, and operates through internal networks. AI-based intelligent decision support systems (IDSS) execute specific cognitive decision-making processes, according to Burstein and Holsapple [9]. The IDSS can make pre-programmed decisions in predefined situations, like supply chain management, medical diagnostics, manufacturing operations scheduling, agriculture production planning, fraud detection, transaction delay mitigation, and web advisory systems [10]. This study is not concerned with such IDSS since it uses a sample of hospitals to leverage data, reports, and options provided by the compound DSS for daily decisions.

CDSS supports healthcare professionals (HCP) in routine tasks to enhance the quality and safety of healthcare. They are also essential to overlook inefficiencies such as expenditure on, treatment decisions, specialist referrals and diagnostic tests [11]. Previous studies have utilized a Task-Technology Fit (TTF) framework to determine the significance of a clinical decision support system (CDSS) by getting qualitative data [12]. Patni, Sharma [4] studied a machine learning (ML) based model to diagnose the CT images of the chest and cross-examination under the CDSS during the pandemic. These studies utilized a qualitative-based model; therefore, we filled a research gap by conducting our study through surveys (237 participants) and analyzing the level of HCP satisfaction and intention toward adopting CDSS.

Healthcare organizations have implemented specific information systems over the years to integrate technology to reduce medical errors, reduce costs, assist decision making, and facilitate medical solutions [13]. These technologies help HCP to work across the organization and around the globe. One of these inventions is the CDSS, which uses information systems to offer superior health services for patients and solve troublesome problems [14]. Clinical decision-making requires an increasing amount of medical information in emerging nations. Nevertheless, the structure and access to medical information remained poor, frequently leading to incorrect decisions and medical errors [15]. By using CDSS integrated systems to improve work speed and efficiency, HCP will be able to provide better care through high-quality IS [16, 17]. An effective CDSS system assures that system resources can be accessed only by authorized users, often used to ensure data security, biometric technological access, certifications, and smart cards [17].

Research on the factors influencing the adoption of CDSS is critical for practical purposes from the behavioral perspective of HCP. The results obtained through CDSS will provide decision-making support. There are specific problems and challenges relating to internal and external factors concerning the adoption of CDSS [18]. HIS initiatives have failed due to a lack of concern for healthcare workers and end-users while developing health systems [19]. Furthermore, Kabukye, Koch [20] discovered that, while CDSS can improve health care, adoption remains low because their systems do not meet the needs of HCP. This system's primary purpose is to improve patient care quality [21]. However, there is limited research on CDSS healthcare in developing countries, especially after COVID-19, to provide understanding about factors affecting the level of HCP satisfaction.

Our study makes several contributions. First, this study helps assess the influencing factors on the adoption of CDSS by HCP, and in doing so, it responds to a call for research by Aljarboa and Miah [12] to analyze factors that affect the HCP satisfaction and adoption of CDSS system. Second, it adds value to the literature by providing empirical evidence to establish an extension of the Delone & Mclean model, forming a foundation for CDSS adoption in the public sector hospitals. Finally, our research is based on the above-cited call for research which was based on a qualitative survey in two big cities in Saudi Arabia that interviewed only 54 General Practitioners (GPs); our study adds empirical evidence through data collected from 237 healthcare professionals in three public hospitals in Wuhan, China and found out their satisfaction level and CDSS adoption.

2 Literature review and hypothesis development

2.1 Clinical decision support system (CDSS)

CDSS is an electronic system to collect, store, and retrieve patient information, including the history of patients, laboratory test results, billing processes, and other related hospital procedures that can be used in various hospital departments [22]. CDSS is an electronic paperless system that covers all hospital administrative, financial, and clinical procedures [18]; therefore, it is necessary to develop and implement CDSS [23].

DSS are Information Systems (IS) domains that assist and improve organizations' decision-making processes. Numerous structured, semi-structured, and unstructured issues have specific standard criteria [24]. Thus, DSS is an interactive computer-based system designed to assist decision-makers in defining, solving, and determining problems using data and models. It is helpful in various industries, including inventory management, farming, sales optimization, healthcare, and education. CDSS enhances the performance and speed of decision-making activities, promotes learning, and is time-saving. In addition to providing focused clinical information, the CDSS system is expected to provide persistent data and relevant information that will improve human services [25]. Typically, CDSS is a collection of software created to assist healthcare professionals and patients [24].

Moreover, Artificial intelligence can be used to develop alternative techniques known as intelligent decision support systems (IDSS) [4, 26]. When combined with DSS, AI methods such as Intelligent Agents, ML (Machine Learning), Fuzzy Logic, and ANN (Artificial Neural Networks) can help solve complex, real-time problems involving massive amounts of data such as patient health reports. In contrast, CDSS managers and users will analyze such systems accurately [27]. The amount and quality of information available to HCP have an impact patient care outcomes and consistency. Therefore, hospitals have introduced CDSS to provide accurate, timely information to meet organizational needs and improve effectiveness and efficiency at an affordable cost [28, 29].

2.2 CDSS significance and intention to use (IU)

CDS systems incorporate Decision Support Systems (DSS) increasingly in the healthcare sector in developing nations. Underdeveloped countries lacked up-to-date infrastructure and well-trained technical staff to use and manage the information system. The successful implementation of CDSS in such countries depends on factors such as Government support, private investment, and technological infrastructure [30]. In developing countries, several researchers have focused on issues, including political support from the government, active management, and HCP satisfaction [31]. Moreover, researchers also studied complicated software systems and other relevant factors which influence the adoption of CDSS, such as software's functionality, adequate supply of electricity and internet access, lack of funding, lack of government support for IT use in hospitals and lack of CDSS maintenance [32]. Iskandar, Subramaniam [33] applied ISSM to evaluate the success of implementing the ward cleaning logistics system at Taiwan medical center and identify predictive factors among HCP affecting the intention to use (IU) in the PIS (Poison Information System). Another study analyzed the quality of system influence on HCP satisfaction [34]. Therefore, it is crucial to explore CDSS significance and HCP intention to use CDSS after the Covid-19 pandemic.

2.3 Delone and McLean's ISSM

Many existing frameworks for the evaluation of information systems (IS) exist; among the most common and valid systems for evaluating IS is DeLone and McLean's ISSM (information system success model) (D&M and ISSM) [35]. ISSM was established by D&M in 1992 and later developed in 2003 [36]. The seven dimensions of ISSM include system quality, service quality, information quality, user satisfaction, system utilization, usefulness, and net benefits [37]. In this study, we addressed the four main aspects such as IS quality: (1) System quality, (2) Information quality, (3) Quality of service, and (4) user satisfaction [38, 39]. ISSM focuses on evaluating the technological features of IS based on user views and describes the technological impact on system use and user satisfaction [40]. Isfahan and Mashhad, Iran's teaching hospitals, have been analyzed based on ISSM, and the user's satisfaction with HIS adoption is explored, which indicates the extent to which the user is satisfied with the success of the adoption of the HIS [28, 41].

2.4 Information system service quality (ISQ)

The system quality in literature has been primarily defined using three fundamental characteristics. Measuring success in an information system is difficult because success is not commonly defined explicitly and depends on expectations [42]. In the hospital quality system, we addressed the three main aspects of the quality system: (1) System quality, (2) Information quality, and (3) Quality of service.

2.4.1 Information quality

Information quality is defined as a system in which users believe that the information is accurate, up to date, reliable, complete, understandable, interpretable, and systematic [43, 44]. The quality of information refers to the content and structure of the outputs of the system to ensure that the data is accessible, adequately accurate, meaningful, easy to understand and read, and valuable for completing tasks and decision making [44, 45]. HCP expect CDSS to make quality information available, enabling them to do better work in the treatment, diagnosis, and care delivery [46]. HCP expectations of information output quality are significant in CDSS intention and system evaluation [47].

Improving and sustaining information quality is the fundamental approach of the ISSM. However, limited information, incomplete information, and language that is not understandable could reduce the degree of HCP satisfaction and implementation of the IS [48]. HCP may be able to reduce work time and improve work speed by using integrated systems [16]. HCP care will be indirectly improved by a high-quality IS [17]. Evaluating CDSS adoption based on the HCP satisfaction criterion is of utmost importance to HCP and if the information is incomplete and difficult to analyze may account for the dissatisfaction of HCP [28]. Therefore, based on the above arguments, we hypothesized the following:

Hypothesis 1 Information quality has a significant impact on HCP satisfaction.

2.4.2 System quality

The system's quality can be measured through its simplicity in learning and user-friendliness [49]. System quality is the user's system experience from a technological and operational perspective. Such characteristics have been deemed necessary in several contexts for healthcare IT and IS success [50, 51]. Slow response time and problems in CDSS usage can lead to severe dissatisfaction, eventually leading to a CDS system shutdown [52].

Systems based on different types of networks and programming languages seem to threaten the advancement of CDDS projects by producing multiple heterogeneous systems in an organization. Therefore, open-source tools, web-based implementation, and approved specifications will help build future applications as part of the system design requirements [53]. The CDSS framework should provide security measures to track user access and confidentiality as security challenges hinder the application and implementation of the healthcare IS [17]. The system quality ISSM approach has demonstrated an impact on consumer satisfaction in e-commerce, particularly in the COVID-19 pandemic. The e-commerce company will improve the system's quality as customer standards demand to increase user satisfaction in the future [48]. The CDSS adoption assessment based on the HCP satisfaction criteria enhances the system quality and improves medical care [28]. Based on the previous literature, our second hypothesis is given below:

Hypothesis 2 System quality has a significant impact on HCP satisfaction.

2.4.3 Service quality

Quality of service is defined as a degree to measures system characteristics such as tangibility, reliability, functionality, interactivity, and understanding [38, 54]. Quality of service is considered to meet or exceed the customer's expectations regarding the service [55]. Moreover, the systematic review identified user support as extremely important for the success of clinical IS projects[56, 57]. A study found that training and user support is one of the main contributors to the success of an IS by HCP in the early and later stages of execution [58]. The lack of satisfaction and use of the EMR by HCP is mainly and strongly due to the poor quality of service. The focus should be on improving service quality in future projects, including HCP support, power infrastructure, training, and technical support [35]. A service quality ISSM-based approach has generally affected user satisfaction in e-commerce, particularly in the COVID-19 pandemic. If the quality of the service is low, customer satisfaction will effect and disturb daily base operations [48]. Therefore, we hypothesized the following:

Hypothesis 3 Service quality has a significant positive impact on HCP satisfaction.

2.5 User satisfaction and intention to use

The acceptance or rejection by users of a system determines the success or failure of the system [59]. The successful implementation is based on the user's satisfaction [60]. Low level of user satisfaction may reflect anger, dissatisfaction, and stress caused by system inefficiencies [61] Although high satisfaction levels can not only encourage better IS use, but also affect the quality of the working life of the users [27].

Unfortunately, HCP are worried about the purposes of IS and its consequences for their job [62]. System adoption and acceptance of HCP are now considered among the most significant obstacles to the spread of CDSS in the healthcare sector [63]. Vassilios mentioned the satisfaction of the HCP as one of the fundamental approaches for evaluating HIS success. Finally, the author concludes that the HCP satisfaction with the IS could be the most successful evaluation method [27]. These findings specify that the HCP satisfaction with CDSS adoption measurements is paramount among various success factors [27, 64]. Possibly this element is the most common method used to measure success [27, 65].

The various implemented projects that failed were often those in which end users were frustrated, or the core system functions were not adequately utilized [66]. Although most HCP generally believe that technology can help reduce the paper documentation burden and patient database availability in critical situations, they are also quickly disappointed and unhappy when an introduced system or service fails to meet their standards [67]. Consequently, many studies have proposed that user satisfaction is the principal determinant of the user adoption of CDSS [38, 68]. Thus, we proposed the following hypothesis:

Hypothesis 4 User Satisfaction has a significant impact on CDSS adoption intentions.

3 Research methodology

3.1 Participants and procedure

This cross-sectional study was carried out during the COVID-19 pandemic, and data were collected between 27 March 2021 and 24 May 2021. The research population consists of managers, faculty, physicians, and health care professionals HCP (including nurses, chemists, laboratory technicians, administrative support staff, and finance department) who have a comprehensive knowledge of IT and have used the CDSS/HIS/IS. The study was carried out at three public hospitals in Wuhan, Mainland China, and data was collected by filling out a standardized questionnaire about the CDSS adoption intention factors during the COVID-19 pandemic emergency. In hospitals, unrelated individuals are restricted in their mobility, so a web-based questionnaire was used. The questionnaire explained briefly that the objective of the study is to examine AI base CDSS adoption success factors. There are two major sections in the questionnaire: the first section with demographic characteristics of the respondent, including gender, age, experience, education, and position in the hospital. The second part examines CDSS usage intention and its determinants (i.e., IS qualities like information, system, service quality, HCP satisfaction). From a convenience sample of the HCP, we obtained 254 responses out of 270 distributed questionnaires. However, 237 usable responses remained for analysis after the elimination of responses with large quantities of missing data and those from the HCP that are not actual system users. Finally, an analysis with an 87% response rate was found useful. The descriptive statistics of the sample profile are given below.

3.2 Measures

A five-point Likert scale was used to capture perceptions of the success of the system attributes, reflecting system, information, and service quality. A survey designed by Alzahrani, Mahmud [69] was carried out using the D&M IS model for the successful information system (ISSM). An ISSM-based self-administered structured questionnaire was developed to collect data. The questionnaire included five dimensions: information quality, system quality, service quality, HCP satisfaction, and intention to use CDSS. The construct items are given by Appendix A.

The measurement items for the quality of information were adapted from Shaltoni, Khraim [70]. INFQ1, INFQ2, INFQ3, and INFQ4 reflect the relevance, usefulness, accuracy, and comprehensiveness of the information provided by the CDSS. System Quality (four items) was adapted from Pituch and Lee [71] and, more recently, used by Rana, Dwivedi [72] and Shaltoni, Khraim [70]. Service Quality (five items) was adapted from Ismail, Razak [73, 74]. HCP satisfaction has been measured by three adjusted items [73], which SAT1, SAT2, and SAT3 have been designed to fulfill the HCP experience, information worth, and system interactions. The CDSS intention was measured with four items adapted from [75–77] and [78], respectively. The questionnaire also contained various questions concerning the pandemic, based on HCP attitudes and knowledge of the CDS system, COVID-19 information, its spread, prevention, control measures, and how it may affect the CDSS, particularly in the current emergency outbreak. The HCP were asked to choose from specific options or write their own opinions. Table 1 presents the demographics of the participants, Table 2 displays the cross loadings, and Table 3 illustrates the confirmatory analysis conducted in this study.

4 Results

4.1 Data analysis

The research was performed on SmartPLS 3.2.8 [79] and IBM SPSS Statistics 22. However, SmartPLS was primarily used for data analysis because PLS-SEM has higher

Table 1 Demographics and descriptive statistics

	Freq	Percentage (%)
Gender		
Male	149	62.87
Female	88	37.13
Age (years)		
20–29	103	43.46
30–39	68	28.69
40–49	39	16.46
50 and above	27	11.39
Experience (years)		
01–03	38	16.03
04–06	117	49.37
07–09	49	20.68
10 or more	33	13.92
Education		
Bachelor's degree	169	71.31
Master's degree	42	17.72
Higher degree	26	10.97
Designation		
Hospital managers	22	9.28
Physicians	87	36.71
Nurses	65	27.43
Lab and pharmacists	29	12.24
CDSS staff	34	14.35

Table 2 Cross loadings

	INFQ	SERQ	SYSQ	SAT	IU
INFQ1	**0.695**	0.486	0.452	0.449	0.368
INFQ3	**0.780**	0.479	0.440	0.465	0.439
INFQ2	**0.830**	0.451	0.403	0.329	0.333
INFQ4	**0.861**	0.417	0.496	0.396	0.314
SERQ1	0.413	**0.697**	0.273	0.442	0.434
SERQ2	0.243	**0.794**	0.085	0.277	0.447
SERQ3	0.454	**0.776**	0.491	0.454	0.447
SERQ4	0.292	**0.643**	0.306	0.275	0.490
SERQ5	0.467	**0.613**	0.154	0.376	0.482
SYSQ1	0.445	0.365	**0.879**	0.499	0.308
SYSQ2	0.462	0.212	**0.792**	0.323	0.067
SYSQ3	0.428	0.288	**0.550**	0.300	0.483
SYSQ4	0.415	0.339	**0.781**	0.340	0.171
SAT1	0.477	0.442	0.477	**0.906**	0.490
SAT2	0.473	0.443	0.401	**0.926**	0.437
SAT3	0.458	0.466	0.382	**0.818**	0.434
SAT4	0.456	0.403	0.462	**0.844**	0.483
IU1	0.280	0.247	0.389	0.245	**0.623**
IU2	0.349	0.375	0.322	0.440	**0.664**
IU3	0.292	0.445	0.016	0.314	**0.703**
IU4	0.430	0.413	0.232	0.293	**0.838**

Important values are given in bold

predictive power than SEM-dependent factors [80]. Researchers in information systems, social sciences, and business management often use this technique for their research [81]. The partial least squares (PLS) method was used to analyze the research model with SmartPLS 3.2.8 [82]. The measuring model is tested for its validity and reliability following the two-stage analytical process [69, 83]. The hypothesis is subsequently evaluated, and the structural model estimates the path coefficient [84]. To assess the significance of the path coefficients and the loadings, a bootstrapping mechanism with 5,000 re-samples was used. The PLS-SEM goal focuses on endogenous variables and aims to optimize the variance described [69, 84].

4.2 Measurement model

Reflective indicators were used to test the measurement model's reliability and validity. A composite reliability (CR) measure has been proposed as a better measure of reliability than Cronbach's alpha, since PLS does not require all indicators to be equally reliable [85], which in other software is a limitation. As shown in Table 4, most items have an outer load above 0.70 to assess the reliability of latent variables. However, some items with lower outer loads are retained because they contribute to content validity [86].

Considering that the minimum limit of 0.40 is an appropriate value for loading items [87], none of the items had to be excluded since all loadings were above 0.4. In addition,

Table 3 Confirmatory factor analysis

Items	Item loadings (O)	Mean (M)	Standard deviation (SD)	T statistics (|O/SD|)	*P* values
INFQ1	0.695	0.701	0.079	8.842	< 0.001
INFQ3	0.780	0.775	0.036	21.598	< 0.001
INFQ2	0.830	0.831	0.026	31.357	< 0.001
INFQ4	0.861	0.857	0.036	24.100	< 0.001
SERQ1	0.697	0.696	0.055	12.629	< 0.001
SERQ2	0.794	0.791	0.035	22.578	< 0.001
SERQ3	0.776	0.772	0.032	24.285	< 0.001
SERQ4	0.643	0.644	0.062	10.355	< 0.001
SERQ5	0.613	0.611	0.056	10.868	< 0.001
SYSQ1	0.879	0.878	0.019	46.539	< 0.001
SYSQ2	0.781	0.778	0.066	11.786	< 0.001
SYSQ3	0.792	0.787	0.062	12.703	< 0.001
SYSQ4	0.550	0.550	0.087	6.295	< 0.001
SAT1	0.906	0.904	0.018	51.290	< 0.001
SAT2	0.926	0.922	0.019	47.980	< 0.001
SAT3	0.818	0.808	0.059	13.960	< 0.001
SAT4	0.844	0.838	0.033	25.614	< 0.001
IU1	0.623	0.620	0.063	9.826	< 0.001
IU2	0.664	0.672	0.065	10.262	< 0.001
IU3	0.703	0.698	0.064	11.041	< 0.001
IU4	0.838	0.831	0.045	18.669	< 0.001

Table 4 Internal consistency reliability and convergent validity

	Cronbach's alpha	rho_A	Composite reliability	Average variance extracted (AVE)
INFQ	0.808	0.855	0.872	0.631
IU	0.701	0.760	0.802	0.507
SAT	0.897	0.898	0.929	0.765
SERQ	0.757	0.783	0.833	0.502
SYSQ	0.753	0.852	0.842	0.578

Table 5 Discriminant validity—Fornel–Larcker criterion

	INFQ	IU	SAT	SERQ	SYSQ
INFQ	***0.794***				
IU	0.468	***0.712***			
SAT	0.648	0.528	***0.875***		
SERQ	0.663	0.636	0.616	***0.708***	
SYSQ	0.615	0.337	0.551	0.403	***0.76***

*Square root of AVE values is given on the diagonal in bold and italic

high composite reliability scores above 0.8 were seen in all the constructs. The values ranged confirming adequate reliability [85]. The Cronbach's alpha and rho_A values and Table 5 discriminant validity were also relatively high and well above the benchmarks set in the literature.

To assess the validity of the construct, both convergent and discriminant validity [88] suggestions have been made, and 0.5 or above has been identified as an appropriate value of the Average Variance Extracted (AVE) [89]. As a result, AVE values for all constructs were larger than 0.5 and ranged from 0.502 to 0.765, confirming convergent validity and evaluating discriminant validity [88].

4.3 Structural model

The authors assessed the structural model in three stages (Solano Acosta, 2018); as a first step, each latent variable was given an R^2 value. Second, the redundancy check for Q^2 was determined using the Blindfolding feature, which assesses the consistency of predictive significance. A sample of 5000 bootstraps was used to make the same number of observations as the original sample for standard errors and t-values [90]. F^2 values of effect size were used to check the interaction impact. Chin [91] proposed 0.67 for significant, 0.33 for moderate strong, and 0.19 for weak R-square benchmarking values. The Figure 1 displays R-square variance inside the constructs, path coefficient values, and t-values in parentheses. The three independent variables (INFQ $\beta = 0.273$, SYSQ $\beta = 0.248$, SERVQ $\beta = 0.334$) explained a 52% variance in satisfaction ($\beta = 0.528$) in turn explained 27.9% variance in intention to use.

In Table 6, INFQ had a significant positive impact on SAT ($t = 4.779$, $p = < 0.001$). SYSQ had a significant positive relationship with SAT ($t = 3.705$, $p < 0.001$). SERQ also had a significant positive effect on SAT ($t = 7.243$, $p < 0.001$). Moreover, SAT ($t = 8.238$, $p < 0.001$) had a significant positive effect on the intention to use.

4.4 Model strength and quality

F^2 values of 0.02, 0.15, and 0.35 suggest that the interaction term on the criterion variable is low, medium, or high. A

Fig. 1 Results of the structural model

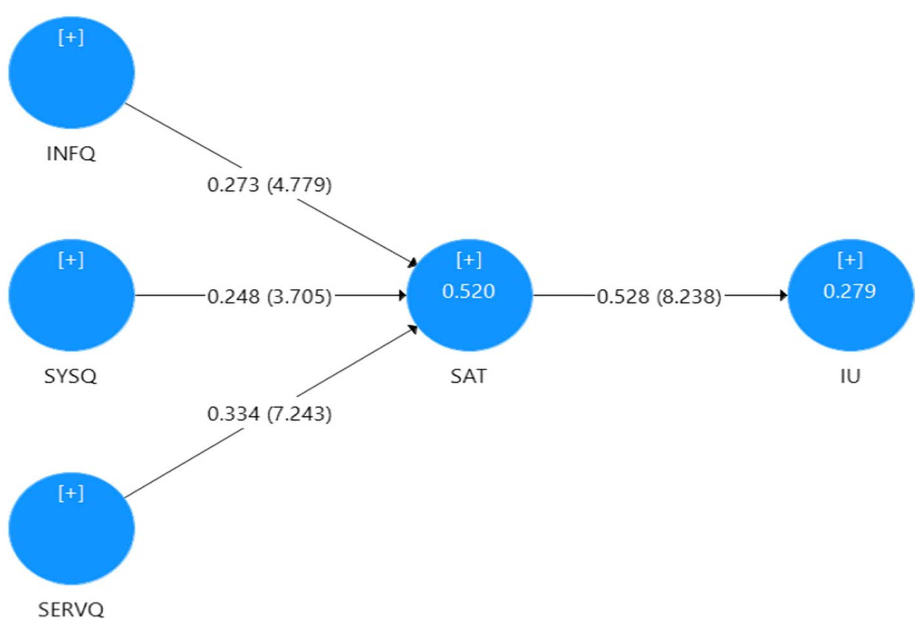

Table 6 Results of structural model

Path	Original sample (β)	Sample mean (M)	Standard deviation (SD)	T statistics (|(β)/SD|)	*P* values	Hypothesis remarks
INFQ → SAT	0.273	0.274	0.057	4.779	< 0.001	Supported
SERQ → SAT	0.334	0.340	0.046	7.243	< 0.001	Supported
SYSQ → SAT	0.248	0.253	0.067	3.705	< 0.001	Supported
SAT → IU	0.528	0.531	0.064	8.238	< 0.001	Supported

Table 7 Model quality and strength

	F square		Q square		
	IU	SAT	SSO	SSE	Q^2 (= 1 − SSE/SSO)
INFQ		0.065	948	948	
SERQ		0.130	1185	1185	
SYSQ		0.080	948	948	
SAT	0.387		948	596.723	0.371
IU			948	830.757	0.124

Q^2 value greater than zero means that the model has ethical predictive relevance [92].

The values for F^2 were calculated from the results of the measuring model, while the Q^2 values were calculated via the Blindfolding function under the SmartPLS software tab. In Table 7 the relationship paths from INFQ to SAT ($F^2 = 0.065$), SYSQ to SAT ($F^2 = 0.080$) and SERQ to SAT ($F^2 = 0.130$) are obvious from the statistics, since F^2 values are below the minimum threshold of 0.02. With an F^2 value of 0.387, which is significantly high, SAT and IU were the strongest interactions. All relationships met the minimum literature criterion of having Q^2 values above zero. Table 8 displays the t-values and p-values showing that INFQ, SYSQ and SERVQ indicate a significantly positive relationship with satisfaction ($t = 3.589$, $p = 0.000$), ($t = 4.331$, $p = 0.000$) and ($t = 5.019$, $p = 0.000$). The relationships with t-values well above 1.96 thresholds and *p*-values of less than 0.05 have proven important. According to the thumb rule of t-value for a two-tailed test, $t = 1.96$, all hypotheses are supported.

5 Discussion

The purpose of this study was to evaluate the role of HCP satisfaction in determining the relationship between IS qualities and intention to use CDSS. A better-quality system creates an environment of CDSS successful implementation; HCP level of satisfaction, and through this mechanism, adoption of CDSS is facilitated. The continuity of safety and patient care in organizations that rely heavily on computerized health care systems requires zero downtime and business continuity protocols [93]. Previous studies affirm that user satisfaction in measuring CDSS adoption is significant [59, 64]. The results of the studies have shown that satisfaction is a valuable criterion for determining the CDSS system adoption [48].

This study supports the recent findings of Aljarboa and Miah [12] work on CDSS. According to Table 6, our IS qualities highly influence HCP satisfaction with adopting CDSS. This study developed hypotheses and established a correlation between CDSS adoption, information quality, and HCP satisfaction, as represented by H1. Previous researchers have supported these conclusions [35]. Wibowo [94] also found that information quality has a dominant influence on HCP satisfaction because information quality relates to the delivery of information about the stages that must be passed by the HCP. An information system of high quality will contribute indirectly to HCP quality of care [17].

The second hypothesis concerns the effect of system quality on HCP satisfaction. Based on these findings, system quality positively affects the HCP satisfaction. The outcome of our hypothesis is thus consistent with previous research [95, 96]. An effective CDSS assures that system resources can be accessed only by approved users; thus, the findings

Table 8 Results of specific indirect effects

	Original sample (O)	Mean (M)	Standard deviation (SD)	T statistics (|O/SD|)	*P* values
INFQ → SAT → IU	0.144	0.147	0.040	3.589	0.000
SERQ → SAT → IU	0.177	0.181	0.035	5.019	0.000
SYSQ → SAT → IU	0.131	0.132	0.030	4.331	0.000

support that system quality attributes are crucial for user satisfaction [97] and to intention to adopt CDSS [52].

Results also support the third hypothesis that service quality significantly influences HCP satisfaction. Our findings are in line with previous studies [98, 99] that contradict earlier research in the healthcare sector, which has advocated for a greater focus on service quality to improve HCP satisfaction and, as a result, achieve system success [35, 98]. The dissatisfaction with this area, emphasized in multiple researches, has been identified as a barrier to using electronic health records (EHR) and the primary cause for HCP abandoning them [17]. As a broad technological characteristic of the HIS/CDSS, timely high-speed system access has been identified as a significant efficiency aspect [100]. HCP adoption of the system and its successful deployment are less likely when the system response time is slow [101]. The IS quality dimensions and the ISSM approach has impacted user satisfaction and information system in e-commerce, particularly in the current COVID-19 pandemic [48].

The fourth hypothesis in this study is the effect of an HCP satisfaction on intention to use, which significantly influence the CDSS adoption. Technological change needs to address HCP satisfaction [102, 103]; as a result, what motivates people to use the technical system, technology varies based on their expectations needs, and values [104]. As a result, hospital administration should give enough training to raise user awareness and understanding of the relevance of CDSS and its significant implications, as well as implement and deploy CDSS. According to Lee, Ramayah [14], the more uneasy people are about the technology, the less likely they are to implement it. Consequently, the hypothesis of our study shows factors influencing the intentions to adopt CDSS. The findings of this research would be valued for the effective implementation of CDSS in public sector hospitals. Hence, IT plans, and roadmaps are required by government and hospital administration to ensure that the deployment of integrated CDSS goes smoothly. To achieve positive benefits from CDSS, it is important to communicate this roadmap to all stakeholders. If HCP satisfaction, government policies and infrastructure that meet all IS criteria for CDSS, should all contribute to a successful CDSS implementation. Finally, HCP participation in all phases of the CDSS development cycle is critical for delivering a high-quality CDSS.

6 Practical implication

Apart from a load of HCP activities, the knowledge codification required by CDSS allows medical and non-medical personnel access to a broader level of knowledge in organizations. [102, 105]. Furthermore, HCP are concerned about a loss of privacy, increased workload and costs, medical liability, and inadequate usability, particularly regarding the medical record system. [102]. This could result in satisfaction or dissatisfaction among healthcare workers, affecting their intentions to use the system. In this regard, the government should establish policies that contain a unique set of rules and plans to pursue the goal of CDSS adoption, which will result in hospitals implementing CDSS [30, 106].

7 Conclusion

This study aimed to investigate the change in HCP satisfactory level toward the success of CDSS in a developing country. The primary goal of this research is to determine the critical factors influencing CDSS adoption in public hospitals in the light of the D&M and ISSM framework after the COVID-19 pandemic. We have seen that a Clinical Decision Support System using AI is beneficial, fast, and reliable. The number of cases increases exponentially during pandemics such as COVID-19, making it impossible to diagnose each patient manually. As AI came into trend later, it wasn't used efficiently in earlier pandemics, so these are very useful for areas where there are still low levels of HCP satisfaction and intention to use CDSS. As a result, we can assure that the designed system meets the needs HCP satisfaction. The results of our study indicate that all our independent variables positively influence the success of CDSS. The findings imply that HCP satisfaction is an essential factor for the success of CDSS.

7.1 Limitations and suggestions for future research

This study has some limitations, even though it has contributed to theory and practice. It's a cross-sectional study involving just HCP, so extra attention is recommended when applying the findings to another cadre, industry, or business type. Future research could increase the generalizability of this study, which was conducted in Wuhan, the outbreak's epicenter, such as collecting samples from other regions where COVID-19 is currently in a highly infectious phase, and HCP are likely to face satisfaction, safety, and CDSS challenges.

Further study on CDSS adoption may be undertaken with the roles of management and leadership behavior on how hospital leaders' actions can affect employee behaviors in adopting the technology. Furthermore, this study is based on the D&M and ISSM frameworks. Further research should be conducted using different contexts such as the Human Organization Technology (HOT) Fit model to understand CDSS adoption better.

Appendix A: Questionnaire

System quality (information system and service quality)

1. The AI-based CDSS that I am using is user friendly.
2. The work flow is improved by AI-based CDSS.
3. The AI-based CDSS that I am using is easy to use.
4. The AI-based CDSS responds quickly enough.
5. The information that I get from AI-based CDSS is complete.
6. The information that I get from AI-based CDSS is on time.
7. The quality of the information that I get from AI-based CDSS is valid.
8. The information from AI-based CDSS is useful for decision making.
9. Service quality support provided by AI-based CDSS is sufficient.
10. The AI-based CDSS has provided me with the assistance I need.
11. Training on the use of AI-based CDSS is sufficient.
12. There is always someone to turn to if we need help with the AI-based CDSS.
13. Clinically critical decisions are supported by the AI-based CDSS.

User (HCP) satisfaction

14. Using AI-based CDSS has been a pleasant experience for me.
15. I am very satisfied with the information I receive through AI-based CDSS.
16. AI-based CDSS has helped to provide reliable services.
17. Overall, my interaction with AI-based CDSS is very satisfying.

Intention to adopt CDSS

18. I intend to use AI-based CDSS to do my work.
19. I will return to AI-based CDSS often.
20. I intend to use AI-based CDSS frequently to get services.
21. Given the opportunity, I will use AI-based CDSS.

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Declarations

Conflict of interest The authors declare no conflict of interest.

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