

Impact of AI Diagnostic Accuracy, Clinical Decision Support System and System Responsiveness on Decision Quality and Personalized Digital Health System

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ABSTRACT

Purpose: In the present healthcare system, it is important to provide personalized healthcare to patients. Therefore, the aim of this study was to examine the effect of system responsiveness, clinical decision support system, perceived AI diagnostic accuracy, and clinical decision quality on the effectiveness of personalized digital health systems. The study also explored the moderating effect of patient e-health literacy and the mediating role of clinical decision quality. **Design/ method/ approach:** Quantitative research approach was employed in this study. Data were collected in the form of a questionnaire using simple random sampling. The respondents of the study were doctors. Collected data were analyzed using AMOS. **Findings:** Findings of the research show that system responsiveness, clinical decision support system, and perceived AI diagnostic accuracy have a positive effect on clinical decision quality. Moreover, statistical figures confirmed the direct effect of clinical decision quality on the effectiveness of personalized digital health systems. The mediating effect of clinical decision quality and the moderating role of patient e-health literacy are also supported. **Originality:** This research is among the few that have studied the mediating effect of clinical decision quality and the moderating role of patient e-health literacy within a single framework.

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1. Introduction

In the last few years, the healthcare sector has been going through a profound transformation fueled by the exponential growth of data and the proliferation of digital technologies. Traditional models of healthcare are largely characterized by conventional methods of treatment and diagnosis. These treatment methods are increasingly being replaced by digital systems that leverage data for tailored medical interventions (Hazra & Bora, 2025). This transformation in the literature is known as data-driven personalization, where patient-related data, ranging from lifestyle information to genomics, provide guidance to doctors for informed and effective decisions (Ahmad et al., 2025). Personalization in digital health is not just a technical revolution but a realignment of concepts that gives importance to patients. Personalized digital health systems use different digital techniques, such as wearable technologies, big data analytics, and artificial intelligence, to integrate and capture multifaceted streams of data (Shahzad et al., 2025). Therefore, personalized digital health systems provide support for precise medication and real-time health monitoring. The shift toward personalized digital health systems is driven by the need for cost-effective healthcare and proactive, effective healthcare delivery, especially in light of resource constraints, the prevalence of chronic diseases, and an aging population (Haydon et al., 2023). Whereas implementation of personalized digital health system mostly face a number of challenges including systematic interoperability, algorithm transparency and data privacy (Peyroteo & Lapão, 2025).

The main aim of the modern healthcare system is to diagnose diseases as early as possible using well-managed methods at minimum cost. One of the ways to achieve this is through the use of AI for diagnostic accuracy (Yao & Chiang, 2025). There are a number of different challenges linked to usage of AI Diagnostic for Accuracy but its usage is important for progress of healthcare sector (Asif et al., 2025). AI has the ability to address the shortage of healthcare professionals. Moreover, AI-based diagnosis can improve the quality-of-care outcomes by enhancing and supporting the accessibility of healthcare professionals. Therefore, AI makes it easier to provide timely and accurate diagnoses to patients (Alqurashi &

Alshagrawi, 2025). AI diagnostic accuracy is important to ensure effective, reliable, and safe clinical decision-making. AI diagnostic accuracy enhances the timely detection of diseases, supports doctors, and reduces diagnostic errors by providing evidence-based insights (Hajiheydari et al., 2025). AI diagnostic accuracy develops trust of doctors on AI tools. Therefore, treatment selection is improved and later promotes personalized care.

In modern healthcare, clinical decision support systems are considered essential due to increasing patient management through machine learning and artificial intelligence. Clinical decision support systems have the potential to process complex data. Therefore, clinical decision support systems provide real-time support for personalized treatment and diagnosis by addressing human limitations in healthcare processes. Studies have identified several benefits of clinical decision support systems in the healthcare sector. Clinical decision support systems play a pivotal role in improving patient care by delivering services to patients through various innovative approaches (Grechuta et al., 2024). Clinical decision support systems are a type of intelligent system that offer real-time insights to doctors, helping them make timely decisions. One of the main benefits of clinical decision support systems is their ability to support decision-making by providing access to critical patient data. As a result, diagnostic accuracy is enhanced (Schäfer et al., 2025).

Responsiveness is one of the four goals of the health system, along with health, efficiency, and equity in financing, as mentioned by the World Health Organization. According to researchers, system responsiveness in the healthcare context is mainly perceived as the quality of interaction between health services and patients. System responsiveness contributes to well-being and health by providing an environment in which patients can receive care at an early stage (Khammarnia et al., 2024). Studies have reported that patients achieve satisfaction as result of responsiveness from health care providers. Moreover, system responsiveness is individual level feedback to patient from health care provider (Kagwanja et al., 2024). System responsiveness is very important in healthcare because timely system responsiveness ensures access to decision support information, clinical alerts, and patient data. System responsiveness enables doctors to make more timely, confident, and accurate medical decisions. Moreover, the quality of care is also enhanced through system responsiveness.

In the present complex healthcare environment, doctors must interpret large amounts of patient information, diagnostic results, and clinical data, making it more challenging to make high-quality decisions. Clinical decision quality is important because it directly affects treatment effectiveness and patient safety (Gupta et al., 2025). Sound clinical decisions minimize the risk of inappropriate interventions, medical errors, and misdiagnosis. Therefore, patient satisfaction and clinical outcomes are improved. Furthermore, clinical decision quality supports personalized care through the integration of clinical evidence with patient-specific factors such as lifestyle, comorbidities, and medical history, which is vital for appropriate treatment (Flumignan & Lopes, 2025). Strong clinical decision quality is important for efficient utilization of resources, improved care coordination and reduced healthcare costs. Clinical decision quality improves consistency and confidence of doctors to make decisions in uncertain situations (İlaslan et al., 2023).

In present healthcare systems, patient e-health literacy is vital because doctors and patients currently rely heavily on digital technologies for care management, communication, and information delivery. Patient e-health literacy refers to the ability of patients to seek, understand, evaluate, and apply health-related information obtained from various electronic and digital sources. Patient e-health literacy plays a very important role in making appropriate health decisions that are sometimes lifesaving (Cheng et al., 2025). Moreover, e-health literacy of patient is important to maximize advantages of digital healthcare. On the other hand, e-health literacy ensures patient centred and equitable care of patients.

The objective of this study is to examine the effect of clinical decision support system, perceived AI diagnostic accuracy, system responsiveness, and clinical decision quality on the effectiveness of personalized digital health systems. The study also examines the moderating effect of patient e-health literacy and the mediating role of clinical decision quality.

2. Literature Review

2.1 Clinical Decision Quality and Effectiveness of Personalized Digital Health System

Since last few decades, digital health system have gained significant attention in literature of healthcare sector (Mauro et al., 2024). It is because of potential of health care system to improve care efficiency, patient engagement and clinical outcomes. Studies mentioned that digital health personalization is an important factor of engagement of patients and to improve outcomes of healthcare system (Caffery et al., 2025). There can be a number of different types of personalization in digital health products ranging from predictive analytics, communication interface and customized content (Winkens et al., 2025). The users of healthcare system feel valued and understood because these tailored experiences that later enhance motivation of patients and trust on health management plans. Patients can get more timely interventions, and accurate guidance because of digital health solutions. They have potential as well to prevent different health issues that could escalate otherwise (Mwendwa, 2024).

Digital health facilitates and connects personalized public health and health care. Digital Health enables semi-automated, remote, and frequent health services. With the passage of time healthcare system is becoming increasingly

digital. Therefore, it is becoming easy to provide personalized experiences to patients which is important feature of digital health products. This feature becomes more important in case of disease prevention. Studies also demonstrated that strategies that are being used personalized medicine can also be used for other purpose like prevention of disease (Chén & Roberts, 2021). Whereas there are a number of factors upon which effectiveness of personalized system is dependent. These factors include user trust, system usability and data quality. Personalized health system plays very important role for effectiveness and quality of healthcare (Sunyaev et al., 2024).

Studies mentioned three important stages of clinical decision-making including management, assessment of severity and diagnosis. Quality of patients' results is dependent on all these three stages. Information and data are provided in electronic form within healthcare sector that has potential to increase efficiency and quality of clinical decision making. It also play very important role to improve care of the patients (Laker et al., 2018). Proper clinical decision making keeps in view the need to make accurate diagnosis along with cost linked with indiscriminate or inappropriate usage of diagnostic tests. It also evaluates the risk for worst outcome because of bad management practices, possible harmful effect and cost of therapeutic interventions. Studies emphasized that decision making is important factor for healthcare efficiency, care effectiveness and patient safety (Schuler et al., 2025). Quality decisions of medical clinic integrate contextual information, patient preferences, update medical evidence, and clinical expertise (Walsh et al., 2020). Clinical decisions that are of high quality are aligned, timely, evidence based and accurate with individuals need of the patients. When digital health system in the form of personalized treatment of algorithms, wearable based monitoring platforms, and AI based decision support tools, develop clinically sound and reliable recommendations. Therefore, doctors most likely adopt and trust (Elhaddad & Hamam, 2024).

Thus, the quality of decision-making is impacted by quality of data. Different tools of clinical decisions are designed to be used to take care of patients. Whereas it is very difficult for the tools to work properly. Improved quality of decisions make sure that insights of a person including pare pathways, medication suggestions, and risk predictions are important for the unique profile, preferences and lifestyle of a patient (Mohammed et al., 2024). This situation leads to better alignment, reduced medical errors and precise interventions between patients' outcomes, and treatment plans. Additionally, strong decision quality has positive influence on engagement, satisfaction and patient safety as experience of patient care is effective and tailored (Parveen et al., 2025). The effectiveness and efficiency of personalized digital health system mainly rely on the system's ability to support clinical decisions of high level that later translate personalized data into important improvement in healthcare. Studies revealed that effectiveness of clinical decision quality mainly relies on evidence that is used for its development. Empirical studies mentioned that clinical decision quality has positive influence on personalized digital health systems (Alexiuk et al., 2024). So, we hypothesize that

H1: Clinical decision quality has positive influence on effectiveness of personalized digital health systems.

2.2 Perceived AI Diagnostic Accuracy and Clinical Decision Quality

Studies mentioned the importance and potential of Artificial intelligence in efficiency pf radiology and accuracy of diagnosis. It is discussed as the amount of believe clinicians and patients have on system of AI for diagnosing of their condition. On the other hand, it also measures the accuracy of models of AI. The usage of data analysis and advanced algorithms of machine learning has made manufacturing of medical equipment possible having high accuracy. These machines can play very important role in the process of diagnosis and treatment of patients. As a result, it becomes possible for organizations to manufacture medical equipment with improved quality. This need of improved effectiveness is also possible by AI usage (Tetty-Engmann et al., 2025). Organizations can use more efficient and accurate tools for medical diagnosis with the help of AI in process of production.

Scholars mentioned that using AI for the evaluation of images of medical has resulted in accurate evaluation of images. It is because automation is used for this process. Since last few years, usage of AI for the process of screening has increased and shows its potential for accurate diagnosis. The main purpose of using AI in medical devices is to enhance effectiveness and accuracy of diagnosis. Another reason is to have increase quality of treatment for patients, reduce costs and errors, and accurate treatment of disease. Doctors can also use AI for efficient and timely decisions (Ahmad et al., 2025). The accuracy of diagnosing the disease by doctors has also improved by using AI. Doctors play very important role in deciding treatment and diagnosing disease for patients on the basis of their experience and knowledge. In the process of diagnosing disease, artificial intelligence can play key role in helping doctors so they can make accurate decisions in diagnosing patients through radiology images and analysis of clinical data (Arzikulov & Komiljonov, 2025). Additionally, AI can also be used in the form of robotics surgeries where doctors control the robots for the process of surgery and treatment. AI is used in this process to improve accuracy of correct decisions, treatment and diagnosis (Hanif, 2025).

AI diagnostic accuracy positively influences clinical decision quality by enhancing trust of doctors and relying more on the recommendations of AI. When doctors perceive the recommendations of AI to be accurate, they integrate this recommendation into diagnostic reasoning, leading to evidence-based decisions, consistent decisions and timely decisions

(Oei et al., 2025). As a result, diagnostic uncertainty is reduced, errors and bias are minimized and diagnostic process is supported. Study by Hajiheydari et al. (2025) mentioned AI diagnostic accuracy has positive effect on clinical decision quality.

H2: Perceived AI Diagnostic Accuracy has positive influence on Clinical Decision Quality.

2.3 Clinical Decision Support System and Clinical Decision Quality

Clinical decision support is based on a number of interventions and tools that are non-computerized and computerized (Bayer et al., 2025). Whereas clinical decision support system is an electronic system that is used to retrieve, store and collect patient information. This information include billing processes, laboratory test results, and history of patients that can be used in a number of different hospitals and departments (Sutton et al., 2020). Scholars pointed out that Clinical decision support system is the paperless and electronic system that covers all clinical procedures, financial data and administrative data. Therefore, it is very important for hospitals to implement and develop Clinical decision support system.

Domain of decision support system improves and assists the organization in process of decision making. A number of different unstructured, semi structured and structured issues have certain standard criteria. Therefore, decision support system is vital interactive system that is computer based (Fernando & Baldeovar, 2022). It plays important role in determining, solving and defining problems during the process of decision making by using different models and data. Decision support systems are helpful in a number of industries including education, healthcare, sales optimization, farming and inventory management (Tawfik et al., 2017). Clinical decision support system improves speed and performance of decision-making activities that promote time saving and learning. Additionally, it helps in providing accurate clinical information. It is expected that Clinical decision support system will provide relevant information and persistent data that will later improve medical services. In other words, Clinical decision support system is built to help the patients and health care professionals with the help of different software (Grechuta et al., 2024).

The association between clinical decision support system and clinical decision quality is based on the ability of system to operate data of large volume. It must have the ability to handle data in the form of medical records, laboratory results, diagnostic reports and medical history of patients. Integration of clinical decision support system enables doctors to make precise and informed decisions by minimizing reliance on memory. The decision quality is improved through clinical decision support system through minimum errors related to treatment selection, interactions of drugs and diagnosis (Armando et al., 2023). Automated reminders and alerts help doctors to follow best practices and clinical guidelines to ensure standardization and consistency while delivering medical treatment. With the passage of time, regular use of Clinical decision support system promotes organizational learning and enforced evidence based operations among doctors (Montagna et al., 2025). The research by Ayed Aloufi (2020) revealed significant effect of Clinical decision support system on clinical decision quality of doctors. So, it is hypothesized that

H3: Clinical Decision support system has positive influence on Clinical Decision Quality.

2.4 System Responsiveness and Clinical Decision Quality

Responsiveness is important goal of any healthcare system. Health systems that is responsive often adapt and anticipate to future and existing health needs that later contribute to better health results. In past, responsiveness in terms of health system is least researched (Khanpoor et al., 2025). Understanding health system responsiveness is very important for every nation. Responsive health system has the ability to adapt and anticipate the altering needs patients (Iqbal et al., 2024). It harnesses the opportunities to promote effective intervention access and to improve quality of medical services. All these factors ultimately lead to better health results. In literature term health system responsiveness is also referred to as system responsiveness.

System responsiveness is recognized as important factor in health information system. Past studies mentioned that reliable and fast system responses provide support in terms of timely access to decision support alerts, clinical guidelines and patients data that later enhance accuracy of diagnostic and treatment (Khan et al., 2021). Responsive system minimizes interruption in workflow that are burden on doctors. Therefore, the efficiency and confidence to make decisions among doctors is enhanced. Studies mentioned that acceptability, trust and accountability is are linked to health system responsiveness (Mirzoev & Kane, 2017).

Studies revealed that system responsiveness significantly affects clinical decision quality by providing timely access to relevant and accurate information of patients. When clinical system provides response in a quick manner, it becomes easier for doctors to get recommendations, alerts and data without any delay. This information is most of the time important in time sensitive cases (Maqbool & Herold, 2024). High responsiveness minimize frustration and cognitive load, that allows doctors to focus on patients rather than system navigation, it helps in real time decision making by making sure that data of the patient is updated and all evidence is are quickly available (Achrekar et al., 2024). Thus, responsive system improves confidence, accuracy and efficiency in clinical settings. The empirical study by Khan et al. (2021) demonstrated positive effect of system responsiveness on clinical decision quality.

H4: System Responsiveness has positive influence on Clinical Decision Quality.

2.5 Clinical Decision Quality as mediator

When doctors assume AI diagnostics as accurate, it is highly likely that they will rely on the usage of AI for diagnostic purposes. It will improve clinical decision quality by appropriate selection of treatment, reduced uncertainty and improved diagnostic confidants (Liu et al., 2025). High quality decisions are also supported by alignment of care, timely interventions and risk stratification with the needs of individual patients. As a result, personalized digital health systems are enabled by improved decisions to deliver more effective and precise patient centered interventions. Moreover, studies like Kim et al. (2022) discussed mediating role of clinical decision quality in their study also. Therefore, clinical decision quality has the potential to mediate between AI diagnostic accuracy and effectiveness of personalized digital health systems. So, we assume that

H5: Clinical Decision Quality acts as mediator between Perceived AI Diagnostic Accuracy and personalized digital health system.

Studies mentioned that clinical decision systems have the potential to serve as bridge between clinical decision support systems and personalized digital health systems. It is because clinical decision quality has the ability to convert technology into clinical actions. The decision support system that is well designed develops integration among real time analytics, clinical guidance and patient data. As a result of this support, judgement is strengthened, clinical errors are minimized and cognitive burden is reduced (Khude & Shende, 2025). As quality is improved through clinical decisions, customized care pathways can be more customized more effectively by personalized digital health systems. It also aligns the treatment as per the profile of individual patients and improves effectiveness of overall health system. Therefore, importance of decision support system can be determined through enhanced decision quality which drives personalized digital health delivery. The study Yu et al. (2019) in literature discussed mediating effect of decision quality in their study. So, it is hypothesized that

H6: Clinical Decision Quality acts as mediator between Clinical Decision support system and personalized digital health system.

According to scholars, clinical decision quality may serve as important mediating factors between system responsiveness and effectiveness of personalized digital health systems. It is achieved by altering performance that is technologically based into clinical values. When high responsiveness is demonstrated by digital health systems, doctors are able to receive real time alerts and data. It helps in making timely decisions without any disruptions or delay. As a result of timely access of information, faster support to patient is provided, improves awareness of situation and minimize information gaps, helping in making accurate judgement of patient (Ahmed et al., 2025). Therefore, improved clinical decision quality makes sure that system responsiveness led to individualized care delivery, timely interventions and appropriate choice of treatment. Consequently, responsive system plays key role to personalized digital health outcome by influencing positively on clinical decision quality. The research by Crijns et al. (2023) also highlighted mediating effect of clinical decision quality. So,

H7: Clinical Decision Quality acts as mediator between System Responsiveness and personalized digital health system.

2.6 Patient e-health Literacy as Moderator

Studies mentioned that e-health literacy is the ability to apply, evaluate, understand and find health information by using different electronic sources in the form of applications and websites. It helps the users to make informed decisions about health, integrate digital skills, and solve health problems with traditional literacy about health (Morales & Eguia, 2025). Patients having higher levels of e-health literacy has the ability to understand self-management guidance, risk alerts and recommendations generated through digital health systems. This will lead to improved treatment of patients and informed health decisions.

Patients having high level of e-health literacy have the ability to handle personalized problems, get engage with decision support outcomes, and follow digital care plans. Patients having such literacy can make timely health related decisions strengthening positive effect of decision quality on effectiveness of system (Kouris et al., 2010). On the other hand, low e-health literacy has the ability to make this relationship weak because patients may not fully understand the instructions. It may also be because of underutilizing the system and tools that may reduce medical outcomes. Therefore, patient e-health literacy has the ability to minimize or amplify the way clinical decisions of high quality is converted into personalized digital health results.

H 8: Patient e-health literacy as moderator between Clinical Decision Quality and Effectiveness of personalized Digital Health System.

Thus, Theoretical framework in figure 1 is developed in response to above literature.

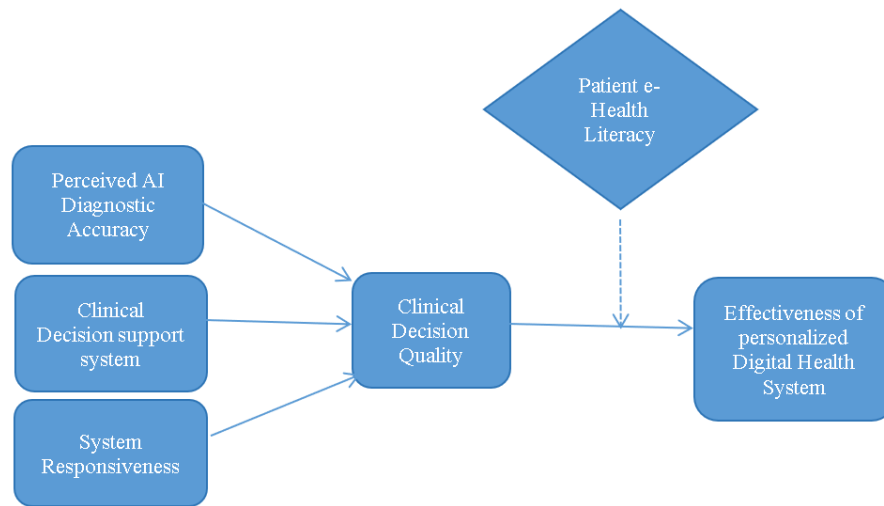


Figure 1: Theoretical Framework

3. Methodology

To understand the impact of AI and its role in the determination of health services quality, researchers used quantitative research design. Population was the doctors of the hospital, how they perceive the effect of digital interventions in enhancing the effectiveness of the digital health system. Simple random sampling technique were used for the selection of sampling units. Researchers utilized face to face methods for the collection of data. Simple survey methodology was used, and cross-sectional research design was used. For the collection of data research instruments were used. A well-developed questionnaire used for recording the respondents' responses. All the latent variables were measured by using 5 points Likert scale and the well-developed scale was used adapted by previous studies having good reliability and validity.

Perceived AI diagnostic Accuracy, measured with items scale used by Yao and Chiang (2025). Clinical Decision Support system, measured by items scale adopted by Ahmad et al. (2025). System Responsiveness measured by items scale used by Valentine et al. (2003). Clinical Decision Quality measured by items scale adapted by Slade et al. (2014). E-Health Literacy measured by items scale adapted by Norman and Skinner (2006). Effectiveness of personalized digital health system measured by items scale adapted by Haydon et al. (2023).

Pretest reliability and validity tested by health professionals before distributing to the ultimate respondents, split half technique was used, test-retest reliability was tested. After the recommendations of the professional researcher, we adopted some minor recommended changes. Consent of the respondents were taken and ensured that the privacy of the data will be maintained. Total 300 questionnaires were distributed and received back 248. After data cleaning process, we retained 214 responses for the final analysis, that is 71%. So, the response rate was satisfactory.

3.1 Demographics

Initially respondents' demographics were examined. Demographics effect significantly on the patterns of the cognitive processes. 64.5% respondents were male and 35.5% were female. 27.6% were 13 to 23 years old. 26.2% were 24 to 34 years old. 31.3% were 35 to 45 years old. 14.9% were above 46 years. 22.4% were SSC degree holders, 29.4% were HSSC. 24.8% were having Bachelor's degree and 23.4% were masters and above qualified (Table-1).

Table 1: Demographics of Respondents

Variable	Class	Number	%
Gender	Male	138	64.5
	Female	76	35.5
Age	13-23	59	27.6
	24-34	56	26.2
	35-45	67	31.3
	Above 46	32	14.9
Qualification	SSC	48	22.4
	HSSC	63	29.4
	Bachelors	53	24.8
	Master and above	50	23.4

3.2 Confirmatory Factor Analysis

For the evaluation of the strength of the construct's items, CFA was conducted. Six factors CFA was performed using SEM in AMOS (Figure-2). For the evaluation of the goodness of fitness, values of TLI, CFI, NFI GFI and RMSEA were used. Table-2 Shows that the model is a good fit model having values of CFI, NFI TLI greater than 0.90. On the other hand, values of one factor model shows low model fitness ([Anderson & Gerbing, 1988](#)). Thus, researchers proceed with six latent factors model having good model fitness (Table-2).

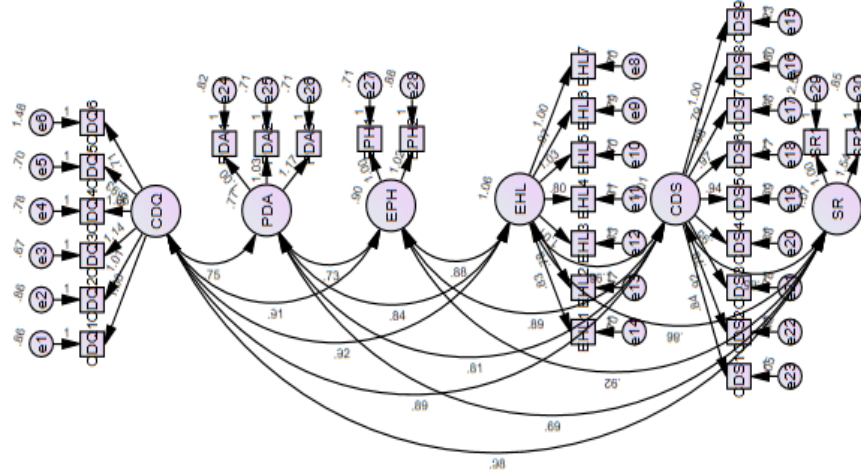


Figure 2: Confirmatory Factor Analysis

Table 2: Model Fitness

	IFI	CFI	NFI	GFI	TLI	RMSEA
Single Factor	0.64	0.73	0.68	0.59	0.43	0.089
Six Factors	0.93	0.93	0.86	0.86	0.92	0.006

Table 2 shows that the model is good fit having values of indices like CFI, IFI, TLI greater than 0.90 and the value of RMSEA is less than 0.03. It also demonstrate that the values of model fitness increased when we shifted to six factor CFA from one factor CFA ([Anderson & Gerbing, 1988](#)). Confirmatory factor analysis confirmed the loadings of the latent factors, explaining what the degree of contribution is of a single item of the scale towards its latent variable.

Table 3 (a): Construct Reliability and Validity

	Items	Loading	CR	AVE	α
Clinical Decision Quality (CDQ)	CDQ1	.738	0.89	0.57	0.82
	CDQ2	.760			
	CDQ3	.827			
	CDQ4	.731			
	CDQ5	.713			
	CDQ6	.770			
E-Health Literacy (HI)	EHL1	.777	0.91	0.59	0.87
	EHL2	.748			
	EHL3	.786			
	EHL4	.828			
	EHL5	.794			
	EHL6	.759			
	EHL7	.716			
Clinical Decision Support System (CDS)	CDS1	.902	0.93	0.59	0.89
	CDS2	.883			
	CDS3	.733			
	CDS4	.745			
	CDS5	.774			
	CDS6	.782			
	CDS7	.659			
	CDS8	.705			

Table 3 (b): Construct Reliability and Validity

	Items	Loading	CR	AVE	α
Perceived AI Diagnostic Efficiency (PDA)	CDS9	.741	0.84	0.64	0.79
	PDA1	.891			
	PDA2	.722			
	PDA3	.784			
Health System Responsiveness (SR)	SR1	.860	0.74	0.58	0.83
	SR2	.659			
Effectiveness of Personalized Health System (EPH)			0.76	0.61	0.80
	EPH1	.800			
	EPH2	.761			

Table-3 shows that loading of all items are greater than 0.60, thus retained for the further analysis, except 4 items of clinical decision support system and one item of E-health literacy of the patients removed from the analysis due to having factor loading less than 0.50 (Kline, 2014). The reliability of construct moves from 0.74 to 0.89 that is greater than 0.70 (Nunnally, 1978). For the convergent validity Fornell and Larcker (1981) established the criteria that values of average variance extracted must be greater than or equals to 0.50. Table- 3 shows that values of AVE move from 0.57 to 0.64, thus establishing convergent validity. Similarly according to the standard defined by Fornell and Larcker (1981) values of the AVEs must be higher than the values of squared correlation, researcher taken the values at the diagonal and the values below the diagonal are the squared correlation, values at the diagonal are higher than the values below the diagonal (See Table#4).

Table 4: Discriminant Validity

	i.	ii.	iii.	iv.	v.	vi.
CDQ	0.57					
EHL	0.27	0.59				
CDS	0.35	0.34	0.59			
PDA	0.26	0.32	0.26	0.64		
SR	0.29	0.24	0.39	0.36	0.58	
EPH	0.31	0.38	0.26	0.28	0.39	0.61

Table-4 shows that all the values at the diagonal are higher than the values below diagonal, thus establishing the discriminant validity of the construct according to the standard described by Fornell and Larcker (1981).

3.3 Testing of Model

For quantitative testing the hypothesis researcher used AMOS. Hypothesized model was tested and implications were analyzed.

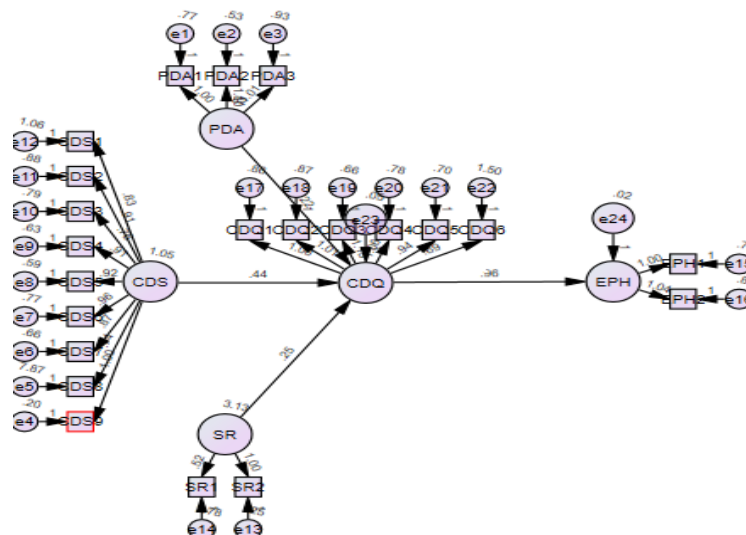
**Figure 3:** Structural Equation Modeling (Hypothesized Model Test)

Table 5: Model Test

Hypothesis	Effect
PDA----->CDQ	0.42**
CDS----->CDQ	0.44**
SR----->CDQ	0.25**
CDQ----->EPH	0.36**
PDA---->(CDQ)EPH	0.1512*
CDS---->(CDQ)EPH	0.1584**
SR---->(CDQ)EPH	0.09*

*Significant at $p < 0.05$ **Significance at $p < 0.01$

Table-5 and Figure 3 show that perceived AI diagnostic accuracy positively significantly effects the clinical decision quality with effect 0.42 and significance 1%. Clinical decision support system positively significantly effects the clinical decision quality with effect 0.44 and the significant at 1%. Health system responsiveness positively significantly affects the clinical decision quality with effect 0.25 and significance at 1%. clinical decision quality positively significantly affects the Effectiveness of personalized health system having effect 0.36 and significance 1%.

Clinical decision quality positively significantly mediates the link between perceived AI diagnostic accuracy and the Effectiveness of personalized health system having effect 0.1512 and significance 5%. Clinical decision quality positively significantly mediates the link between clinical decision support system and the Effectiveness of personalized health system having effect 0.1584 and significance 5%. Clinical decision quality positively significantly mediates the link between health system responsiveness and the effectiveness of personalized health system having effect 0.1584 and significance 5%.

3.4 Moderation of E-health Literacy

Moderation of patients e-health literacy on the effect of clinical decision quality and the effectiveness of personalized health system was tested using process macro model 1 by Hayes (2013).

Table 6: Moderation of Environmental Commitment

IV	DV	Moderator	Effect	LLCI	ULCI
CDQ	Effectiveness of Personalized Health System	Low Value of EHL	0.168	0.0217	0.5347
		High Value of EHL	0.297	0.1660	0.7316

Table-6 shows that e health literacy positively significantly moderates the effect of CDQ on the effectiveness of personalized health system for both at high value and the low value of moderator. The effect at low value is 0.168 and at high value 0.297. The values for both low and high LLCI and ULCI have same direction including no zero in between. Thus, moderation is significant and positive.

4. Discussion

In evolving and complex healthcare systems, it is important for health care organizations to provide personalized health to patients. Therefore, this research explored the antecedents of effectiveness of personalized digital health system. Results revealed that clinical decision quality has positive effect on personalized digital health system. These results highlight the main role of high level of clinical judgement to achieve meaningful personalization. When there is high level of clinical decision quality, doctors are able to make timely decision, apply evidence-based reasoning and interpret data of patients accurately. As a result, effectiveness of personalized digital health systems is enhanced because such system mainly rely on authenticated inputs to generate targeted interventions, adaptive care pathways and relevant recommendations.

Furthermore, strong clinical decision quality is vital to ensure reliability and consistency in medical actions that allows personalized digital platform to operate according to intentions. Results also illustrated that effectiveness of personalized digital health system is strengthened further when doctors have trust on the outputs of the system and they integrate these outputs with confidence in daily routine. Thus, clinical decision quality plays the key role to convert capability of digital technology into real time clinical value. In absence of clinical decision quality, it will be difficult for advanced digital systems to provide personalization. So, it is confirmed through findings of the study that effectiveness of personalized digital health system can be maximized by improving clinical decision quality. These findings are similar to the results of Alexiuk et al. (2024).

Results of the study also illustrated that Perceived AI Diagnostic Accuracy has positive effect on clinical decision quality. In past, Hajiheydari et al. (2025) also presented similar results in their study. These findings emphasized the key role of physician's confidence in AI based diagnostic outputs. In case of higher perceived AI diagnostic accuracy, it is highly

likely that doctors will regard diagnosis generated through AI as reliable source of clinical insights. They will noy consider it only the supplementary information. As a result of this increased trust doctors are enabled to integrate AI based recommendations into diagnostic reasoning that has direct positive influence on clinical decision quality.

Additionally, perceived AI diagnostic accuracy minimize uncertainty in complex clinical issues by providing data driven diagnostic cues consistently. As doctors rely more and more on perceived AI diagnostic accuracy, their level of confidence on diagnosis improves. This situation leads to more accurate evaluation and less errors. Increased perceived AI diagnostic accuracy provide support for validation of clinical issues more quickly that allows doctors to focus on patient related issues and treatment planning. As a result, enhanced clinical decision quality is the result because doctors combine professional expertise with accurate diagnostic on the basis of AI.

The findings of the research demonstrate that clinical decision support system has positive effect on clinical decision quality (Ayed Aloufi, 2020). These findings show the importance of well-structured decision-making system in the field of medical and health sciences. Doctors will get relevant information about patient, evidence-based guidelines and timely alerts with the help of clinical decision support system. It will support more informed and systematic clinical judgements. Clinical decision support system minimizes reliance of system on intuition by organizing complex medical information and data into actionable insights. It also allows to promote consistency in processes of decision-making leading to improved clinical decision quality.

Furthermore, assistance is provided to doctors by clinical decision support system to minimize errors of diagnostic and treatment by offering standardized recommendations, risk management and reminders. Analytical capability and support of doctors is further strengthened by this regular guidance. Therefore, doctors are able to provide more accurate diagnostics of the patients. Doctors also interact on regular basis with clinical decision support system; they gain confidence in terms of their actions. These doctors are better equipped to handle difficult and complex cases. As a result, enhanced clinical decision quality is the outcome of well-designed integration of clinical decision support system.

The results also confirms positive effect of system responsiveness on clinical decision quality as reported in the study of Khan et al. (2021). These findings emphasized the importance of reliable and timely system performance in healthcare environment. It is ensured that doctors received clinical insights, alerts and patients' data by high system responsiveness without any delay. This access of quick information becomes important in situation where quick decisions are needed. In case of strong system responsiveness, doctors have updated and quick access of patient's information that allows them to make quick evaluation of patient's condition. So, the clinical decision quality is improved.

Also, system responsiveness on regular basis minimizes workflow in-efficiency and interruptions that mostly distract doctors during process of decision-making. By minimizing system lag and waiting time, system responsiveness provide support to cognitive focus that enables doctors concentrate on medical reasoning and neglect technical obstacles. The trust of doctors towards digital platforms is also improved through enhanced system responsiveness. It encourages doctors to regular use of system in their daily practices. Resultantly, clinical decision quality is improved through better alignment, reduced uncertainty and timely judgement between patients' needs and clinical insights. These findings show the importance of system responsiveness as key factor of clinical decisions.

The findings state mediating role of clinical decision quality, between perceived AI diagnostic accuracy and effectiveness of personalized digital health system. The results how the way Perceived AI accuracy is converted into effectiveness of personalized digital health systems. When doctors have trust on AI diagnostic accuracy, they develop integration among AI based outputs into judgements. This integration leads to enhanced clinical decision quality. Improved quality of decision making by doctors enhances timely application, personalization and appropriate interpretation of AI based recommendations. Therefore, effectiveness cannot be achieved only through AI accuracy. Its impact is takes place through improved decision making by the doctors that convert information into personalized digital actions.

Results also support mediating effect of clinical decision quality between clinical decision support system and effectiveness of personalized digital health systems. These results make clear the process by which clinical decision support system improves effectiveness of personalized digital health systems. The decision support systems that are well designed are able to handle complex medical data. It provides guidance in structured way and minimizes load on the doctors. Clinical decision quality is strengthened by this support that improves confidence, precisions and consistency in medical judgement. Then, improved decision quality enables personalized digital health system to provide accurate data by making sure that support of system is converted into effective and meaningful personalized care.

Statistical findings also confirm mediating role of clinical decision quality between system responsiveness and effectiveness of personalized digital health systems. This mediating findings regarding clinical decisions quality explains the way system responsiveness plays its role for effectiveness of personalized digital health systems. Responsive system provides intime recommendations, alerts and data of patients to doctors. That enables doctors to make well informed and prompt decisions. As a result of this timeliness, doctors improve decision quality by minimizing uncertainty. As a result, improved decision quality translates responsiveness into personalized outcomes. These mediating results are in line with result mentioned by Crijns et al. (2023).

The results also support moderating role of patient e-health literacy on the path of clinical decision support system

and effectiveness of personalized digital health systems as mentioned by Alshammari et al. (2021). This moderating finding explain variation between clinical decision support systems and effectiveness of personalized digital health systems. When there is high level of e-health literacy among patients, they have the ability to understand digital recommendations in better way. Patients can also get engaged with guidance that is generated by system and follow personalized care plans. As a result of this active engagement, the relationship among clinical decision support system and effectiveness of personalized digital health systems is strengthened. On the other hand, in case of low e-health literacy among patients, there will be limited ability of patient to understand clinical data. Patients will not be able to use digital information which will weaken the relationship between clinical decision quality and effectiveness of personalized digital health systems.

5. Limitations

At this stage, few limitations of the study will be discussed. Firstly, this study used e-health literacy as moderating variables. It will be interesting to see patients' motivation as moderator in future on the given framework. Secondly, study used quantitative research methods for data collection and analysis purpose. It is proposed that future studies may use qualitative research approach for more in-depth analysis of data. Thirdly, three IVs are used in present study as predicting variables. It is proposed that number of variables as independent variables may be increased in future.

Fourthly, this study used AMOS as a tool for analysis of data. It is proposed by researchers to use Smart PLS in case of complex frameworks. The framework of the present study is complex having one mediator and one moderator along with three IVs and one DV. Therefore, it is recommended that studies may use Smart PLS for analysis in similar studies in future. In the end, respondents of present study are doctors. Future studies may collect data from nurses for same framework.

6. Theoretical and Managerial Contributions

Present study makes key theoretical contributions in literature by improving understanding the way technological capabilities in digital healthcare can be used for value creation. Present study add to the body of knowledge by conceptualizing clinical decision quality as important mechanism system responsiveness, AI-based diagnostic accuracy and clinical decision support systems make influence on effectiveness of personalized digital health systems. By making clear these important pathways, this study enriches studies of clinical decision making and provide more in-depth explanation of digital health technologies to achieve personalized care outcomes.

In terms of managerial contributions, these results provide guidance to administrators and decision-makers of health care system to give priority to technology accuracy and quality-oriented systems. Managers must invest in infrastructure of responsive decision support along with e-health literacy of patients to enhance effectiveness of personalized digital health systems. This study can be used by academicians for future research.

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8. References

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