Original Article

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Factors Affecting the Attitudes of Medical Doctors in Turkey towards Using Artificial Intelligence Applications in Healthcare Services

Türkiye'de Tıp Doktorlarının Sağlık Hizmetlerinde Yapay Zeka Uygulamalarını Kullanmaya Yönelik Tutumlarını Etkileyen Faktörler

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ABSTRACT

Objective: Artificial Intelligence (AI) is transforming various sectors, including healthcare. The aim of this research is to examine the factors that determine acceptance of and intention to use AI applications by medical doctors (MDs).

Methods: This research was based on an online survey conducted with 275 MDs in Turkey. The survey was prepared in English and was later translated into Turkish by the researchers. The study employed a convenience sampling technique. The partial least squares-structural equation modeling (PLS-SEM) was employed to ascertain causal relationships for theory confirmation. The data analysis utilized SmartPLS 3. Descriptive statistics were calculated with the SPSS 25 software.

Results: According to the findings, Trust (β =.651; t = 25.876; p <.01) is the strongest positive factor for increased intention to use AI applications. Perceived Usefulness (β =.613; t = 22.851; p <.01) and Perceived Ease of Use (β =.644; t = 14.577; p <.01), significantly predicted Intension to Use. Technological Anxiety was not a significant predictor for Intension to Use (β =.067; t = 1.014; p =.093) as well as Facilitating Conditions (β =.071; t = 1.041; p =.102).

Conclusion: This research reveals that trust, perceived usefulness, and perceived ease of use are the major positive factors for AI to be accepted and used by MDs. The greater trust and ease of use

ÖZ

Amaç: Yapay zekâ, sağlık hizmetleri de dahil olmak üzere çeşitli sektörleri dönüştürmektedir. Bu araştırmanın amacı, tıp doktorlarının yapay zekâ uygulamalarına yönelik kabullerini ve kullanım niyetlerini belirleyen faktörlerin incelenmesidir.

Yöntemler: Bu araştırma, Türkiye'deki 275 tıp doktoru ile yapılan çevrimiçi ankete dayanmaktadır. Anket İngilizce olarak hazırlanmış ve daha sonra araştırmacılar tarafından Türkçeye çevrilmiştir. Araştırmada kolayda örnekleme tekniği kullanılmıştır. Kısmi en küçük kareler yapısal denklem modellemesi (PLS-SEM), teorinin doğrulanması amacıyla nedensel ilişkileri tespit etmek için kullanılmıştır. Veri analizinde SmartPLS 3 kullanılmıştır. Betimleyici istatistikler SPSS 25 yazılımıyla hesaplanmıştır.

Bulgular: Bulgulara göre, Güven (T) (β = 0,651; t = 25,876; p <0,01), yapay zekâ uygulamalarını kullanma niyetinin artmasında en güçlü pozitif faktördür. Algılanan Fayda (PU) (β = 0,613; t = 22,851; p <0,01) ve Algılanan Kullanım Kolaylığı (PEOU) (β = 0,644; t = 14,577; p <0,01), kullanma niyetini anlamlı şekilde öngörmektedir. Teknolojik Kaygı (TA) (β = 0,067; t = 1,014; p = 0,093) ve Kolaylaştırıcı Koşullar (FC) (β = 0,071; t = 1,041; p = 0,102) kullanım niyeti için anlamlı bir yordayıcı değildir.

Sonuç: Bu araştırma, yapay zekanın tıp doktorları tarafından kabul edilmesi ve kullanılmasında güven, algılanan fayda ve algılanan kullanım kolaylığının başlıca olumlu faktörler olduğunu ortaya

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ABSTRACT

that comes with more knowledge and experience about artificial intelligence may lead to more action to be taken to benefit from AI in the healthcare sector.

Keywords: AI in healthcare service, Extended TAM, AI Acceptance, PLS-SEM

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koymaktadır. Yapay zekâ hakkında daha fazla bilgi ve deneyimin getirdiği daha fazla güven ve kullanım kolaylığı, sağlık sektöründe yapay zekadan yararlanmak için daha fazla adım atılmasını sağlayabilir.

Anahtar Sözcükler: Sağlık hizmetlerinde yapay zekâ, E-TAM, yapay zekâ kabulü, PLS-SEM

Introduction

AI is undoubtedly the most debated technological development of today. Aside from the technical improvements in AI, the expansion of AI implementations is the major reason for this debate in business world, media, and science community. AI which entered our lives with automation, production systems and sales/marketing applications is now being used in essential sectors such as education and health. It is frequently suggested that in a global scale, AI is affecting individual as well as industrial activities (1). Therefore, it became a transforming element for the society as a whole.

It can be said that there is a clear relationship between a series of developments in recent years and the widening use of artificial intelligence. The most important of these is the increasing volume of recorded data due to digitalization. These digital records, known as big data, constitute an almost endless resource that can be processed by artificial intelligence algorithms through machine learning. Today, all transactions occurring in the digital environment, such as sounds, images, numbers and those that can be referred to as behaviors, have become data that can be used by artificial intelligence. Another feature of big data that can be accessed, stored, and processed is that it can be collected in real time, too. This offers exceptional opportunities for the development of artificial intelligence.

On the other hand, the COVID-19 pandemic has accelerated digitalization in all areas of life. In line with the increasing digitalization, developments in artificial intelligence gained momentum. The spread of artificial intelligence in different sectors and its new functions also followed these developments. AI technology provides a base for continued innovation in various sectors (2). In recent years, as one of the sectors where digitalization and datafication are advancing most rapidly, medicine and health sector have become one of the prominent areas in terms of the use of artificial intelligence. It is also predicted that the opportunities provided by these technologies will create new industries and roles (3). While artificial intelligence offers great opportunities, it will also pose a threat, especially to manufacturing and process-oriented sectors; and health sector is among them (3).

Apparently, there is an increasing interest in technology to solve problems of today's society such as global warming, sustainable use of resources and public health. Among these, the most pressing societal issues regarding health are increasing workload of the health sector, high costs, and the scarcity of trained personnel due to the increasing and aging population (4). Recent developments in machine learning and artificial intelligence accelerated efforts to mitigate these problems using technological solutions. Policy makers and politicians are also eager to introduce more state-of-the-art tools to the health system (5). In this context, it is also possible to talk about the digitalization of health data which paved the way to applications that adopt a data-driven approach started to be implemented (6,7). In this context, the healthcare sector has become one of the areas where artificial intelligence is rapidly developing from managerial, clinical, and patient perspectives. Most importantly, AI is already being applied to clinical tasks normally performed by doctors which draws attention to the positions of them in an AI supported health system (8). Thus, it is possible to suggest that the circumstances for both doctors and patients have been transformed by the introduction of AI (9). In the future, if/when AI becomes a routine part of clinical practice, the self- image of doctors will also be affected (10). From the vantage point of patients, on the other hand, receiving health services is also likely to be converted into a completely new experience. It is also important to note the fact that use of AI should be considered different from the use of AI in other sectors, given the highly sensitive nature of health data and vulnerability of the consumers (2).

The current literature on AI in health sector covers various aspects of the subject, however it does not sufficiently explain the factors shaping the attitudes and willingness of MDs to use AI applications. Therefore, this research aims to examine the attitudes of MDs towards AI applications and the factors that determine their intention to use. In this context, it is believed that the expanded technology acceptance model will provide a distinctive perspective in explaining doctors' intentions to use AI tools.

AI in Health

Artificial Intelligence is basically composed of machine learning, algorithms, and (big)data. In the context of these components, AI can be described as a smart machine-based system that recognizes patterns in data which can also apply these patterns to new data for particular tasks and purposes (11,12). AI has the ability to replace many human tasks and activities in various industries which is likely to have impact in terms of productivity and performance (2). Since health has become one of the major fields which produces big data, the utilization of AI was foreseeable; especially through machine learning and deep learning (13,14). It can be suggested that AI has already started to cause a paradigm change in the field of healthcare (15).

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It is possible to consider the use of artificial intelligence in the field of healthcare in three different dimensions. The first of these is public health applications, while the other two are in the field of medicine, that is, clinical applications for doctors and applications for the use of patients and/or for doctor- patient communication (16,17). AI can be used for diagnosis, treatment, and patient monitoring, as well as image processing and analysis (14,18). In this context, when we look at the artificial intelligence applications developed for the use of doctors, it can be said that the developments are shaped in line with the promises of data and technology. Different fields of medical research and practice are aimed at by tech companies in terms of helping doctors find all the information and accurate data at once to make precise diagnosis and establish better plans for treatment (19,20). For example, thanks to the developments in artificial intelligence and image processing technology, artificial intelligence applications in radiology stand out among other specializations (13,14,17,21). This distinction between areas of expertise is also seen in various studies on the relationship between health and artificial intelligence in the literature. However, it is possible to suggest that other specialties are catching up quite rapidly. Moreover, AI is becoming increasingly capable at clinical tasks aside from diagnosis and early detection (15).

Risks and Concerns Regarding AI in Health

It is unclear if the doctors will adopt AI technology in clinical practice at some point in the future (15). This is very much related to the perception of risks and concerns as well as the potential benefits that are comprehended by the doctors. Like every technological innovation, there are risks and benefits associated with the use of artificial intelligence. The concerns and arguments regarding potential risks and drawbacks of the use of AI in health sector are various. Data privacy and security, bias, black-box effect, the question of liability, accountability, and doctors' lack of AI knowledge are among the most significant concerns (8,10,13),(22). It is clear that some of these problematic areas are related to the technology itself, while others arise from the utilization and the approach of the users.

Data privacy and security are among major topics of debate when it comes to proliferating digital technologies that utilize data. For machine learning and AI, digital health records of all kinds are essential to achieve desired results. The data used for machine learning is assumed to be flawless by the developers. However, personal health records may be destroyed, stolen, or altered, if there is a security problem with the system. On the other hand, the data is recorded by humans, and they can make mistakes when collecting, classifying, and categorizing the gathered data (22) . In these stages implemented by humans (not machines) mostly, it is vital to establish appropriate guidelines and apply them correctly.

AI and machine learning are criticized for giving biased outcomes that may lead to imperfect decisions. The bias may be resulting from bias in training data and/or flawed algorithms. In this sense, the decisions relying on AI supported systems that have social impact are mostly accused of reproducing social inequalities, which also exist in public health. For example, the training data may only represent a certain ethnic or geographical population, while excluding other groups, or some of the critical data about the patients can be in a format that cannot be entered into the system (10). In such cases, the data may not be comprehensive and inclusive enough to give accurate results.

Black-box effect refers to the opacity of algorithms used in AI systems. If the AI system is too complex for any one or more of the stakeholders, then it is considered problematic (23). Some models may lack transparency in terms of interpretable processes including parameters and criteria on which 'deep learning' is mostly based on (22). This 'black- box' type of AI systems may not be trustworthy both for doctors and patients, since the outcome/ diagnosis cannot be explained (22). This issue also raises debates regarding accountability. In an opaque AI system, it is impossible to reduce the risks through verification (23), since the doctor cannot follow the process of decision making. In that context, the allocation of responsibility or liability also becomes an issue in case of unexpected/unwanted effects of decisions made by AI systems and applied by the doctors who followed these decisions. The question of whether AI systems can be hold responsible for their decisions is beyond the scope of this article. However, it is widely suggested that the doctors who make the final decisions should be hold responsible (23). From the viewpoint of doctors, this may be an obstacle in terms of building trust and willingness to use AI support.

Level of knowledge about AI is another concern from the standpoint of doctors and medical students alike. The efficient and accurate use of AI tools requires knowledge of AI processes starting with data collection and including deep learning. Only with a certain level of knowledge doctors can adopt AI systems to their routines with confidence. On the other hand, if they know the AI processes well, they can support the developers to optimize the system (10).

Questions such as whether artificial intelligence will replace doctors, whether it will remain only as a decision support technology, and whether the role of doctors (and other healthcare professionals) will change have begun to be asked frequently in recent years and have become one of the popular research topics in the field of artificial intelligence (8). Aside from the answers to these questions, it is already possible to argue that required skillsets and attitudes for being a good doctor will be redefined in the new era of AI (20). The speed and the extent to which artificial intelligence will affect the professional practices of doctors is largely related to the answers to the questions above.

Previous Research on Perception and Acceptance of AI among MDs

In recent years, with the increase in the use of tools and applications with artificial intelligence technology in health sector, various studies have been conducted to examine the knowledge, opinions or attitudes of various professional groups working in this sector. These studies mainly focus on artificial intelligence in general and on the way in which members of the

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sector are approaching the use of artificial intelligence in the field of health and medicine. The results of such research, which analyze the subject in different contexts and for various research purposes, are noteworthy. Despite the fact that most AI tools for clinical use are still at the research or pilot study phase, the members of health sector are already more or less aware of the imminent change. Therefore, the evolution of the perception and attitude of doctors is an important input for the penetration of AI into the healthcare sector. The effective human (doctor) – AI collaboration is especially very vital for successful applications, so recent research also aims at finding out the relevant factors (24). The literature suggests that the factors such as trust in AI and hesitancy to accept the use of AI tools are slowing down the adoption (7,25).

Doctors' attitudes and perceptions towards artificial intelligence are related to several variables.

However, when the relevant literature is examined, it is understood that the relationship between healthcare and artificial intelligence is questioned by both doctors and researchers in certain areas of discussion.

For example, a study conducted with doctors in the Netherlands, Portugal and the United States focused on ethics. This research revealed that MDs do not have enough insight into artificial intelligence issues such as bias and social inequalities in health, but they have concerns about the involvement of the private sector and large companies in the process since they are believed to be profit-oriented and unaware of the core values of healthcare. Additionally, in this research doctors expressed their interest in learning AI technology in order to be able to explain the outcomes (6).

Another research on the perceptions of trainee doctors in London found that 58% believe AI will have a positive impact on their training, mainly in terms of research and quality as well as time- effectiveness for allocating more time for other educational activities. The findings showed that trainee doctors were optimistic about clinical AI to keep them updated about latest literature and latest evidence to improve their practice. On the other hand, as for the negative opinions about clinical AI, the respondents were concerned about the development of their practical skills and clinical judgement because of the reduced opportunities to train, which in turn could harm accountability (8).

According to a survey on the opinions of Pakistani medical students and doctors more than one-third of the respondents agreed and strongly agreed the statement that AI would reduce errors in diagnosis, which shows a partial trust in this technology. Plus, despite limited trust in AI, they do not consider it as a threat to their occupation (13).

Another research in which data was collected via an online questionnaire revealed contradicting results about knowledge of AI among MDs. The level of knowledge of AI elements such as deep learning and neural networks were more familiar for the respondents who had a clear understanding of AI, whereas they did not have much idea about supervised and unsupervised learning. However, they were concerned about the safe use of AI in health, even though they had little awareness about the lack of transparency. Other results of this study showed that both medical students and doctors feared deskilling as well as doctors becoming redundant (18). This may be because the knowledge about AI is related to personal interest in technology and innovation.

The findings of another survey conducted in UK revealed that half of the 411 radiographers did not feel confident about understanding AI terminology and 64% told they did not develop any skills regarding use of AI in their field. The overall results of the survey indicated a willingness among the radiographers to receive training about AI applications in their field of expertise(26).

13.8% of 297 participants from England who responded to another online questionnaire about AI use in clinical practice indicated that they were aware of the use of AI technology. When they were asked to rate their level of knowledge about AI use in healthcare specifically, the mean rating was 3.68 out of 10, which shows an insufficient level of knowledge (27).

According to the findings of a survey conducted in Italy among 1032 radiologist members of The Italian Society of Medical and Interventional Radiology (SIRM), most radiologists expected AI to improve their workflow. Even though they had a positive attitude towards use of AI, they were concerned about their possibly reduced reputation (28).

As understood from a bird's eye view of previous research on the topic, the subject of AI acceptance and use by MDs is a multifaceted issue. These are several factors from the perspective of doctors that determine their level of acceptance and most of these factors are based on their perceptions, rather than lived experience.

Extended Technology Acceptance Model (E-TAM)

Technology acceptance can be expressed as the choice of individuals to voluntarily accept new technologies. The primary aim of the Technology Acceptance Model (TAM) is to prognosticate the adoption of novel technologies among end-users and illuminate challenges prior to their ubiquitous integration within the general populace (29). In recent decades, researchers have formulated diverse models aimed at comprehending the dynamics of user acceptance toward technology. However, Davis's Technology Acceptance Model represents the most fundamental and significant foundation for technology acceptance to date. TAM consists of two primary constructs commonly employed in various technological contexts: perceived usefulness and perceived ease of use (30). However, some researchers have expressed concerns about the inadequacy of the original frameworks of the Technology Acceptance Model (TAM) in elucidating users' intentions towards the adoption of healthcare Technologies (29). In specific user contexts, such as the acceptance of artificial intelligence tools, participants' intentions to use are contingent upon many social and behavioral factors that remain unaddressed

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within the confines of the TAM model. Therefore, the current research has focused on incorporating additional social and behavioral variables into the TAM model and how these variables may affect perception of users. Accordingly, variables such as "facilitating conditions", "trust", "perceived risk", "technological anxiety", and "resistance to use" were included in the scope of the research in order to better understand the user's perception.

Methods

The objective of this study is to scrutinize and elucidate the determinants that mold and impact the attitudes of MDs towards AI applications. The research model, with "AI Intention to Use (IU)" identified as the dependent variable, is shown in Figure 1. The targeted population for this research comprises doctors working in hospitals and clinics in Turkey. To ensure the validity of the measurements, the details of the identified determinant structures were adopted from previous studies, as outlined in Appendix A. Proposed Hypotheses are shown in Table 1.

Data Collection Method and Measurements

This research was based on an online survey. The survey was conducted with 275 MDs in Turkey. The study employed a convenience sampling technique. The survey created using Google Forms and participants were contacted via email. All participants were briefed on the research and their explicit consent was obtained. Initial survey for this study was developed in English and was later translated into Turkish by the researchers. Both surveys were carefully crafted to convey the same meaning in terms of perception. The survey was pilot tested for clarity on ten MDs. Data collection was carried out between September 1, 2023, and October 28, 2023.

The survey was divided into two parts. In the first part, there was a brief introduction and five questions related to the profile of participants such as gender, age, institution, clinical specialization, and professional experience. Second part consist of 21 questions for various constructs shown in Figure 1. The five-point Likert-type scale with a range from 1 (Strongly Disagree) to 5 (Strongly Agree) was employed was used to measures for responses.

The survey instruments for each of the constructs were designed to gather exhaustive details and adapted from the literature, including IU -three items(31); PU -two items (32,33); PEOU -three items (34,35); RC - three items (36); T -two items (37); TA -two items (31); FC -three items (38) and PR -three items (37,39).

Statistic Analysis

In this study, the partial least squares-structural equation modeling (PLS-SEM) was employed to ascertain causal relationships for theory confirmation. The data analysis utilized SmartPLS 3. Descriptive statistics were calculated with the SPSS 25 software. The PLS-SEM analysis is divided into two sections for analysis. Part one is based on an evaluation of the outer model's reliability and validity. The second part is based on a model evaluation within which hypotheses were evaluated.

Results

Demographics

A total of 275 MDs responded to the survey. The sample was slightly skewed toward females (52%). The mean age for the entire sample was 48,3 (SD= 12.7). The participants were distributed among different clinical specialties as follows: internal medicine (n= 82, 30%), pediatrics: (n= 55, 20%, general surgery (n= 41, %15), obstetrics and gynecology (n= 41, 15%), orthopedics: (n= 28, 10%), psychiatry (n= 14, 5%), other specialties (n= 14, 5%). The survey revealed that 31% of the participants had 15-20 years of work experience and 28% had less than 10 years of work experience.

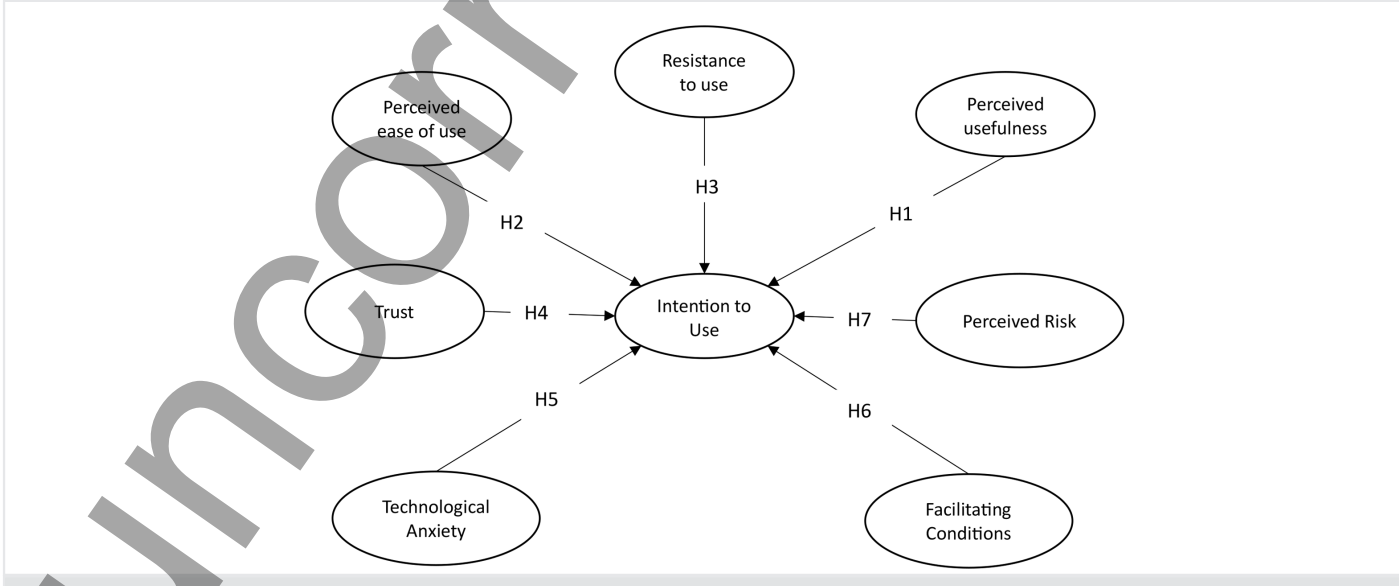

Figure 1. Research Model: extension TAM with social and behavioral factors

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Measurement Model

The measurement model encompasses assessment procedures for testing the reliability and validity of the measures. The current study followed three measurements suggested by Hair et al.(40); 1) indicator loadings and internal consistency reliability, 2) convergent validity, and 3) discriminant validity.

In this study, the item loads for each construct were obtained through PLS-SEM analysis. Table 2 shows the detail of loadings. All items achieved the recommended loading values of > .700(40). Internal consistency reliability refers to the evaluation findings for the statistical consistency across indicators and it was assessed using Cronbach's Alpha (CA) and Composite Reliability (CR). The values of CA and CR in this study adhered to the threshold set by Hair et al.(40); CA and CR >.700. It can be seen from the Table 2 that both CA and CR values for all construct shave good internal consistencies. The reliability ranging from .732 to .816 for the CA and .813 to .880 for the CR (see Table 2).

Convergent validity is a statistical concern associated with the concept of construct validity. The Average Variance Extracted (AVE) is an attempt to determine convergent validity. If the AVE is greater than .500; it explains 50% or more of the variance (40). In this research, it is known that all constructs had an AVE score that is greater than .500 that explains more than 50% of the variance (see Table 2).

According to Hair et al.(40), discriminant validity refers to the degree to which a construct differs from other constructs. Through the implementation of the Fornell-Larcker criterion, it is expected that the square root of the AVEs of all constructs should be greater than the highest correlation value for other constructs in the measurement model. Based on the study

Table 1. Proposed hypotheses

Factors	Abbreviation	Hypothesis
Perceived Usefulness	PU	**H1.** Perceived usefulness positively effects the intention to use AI applications.
Perceived ease of use	PEOU	**H2.** Perceived ease of use positively effects the intention to use AI applications.
Resistance to use	RC	**H3.** Resistance to use negatively effects the intention to use AI applications.
Trust	T	**H4.** Trust positively effects the intention to use AI applications.
Technological Anxiety	TA	**H5.** Technological anxiety negatively effects the intention to use AI applications.
Facilitating Conditions	FC	**H6.** Facilitating conditions positively effects the intention to use AI applications.
Perceived Risk	PR	**H7.** Perceived risk negatively effects the intention to use AI applications.

Table 2. Measurement model, construct reliability and validity values

	Items	Loadings	CA	CR	AVE
IU	IU1	.832	.801	.871	.696
	IU2	.855			
	IU3	.815			
PU	PU1	.748	.730	.855	.751
	PU2	.972			
PEOU	PEOU1	.876	.799	.878	.710
	PEOU2	.888			
	PEOU3	.870			
RC	RC1	.814	.781	.840	.637
	RC2	.832			
	RC3	.840			
T	T1	.891	.754	.880	.803
	T2	.900			
TA	TA1	.946	.816	.813	.843
	TA2	.905			
FC	FC1	.840	.732	.873	.778
	FC2	.832			
	FC3	.813			
PR	PR1	.826	.752	.850	.728
	PR2	.935			
	PR3	.973			

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findings, the square root of the AVEs for each construct are greater than that it's shared variance. Thus, discriminant validity was confirmed through the assessment of the Fornell-Larcker criterion (see Table 3).

On the one hand, heterotrait–monotrait ratio (HTMT) values exceeding .900 appear discriminant validity problems. It is observed that all HTMT values are below .900 (see Table 4).

Further, discriminant validity can be assessed by examining cross-loadings. Discriminant validity is demonstrated when the loading value on a construct bigger than all of its cross-loading values on other constructs (Table 5).

It has been determined that the values of all indicators for each construct's outer loading exceed all cross-loading values on other constructs (see Table 5). In this context, it can be said that discriminant validity has been emerged.

Following the evaluation of the measurement model, it is evident that the construct is deemed suitable for use. This is evidenced by meeting the criteria for loading indicators, internal consistency reliability, convergent validity, and discriminant validity. Thus, the model can proceed to undergo inspection in the structural model.

Structural Model

The structural model assessment process began with the determination of whether there was collinearity problem. Reporting Variance Inflation Factor (VIF) values is a good indicator of collinearity. The VIF value of each indicator >3.000 indicates the existing of collinearity problem. PU (VIF= 1.233), PEOU (VIF= 1.890), RC (VIF= 1.567), T (VIF= 1.241), TA (VIF= 1.712), FC (VIF= 1.213) and PR (VIF= 1.663) are the predictor of IU (VIF= 1.000). As seen all values of VIF are below three. Therefore, collinearity problem does not exist in the current research.

Structural model evaluation is also known as an inner model evaluation, as it examines the relationship between latent variables (41). In reflective models, recent studies suggest conducting an evaluation that includes determination coefficients, path coefficients, and predictability(40,42). For this purpose, the sample was performed a complete bootstrap analysis with 5000 subsample parameters. At a 5% significance level, the majority of hypotheses were supported, except for H5 and H6.

TA was not a significant predictor for IU (β = .067; t = 1.014; p = .093). FC is also reported to have not a significant effect on IU (β = .071; t = 1.041; p = .102). PU (β = .613; t = 22.851; p < .01), PEOU (β = .644; t = 14.577; p < .01), RC (β = -.416; t = 7.150; p < .01), T (β = .651; t = 25.876; p < .01), PR (β = -.530; t = 14.771; p < .01) significantly predicted IU. Final results are shown in Table 6.

The explanatory power of the model was determined by measuring R^2 value. The R^2 value represents the proportion of variance in the endogenous variable explained by the exogenous variable. From the results of the PLS-SEM analysis, R^2 IU is 0.615, implying that PU, PEOU, RC, T, TA, FC, and PR can explain 61.5% of the variance in IU. Hair et al.(40) categorized R^2 into the following groups: .25 falls into the weak category, .50 into the moderate category, and .75 into the substantial category. Based on the analysis results, the R^2 value can be classified within the moderate category.

Table 3. The Fornell-Larcker criterion (latent variable correlation and square root of AVE)

	IU	PU	PEOU	RC	T	TA	FC	PR
IU	.834							
PU	.467	.866						
PEOU	.453	.611	.842					
RC	.391	.569	.386	.798				
T	.601	.346	.512	.465	.896			
TA	.513	.430	.647	.342	.421	0.918		
FC	.431	.444	.543	.431	.545	.567	.882	
PR	.348	.565	.465	.673	.341	.603	.564	.853

Table 4. HTMT values (heterotrait–monotrait ratio)

	IU	PU	PEOU	RC	T	TA	FC	PR
IU								
PU	.677							
PEOU	.832	.669						
RC	.476	.693	.728					
T	.601	.510	.721	.712				
TA	.527	.765	.480	.526	.632			
FC	.398	.428	.635	.469	.564	.784		
PR	.803	.586	.482	.657	.498	.414	.593	

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Table 5. The item loadings and cross-loadings

	IU	PU	PEOU	RC	T	TA	FC	PR
IU1	**.832**	.365	.365	.324	.367	.287	.498	.389
IU2	**.855**	.454	.552	.378	.228	.443	.563	.413
IU3	**.815**	.288	.288	.437	.415	.369	.317	.515
PU1	.489	**.748**	.417	.269	.294	.414	.489	.446
PU2	.374	**.972**	.469	.412	.487	.352	.431	.362
PEOU1	.312	.417	**.876**	.321	.311	.318	.365	.243
PEOU2	.363	.469	**.888**	.245	.253	.498	.578	.405
PEOU3	.398	.335	**.870**	.198	.192	.265	.422	.297
RC1	.577	.249	.335	**.814**	.425	.497	.399	.474
RC2	.392	.218	.249	**.832**	.459	.432	.687	.421
RC3	.468	.385	.218	**.840**	.315	.375	.347	.388
T1	.401	.292	.385	.387	**.891**	.246	.418	.374
T2	.385	.197	.292	.473	**.900**	.589	.254	.298
TA1	.596	.468	.197	.292	.402	**.946**	.572	.435
TA2	.578	.298	.468	.421	.356	**.905**	.433	.192
FC1	.567	.176	.298	.356	.267	.411	**.840**	.359
FC2	.494	.369	.176	.298	.183	.337	**.832**	.389
FC3	.389	.422	.369	.175	.391	.298	**.813**	.313
PR1	.401	.316	.422	.389	.475	.461	.675	**.826**
PR2	.396	.417	.316	.469	.402	.281	.541	**.935**
PR3	.482	.469	.245	.377	.336	.376	.438	**.973**

Table 6. Final results

Hypothesis	Path Coefficient (β)	t	Conclusion
H1	.613	22.851	Supported
H2	.644	14.577	Supported
H3	-.416	7.150	Supported
H4	.651	25.876	Supported
H5	.067	1.014	Rejected
H6	.071	1.041	Rejected
H7	-.530	14.771	Supported

Next, f^2 was reported to assess the effect sizes of endogenous structures. This involved assessing the change in R^2 between a full model and iterations where each time a distinct exogenous construct was excluded (40,43). According to Hair et al.(40), the f^2 value of .02 is considered a small effect, .15 indicates a medium effect, and .35 is characterized as a large effect. The effect sizes of endogenous structures are shown in Table 7.

PR (f^2 = .345) gained the smallest effect while T (f^2 = .648) obtained the largest f^2 while TA and T have no effect size.

Finally, we calculated Stone-Geisser's Q^2 value to assess the predictive relevance of the model for each endogenous variable (given that our model includes only one endogenous variable, the assessment of predictive relevance focuses on the model's ability to predict IU). When the model undergoes predictive relevance, it demonstrates the accuracy of predicting data points for items in the study (40). The obtained Q^2 value for this variable is 0.41, indicating substantial predictive relevance.

Discussion

According to the findings of our research which aims to reveal the factors determining the intention to use the AI applications among MDs in Turkey, trust (T) is the strongest determinant. As the trust to AI technology increases, the MDs are more likely to use its applications. Same strong relation between trust and (behavioral) intention was also found in a previous study in China (25). Another research in China found direct and indirect positive effects of trust on AI acceptance among doctors, indicating that increased trust escalates likelihood of acceptance by positively effecting the performance expectancy (44). Perceived ease of use (PEOU) is the second most effective factor. PEOU was also found to be a strong factor that led to positive attitude to use AI in research undertaken in UEA (45). Additionally, the more the MDs perceive AI technology and AI applications as useful for healthcare purposes (PU), their intentions to use them also increase. In a previous survey by Pan et. al (46) PU was found the most effective factor in determining attitudes of doctors towards smart healthcare services in Japan. The results of an online survey with 669 Korean MDs and medical students also found that %83.4 of the respondents considered AI useful for medical field and this contributes to the positive attitude of medical community in Korea (47).

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Table 7. Effect sizes

	f^2	Effect size
PU	.621	Large
PEOU	.642	Large
RC	.398	Large
T	.648	Large
TA	.011	No effect
FC	.009	No effect
PR	.345	Medium

Technological anxiety (TA) is not a factor in determining the intention to use AI in healthcare practices for MDs in Turkey, according to the results of our research. Facilitating conditions (FC) were also found to be not affecting intention to use AI. When it comes to factors that negatively impact the intention of use, perceived risk (PR) comes first, which may explain the strength of trust as the main positive factor that is the opposite of risk. This result supports the findings of a previous qualitative study on doctors' resistance of AI in Tunisia. In this study, performance risk of AI applications was found to be one of the barriers in terms of acceptance in healthcare, even though it was perceived beneficial to the medical field (48). Resistance to use (RC), also negatively impacts intention to use AI applications among MDs in Turkey. As the individual is more resistant towards using new technology the intention to use AI declines. It can be suggested that the general attitude towards using new technology and/or tools determines the attitude towards AI applications in healthcare as well.

Study Limitations

It should be noted that there will be large variations within the population of MDs working in hospitals and clinics; therefore, the results cannot be considered generalizable. Additionally, the possible support of AI in the treatment of one patient may differ significantly from others. The attitude towards specific AI applications may vary.

Conclusion

AI continues to develop at an astonishing speed and touch our entire lives, including healthcare. In the context of this major transformation, the position of doctors becomes very crucial in terms of applying the opportunities of AI technology to medical practice, while eliminating the risks and side effects. The perceptions and attitudes of them will define the trajectory for acceptance and adoption of AI applications in various aspects medical field. This research reveals the fact that trust, perceived usefulness, and perceived ease of use are the major positive factors for AI to be accepted and adopted by MDs. Although it requires further research, this result can be related to the increasing knowledge and experience of doctors regarding artificial intelligence. Providing more trust and ease of use in this way can enable more action to be taken to benefit from artificial intelligence in the healthcare sector.

Ethics

Ethics Committee Approval: Ethics committee approval was obtained from the Ethics Committee of Anadolu University (no: 70/78, date: 28.12.2023).

Informed Consent: All participants were briefed on the research and their explicit consent was obtained.

Authorship Contributions

Concept: A.K.E., Design: E.E.B., Data Collection or Processing: E.E.B., Analysis or Interpretation: E.E.B., Literature Search: A.K.E., Writing: A.K.E.

Conflict of Interest: No conflict of interest was declared by the authors.

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Appendix A.

Constructs	Definitions
Perceived Usefulness (PU)	PU1: Using AI applications would improve the quality of my treats.
	PU1: Using AI applications would improve the quality of my treats.
Perceived ease of use (PEOU)	PEOU1: I would find learning to use AI applications would not be very difficult for me.
	PEOU2: I would find it easy for myself to use AI applications.
	PEOU3: Using AI applications would be clear and understandable for me.
Resistance to use (RC)	RC1: I wouldn't want AI applications to alter my traditional way of treatments.
	RC2: I wouldn't want AI applications to interfere or change the way my treatments routine.
	RC3: I don't want AI applications to change the way I deal with treatment problems and choices.
Trust (T)	T1: AI applications would be trustworthy for improving my treatment routine.
	T2: I feel satisfied and confident that I will be able to rely on the benefits of AI applications.
Technology Anxiety (TA)	TA1: Using AI applications would make me feel nervous.
	TA2: Using AI applications would make me confused and uncomfortable.
Facilitating conditions (FC)	FC1: I would be able to have all the necessary resources for using AI applications.
	FC2: I would acquire sufficient knowledge for using AI applications.
	FC3: AI applications will suite well with my treatment routine.
Perceived Risk (PR)	PR1: Learning how to use AI applications and adapting it would be a loss of my time.
	PR2: Using AI applications would be a loss of money and resources.
	PR3: Using AI applications wouldn't be compatible with my moral values and image.
Intention to Use (IU)	IU1: Assuming that I was given the chance to AI applications, I intend to use AI applications.
	IU2: I would gladly use AI applications.
	IU3: I intend on informing my colleagues and friends about AI applications.

*The five-point Likert-type scale with a range from 1 (Strongly Disagree) to 5 (Strongly Agree) was employed

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