Environment and Social Psychology (2024) Volume 9 Issue 4
doi: 10.54517/esp.v9i4.2308

ORIGINAL RESEARCH ARTICLE

The shift from disease-centric to patient-centric healthcare: Assessing physicians' intention to use AI doctors

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ABSTRACT

This study examines physicians' attitudes toward the intention to use AI doctors in healthcare. Currently, physicians use smart health technologies, health data, and AI in disease-focused research hospitals, and industry regulators hope that AI technology will be extensively used for each person, which means a shift from disease-centric to individual-centric healthcare. Using the theory of technology acceptance and use, a research model was developed to understand physicians' intentions to use AI doctors for data collection, diagnosis, treatment planning, and patient follow-up. The causal comparison screening technique was used to determine the causes and consequences of physicians' attitudes, behaviors, ideas, and beliefs. The responses of 478 physicians were evaluated using structural equation modeling and deep learning (an artificial neural network). It was discovered that physicians intend to use AI doctors first for diagnosis and treatment planning, and then for data collection and patient follow-up. According to the findings, the main constructs are performance expectancy, perceived task technology fit, high-tech habits, and hedonic motivation.

Keywords: individual-centric healthcare; artificial intelligence; healthcare; prevention of diseases; PLS-SEM; artificial neural network

1. Introduction

Artificial intelligence technology (AI) in healthcare is currently a popular topic for research and development, and it is a significant area of investment by industry stakeholders. Each stakeholder, physician, patient, public institution, organization, and insurance company has its reasons. For example, physicians use it to improve diagnosis, patients use it for health coaching, and sector regulators want to make healthcare more accessible and affordable to more people. Because even if a country has enough physicians and nurses, which is impossible, it does not guarantee that people have access to health care 24 h a day, 365 days a year. The demand for public health services is extremely high, while private health care is prohibitively expensive. Another impediment is the unequal geographic distribution of health professionals, who prefer to live in big cities, leaving rural areas without healthcare services[1].

ARTICLE INFO
Received: 4 December 2023 | Accepted: 8 January 2023 | Available online: 15 January 2024

CITATION
Uymaz AO, Uymaz P, Akgül Y. The shift from disease-centric to patient-centric healthcare: Assessing physicians' intention to use AI doctors. *Environment and Social Psychology* 2024; 9(4): 2308. doi: 10.54517/esp.v9i4.2308

AI was first used in healthcare in the 1970s. Edward Shortliffe's MYCIN was a pioneer in AI, assisting physicians with diagnosis and treatment planning[2]. As a result, the primary goal of AI use in the healthcare sector has been disease diagnosis and treatment planning[3]. The advancement of wearable smart technologies has expanded the use of AI while also making it a part of everyday life. Because of its increased accessibility, the healthcare sector has begun to shift from disease-centric to individual-centric[4].

Nowadays, the use of AI in the healthcare sector is both disease- and individual-centric. In the disease-centered use of AI, it is seen that "just on subject AI" developed for a specific disease, such as cardiology or oncology, is used. Surprisingly, these specialized AIs are successful in diagnosis[5–11]. It is important to remember, however, that the success of disease-focused AI is dependent on the specialty for which it was developed. The global regulator, the World Health Organization (WHO)[12], has developed policies and strategies to expand the use of AI healthcare technologies. As a part of its mission to promote "health for everyone, everywhere" the WHO has released a worldwide strategy plan on digital health. In the WHO report, the term "artificial intelligence" refers to the use of medical and clinical information systems, mobile health apps, smart, wearable health technologies, as well as apps to promote healthcare. Not only the WHO, but also the governments, companies, and healthcare professionals[3,13–15] want to expand AI in the healthcare system, which is an affordable one.

The widespread use of AI in healthcare has resulted in three significant changes. Firstly, AI has shifted from being disease-centric to becoming individual-centric[16]. Everyone can be evaluated as a single case, and personalized disease prevention or treatment plans can be defined. Industry regulators hope to transform the electronic health record system, which is currently evolving towards big data, from a component that physicians use only when a disease occurs to a preventive AI system that is constantly active and proactive even before the disease occurs[4,17,18]. This strategy not only reduces costs but also the burden on the health system and, thus, government spending on health.

Second, AI has improved diagnosis and treatment accuracy. It is an effective tool for disease prediction, diagnosis, and treatment[19]. According to studies, using AI for disease diagnosis and treatment reduces costs significantly[5–11].

Thirdly, one of the primary goals of AI is to minimize the need for geographic proximity between patients and healthcare professionals. Rural areas are home to 57% of the world's population. This figure is 83% in North America and 44% in Africa. Even though Africa has a high proportion of people living in cities and towns, access to health services is difficult for a variety of reasons[20]. This is the most important contribution of AI health devices and apps. Hence, AI doctors[21], nurses[22], and health coaches[14,23] have been developed.

When we examine the research on AI in healthcare, we see that there is a wide range of contributions to the development of AI health devices[24–27]. Because it is on the agenda of all healthcare stakeholders, the use of AI in healthcare will inevitably expand.

Patients have varying perspectives on AI. Some patients, for example, do not believe it can diagnose their diseases without human intervention. Instead, they want AI to be used by a physician and only for secondary diseases[28,29]. On the other hand, people who know how AI technologies are used in everyday life and believe that they will significantly improve healthcare are more comfortable with the medical use of AI[30,31]. The social distancing caused by the COVID-19 pandemic, physician errors, and the growing number of open-minded people in society are all contributing to a more positive view of the use of AI technology in healthcare[32]. In the coming years, accessibility, and the price/performance ratio of AI technology in comparison to physicians will be critical factors.

We discovered an unexplored gap in the use of AI in healthcare during our readings. This is the scope of Shortliffe's MYCIN application, which examines the stages of data collection, diagnosis, treatment planning, and patient follow-up in the patient-doctor relationship from the perspective of physicians. This study is motivated by some considerations. The use of AI is not as popular in hospitals as expected[33]. The first motivation is to determine whether physicians have a positive attitude toward the intention to use AI doctors. Second, if they have, what stages do they prefer to use it? The study is noteworthy because it examines every phase of the doctor-patient interaction in a comprehensive manner: data collection, diagnosis, treatment planning, and patient follow-up. This means new insights into individual-level digital healthcare.

A well-researched attitude study is a useful tool for forecasting behaviors[34]. This study investigates physicians' attitudes toward using AI doctors who focus on individual-centric healthcare in their professional practices. This is crucial because industry regulators want to create a patient-centric, holistic AI healthcare system[4,12]. For these reasons, it offers important outputs for all healthcare sector stakeholders.

2. Literature review

2.1. AI and healthcare

Today's technologies were unimaginable a couple of decades ago. We will have more advanced ones soon. With AI tools and applications, many features of a person are instantly measured, collected, evaluated, analyzed, and reported on according to a specified timeframe. Such big data cannot be gathered, managed, or used in conventional ways. In many sectors, data and information are obtained, decisions are made, and business processes are managed by AI. AI replaces humans, and many services become already widely available at a lower cost, faster, and more effectively.

The data collected by AI is an important resource for itself, and professionals. In healthcare, electronic health records are becoming easier to acquire because of wearable devices. With AI, it is hoped that healthcare services will be expanded regardless of place and geography, and accessible at low-cost. These effort aims are not designed at the level of organization or disease, but according to everyone as a single event[35].

AI has already become an important tool in healthcare, as a data collector and an analyst. It was created and enhanced using deep learning approaches that are data-centric to identify complex relationships in massive amounts of health data[36]. AI has been extensively utilized during the past 30 years to improve clinical decision-making[25]. Furthermore, data is collected for the prevention of disease and health promotion rather than diagnosis and treatment. This approach constitutes a more effective, and less costly healthcare policy[37].

2.2. Data collection

Many things in life—cities[38], buildings[39], homes[40], watches[41], glasses[42], and shoes[43]—are becoming health-focused smart technologies. Smart devices such as smartwatches, wristbands, bracelets, glasses, or fitness trackers can instantly measure and provide a clear picture of a user's health, including body mass index, calories burned, sleep duration and quality, heart rate, blood sugar level, and blood pressure[4,44]. This means that the data that shape people's daily lives is collected continuously and regularly. However, this flow of data is not analyzed and managed by a centralized system.

Often, data collected by healthcare professionals and used by AI has been focused primarily on decision support and the development of prediction models for a single disease[45]. Healthcare regulators hope to centralize the seemingly disparate and fragmented systems that manage individual health data collected by AI systems. This will reduce the strain on healthcare workers and the overall healthcare system[46]. Foremost, the primary purpose of a holistic AI health system is the "prevention of diseases"[4,37].

Not only is the data collected important for the individual's health, but it is also required for the AI system to function properly[4]. While AI may manage a person's life, it is the collection of data that shapes AI that is important[14,47]. As a result, it is considered a civic duty for individuals to share their health data for AI to be used more consistently in healthcare[48]. In addition to obtaining permission to share personal data, a data system can be established in the health management system that can be accessed by authorities.

2.3. Diagnosis

Diagnosis can be described as the procedure of determining an illness, disease, or injury based on its clues and symptoms. To support the diagnosis, testing, including blood tests, imaging tests, and biopsies, may be done to collect data in addition to a physical examination and health history[49].

A review of 274 studies using AI in healthcare found data collection in 49 studies; diagnosis in 148 studies; treatment planning in 56 studies; and 21 studies indicated that AI was used for both diagnosis and treatment planning[36]. The use of AI has mostly been concentrated on decision support and the creation of prediction models[45].

The research results indicate that AI diagnoses more successfully than human doctors[5–11,50,51].

However, patients mostly prefer the diagnostic process to be managed by a physician[30] or an AI system with human-like characteristics rather than a fully automated machine[52]. Objective evaluation of the diagnostic results is important for the patient's peace of mind and trust in the healthcare system. When comparing the rates of correct diagnoses between AI and human doctors, AI emerges as the clear winner[5–11,53]. It appears inevitable that the trend toward AI will continue to gain strength, and human doctors will need to work collaboratively with AI technology.

2.4. Treatment planning

Treatment planning can be described as any procedure that physicians perform on a patient to manage a health problem, minimize its symptoms, or cure it. Treatment may take the form of drugs, counseling, surgery, or other methods[54]. Since the beginning of AI, the pioneers have notably aimed to use AI in both diagnosis and treatment planning.

Nowadays, studies seem to focus on non-communicable diseases such as cancer and heart disease[19,55–57]. Beyond that, the most important health sector regulator in the world, the US Government, offers high-budget support for projects that aim to advance AI systems in treatment planning[15].

2.5. The patient follow-up

AI technology can monitor the treatment process, whether it is an inpatient[58] whose treatment is done in the hospital by the order of a doctor or an outpatient whose treatment is planned and performed outside[23,59]. It is aimed by healthcare regulators that AI will be extensively used for outpatients as well as inpatient treatments[1,12]. In developed countries, the population is aging[60], and around fifty percent of Americans currently have a chronic condition. Chronic disease-related expenses constitute eighty-six percent of all medical expenses[61]. More than fifty percent of fatalities globally are caused by chronic illnesses, mainly cardiovascular disease, type 2 diabetes, cancer, and chronic respiratory disorders[62]. Globally, noncommunicable diseases account for seventy-four percent of fatalities, or numerically forty-one million people every year[63].

Smart devices and AI systems can monitor patients' conditions as well as manage their lives according to treatment requirements[64–67].

AI, which is used in hospitals as disease-centric, is desired to be used in an individual-centric and holistic manner by health sector regulators. Disease prevention and chronic disease management are good starting points in managing healthcare workload and expenses because AI is capable of handling the health activities of patients[68,69]. For example, companies such as Omada, Glooko, Virta, Living, and Lark offer AI health coaching to their customers (who are patients) who have diabetes, hypertension, and obesity[14,70]. Even for follow-up patients in the treatment process, AI is in use not only for physicians' tasks but also for nurses'[46] and pharmacists'[71] tasks.

AI is a tool that can be used to collect data, diagnose, treatment planning, and follow up on the treatment and patient's condition. The acceptance and performance of AI technology will vary depending on both patients' and physicians' usage behavior. Considering physicians' intent to use AI doctors, as seen in **Figure 1**, the research model and the following hypotheses have been developed.

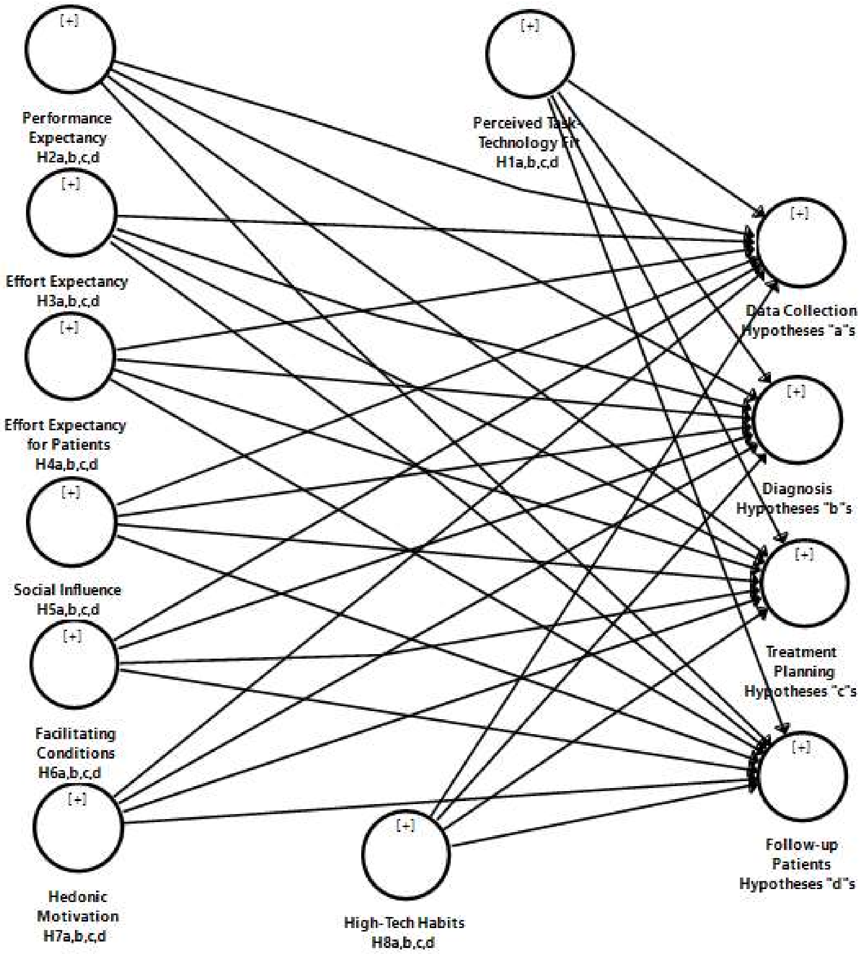

Figure 1. Research model and hypotheses.

3. Research methodology

3.1. Research model and hypotheses development

Although disease-focused intelligent technologies and disease-focused AI have been deployed in hospitals, AI technology that holistically manages the doctor-patient relationship with a patient-centric approach has not yet been deployed. However, industry regulators look forward to building a patient-centric AI system soon, managing individuals' health (especially outpatients) holistically, with a 'disease prevention' strategy.

This study's conceptual framework is based on the Unified Theory of Acceptance and the Use of Technology (UTAUT2) model developed by Venkatesh and colleagues[72]. UTAUT2 is designed to measure how people intend to use and behave with technology. The UTAUT2 model was preferred because physicians have experience with disease-focused AI for inpatients.

The study was designed to assess the behavioral intention of physicians to use AI-doctors for data collection, diagnosis, treatment planning, and follow-up in or outpatients in a holistic way.

In addition to the UTAUT2 model constructs, as seen in **Figure 1**, the perceived task-technology fit was added[73] to the research model. Since physicians working in research hospitals have experience using smart technologies and "just on the subject AI", our objective is to determine their perception of AI technology's competence to meet the requirements of physicians' tasks. Besides this, the price was removed from the research model. Since AI doctor technology is not a common product or service on the market yet, its price, which will be paid by users, is not defined yet.

Before the hypothesis development section, it is important to underline the difference between a behavioral intention, which is an attitude, and a behavior[74–76]. The existence of an attitude is not an absolute statement that the behavior will occur. The emergence of a behavior depends on many factors[32,77]. The current study measures physicians' intentions scientifically to predict their behaviors in the future. And we know that physicians are already using smart technologies and disease-oriented, "just on the subject AI" for inpatients[19,51,70,78], which shapes their attitudes, and behavioral intention to use a holistic AI doctor system for all patients. Past research has proved that people who are aware of the uses and outcomes of AI technology accept AI-based decision-making systems more easily[13,30].

We would like to point out that this study focuses specifically on physicians' intentions to use AI doctors in a holistic AI healthcare system, as they already see such a system as a threat to them. Therefore, this study's results are critical for stakeholders in the healthcare sector. Consequently, well-studied attitude research is a valuable tool for forecasting behaviors[34].

3.1.1. Perceived task-technology fit (PTTF)

In the PTTF dimension, it has been assessed how fitting AI doctors are for the profession of physician, according to physicians. TAM asserts that PTTF and PE serve as the primary driving forces for accepting and utilizing new technology[79]. AI can gather and analyze real-time health data, diagnose diseases[19], recommend treatment[36], follow up with patients[14], make decisions for some healthcare activities, and share the status of the patient with human nurses or physicians.

H_{1a} PTTF affects physicians' intentions to use AI doctors for data collecting.

H_{1b} PTTF affects physicians' intentions to use AI doctors for diagnosing.

H_{1c} PTTF affects physicians' intentions to use AI doctors for treatment planning.

H_{1d} PTTF affects physicians' intentions to use AI doctors for patient follow-up.

3.1.2. Performance expectancy (PE)

In this study, PE describes the extent to which physicians think using an AI doctor system would improve their work performance[79,80]. The most reliable indicator of intent to utilize, it is relevant in both voluntary and essential circumstances[72]. The results of many studies show that the contribution of AI technology to the performance of healthcare professionals is remarkable[5–11]. Furthermore, medical students are convinced that although AI technology poses a threat to human doctors, it will greatly contribute to their performance in the future[81].

H_{2a} PE affects physicians’ intentions to use AI doctors for data collecting.

H_{2b} PE affects physicians’ intentions to use AI doctors for diagnosis.

H_{2c} PE affects physicians’ intentions to use AI doctors for treatment planning.

H_{2d} PE affects physicians’ intentions to use AI doctors for patient follow-up.

3.1.3. Effort expectancy (EE)

EE describes the extent to which doctors think that utilizing a specific system would not require any physical or mental effort[79]. In this regard, EE may be viewed as an important factor, one of the features that have the most influence on acceptance, and a predictor of the intention to accept new technology.

H_{3a} EE affects physicians’ intentions to use AI doctors for data collecting.

H_{3b} EE affects physicians’ intentions to use AI doctors for diagnosis.

H_{3c} EE affects physicians’ intentions to use AI doctors for treatment planning.

H_{3d} EE affects physicians’ intentions to use AI doctors for patient follow-up.

3.1.4. Effort expectancy for patients (EEP)

AI technology is used not only by healthcare professionals but also by anyone who wants to manage their health[16]. For the AI system to achieve its goals, the user behavior of patients, who both provide data as input and as end users, is also important. The AI user behavior of patients is of great importance for a reliable AI system. Also, AI devices and applications must be user-friendly for patients, as they are the source of data.

H_{4a} EEP affects physicians’ intentions to use AI doctors for data collecting.

H_{4b} EEP affects physicians’ intentions to use AI doctors for diagnosing.

H_{4c} EEP affects physicians’ intentions to use AI doctors for treatment planning.

H_{4d} EEP affects physicians’ intentions to use AI doctors for patient follow-up.

3.1.5. Social influence (SI)

Someone’s assumptions about how other people would see a certain person’s behavior are known as SI[82]. The degree to which physicians behave under the influence of another individual, a group, or a social occasion is known as SI[83]. SI is essential for predicting if technology will be utilized[84,85].

H_{5a} SI affects physicians’ intentions to use AI doctors for data collecting.

H_{5b} SI affects physicians’ intentions to use AI doctors for diagnosis.

H_{5c} SI affects physicians’ intentions to use AI doctors for treatment planning.

H_{5d} SI affects physicians’ intentions to use AI doctors for patient follow-up.

3.1.6. Facilitating conditions (FC)

The degree to which the user has the resources and assistance required to utilize the technology is known as the facilitating conditions[72,84]. The user’s ability to get access to sufficient assets, necessary information, and support when needed facilitates the acceptance and utilization of the technology.

H_{6a} FC affects physicians’ intentions to use AI doctors for data collecting.

H_{6b} FC affects physicians' intentions to use AI doctors for diagnosis.

H_{6c} FC affects physicians' intentions to use AI doctors for treatment planning.

H_{6d} FC affects physicians' intentions to use AI doctors for patient follow-up.

3.1.7. Hedonic motivation (HM)

When utilizing technology, the sense of delight and pleasure is known as hedonic motivation. It is believed that feelings derived from human experience aid in technological adaptation[72]. Positive emotions have also been demonstrated to boost technology adoption and drive to utilize it. One of the most significant variables impacting behavioral intention is HM[84,86].

H_{7a} HM affects physicians' intentions to use AI doctors for data collecting.

H_{7b} HM affects physicians' intentions to use AI doctors for diagnosis.

H_{7c} HM affects physicians' intentions to use AI doctors for treatment planning.

H_{7d} HM affects physicians' intentions to use AI doctors for patient follow-up.

3.1.8. High-technology habit (HTH)

Habit is the degree to which people typically carry out activities automatically as a result of learning and experiences[72]. Familiarity with technologies facilitates the acceptance of new technologies. The adoption of AI doctors in healthcare is facilitated by features such as physicians' education and prior familiarity with information technologies[87].

H_{8a} HTH affects physicians' intentions to use AI doctors for disease prevention.

H_{8b} HTH affects physicians' intentions to use AI doctors for diagnosis.

H_{8c} HTH affects physicians' intentions to use AI doctors for treatment planning.

H_{8d} HTH affects physicians' intentions to use AI doctors for patient follow-up.

3.2. Measurement of variables

In this study, as in other studies on the acceptance of technologies[72,79,80,86], the intention to use the technology or the variables influencing its present usage is examined.

As seen in **Figure 1**, the research has been designed to measure physicians' intentions to use AI doctors. Previously validated measurements were used. Perceived task technology fit (PTTF)[4,73], performance expectancy (PE), effort expectancy (EE), effort expectancy (EEP), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), high-technology habit (HTH), and acceptance to use AI doctors (for data collection, diagnosis, treatment planning, and follow-up patients) were adapted from the UTAUT model[72].

In the instruction section of the data collection measurement, the definition of "AI doctors or AI-based decision support systems" was based on the WHO Digital Health Strategy Report: "The term refers to the use of medical and clinical information systems, mobile health apps, smart wearable health technologies, and health promotion apps" and physicians were asked to respond to the statements by rating how they intend to use AI to interact with patients in a holistic and patient-centric. Each indicator (as seen in **Table 1**) was rated on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree).

Table 1. Constructs' reliability, validity results.

Indicators					**Reliability**	**Validity**			
			Excess Kurtosis +/− 7	**Skewness +/− 2**	**Indicator reliability construct loading ≥ 0.70**		**Internal consistency reliability**		**Conv.Validity**
	Mean	**SD**				**VIF < 5**	**Cronbach's Alpha α ≥ 0.70**	**Composite reliability CR ≥ 0.70**	**AVE ≥ 0.50**
Perceived task-technology fit (PTTF)	4.29	0.96				2.69	0.920	0.944	0.808
I think that using AI will be well–suited to the way to do the doctor profession.	4.30	0.99	2.726	−1.699	0.868	2.492			
AI technology will be an excellent medium to provide a way to do doctors' professions.	4.30	0.96	2.119	−1.535	0.923	3.805			
Using AI doctors will fit well with the way to manage healthcare services.	4.19	0.96	1.508	−1.274	0.893	2.879			
I think that using AI doctors will be a good way to manage medical practices.	4.37	0.92	3.042	−1.746	0.910	3.409			
Performance expectancy (PE)	4.126	0.992				2.90	0.895	0.934	0.826
I find AI technology useful in my work life.	4.082	0.991	0.213	−0.888	0.932	3.533			
In my work. using AI Technology helps me accomplish things more quickly.	4.153	0.991	0.611	−1.085	0.900	2.777			
Using AI technology increases my productivity.	4.144	0.995	0.925	−1.150	0.894	2.398			
Effort expectancy (EE)	3.784	1.036				1.92	0.723	0.816	0.528
Learning how to use AI doctors is easy for me.	3.709	1.042	–0.388	−0.466	0.809	1.582			
My interaction with AI doctors is clear and understandable.	4.224	0.850	1.029	−1.061	0.791	1.284			
I find AI doctors easy to use.	3.588	1.168	–0.793	−0.34	0.634	1.490			
It is easy for me to become skillful at using AI doctors.	3.613	1.084	–0.541	−0.372	0.656	1.556			
Effort expectancy for patient (EEP)	1.814	0.943				1.14	0.892	0.923	0.750
For Patients. their interaction with AI doctors will be clear and understandable.	1.780	0.926	1.464	1.258	0.839	1.902			
Patients will find AI doctors easy to use.	1.711	0.926	1.470	1.349	0.853	3.087			
It will be easy for patients skillful use AI doctors.	1.741	0.889	1.445	1.232	0.920	3.483			
Learning how to use AI doctors will be easy for patients.	2.025	1.031	0.619	1.008	0.849	2.297			

Table 1. (*Continued*).

Indicators					**Reliability**	**Validity**			
			Excess Kurtosis +/− 7	**Skewness +/− 2**	**Indicator reliability construct loading ≥ 0.70**		**Internal consistency reliability**		**Conv.Validity**
	Mean	**SD**				**VIF < 5**	**Cronbach's Alpha α ≥ 0.70**	**Composite reliability CR ≥ 0.70**	**AVE ≥ 0.50**
Social influence (SI)	3.720	0.999				2.01	0.782	0.873	0.697
People who are important to me think that I should use AI doctors.	3.776	1.007	−0.004	−0.599	0.859	1.729			
People who influence my behavior think that I should use AI doctors.	3.619	1.048	−0.336	−0.406	0.778	1.464			
People whose opinions I value prefer that I use AI doctors.	3.766	0.942	0.091	−0.528	0.864	1.858			
Facilitating conditions (FC)	4.215	0.999				1.84	0.864	0.916	0.786
I have the resources necessary to use AI doctors.	4.044	1.146	0.425	−1.098	0.778	1.645			
I know necessary to use AI doctors	4.314	0.916	2.491	−1.531	0.939	3.568			
I can get help from others when I have difficulties using AI tech.	4.287	0.935	1.790	−1.401	0.935	3.507			
Hedonic motivation (HM)	3.506	1.125				1.88	0.818	0.892	0.734
As a doctor. using AI technology is fun.	3.234	1.086	−0.631	0.055	0.872	2.623			
Using AI doctors is enjoyable.	3.513	1.026	−0.577	−0.15	0.889	2.686			
As a doctor. using AI doctors is very entertaining.	3.770	1.262	−0.597	−0.701	0.807	1.416			
High–tech habit (HTH)	4.258	0.973				3.13	0.810	0.888	0.725
The use of high–tech devices/apps has become a habit for me.	4.287	0.961	1.285	−1.366	0.824	1.545			
I am addicted to using high–tech devices/apps.	4.157	1.012	0.502	−1.072	0.853	1.952			
I must use AI tech devices/apps.	4.331	0.946	1.999	−1.536	0.878	2.137			
Behavioral intention data collection	4.043	1.043					0.866	0.918	0.790
I intend to use AI tech for patients' health data in the future.	3.914	1.086	−0.565	−0.616	0.917	2.939			
I will always try to use AI tech for collecting data in my daily work life.	4.197	0.976	0.54	−1.093	0.920	3.037			
I plan to use AI technology frequently for collecting patients' health data.	4.019	1.068	−0.321	−0.783	0.825	1.768			
Behavioral intention for diagnose	4.125	0.997					0.744	0.853	0.660
I intend to use AI tech for diagnosing in the future.	4.188	1.009	1.392	−1.339	0.750	1.423			
I will always try to use AI doctors in diagnosing in my daily work life.	3.895	1.056	−0.215	−0.646	0.859	1.692			
I plan to use AI technology frequently for diagnosing.	4.293	0.927	1.655	−1.388	0.824	1.460			

Table 1. (*Continued*).

Indicators					**Reliability**		**Validity**		
			Excess Kurtosis +/− 7	**Skewness +/− 2**	**Indicator reliability construct loading ≥ 0.70**		**Internal consistency reliability**		**Conv.Validity**
						VIF < 5	**Cronbach's Alpha α ≥ 0.70**	**Composite reliability CR ≥ 0.70**	**AVE ≥ 0.50**
	Mean	**SD**							
Behavioral intention for treatment planning	4.029	1.062					0.782	0.872	0.694
I intend to use AI tech for treatment in the future.	4.029	1.103	0.233	−1.043	0.861	2.645			
I will always try to use AI doctors in treatment in my daily work life.	4.002	1.099	−0.26	−0.859	0.848	2.558			
I plan to use AI technology frequently for treatment.	4.056	0.985	0.471	−0.971	0.788	1.266			
Behavioral intention for patient follow–up	4.081	1.01					0.726	0.845	0.646
I intend to use AI tech for follow–up with regular patients in the future.	4.238	0.949	1.476	−1.331	0.874	1.772			
I will always try to use AI doctors in following patients in my daily work life.	4.504	0.745	3.839	−1.763	0.793	1.385			
I plan to use AI technology frequently for follow–up patients.	3.500	1.324	−0.969	−0.442	0.738	1.441			

The research model utilized the causal comparison screening approach, which is useful when it is required to discover the causes and effects of a person's attitudes, and behaviors[88]. On 478 replies, two statistical methods, called Partial Least Squares Structural Equation Modeling (PLS-SEM), and artificial neural network (ANN) have been employed. Firstly, the research model hypotheses have been evaluated by SEM to explore the linear relationships between the constructs. In the second phase, the nonlinear relationships between the constructs have been examined by ANN. SEM analysis was done with SmartPLS 3.3.2 and ANN analysis was done with the SPPS 25 statistical program.

3.3. Sample and data collection

The data was collected on paper from physicians who are currently using smart health technologies and AIs in research hospitals. The study included 503 physicians, missing survey responses were excluded, and 478 responses were used for analysis. There are 247 females and 231 males in the sample. 179 participants are between the ages of 22 and 72, 176 are between the ages of 30–39, 147 are between the ages of 40 and 49, and 83 are over the age of 50. There are 144 specialists and 334 generalists among the participants.

3.4. PLS-SEM analysis

Preliminary analysis of the research model

A preliminary analysis of the research model has been performed, as proposed by Hair and his co-authors[89]. As seen in **Table 1**, the outer loadings of the indicators, Cronbach's alpha, and composite reliabilities (CRs) of constructs are greater than the cut-off of 0.70, and all average variance extracted values (AVEs) of the constructs are greater than 0.50. The indicators' Excess Kurtosis values are between +/− 7, and the skewness values are between +/− 2. For collinearity between the indicators, the variance inflation factor (VIF) values have been examined. If the VIF values are equal to or more than 5, this indicates that the model may have been contaminated by common method bias. The collinearity of the indicators included in the research model study is unproblematic, the indicators' VIF values range between 1.266 and 3.805.

Additionally, Harman's single-factor analysis has also been conducted for the common method bias analysis. As the result of the analysis, the extraction sum of squared loadings is 0.42 (Cumulative). Since the threshold value is 0.50, it is accepted that there is no common method bias problem[90,91].

As seen in **Table 2**, the Heterotrait-Monotrait (HTMT) correlation ratios are less than 0.95, the AVEs are larger than squared inter-construct correlations, and the HTMT-ratio and Fornell-Larcker standards for discriminant validity have been satisfied.

Table 2. The fornel-larcker discriminant validity and the HTMT correlation matrix.

	Fornel-lacker												**HTMT**											
	DC BI	**D BI**	**EE**	**EEP**	**FC**	**FUP BI**	**HM**	**PTTF**	**PE**	**SI**	**HTH**	**T BI**	**DC BI**	**D BI**	**EE**	**EEP**	**FC**	**FUP BI**	**HM**	**PTTF**	**PE**	**SI**	**HTH**	**T BI**
DC BI	0.889																							
D BI	0.681	0.813											0.834											
EE	0.629	0.613	0.727										0.747	0.737										
EEP	0.140	0.146	0.110	0.866									0.149	0.167	0.166									
FC	0.547	0.559	0.509	–0.012	0.887								0.615	0.685	0.592	0.045								
FUP BI	0.574	0.681	0.553	0.064	0.640	0.804							0.714	0.922	0.656	0.112	0.778							
HM	0.609	0.671	0.514	0.277	0.440	0.581	0.856						0.718	0.859	0.621	0.318	0.512	0.753						
PTTF	0.683	0.822	0.616	0.063	0.553	0.615	0.518	0.899					0.761	0.975	0.681	0.073	0.609	0.740	0.592					
PE	0.739	0.721	0.578	0.090	0.575	0.580	0.575	0.720	0.909				0.829	0.869	0.632	0.089	0.641	0.708	0.669	0.792				
SI	0.602	0.625	0.526	0.181	0.521	0.579	0.518	0.611	0.612	0.835			0.724	0.810	0.628	0.206	0.619	0.768	0.638	0.717	0.726			
HTH	0.728	0.742	0.611	0.058	0.624	0.645	0.593	0.708	0.742	0.617	0.852		0.871	0.944	0.747	0.078	0.732	0.826	0.727	0.818	0.871	0.768		
T BI	0.659	0.786	0.597	0.153	0.556	0.688	0.673	0.701	0.690	0.610	0.628	0.833	0.774	0.927	0.686	0.169	0.645	0.893	0.827	0.798	0.802	0.755	0.766	

PTTF: Perceived task-technology fit; **PE**: Performance expectancy, **EE**: Effort expectancy, **EEP**: Effort expectancy for patients; **HTH**: High-tech habit; **FC**: Facilitating conditions; **SI:** Social influence; **HM**: Hedonic motivation; **DCBI**: Data collection behavioral intention; **D BI**: Diagnose behavioral intention; **T BI**: Treatment planning behavioral intention; **FUP BI**: Follow-up patient behavioral intention.

The Standardized Root Mean Square Residual (SRMR), an absolute measurement of model fit, and Root Mean Square Residual (RMStheta) analysis are recommended by Hair and his co-authors[89]. The research model's SRMR value is 0.06, which is lower than the literature's recommended cut-off threshold. The research model's RMStheta result is 0.12, which indicates a moderate research model.

The internal consistency reliability, convergent, and divergent validity of the research model are all granted.

3.5. Structural equation modeling path analysis

Following the approval of the research model's convergent, divergent, and internal consistency, as stated by Hair and his co-authors[89], the research model path analysis was completed. The bootstrapping approach (5000 resamples) was used to assess the hypotheses.

According to SEM results, as shown in **Table 3**:

Table 3. Results of structural equation modeling path analysis and hypothesis testing.

	Hypothesized paths		R^2	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	*P* values	
H_{1a}	Perceived task-technology fit ->	Data Collection	0.67	0.118	0.115	0.062	1.903	0.056	Not supported
H_{2a}	Performance expectancy ->			0.279	0.282	0.052	5.384	0.000	Supported
H_{3a}	Effort expectancy ->			0.149	0.149	0.038	3.920	0.000	Supported
H_{4a}	Effort expectancy for patients ->			0.030	0.030	0.028	1.064	0.287	Not supported
H_{5a}	Social influence ->			0.065	0.065	0.042	1.558	0.119	Not supported
H_{6a}	Facilitating conditions ->			0.021	0.023	0.045	0.464	0.643	Not supported
H_{7a}	Hedonic motivation ->			0.135	0.133	0.035	3.874	0.000	Supported
H_{8a}	High-tech habit ->			0.212	0.210	0.062	3.410	0.001	Supported
H_{1b}	Perceived task-technology fit ->	Diagnosis	0.78	0.494	0.493	0.039	12.551	0.000	Supported
H_{2b}	Performance expectancy ->			0.066	0.067	0.040	1.665	0.096	Not supported
H_{3b}	Effort expectancy ->			0.022	0.023	0.030	0.758	0.448	Not supported
H_{4b}	Effort expectancy for patients ->			0.024	0.025	0.020	1.190	0.234	Not supported
H_{5b}	Social influence ->			0.041	0.041	0.032	1.274	0.203	Not supported
H_{6b}	Facilitating conditions ->			0.016	0.016	0.032	0.510	0.610	Not supported
H_{7b}	Hedonic motivation ->			0.242	0.239	0.040	6.123	0.000	Supported
H_{8b}	High-tech habit ->			0.149	0.151	0.039	3.849	0.000	Supported
H_{1c}	Perceived task-technology fit ->	Treatment Planning	0.67	0.282	0.277	0.049	5.741	0.000	Supported
H_{2c}	Performance expectancy ->			0.191	0.190	0.054	3.532	0.000	Supported
H_{3c}	Effort expectancy ->			0.095	0.097	0.040	2.365	0.018	Supported
H_{4c}	Effort expectancy for patients ->			0.007	0.008	0.026	0.263	0.793	Not supported
H_{5c}	Social influence ->			0.106	0.105	0.043	2.480	0.013	Supported
H_{6c}	Facilitating conditions ->			0.103	0.104	0.036	2.841	0.005	Supported
H_{7c}	Hedonic motivation ->			0.321	0.320	0.053	6.022	0.000	Supported
H_{8c}	High-tech habit ->			–0.092	–0.088	0.053	1.722	0.085	Not supported
H_{1d}	Perceived task-technology fit ->	Follow-up Patients	0.59	0.153	0.151	0.047	3.229	0.001	Supported
H_{2d}	Performance expectancy ->			–0.044	–0.046	0.047	0.920	0.357	Not supported
H_{3d}	Effort expectancy ->			0.076	0.076	0.045	1.690	0.091	Not supported
H_{4d}	Effort expectancy for patients ->			–0.041	–0.041	0.033	1.213	0.225	Not supported
H_{5d}	Social influence ->			0.131	0.132	0.049	2.673	0.008	Supported
H_{6d}	Facilitating conditions ->			0.296	0.297	0.051	5.857	0.000	Supported
H_{7d}	Hedonic motivation ->			0.227	0.229	0.040	5.649	0.000	Supported
H_{8d}	High-tech habit ->			0.124	0.126	0.061	2.026	0.043	Supported

From perceived task-technology fit to diagnosis (H1b - β: 0.493; *t*-value: 12.551; *p*-value: 0.000), to treatment planning (H1c - β: 0.282; *t*-value: 5.741; *p*-value: 0.000); to follow-up patients (H1d - β: 0.153; *t*-value: 3.229; *p*-value: 0.001);

From performance expectancy to data collection (H2a - β: 0.279; *t*-value: 5.384; *p*-value: 0.000), to treatment planning (H2c - β: 0.190; *t*-value: 3.532; *p*-value: 0.000);

From effort expectancy to data collection (H3a - β: 0.149; *t*-value: 3.920; *p*-value: 0,000); to treatment planning (H3c - β: 0.095; *t*-value: 2.365; *p*-value: 0.018);

From social influence on treatment planning (H5c - β: 0.106; *t*-value: 2.480; *p*-value: 0.013); to follow-up patients (H5d - β: 0.131; *t*-value: 2.673; *p*-value: 0.008);

From facilitating conditions to treatment planning (H6c - β: 0.104; *t*-value: 2.841; *p*-value: 0.005); to follow-up patients (H6d - β: 0.297; *t*-value: 5.857; *p*-value: 0.000);

From hedonic motivation to data collection (H7a - β: 0.135; *t*-value: 3.874; *p*-value: 0.000), to diagnosis (H7b - β: 0.242; *t*-value: 6.123; *p*-value: 0.000), to treatment planning (H7c - β: 0.321; *t*-value: 6.022; *p*-value: 0.000); to follow-up patients (H7d - β: 0.227; *t*-value: 5.649; *p*-value: 0.000).

From high-tech habits to data collection (H8a - β: 0.212; *t*-value: 3.410; *p*-value: 0.001), diagnosis (H8b - β: 0.149; *t*-value: 3.849; *p*-value: 0.000), follow-up patients (H8d - β: 0.124; *t*-value: 2.026; *p*-value: 0.043), positive and significant impacts have been found. H1b, H1c, H1d, H2a, H2c, H3a, H3c, H5c, H5d, H6c, H6d, H7a, H7b, H7c, H7d, H8a, H8b, and H8d have been supported. Other hypotheses have not been statistically supported.

PLS-SEM independent constructs' important-performance map

Table 3 copious amounts of data making it challenging for readers to comprehend and appropriately interpret the findings. Because of this, the goal was to make reading easier for the reader by using IPMA graphics for visualization.

Importance-performance map analysis (IPMA) results are focused on identifying the relative importance of constructs (latent variables) in the PLS model. The importance reflects the absolute overall effect on the selected construct. The performance reflects the strength of the latent variable values[92]. Performance is a measure of the fact that a construct is more powerful if it has higher mean latent variable scores, reflecting stronger measurement paths. **Figures 2**, **3**, **4**, and **5** display the IPMA results, and the study's results and conclusion section provide an interpretation of the results[4].

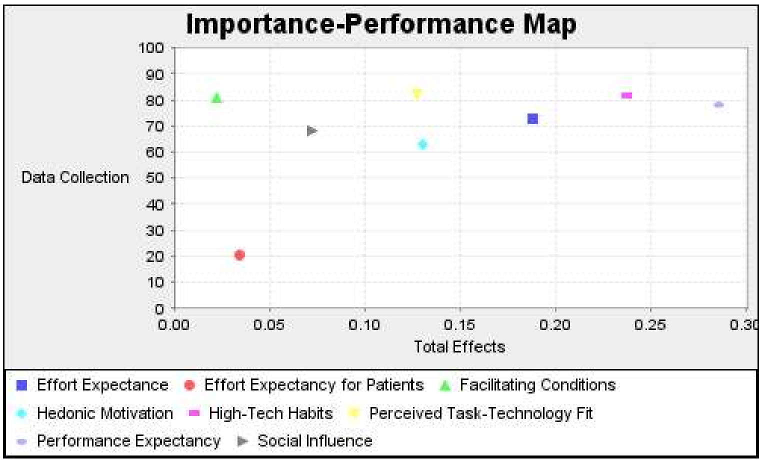

Figure 2. Independent constructs' important-performance map for data collection.

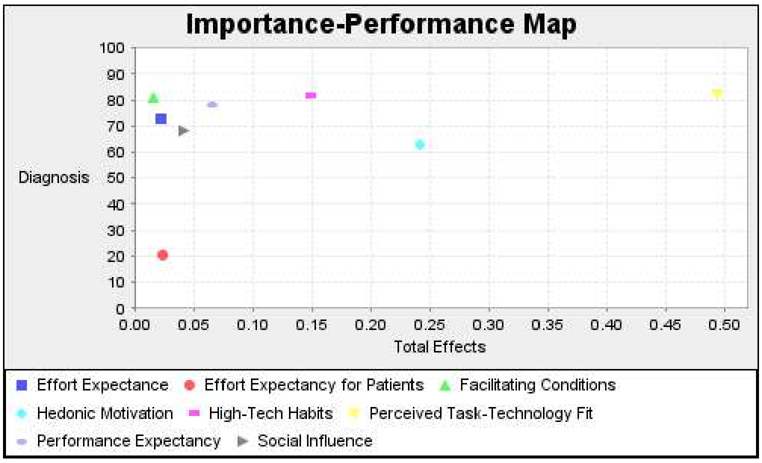

Figure 3. Independent constructs' important-performance map for diagnosis.

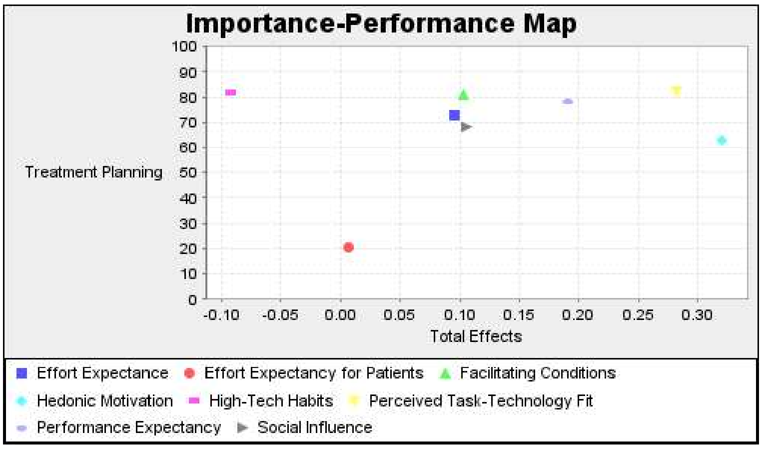

Figure 4. Independent constructs' important-performance map for treatment planning.

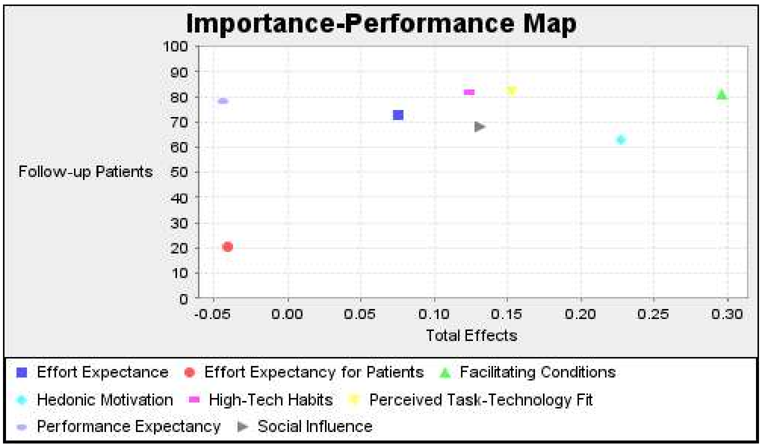

Figure 5. Independent constructs' important-performance map for follow-up patients.

3.6. Artificial neural network analysis (ANN)

ANN, or machine deep learning algorithm, is used to simulate how the human brain performs various tasks and functions[93]. An ANN model has three layers: an input layer, a hidden layer, and an output layer. When a dependent construct is linked to independent constructs, ANN understands, explains, and predicts the dependent construct using feed-forward, back-propagation, and multi-layer perception techniques[94]. This is a computer-generated simulation of human brain neurons and their pre-existing synaptic connections. Neurons connect in a variety of ways to form networks during the learning process. These networks can learn, remember, and connect many different constructs[93]. Synaptic weights store the knowledge gained during learning[95].

According to the study's goals four sub-models, as seen in **Figure 6** (disease prevention, diagnosis, treatment planning, and follow-up patient) were created for the ANN test inside the context of the research model. The models have nine neurons (with bias). In **Figure 2**, biases, H (1:1), and H (1:2) are shown as the ANN's hidden layers. Each dependent construct has been reflected by one neuron in the output layer.

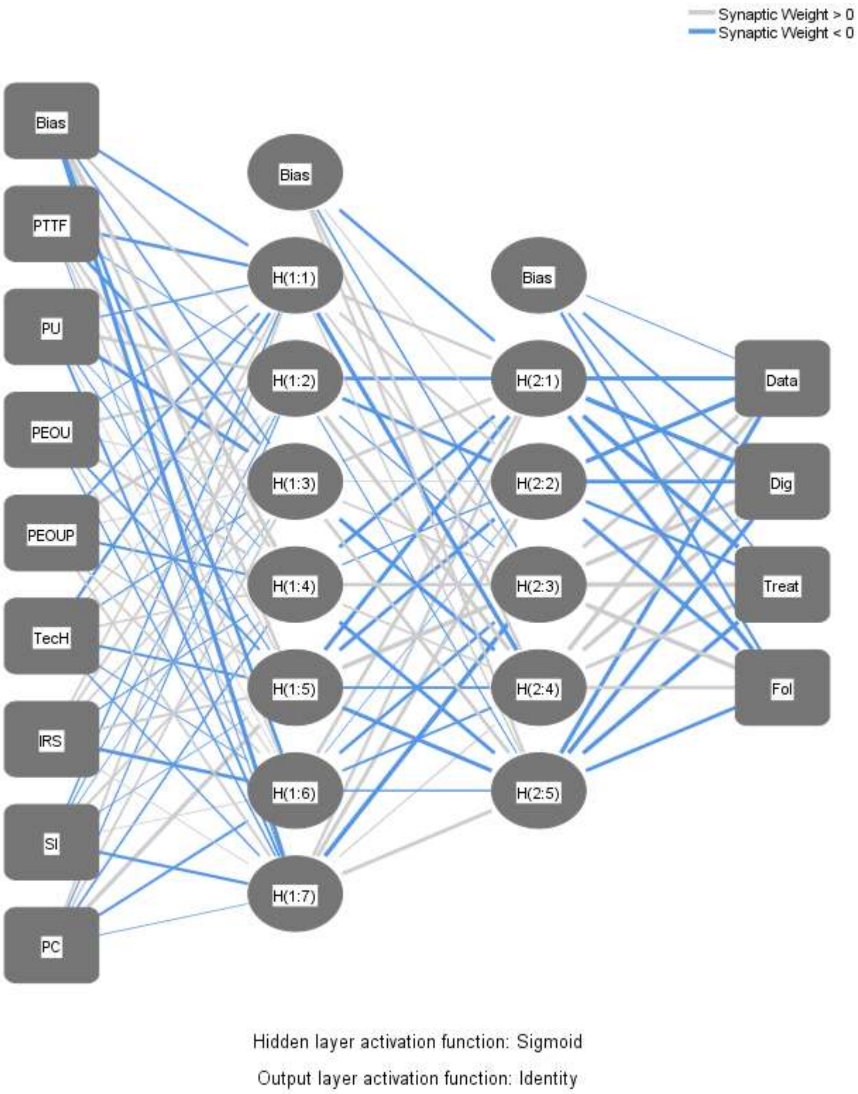

Figure 6. Artificial neural networks analysis models.

Seventy percent of the data was used for training, while thirty percent was used for testing. **Table 4** shows that the ANN models have been trained ten times without any assumption about a research model. Training can create connections between independent and dependent constructs, as illustrated in **Figure 6**. A ten-fold cross-validation method has been utilized to avoid overfitting[93,94,96].

Table 4. RMSE and R^2 values.

Data collection							**Diagnosis**						
Training			**Testing**				**Training**			**Testing**			
N	**SSE**	**RMSE**	**N**	**SSE**	**RMSE**	**R^2**	**N**	**SSE**	**RMSE**	**N**	**SSE**	**RMSE**	**R^2**
326	3.142	0.098	152	1.466	0.098	0.990	345	1.643	0.069	133	0.846	0.080	0.995
340	2.946	0.093	138	1.159	0.092	0.991	335	1.743	0.072	143	0.686	0.069	0.995
322	2.785	0.093	156	1.341	0.093	0.991	332	1.683	0.071	146	0.622	0.065	0.995
321	3.306	0.101	157	1.255	0.089	0.990	352	1.971	0.075	126	0.775	0.078	0.994
329	2.704	0.091	149	1.563	0.102	0.992	331	1.793	0.074	147	0.782	0.073	0.995
346	3.281	0.097	142	0.881	0.079	0.991	329	1.659	0.071	149	0.783	0.072	0.995
329	3.217	0.099	149	1.58	0.103	0.990	337	1.468	0.066	141	0.788	0.075	0.996
333	3.104	0.097	145	1.427	0.099	0.991	322	1.615	0.071	156	0.712	0.068	0.995
338	3.153	0.097	140	1.275	0.095	0.991	348	1.883	0.074	130	0.559	0.066	0.995
338	2.784	0.091	140	1.511	0.104	0.992	326	1.803	0.074	152	0.716	0.069	0.994
Average	3.042	0.096		1.346	0.095	0.991		1.726	0.078		0.727	0.072	0.995
Treatment planning							**Follow-up patient**						
Training			**Testing**				**Training**			**Testing**			
N	**SSE**	**RMSE**	**N**	**SSE**	**RMSE**	**R^2**	**N**	**SSE**	**RMSE**	**N**	**SSE**	**RMSE**	**R^2**
329	3.21	0.099	149	1.094	0.086	0.990	335	3.026	0.095	143	1.326	0.096	0.991
328	2.959	0.095	150	1.292	0.093	0.991	325	3.188	0.099	153	1.42	0.096	0.990
328	3.296	0.100	150	1.081	0.085	0.990	314	3.186	0.101	164	1.608	0.099	0.990
327	2.816	0.093	151	1.534	0.101	0.991	325	3.297	0.101	153	1.376	0.095	0.990
333	2.93	0.094	145	1.459	0.100	0.991	357	3.072	0.093	121	1.69	0.118	0.991
318	2.82	0.094	160	1.744	0.104	0.991	317	2.903	0.096	161	1.44	0.095	0.991
351	3.22	0.096	127	1.266	0.100	0.991	327	3.337	0.101	151	1.228	0.090	0.990
332	2.906	0.094	146	1.462	0.100	0.991	324	3.377	0.102	154	1.424	0.096	0.990
351	3.212	0.096	127	1.056	0.091	0.991	341	3.311	0.099	137	1.285	0.097	0.990
330	3.602	0.104	148	1.42	0.098	0.989	339	3.033	0.095	139	1.503	0.104	0.991
Average	3.097	0.097		1.341	0.096	0.991		3.17	0.098		1.43	0.099	0.990

The root-mean-square error (RMSE) values are used to evaluate the results of the ANN model analysis. The minimal and similar RMSE values indicate the high model fit and forecast accuracy[94]. As shown in **Table 4**, the models' RMSE values are low, and ANN models are accurate and effective. The analysis of the R^2 coefficient indicated[95] that ANN models account for 0.99% of the variance in physicians' acceptance of using AI.

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The ANN models' input neurons are ranked according to their normalized importance (NI) using sensitivity analysis[94].

4. Results

As seen in **Table 1**, physicians' intention to use for data collection (avg: 4.04, sd: 1.04), diagnosis (avg: 4.13, sd: 0.99), treatment planning (avg: 4.13, sd: 1.06), and follow-up patients (avg: 4.03, sd: 1.01) is high.

When SEM-IPMA analysis results are examined, as seen in **Figure 3**, the most influential constructs on the behavioral intention of physicians to use AI for data collection are performance expectancy (0.29), high-tech habit (0.24), and effort expectancy (0.19).

As seen in **Figure 4**, the most influential constructs on the behavioral intention of physicians to use AI for diagnosis are perceived task-technology fit (0.47), hedonic motivation (0.21), and high-tech habits (0.15).

In **Figure 5**, the most influential constructs on the behavioral intention of physicians to use AI for treatment planning are perceived task-technology fit (0.29), hedonic motivation (0.29), and performance expectancy (0.19).

In **Figure 6**, the most influential constructs on the behavioral intention of physicians to use AI for follow-up patients are facilitating conditions (0.26), and hedonic motivation (0.18).

According to ANN analysis results as seen in **Figure 7** and **Table 5**, the most influential constructs on the behavioral intention to use for data collection are performance expectancy, high-tech habit, effort expectancy, and perceived task-technology fit.

Table 5. Independent constructs' importance.

	Data collection		**Diagnosis**		**Treatment planning**		**Follow-up patient**	
	I	**NI**	**I**	**NI**	**I**	**NI**	**I**	**NI**
PTTF	0.122	50.80%	0.402	100.00%	0.285	100.00%	0.034	12.30%
PE	0.24	100.00%	0.046	11.50%	0.133	46.70%	0.023	8.40%
EE	0.139	57.80%	0.023	5.80%	0.067	23.60%	0.007	2.40%
EEP	0.041	17.20%	0.037	9.30%	0.058	20.40%	0.025	9.00%
HTH	0.195	81.30%	0.112	27.80%	0.05	17.70%	0.189	67.70%
FC	0.025	10.60%	0.046	11.40%	0.146	51.20%	0.171	61.40%
SI	0.078	32.70%	0.062	15.50%	0.032	11.20%	0.273	97.90%
HM	0.159	66.20%	0.271	67.40%	0.23	80.70%	0.279	100.00%

PTTF: Perceived task-technology fit; **PE**: Performance expectancy, **EE**: Effort expectancy, **EEP**: Effort expectancy for patients; **HTH**: High-tech habit; **FC**: Facilitating conditions; **SI:** Social influence; **HM**: Hedonic motivation.

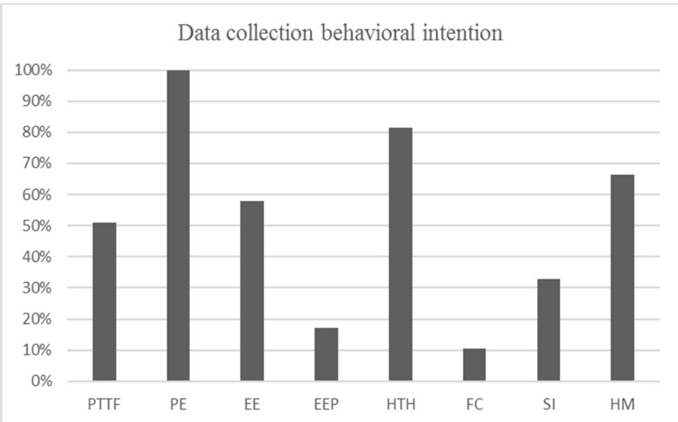

Figure 7. Data collection behavioral intention importance.
PTTF: Perceived task-technology fit; **PE**: Performance expectancy, **EE**: effort expectancy, **EEP**: Effort expectancy for patients; **HTH**: High-tech habit; **FC**: Facilitating conditions; **SI:** Social influence; **HM**: Hedonic motivation.

In **Figure 8** and **Table 5**, the most influential constructs on the behavioral intention to use for diagnosis are perceived task-technology fit, hedonic motivation, and high-tech habits.

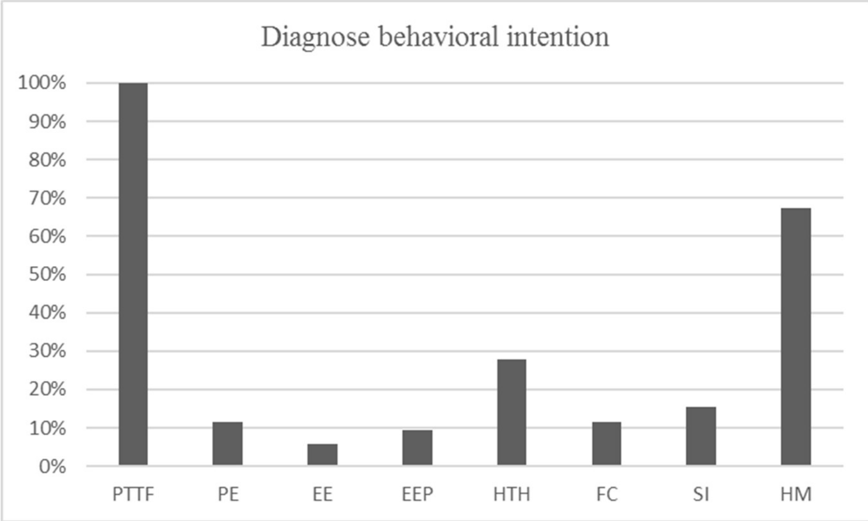

Figure 8. Diagnose behavioral intention importance.
PTTF: Perceived task-technology fit; **PE**: Performance expectancy, **EE**: effort expectancy, **EEP**: Effort expectancy for patients; **HTH**: High-tech habit; **FC**: Facilitating conditions; **SI:** Social influence; **HM**: Hedonic motivation.

In **Figure 9** and **Table 5**, the most influential constructs on the behavioral intention to use for treatment planning are perceived task-technology fit, hedonic motivation, facilitating conditions, and performance expectancy.

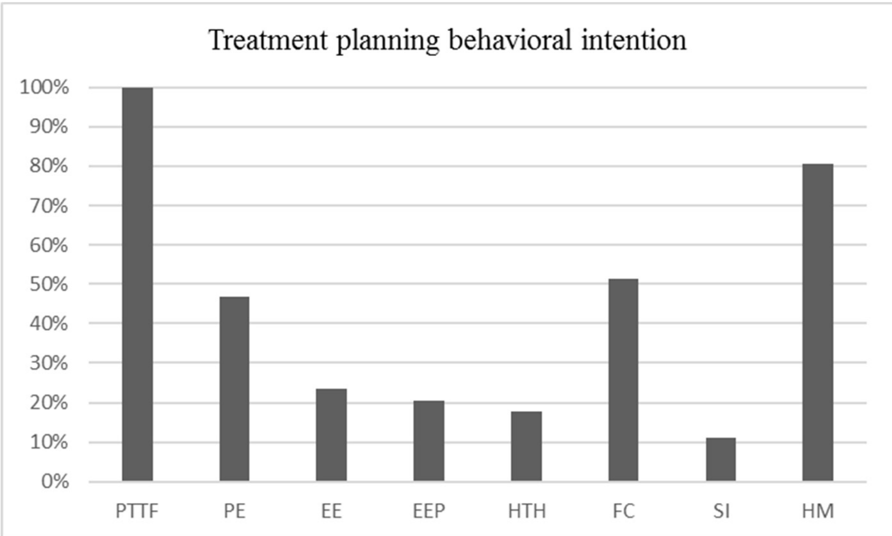

Figure 9. Treatment planning behavioral intention importance.
PTTF: Perceived task-technology fit; **PE**: Performance expectancy, **EE**: effort expectancy, **EEP**: Effort expectancy for patients; **HTH**: High-tech habit; **FC**: Facilitating conditions; **SI:** Social influence; **HM**: Hedonic motivation.

In **Figure 10** and **Table 5**, the most influential constructs on the behavioral intention to use for follow-up patients are facilitating conditions, hedonic motivation, social influence, and high-tech habits.

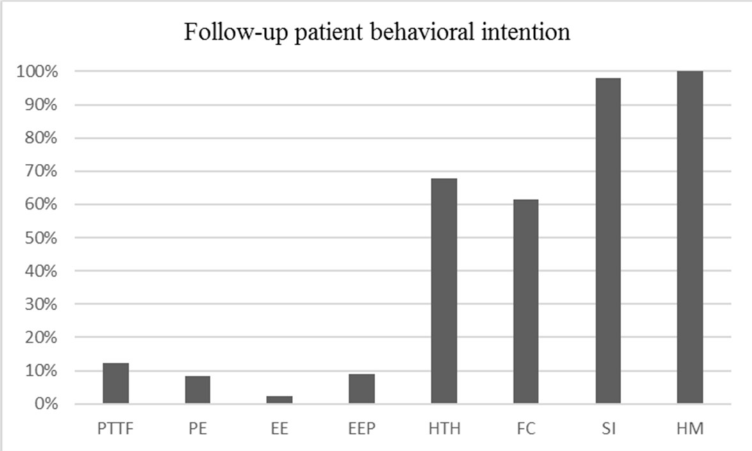

Figure 10. Follow-up patient behavioral intention importance.
PTTF: Perceived task-technology fit; **PE**: Performance expectancy, **EE**: effort expectancy, **EEP**: Effort expectancy for patients; **HTH**: High-tech habit; **FC**: Facilitating conditions; **SI:** Social influence; **HM**: Hedonic motivation.

4.1. Conclusion

The world's population is growing and aging. While people are living longer, chronic diseases are increasing for many reasons. Worldwide, countries' healthcare budgets consume a significant portion of their gross domestic product[97]. Healthcare services and systems are on the verge of major change. This change has begun, albeit piecemeal, and is both imperative and inevitable for almost all stakeholders.

AI technology can provide solutions to the problems and new goals of the healthcare system. In healthcare, AI doctors, AI coaches, and AI nurses are already available, but not as a holistic AI system. Governments, insurance companies, technology research and development companies, device manufacturers, insurance companies, hospitals, and medical professionals—all significant players in the healthcare system—are already searching for ways to expand AI's usability.

According to the results, physicians are convinced that AI is suitable for medical practices. In terms of perceived task-technology fit, physicians believe that AI is a useful tool to perform a physician's tasks. In other words, the technology and the tasks overlap. This result is in line with the goals and expectations of healthcare stakeholders.

When the research results were examined in terms of constructs that can be seen as individual personality traits, high technology habits, and hedonic motivation, as seen in **Table 1**, it was determined that physicians' high-tech habits are significantly high. In the meantime, the effort expectancy construct is moderate, but the "My interaction with AI doctors is clear and understandable" indicator's mean is higher than other indicators. These findings suggest that physicians are predisposed to technology and have the knowledge, expectations, and foresight to raise awareness as users of AI for use in their medical practices.

Based on the results in **Tables 1** and **3**, physicians follow new technologies. Hedonic motivation to use AI is moderate. Although they are willing to adopt new technologies and are aware of the principles and procedures of the AI technology-physician relationship, their motivation is moderate. Even though AI is a popular topic in healthcare, as in many fields, it has been found that physicians perceive it as a threat to themselves[98]. Medical students recognize the contribution of AI to their performance and careers, but they still consider it a threat[99]. Also, it can be said that using AI or high technology in their work will increase both their motivation and job satisfaction.

While social influence is an important construct in many technology acceptance studies[72,80,86], as seen in **Table 1**, it has a moderate value. This raises a critical question: In a market where consumer satisfaction and financial success are critical, is health care a product or a public service?[100–103]. Physicians who embrace healthcare as a public service manage the patient-physician relationship accordingly, so they act independently of the influence of others, including their patients[104,105].

Also, research results indicate a more critical situation in that physicians have hesitations about collecting data where AI technology is already strong. The patient follow-up system also works depending on the data collection function. As a result of the study, there is no statistically significant relationship between AI and data collection. These results do not support the goals and objectives of organizations that determine healthcare policies around the world.

Firstly, AI's data collection capacity with smart devices and revealing information is far beyond human capacity. However, it has been determined that physicians have hesitations about data collection. It is anticipated that this hesitation is related to the reliability of the collected data. Because the same physicians stated that AI is suitable for diagnosis and treatment planning stages. In both stages, valid and reliable data is required to make the right decisions. Studies have emphasized the importance of valid and reliable data for the operation of AI technology[4,14,47,48]. Therefore, it can be said that there are problems in the data collection process due to reasons other than the inadequacy of AI.

Secondly, sector regulators develop policies and strategies to prevent diseases. Being cautious before a disease occurs with a proactive attitude is more meaningful in terms of both the workload of the health system and the health budget. A disease prevention system requires a valid and reliable data flow.

According to the results, physicians are convinced that AI doctors are exceptionally suitable for diagnosis and treatment, and AI increases their efficiency and productivity. When the history of AI is examined, it is evident that diagnosis and treatment planning are the priorities. These research results are not surprising because using these functions is more familiar to physicians.

The use of AI technology in healthcare seems inevitable to some scientists[14]. It is predicted that the formation and operation of the holistic AI health system will be supported by physicians who are moderate to new technologies. It should not be forgotten that other stakeholders in this system should also fulfill the behavioral requirements.

4.2. Public contribution

The outcome of this study contributes to governments, hospitals, universities, insurance companies, technology developers, and healthcare professionals.

Firstly, physicians are convinced that AI doctors will contribute to their performance, and health technology developers are recommended to develop AI health applications and devices for data collection, diagnosis, treatment planning, and follow-up patients. A strong AI health system will reduce the workload and expenditures in healthcare for governments and health sector organizations and professionals.

In terms of physicians, the acceptance and usage intention of AI is moderate at every stage within the patient-doctor relationship. Technology developers and manufacturers can develop AI doctors by considering the patient-doctor relationship holistically, as well as developing AI doctors for the diagnosis and treatment of chronic and rare diseases. AI doctors can collect and analyze various data about a patient and share it with physicians; they can be coaches for patients who have chronic diseases. Furthermore, the outputs of the AI working at the individual level are linked to a system that can be accessed by authorized people and organizations. All shareholders will benefit from the AI healthcare system.

The need for patients and human doctors to be in the same space will be eliminated by AI doctors. Access to basic health services will be made easier for those who live in rural areas. Nonetheless, AI physicians will advise people to take precautions before becoming ill. Risk can be categorized and defined based on how patients behave. Like auto insurance, patients who pose a greater risk to their health may have higher health insurance co-payments, while those who do not pose a risk may have lower co-payments.

A legal framework needs to be in place, regardless of the name given to artificial intelligence in healthcare. For patients, medical professionals, and companies offering AI healthcare services, this legal framework is essential.

AI is already perceived as a threat by healthcare professionals. Studies conducted on students majoring in healthcare fields reveal that these students acknowledge the inevitability of AI use and how it will improve their performance. There will be many people who will not give up their physicians and who will not want to use AI doctors. Therefore, it is recommended that healthcare financiers, such as insurance companies, prepare various healthcare plans, programs, and packages. These packages should be designed not only for patients but also for physicians, because only a portion of the process can be managed by them. When the healthcare system shifts from being disease-oriented to patient-oriented, user-friendly AI technologies must be ready for all users, not just doctors.

4.3. Future studies

This study examines the place of AI in the patient-doctor relationship from the point of view of physicians with a holistic approach. This study can also be done at the primary, secondary, and tertiary levels, but also separately for inpatients, outpatients, and chronic diseases.

Also, qualitative studies are recommended for an in-depth understanding of the AI health system with all stakeholders in the health system. Although the AI system is technically considered sufficient, it is recommended to examine and understand the other factors, especially the attitudes and behaviors of AI healthcare actors, that will affect the operation of the system.

The research data was collected from physicians. It is recommended that the data be collected from nurses, the public, individuals with chronic diseases, elderly people, and the families of these individuals and re-conducted.

It has been identified that issues such as data collection and the right to use and own the collected data need to be addressed.

In the use of AI doctors in the health sector, it is necessary to examine the ethical and legal regulations in terms of both healthcare providers and users. It may be studied in terms of age, gender, generalists and specialists, and developed, developing, and non-developed countries.

4.4. Limitations

This study examines physicians' attitudes toward AI doctors. Well-analyzed attitude research is a valuable tool for forecasting behaviors. However, immediate surveying has been used in this research rather than a long-term inquiry. It is important to remember that attitudes may change with time. The individuals stated their self-reported use intentions. By assuming that their statements were accurate, the study was conducted.

AI technology has been examined from a technical perspective in terms of data collection, diagnosis, treatment planning, and patient follow-up in healthcare. However, we would like to point out that the medical profession does not only consist of medical knowledge; other aspects should also be examined. Results may be different if the research is replicated at the chronic disease or patient level, for example.

The study was conducted among physicians at research hospitals in one geographic area. Results may differ from studies conducted in other countries.

Ethics statement

The University's Human Sciences Scientific Research and Publication Ethics Committee has supplied its clearance (reference number E-70561447-050.01.04-35758).

Research data

UYMAZ, Ali Osman (2023), "Shifting from Disease-Centric to Patient-Centric Healthcare: Evaluating the Acceptance of AI Doctors among Physicians for Data Collection, Diagnosis, Treatment Planning, and Follow-Up Patients", Mendeley Data, V4, doi: 10.17632/wz6nhr84pc.4

Authors' contributions

Conceptualization, AOU, PU and YA; methodology, AOU, PU and YA; validation, AOU, PU and YA; formal analysis, AOU, PU and YA; investigation, AOU, PU and YA; resources, AOU, PU and YA; data curation, AOU, PU and YA; writing—original draft preparation, AOU, PU and YA; writing—review and editing, AOU, PU and YA; visualization, AOU, PU and YA. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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