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Prediction of the intention to use a smartwatch: A comparative approach using machine learning and partial least squares structural equation modeling

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ABSTRACT

This study makes use of a cohesive yet innovative research model to identify the determinants of the adoption of smart watches using constructs from the Technology Acceptance Model (TAM) and constructs of smartwatches, including effectiveness, content richness, and personal innovativeness. The chief objective of the study was to encourage the use of smartwatches for medical purposes so that the role of doctors can be made more effective and to facilitate access to patient records. Our conceptual framework highlights the association of TAM constructs (i.e., perceived usefulness and perceived ease of use) with the content richness, the construct of user satisfaction, and innovativeness. To measure the effectiveness of the smartwatch, an external factor based on the flow theory was added, which emphasizes the control over the smartwatch and the degree of involvement. The study employs data from 385 respondents involved in the field of medicine, such as doctors, patients, and nurses. The data were gathered through a survey and used for evaluation of the research model using partial least squares structural equation modeling (PLS-SEM) and machine learning (ML) models. The significance and performance of factors impacting THE adoption of smartwatches were also identified using Importance-Performance Map Analysis (IPMA). User satisfaction is the most important predictor of intention to adopt a medical smartwatch according to the ML and IPMA analyses. The fitting of the structural equation model to the sample showed a high dependence of user satisfaction on perceived usefulness and perceived ease of use. Furthermore, two critical factors, innovativeness and content richness, are demonstrated to enhance perceived usefulness. However, one should consider that perceived usefulness or behavioral intention could not be determined based on perceived ease of use. In general, the findings suggest that smartwatch usage could become critically important in the medical field as a mediator that allows doctors, patients, and other users to access essential information.

1. Introduction

The Internet of Things (IoT) has developed exponentially in recent years and allows users to access information regardless of their location and time. Applications of IoT include smartwatches and other wearable technology devices. Such devices allows users to obtain feedback related to various physical activities and access to medical data [1,2]. Companies are now developing and selling smartwatches, and the number of sales is rapidly rising. The unique features of smartwatches include providing notifications, pairing with mobile phones for exploiting various features, timekeeping, and different watch faces, which have attracted many users to embrace this technology [3–5].

Medical centers have also started adopting such technologies to address growing needs and improve infrastructure. Smartwatches have been shown to be capable of performing numerous medical tasks, including checking levels of insulin, blood glucose, and carbohydrate

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units; tracking required physical activities; and accessing previously recorded values [6,7]. Researchers are placing greater focus on this area given the increasing interest in the development of more medical-related apps.

Accordingly, this study evaluates the consequences of smartwatch adoption, which can be applied to improve perceptions of the determinants of smartwatch adoption through the use of an advanced and integrated research model. In this context, a conceptual model was developed that combines Technology Acceptance Model (TAM) [8], diffusion of innovation (DOI) theory [9], and flow theory [10]. The second objective of this study is to assess the progress of smartwatch adoption in the area of health care, which could be of great interest to physicians and patients.

Users in the medical sector are showing interest in making the best use of this technology for better outcomes. Rather than being associated with individual user's decisions, it has been recognized that smartwatch acceptance relates to acceptance by all those connected to the medical sector, including patients for sharing information and for the depiction of attitudes and behaviors. The current study utilizes certain external factors evaluated in previous research. This research adopts an external variable associated with the significance of the external role of the smartwatch in the medical field. The external factors of mobility and availability have been used in previous studies [11,12]. However, the external factors of this study are different from those of previous studies. They include the degree of satisfaction, content richness, and innovations with respect to use of smartwatches. An aim of this study is to make a significant contribution to the current literature as the first to explore smartwatch acceptance in the context of the medical field using an integrated model.

Researchers in mainly Malaysia, Korea, and Taiwan have looked at the implementation of smartwatches. In these countries, surveys were used for data collection, and the only difference was the choice of external factors. While some studies [11,12] adopted diverse external factors, another [11] used mobility and availability, whereas another [12] focused on social dimension and novelty. Research in Taiwan focused on dominant external factors, including complexity, relative advantage and design aesthetics [13]. Another study [11] examined the psychological implications of the adoption of smartwatches as the reason behind the use of external factors are different from those commonly used in other studies. Another study [14] used external factors of availability and attitude associated with the adoption of smartwatches.

Lately, it appears that smartwatches have had a significant impact on their users. One type of research has looked at how people feel about smartwatches from all around the globe to measure their usefulness. Such research performs a kind of comparable assessment and has demonstrated that there is a considerable accessibility gap between France and Thailand. Furthermore, there is a distinction between France and China in terms of trust. Two studies [15,16] have concentrated on wearable devices and how they are linked to many external factors, such as mobility, trust, cost, usefulness, enjoyment, and so on. As a result, the following questions are addressed in this study:

RQ1. What factors influence a user's decision to adopt a smartwatch for medical purposes?
RQ2. Is it possible to adapt the TAM to smartwatch technology in the United Arab Emirates (UAE) to address the obstacles of employing smartwatch technology and providing holistic smartwatch technology?

2. Literature review

Users have apparently enjoyed the beneficial effects of smartwatches. Research has been performed in various parts of the world to determine the efficacy of smartwatches by concentrating on the attitudes of users. A comparative analysis indicated a substantial gap between Thailand and France in terms of smartwatch availability. In addition, China and France show disparity with respect to true factors. Previous studies [15,16] explored various external factors, such as usefulness, mobility, cost, trust, enjoyment, and many more with regard to the use of wearable devices. Previous research [11–25] suggests that smartwatch-adoption studies have only used questionnaires as unified data-collection instruments, where the TAM serves as the essential part of the models proposed [19–21]. Only one study [18] did not fit this criterion, and the Unified Theory of Acceptance and Use of Technology (UTAUT2) model was introduced as an extended model.

In the TAM, two different factors tend to impact adoption: perceived usefulness (depending on several extended variables) and perceived ease of use, which acts as a key element associated with the external factors of fashion and innovativeness, which influence smartwatch adoption [19–21]. It can be deduced from available literature that the adoption of smartwatches in the medical sector in the UAE remains unsupported as a consequence of insufficient empirical research, suggesting a lack of understanding of factors that have a direct influence on students' potential use of a smartwatch. The structural equation modeling (SEM) approach has been adopted by most technology acceptance studies as a methodology for theoretical model assessment. Thus, this research has two objectives. Firstly, smartwatch adoption will be estimated through integration of the TAM [26,27] and flow theory [28]. Secondly, smartwatch adoption will be estimated by authenticating the created theoretical model by employing the PLS-SEM and ML algorithms.

The true worth of this study comes from the fact that it is based on a conceptual framework that places considerable emphasis on the relationship that exists of TAM constructs of perceived usefulness and perceived ease of use with the constructs of user satisfaction, content richness, and level of innovation. In addition, flow theory adds another dimension to this study as the levels of involvement and control over the smartwatch are focuses of attention. Lastly, this study identifies the embedded motives of using a smartwatch in a medical setting where the principal objective is to improve the doctor-patient relationship and medical outcomes.

3. The research model and development of the hypotheses

3.1. Content richness

Content richness comprises three dimensions of learning resources: adequacy, relevance, and timeliness [29]. Adequacy of content richness represents the variety of information given to users. Timeliness or currency represents the degree to which users can be provided with up-to-date information [30,31] as out of date information is not beneficial. Therefore, technology-driven information is considered as time critical [32]. The correspondence of collected information with the needs of users is termed as relevance [33]. Studies [34,35] have investigated the association between perceived usefulness and content richness. Technology that is beneficial for users and fulfils their needs is considered to be characterized by high quality or high content richness. Consequently, the following hypotheses have been developed:

H1. Sufficiency (SUFF) predicts the understood usefulness of a smartwatch (UU).

H2. Timeliness (TIML) predicts the understood usefulness of a smartwatch (UU).

H3. Relevance (RELV) predicts the understood usefulness of a smartwatch (UU).

3.2. Personal innovativeness

Personal ingenuity is connected with the readiness and willingness of users to use modern technology upon its introduction to the market

[36]. Personal innovativeness is highly dependent on the understanding of the introduced technology and the confidence associated with it. Users with high levels of self-confidence are believed to have a greater level of personal innovativeness. Likewise, users who perceive technology to be of high value tend to have more personal innovativeness [37,38].

User adoption of technology is dependent on various decisions, including that of personal innovativeness. User acceptance and adoption of any new technology are positively affected by the degree of personal innovativeness. This is in accordance with TAM theory, which suggests a positive impact of the factors of ease of use and perceived usefulness on personal innovativeness [39–42]. Consequently, the hypotheses below were developed:

H4. Personal innovativeness (PERI) predicts the perceived usefulness of a smartwatch (PU).

H5. Personal innovativeness (PERI) predicts the perceived ease of use of a smartwatch (PEOU).

3.3. User satisfaction

The psychological state where the emotions of users are related to their expectations with regard to specific past experience is usually referred to as satisfaction. Satisfaction with a technology is dependent on the positive or negative sense associated with its use. When users find technology easy to use, useful, and fruitful, it induces extrinsic and intrinsic motivation. Therefore, their level of expectation is guided by their personal innovativeness and self-efficacy. This implies that satisfaction of users is achieved when the expectation is satisfied [43–45]. User satisfaction is also a key aspect of product/service adoption. Researchers consider the link between satisfaction with continuous intention to use technology as an important determinant of usage of technology in the long term [46–48]. The related hypothesis is given below:

H6. User satisfaction (USAT) predicts the adoption of smartwatches (ADSW).

3.4. The Technology Acceptance Model (TAM)

Earlier studies have extensively used the TAM to make predictions about the reception, acceptance, and intention to use technology in distinct fields [49,50]. This research has concentrated on two TAM constructs that are connected to the adoption of smartwatches as a wearable technology. The first variable is perceived usefulness, which can be best described as the attitude of users regarding the usefulness of a technology. The second variable is the perceived ease of use of the technology, which implies the degree of convenience offered from the user perspective [8,51]. The following hypotheses are based on these aspects:

H7. Perceived usefulness (UU) predicts ADSW.

H8. Perceived ease of use (PEOU) predicts ADSW.

3.5. Flow theory

The sense of control, enjoyment, and judgment is defined as flow. Once users believe in the maximum enjoyment aspects offered by a technology, they will be more inclined to use it regularly. Therefore, through activation of the attention, thoughts, and behavioral repertoire of users, various positive aspects lead to an experience of flow of the technology [10,52,53]. The experience of flow allows users to feel motivated due to the rapid passage of time. This means that development of a consistent flow online provides continuous interactivity associated with pleasant, enjoyable, immersed, and insolvent experiences [54,55].

The adoption of IT systems like e-learning, the internet, and online entertainment has recently also incorporated the flow experience. We can define it as the variety of ways in which technology is used without self-consciousness [56]. Hence, technology adoption can be predicted based on flow theory. Consequently, a hypothesis was developed as follows:

H9. Flow experience (FEXP) predicts the ADSW.

4. Research methodology

This research is a descriptive analytical study that has used a cross-sectional design and a deductive strategy. For this research, a self-administrated online questionnaire was prepared and then used to collect data from personnel working in the healthcare sector in the UAE in the Emirate of Dubai. The study was done from December 15, 2020, to January 15, 2021.

Data were collected from healthcare organizations in Dubai, including 5 hospitals and 7 primary healthcare clinics. Healthcare providers received a link to the questionnaire via their registered email addresses or social media platforms. The data for the study were obtained from healthcare providers such as physicians, nurses, and allied healthcare professionals, as well as administrative staff such as receptionists, registrars, administrative support, and quality support workers at healthcare centers. According to another study [57], people serving in healthcare organizations are a valuable source of information for such studies. In addition, as in this study, several other researchers have chosen this specific population as a unit of analysis for other empirical studies of healthcare service management [58–62]. The authors in another study [61] indicated that these individuals have sufficient knowledge regarding their healthcare management organizational practices and have a strong understanding of the level of quality of service and customer loyalty in their respective organizations.

Convenience sampling was utilized in this research while applying a non-probability sampling process. In general, this technique is selected because it is not possible for employees of such organizations to access and supply employee lists for sampling. Dubai healthcare organizations have several policies to protect their staff's details and to ensure the privacy and security of such sensitive information. According to a study [63], convenience sampling is known to not only save time, but also cut costs and easily access large samples.

Subsequently, this study verified the formulated theoretical model using Machine Learning (ML) algorithms and PLS-SEM. The main reason for employing PLS-SEM in this research is because it provides a simultaneous analysis process for both measurement and the structural model, leading to improved accuracy of results [64–66]. As for the second technique, this research utilizes ML algorithms through Weka for the prediction of dependent variables in the conceptual model [64]. In addition, employing a multi-analytical approach results in a novel contribution to current literature on information systems (IS) as this is one of very few attempts to apply ML algorithms in order to predict smartwatch adoption in the field of medicine.

The results of this study reveal how critical certain external factors are in relation to technology acceptance. The true value of this research is that it is based on a conceptual framework that places emphasis on the relationship of the TAM constructs of perceived usefulness and perceived ease of use with the constructs of user satisfaction, content richness, and innovativeness. In addition, flow theory is used to focus on the level of engagement and control over smartwatches. Lastly, this research aids in the recognition of embedded motives for using smartwatches in the field of medicine, where the principal objective is to improve and assist doctor-patient relationships and medical outcomes.

4.1. Data collection

In this study, 400 questionnaires were randomly distributed, but 15 were rejected because of missing values. A response rate of 96% was achieved for the remaining 385 correctly completed and useable questionnaires, which were then evaluated. The required sampling size of a population of 1500 is 306 respondents, so the 385 questionnaires completed for this study constituted an adequate sample size [67]. In this particular study, the use of structural equation modeling was feasible because a sample size of 385 is much larger than the required sample size [68].

An information paper and a consent form were given on the first page of the survey in both Arabic and English using Google Forms. Participants were able to leave at any moment without justification, and no personal information was required to protect the privacy of the data. Participants were not compensated in any way for taking part in the survey. The Google Forms system only responds to questionnaires that are 96% complete. The responses were saved in a password-protected cloud database after downloading them as an Excel file.

This research adhered to the ethical code for web-based research [69] and the concepts outlined elsewhere [70]. The hypotheses were tested based on the model. Despite the development of hypotheses based on existing theories, they were adjusted to meet the needs of the framework of smartwatch adoption. SEM was implemented for assessment of the measurement model, followed by the final path model.

4.2. Demographic statistics

Table 1 represents the personal/demographic data of participants. The age of 92% of the respondents exceeded 29 years, whereas the remaining 8% belonged to the age group of 18–29 years. The representations of females and males were 54% and 46%, respectively. Most of the respondents came from a cultured background and have obtained university degrees. The proportions of bachelor's, master's, and doctorate degree holders were 78%, 14%, and 6%, respectively, while the remaining respondents had high school diplomas. Since the respondents showed eagerness to participate in the study voluntarily, a purposive sampling approach was adopted [71]. The study sample included respondents belonging to several sectors, different ages, and various programs of study at various levels. IBM SPSS Statistics was utilized for analysis of the demographic data.

4.3. Study instrument

The survey instrument was prepared for confirmation of the hypotheses. The survey was prepared with 25 items to evaluate the four constructs represented in the questionnaire. Questions from previous research were updated and revamped before being included in the questionnaire in order to improve the research applicability. Table 2 shows the sources of the constructs used.

Table 1
Respondent profile.

Criterion	Factor	Frequency	Percentage
Gender	Female	209	54%
	Male	176	46%
Age (yrs)	18 to 29	32	8%
	30 to 39	242	63%
	40 to 49	79	21%
	50 to 59	32	8%
Education Qualification	Diploma	7	2%
	Bachelor	301	78%
	Master	52	14%
	Doctorate	25	6%
Experience (yrs)	1–5	39	10%
	5–10	109	28%
	10–15	188	49%
	15–20	29	8%
	20+	20	5%
Type of Sector	Federal/Government	329	85%
	Private	56	15%

Table 2
Construct measurement and sources.

Constructs	Items	Instrument	Sources
Adoption of Smartwatch	ADSW1	Using a smartwatch is recommended within medical environments	[51,72,73]
	ADSW2	Using a smartwatch both with patients and peers assists me in my career	
Innovativeness	PERI1	Where new technology is concerned, I am always willing to try it out	[74]
	PERI2	I am at the head of the queue when it comes to trying out new technology among my peers	
	PERI3	I am often reluctant to use new technology	
Perceived Ease of Use	PEOU1	I believe a smartwatch is easy to use in the patient-doctor setting	[26,27]
	PEOU2	I believe a smartwatch can be a substitute for alternative technology as it is simple to utilize	
	PEOU3	I think a smartwatch is too technical a device and requires too much thought to use effectively	
Perceived Usefulness	PU1	I feel that a smartwatch can assist in improving my workplace abilities	[26,27]
	PU2	I believe a smartwatch encourages me to regularly check for new information	
	PU3	I feel that a smartwatch is an excellent source of information both for doctors and patients	
Relevance	RELV1	A smartwatch provides me with sufficient necessary information	[30]
	RELV2	A smartwatch provides extremely useful information whether for a doctor or patient	
	RELV3	A feel a smartwatch doesn't provide sufficient information that I need	
Sufficiency	USAT1	A smartphone can provide a useful amount of information	[30]
	USAT2	A smartwatch has provided me with enough information when I have needed it	
	USAT3	A smartphone is unable to give me the information I need	
Timeliness	TIML1	A smartwatch has up-to-date medical information that I need	[30]
	TIML2	A smartwatch can't provide me with up-to-date information	
User Satisfaction	SUFF1	On the whole, my experiences using a smartwatch as a doctor/patient were acceptable	[43]
	SUFF2	On the whole, my experience using a smartwatch met all my needs	
	SUFF3	On the whole, my experience using a smartwatch was unsatisfactory	
Flow Experience	FEXP1	I am completely engaged whenever I use a smartwatch	[10,75,76]
	FEXP2	My focus is solely on the smartwatch whenever I use one	

4.4. Survey structure

An online questionnaire survey was circulated by the researcher to participants (N = 400) at the UAE Medical Center and the primary healthcare sector, including the most reputed hospitals in the region. The questionnaire was prepared and circulated among students [71]. The survey had three sections:

- The first section of the survey collected the personal data of the participants
- The second section included two questions investigating the adoption of smartwatches

- The third section comprised 22 elements that relate to user satisfaction, content richness (timeliness, relevance and sufficiency), flow experience, perceived usefulness, perceived ease of use, and personal innovativeness.

All 24 items were measured using a 5-point Likert scale comprising the following choices: strongly agree (5), agree (4), neutral (3), disagree (2), and strongly disagree (1).

5. Findings and discussion

5.1. Data analysis

PLS-SEM [77] was employed for data analysis [78–80]. An assessment model based on two structural and measurement models was used for the data analysis [81,82]. PLS-SEM was chosen for this study first because it is seen as the best option, and adaptation from an existing theory is involved [83]. Second, when complex models require analysis, PLS-SEM is highly effective [84]. Third, PLS-SEM does not require the model to be fragmented; instead, analysis of the whole model is carried out [85]. Lastly, estimations are more accurate when using PLS-SEM as it conducts simultaneous analyses of the measurement model and the structural model [65].

5.2. Convergent validity

Validity should be estimated to successfully evaluate the measurement model, including convergent and discriminant validity, along with construct reliability, Cronbach's alpha, and composite reliability (CR) [81]. Data in Table 3 assisted with the evaluation of the construct reliability. Based on the results, Cronbach's alpha values lie between 0.789 and 0.889, exceeding the threshold value of 0.7 [86]. The results provided in Table 3 also reveal that the CR values lie in the range of 0.760–0.876, which is more than the recommended value of 0.7 [87]. Based on these results, construct reliability has been confirmed as all the constructs have been deemed to be error-free.

To successfully measure convergent validity, one should test the Average Variance Extracted (AVE) and the factor loading [81]. Based on the results of factor loading provided in Table 3, the values are more than the threshold value of 0.7. In addition, AVE values provided in Table 3 lie between 0.623 and 0.771, exceeding the threshold value of 0.5. Based on these results, all the constructs show convergent validity.

Table 3
Tests for construct reliability.

Constructs	Items	Factor Loading	Cronbach's Alpha	CR	AVE
ADSW	ADSW1	0.834	0.815	0.834	0.653
	ADSW2	0.865			
USAT	USAT1	0.863	0.785	0.786	0.625
	USAT2	0.824			
	USAT3	0.829			
FEXP	FEXP1	0.853	0.831	0.853	0.693
	FEXP2	0.882			
PEOU	PEOU1	0.860	0.889	0.817	0.632
	PEOU2	0.822			
	PEOU3	0.808			
PU	PU1	0.803	0.800	0.805	0.771
	PU2	0.805			
	PU3	0.866			
RELV	RELV1	0.865	0.811	0.760	0.623
	RELV2	0.872			
	RELV3	0.828			
TIML	TIML1	0.815	0.835	0.822	0.712
	TIML2	0.845			
SUFF	SUFF1	0.757	0.808	0.763	0.700
	SUFF2	0.894			
	SUFF3	0.849			
PER	PERI1	0.834	0.841	0.876	0.706
	PERI2	0.853			
	PERI3	0.876			

5.3. Discriminant validity

To measure discriminant validity, it is recommended that the Fornell-Larcker criterion, the Heterotrait-Monotrait (HTMT) ratio, and the cross-loading scale be measured [81]. The results in Table 4 reveal that the square root of every AVE value is greater than the correlation constructs, hence satisfying the Fornell-Larcker criterion [88].

The results in Table 5 show that each construct's HTMT ratio value is below the threshold of 0.85 [89], which indicates that the HTMT ratio is confirmed. Discriminant validity is calculated using all these results. Using the following results, the establishment of discriminant validity is achieved. It is evident from the analysis of results that the reliability and validity of the measurement model are error-free. This means that the collated data can be utilized for the assessment of the structural model.

AVE was computed as part of the research to verify that every one of the model constructs had a substantial variance with its measures than that of the variance between a particular construct and the remainder of the latent constructs in the research model. The square root of every construct's AVE must be more than the threshold (0.5) while also being more significant than the variance among constructs and the remainder of the model constructs [90]. If a construct's AVE is greater than 0.5, the construct accounts for roughly 50% of the measurement variance. The discriminate score was determined using PLS-SEM. Table 6 lists the figures for the loadings and cross loadings. The loading and cross-loading results revealed that the measurement items had higher loading under their latent constructs than with other constructs [91].

5.4. Hypothesis testing

This research has examined the proposed model using ML and PLS-SEM classification algorithms. It is assumed that using a multi-analytical approach will contribute to the information system (IS) literature as it utilizes ML algorithms to predict the intention to use a smartwatch. Basically, PLS-SEM utilization is appropriate for forecasting a dependent variable and validating a conceptual model based on the extrapolation of an established theory [92]. Similarly, supervised ML algorithms (those which have a pre-defined dependent variable) can be utilized to predict a dependent variable based on independent variables [93]. In addition, in the analysis, different classification algorithms with different methodologies were used, including correlation laws, Bayesian networks, neural networks, decision trees, and if-then-else rules.

The results indicated that the J48 decision tree in particular outshone other classifiers in terms of performance in most cases. Moreover, a nonparametric decision tree was utilized for classification of continuous (numerical) variables by sample division into homogeneous sub-samples with respect to a highly significant independent variable [94]. In contrast, PLS-SEM, a nonparametric procedure, has been utilized to examine the significant coefficients by taking alternatives from samples to extract sub-samples on a random basis.

5.4.1. Hypothesis testing using PLS-SEM

Structural model assessment follows the assessment of the measurement model [95]. It includes a long and extensive bootstrapping process of 5000 resamples for the evaluation of the coefficient of determination (R^2) and path coefficients [96]. For every hypothesis associated with the path analysis, values of path coefficients, *t*-values, and *p*-values were noted and are provided in Table 8. Every hypothesis is supported by every researcher. The data analysis reveals that all the hypotheses (H1, H2, H3, H4, H5, H6, H7, H8, and H9) are supported by empirical data.

The coefficient of determination (R^2) is used to assess the structural model [84]. The coefficient is equal to the squared correlation of the actual value with the predicted value of an endogenous construct. The

Table 4
Fornell-Larcker scale.

	ADSW	USAT	FEXP	PEOU	PU	RELV	TIML	SUFF	PERI
ADSW	**0.866**								
USAT	0.433	**0.878**							
FEXP	0.565	0.523	**0.809**						
PEOU	0.436	0.442	0.474	**0.872**					
PU	0.457	0.356	0.541	0.468	**0.843**				
RELV	0.469	0.420	0.432	0.523	0.520	**0.886**			
TIML	0.538	0.523	0.434	0.317	0.406	0.210	**0.870**		
SUFF	0.536	0.650	0.450	0.426	0.566	0.226	0.644	**0.816**	
PERI	0.533	0.667	0.496	0.441	0.242	0.285	0.593	0.540	**0.843**

Table 5
Discriminant validity (HTMT).

	ADSW	USAT	FEXP	PEOU	PU	RELV	TIML	SUFF	PERI
ADSW									
USAT	0.245								
FEXP	0.194	0.219							
PEOU	0.249	0.025	0.151						
PU	0.068	0.355	0.352	0.567					
RELV	0.209	0.525	0.467	0.677	0.550				
TIML	0.258	0.593	0.632	0.483	0.569	0.445			
SUFF	0.259	0.446	0.529	0.462	0.299	0.493	0.355		
PERI	0.396	0.559	0.366	0.441	0.348	0.512	0.399	0.616	

Table 6
Cross-loading scale.

	ADSW	USAT	FEXP	PEOU	PU	RELV	TIML	SUFF	PERI
ADSW1	**0.845**	0.523	0.224	0.669	0.672	0.221	0.620	0.513	0.681
ADSW2	**0.883**	0.509	0.110	0.595	0.626	0.323	0.508	0.580	0.648
USAT1	0.657	**0.809**	0.226	0.625	0.581	0.331	0.600	0.593	0.640
USAT2	0.574	**0.878**	0.525	0.688	0.670	0.212	0.592	0.664	0.654
USAT3	0.574	**0.928**	0.501	0.570	0.596	0.330	0.555	0.455	0.573
FEXP1	0.622	0.676	**0.921**	0.587	0.665	0.516	0.651	0.615	0.650
FEXP2	0.559	0.609	**0.918**	0.662	0.694	0.541	0.530	0.670	0.620
PEOU1	0.641	0.634	0.522	**0.877**	0.658	0.521	0.623	0.653	0.617
PEOU2	0.488	0.628	0.427	**0.801**	0.689	0.424	0.609	0.651	0.674
PEOU3	0.677	0.606	0.312	**0.906**	0.577	0.433	0.539	0.611	0.645
PU1	0.672	0.617	0.429	0.627	**0.825**	0.319	0.622	0.589	0.662
PU2	0.587	0.672	0.426	0.636	**0.754**	0.530	0.552	0.658	0.694
PU3	0.657	0.680	0.338	0.606	**0.932**	0.225	0.571	0.655	0.643
RELV1	0.564	0.539	0.230	0.685	0.689	**0.927**	0.653	0.636	0.699
RELV2	0.614	0.545	0.490	0.571	0.497	**0.913**	0.539	0.593	0.610
RELV3	0.656	0.654	0.333	0.579	0.678	**0.928**	0.620	0.560	0.546
TIML1	0.589	0.611	0.419	0.605	0.681	0.322	**0.907**	0.625	0.677
TIML2	0.651	0.661	0.529	0.566	0.608	0.404	**0.837**	0.519	0.574
SUFF1	0.565	0.634	0.512	0.627	0.623	0.507	0.602	**0.838**	0.636
SUFF2	0.506	0.604	0.508	0.585	0.536	0.632	0.586	**0.842**	0.594
SUFF3	0.598	0.600	0.513	0.577	0.622	0.317	0.538	**0.859**	0.679
PERI1	0.571	0.637	0.624	0.597	0.649	0.634	0.530	0.593	**0.814**
PERI2	0.567	0.639	0.326	0.637	0.596	0.627	0.570	0.559	**0.746**
PERI3	0.572	0.524	0.217	0.654	0.658	0.526	0.596	0.644	**0.850**

coefficient represents the model's predictive accuracy [97,98] and also determines the collective effect of all exogenous latent variables on endogenous latent variables. The variance among the endogenous constructs is also augmented since the coefficient indicates the squared correlation of actual values with a variable's predicted value (see Fig. 1).

All values that are higher than 0.67 are considered as high. Similarly, middle values are found between 0.33 and 0.67, while weak ones are found between 0.19 and 0.33. Any value below 0.19 is inadmissible [99]. The model shows moderate predictive power, as reflected in Table 7 and Fig. 2. The data show that the model supports 55.3% variance in perceived usefulness, 58.7% variance in adoption of smartwatches, and 63.1% in perceived ease of use.

Sufficiency (SUFF), timeliness (TIML), relevance (RELV), and personal innovativeness (PERI) have a significant effect on perceived usefulness (PU) (($\beta = 0.359$, $P < 0.001$), ($\beta = 0.402$, $P < 0.01$), ($\beta = 0.471$, $P < 0.01$) and ($\beta = 0.871$, $P < 0.05$), respectively). Hence, H1, H2, H3, and H4 are supported. The relationship between personal innovativeness (PERI) and perceived ease of use (PEOU) ($\beta = 0.692$, $P < 0.01$) is statistically significant, so hypothesis H5 is generally supported. User satisfaction (USAT), perceived usefulness (PU), perceived ease of

Table 7
R^2 of the endogenous latent variables.

Constructs	R^2	Predictive power
Adoption of Smartwatch	0.587	Moderate
Perceived Ease of Use	0.631	Moderate
Perceived Usefulness	0.553	Moderate

Table 8
Output of SEM.

H	Relationship tested	Path	t-value	p-value	Results
H1	Sufficiency - > Perceived Usefulness	0.359	16.002 (382)	0.000	Supported**
H2	Timeliness - > Perceived Usefulness	0.402	15.221 (382)	0.000	Supported**
H3	Relevance - > Perceived Usefulness	0.471	13.589 (382)	0.001	Supported**
H4	Personal Innovativeness - > Perceived Usefulness	0.871	3.029 (382)	0.014	Supported*
H5	Personal Innovativeness - > Perceived Ease of Use	0.692	14.376 (382)	0.000	Supported**
H6	User Satisfaction - > Adoption of the Smartwatch	0.538	17.606 (382)	0.000	Supported**
H7	Perceived Usefulness - > Adoption of the Smartwatch	0.616	5.304 (382)	0.012	Supported*
H8	Perceived Ease of Use - > Adoption of the Smartwatch	0.264	18.770 (382)	0.000	Supported**
H9	Flow Experience - > Adoption of the Smartwatch	0.753	17.058 (382)	0.000	Supported**

use (PEOU), and flow experience (FEXP) have a noticeable effect on ADSW (($\beta = 0.538$, $P < 0.001$), ($\beta = 0.0.616$, $P < 0.05$), ($\beta = 0.0.264$, $P < 0.001$), and ($\beta = 0.753$, $P < 0.001$), respectively). The hypothesis test results are summarized in Table 8.

5.4.2. *Importance-performance map analysis*

IPMA was utilized in PLS-SEM to examine the variables impacting ADSW in this research. IPMA contributes to a deeper comprehension of the PLS-SEM technique [100]. IPMA also includes latent constructs and associated performance metrics such as an additional channel coefficients tester (importance measure) [100]. In this research, the IPMA revealed the cumulative implications of every construct's utility and performance. The IPMA findings in Fig. 3 demonstrate the importance and performance of the model's constructs. According to the graph, USAT is the most important and performs the best, followed by PEOU and PU, and then FEXP. The lowest levels of utility and performance were indicated by SUFF.

5.4.3. *Hypothesis testing using ML algorithms*

To predict the relation between factors within the proposed theoretical model, machine-learning classification algorithms were utilized in this study. To achieve this, multiple methodologies were used, such as decision trees, Bayesian networks, neural networks, and if-then-else rules [94,101]. Weka (ver. 3.8.3) was utilized to test the predictive model. Different classifiers, such as J48, Logistic, OneR, BayesNet, LWL, and AdaBoostM1, were used to test the predictive model [102–106].

The results shown in Table 9 indicate that J48 performs much better than many other classifiers in terms of forecasting the perceived usefulness of a smartwatch (PU). Using 10-fold cross-validation, the prediction of PU by J48 was seen to have an accuracy level of 85.37%. Therefore, H1, H2, H3, and H4 are supported. J48 offered superior performance when compared to other classifiers regarding precision (0.853), TP rate (0.856). and recall (0.852). The results in Table 10 similarly show that when compared to alternative classifiers, J48 showed enhanced classification performance for PEOU prediction with 75.19% accuracy for personal innovativeness (PERI) attributes. Thus, H5 is supported.

J48 showed better performance for ease of use (PEOU), perceived usefulness (PU), perceived flow experience (FEXP), and predicting ADSW by user satisfaction (USAT). According to the results shown in Table 11, ADSW was predicted with 81.38% accuracy by the J48 classifier. Thus, H6, H7, H8, and H9 are supported.

6. Discussion

This research empirically explores the feasibility of the adoption of smartwatches in the field of medicine. An integrated model that incorporates TAM constructs with external factors was utilized to validate the use of smartwatches. The external factors included content richness and personal innovativeness, and flow theory along with user satisfaction were utilized.

This research shows that content richness (determined based on the three main factors of sufficiency, relevancy, and timeliness) can have a beneficial effect on smartwatch adoption and can enhance the adoption of smartwatches. Moreover, content richness seems to have a positive and critical effect on perceived usefulness, which could enable more users to accept smartwatch. The results of the current study appear to be in accordance with previous findings in which quality content affects perceived usefulness and perceived ease of use [21,107,108]. In previous research, content richness was used as an external factor and showed a substantial effect on perceived usefulness in acceptance studies [21, 109].

The personal traits of an individual affect their personal

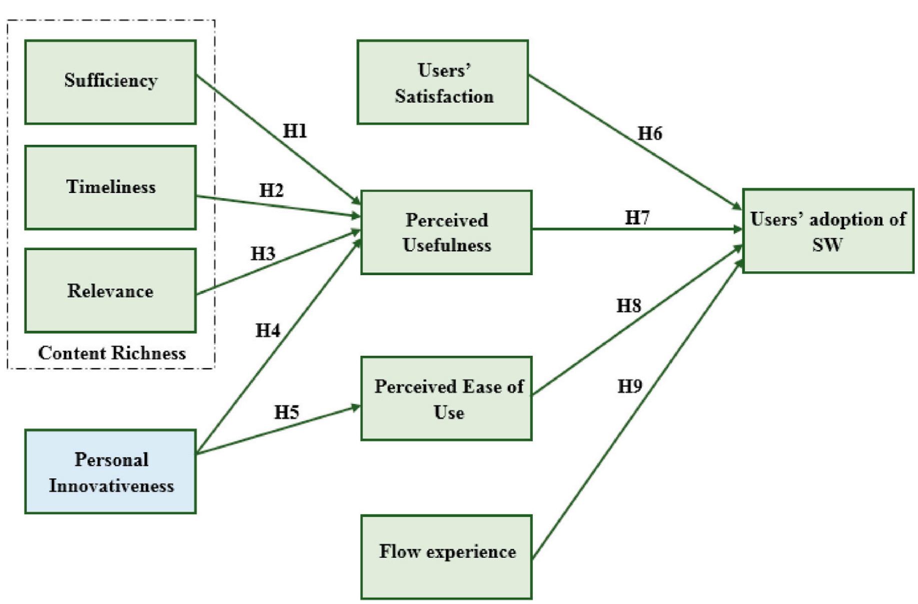

Fig. 1. The research model.

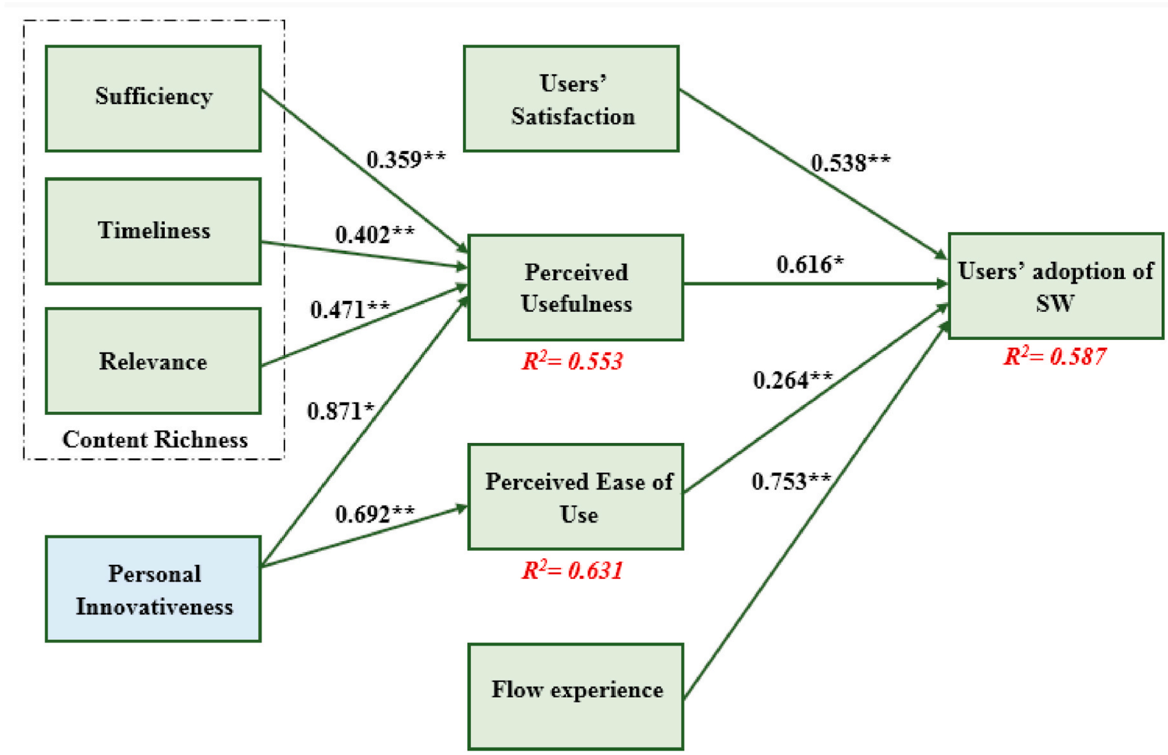

Fig. 2. Structural model results.

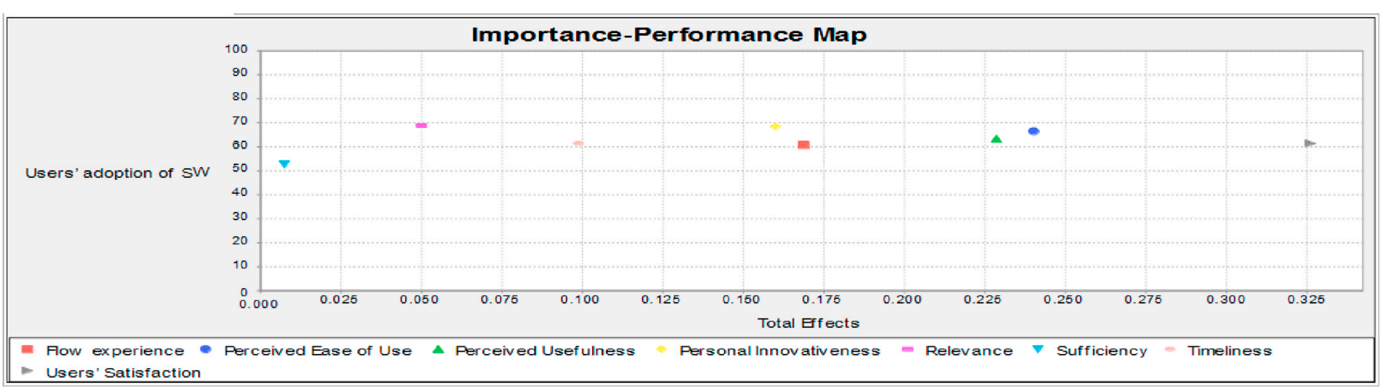

Fig. 3. IPMA results.

Table 9
Prediction of the PU by RELV, TIML, SUFF, and PERI.

Classifier	CCI[a] (%)	TP[b] rate	FP[c] rate	Precision	Recall	F-Measure
BayesNet	83.57	0.836	0.452	0.834	0.833	0.846
Logistic	82.51	0.825	0.412	0.824	0.822	0.825
LWL[d]	79.40	0.794	0.446	0.794	0.793	0.795
AdaBoostM1	81.42	0.814	0.542	0.814	0.813	0.815
OneR	84.01	0.830	0.597	0.841	0.840	0.841
J48	85.37	0.856	0.572	0.853	0.852	0.854

[a] CCI: Correctly Classified Instances.
[b] TP: True Positive.
[c] FP: False Positive.
[d] LWL: Locally Weighted Learning.

Table 10
Prediction of the PEOU by PERI.

Classifier	CCI[a] (%)	TP[b] rate	FP[c] rate	Precision	Recall	F-Measure
BayesNet	71.22	0.712	0.314	0.713	0.712	0.713
Logistic	71.42	0.714	0.258	0.713	0.713	0.714
LWL[d]	73.20	0.732	0.331	0.732	0.731	0.732
AdaBoostM1	74.46	0.744	0.348	0.742	0.731	0.732
OneR	73.57	0.735	0.347	0.740	0.741	0.742
J48	75.19	0.751	0.452	0.753	0.752	0.752

[a] CCI: Correctly Classified Instances.
[b] TP: True Positive.
[c] FP: False Positive.
[d] LWL: Locally Weighted Learning.

innovativeness, and highly innovative individuals show more willingness and enthusiasm when it comes to technology acceptance. The study outcomes suggest that there is a significant influence of personal effectiveness on perceived ease of use and a slight influence on perceived usefulness. The findings of the present study are consistent with earlier findings [110,111], which declared that there is a critical and decisive

Table 11
Predicting the ADSW by USAT, PU, PEOU, and FEXP.

Classifier	CCI[a] (%)	TP[b] rate	FP[c] rate	Precision	Recall	F-Measure
BayesNet	80.30	0.803	0.503	0.802	0.803	0.804
Logistic	80.37	0.803	0.518	0.803	0.803	0.804
LWL[d]	80.70	0.807	0.537	0.806	0.806	0.807
AdaBoostM1	80.39	0.803	0.535	0.803	0.803	0.804
OneR	80.64	0.806	0.558	0.805	0.805	0.807
J48	81.38	0.814	0.610	0.815	0.813	0.814

[a] CCI: Correctly Classified Instances.
[b] TP: True Positive.
[c] FP: False Positive.
[d] LWL: Locally Weighted Learning.

effect of personal innovativeness on technology adoption. It is closely related to personal traits. In addition, innovativeness and enjoyment go hand in hand. Every time users experience a high level of enjoyment, they are likely to have higher personal innovativeness [112].

There is a significant and direct impact of two TAM variables on the adoption of smartwatches. The findings suggest that adoption is dependent on perceived usefulness and perceived ease of use. It can be assumed that once technology is seen to be effortless or helpful, different users in various fields, both academic and non-academic, will show greater demand for it [113,114]. There is agreement between the current research and earlier studies pertaining to the medical field with regard to the fact that technology perceived as useful and easy to use is willingly adopted by doctors, nurses, and patients [115,116].

One of the external factors in this study was flow theory. The results show that flow theory tends to have a critical effect on the adoption of technology. User adoption of technology is highly dependent on their level of engagement, so it seems that smartwatches have improved the level of engagement substantially, contributing to a positive impact on adoption. This assumption is supported by previous studies. According to two studies [117,118], flow experience positively affects the behavior intention of users. The satisfaction of users appears to be influenced by the factors of perceived usefulness and ease of use. This research indicates that users who perceive using a smartwatch as effortless and helpful are more satisfied with the technology's adoption.

The previous results reflect the opinions of other researchers [119,120]. They claim that technology users tend to have a higher degree of satisfaction when they perceive a technology to be of greater value. Consequently, their behavioral intent is positively influenced. Likewise, when individuals perceive a technology to be convenient and easy to use, they have higher satisfaction.

6.1. Theoretical implications

We used a combination of PLS-SEM and ML classification algorithms to validate the proposed model. As previously mentioned, using a complementary multi-analytical approach provides a unique contribution to the existing IS literature as this research project is one of very few where ML algorithms are utilized for adoption prediction of smartwatches in the field of medicine. It should also be noted that PLS-SEM can be utilized for the prediction of dependent variables and to validate mathematical models through extrapolation of current theory [64]. In a similar manner, supervised ML algorithms (where dependent variables are pre-defined) can be deployed to predict a dependent variable based on independent variables [94].

An additional and interesting aspect of this research is the utilization of multiple classification algorithms with varying methodologies, such as decision trees (J48), Bayesian networks, neural networks, and if-then-else rules. In most cases, the results reveal that the performance of decision trees (J48) was better than alternative classifiers. It is worth noting that categorical variables and continuous (numerical) variables were both classified using the nonparametric decision tree, which divided the sample into homogeneous sub-samples based on the most important independent variables [94]. In contrast, the significant coefficients were evaluated using PLS-SEM (a nonparametric procedure) with sample substitutes to obtain a large number of random samples.

6.2. Practical and managerial implications

Wearable technology developers can benefit from this study while developing novel wearable technology (e.g., smartwatches) specifically for the medical sector. Wearable technology must be beneficial for patients, doctors, and the entire medical field at the same time. It is vital for doctors to be aware of the features of wearable technology that are essential for them, and developers must strive to incorporate such features of doctors' needs, which will convince doctors to willingly adopt such new technology. Technology developers must be especially conscious while developing features with crucial and time-critical functions. The decision to use and acceptance of technology by users is highly dependent on the efficiency of such crucial functions [121,122].

According to the current research, users are more willing to use wearable technology on a frequent basis when it effectively performs specific tasks (like quick access to accurate information). Moreover, effective use of wearable technology by both doctors and patients was also observed in cases where the features effectively catered to their individual needs. For better uptake between the functions offered by wearable technology and the requirements of the medical field, it is necessary for wearable technology managers to develop and modify the features in accordance with the end-users' needs. Such compatibility between user needs and wearable technology designers will be essential for both parties and could also fulfil the basic objective behind the development of such devices.

The administration of hospitals should be driven by recommendations to follow while attempting to improve the use of wearable technology because associated technological applications will also be promoted as a result of the use of smart wearable technology in various departments of hospitals. Patients are also advised to learn and understand how to use different smart wearable devices with phone-based features. Furthermore, the results reveal a significant benefit for doctors and patients. For instance, wearable technology has a strong foothold in the medical sector. This means that new features must be introduced in wearable technology that will offer additional benefits to both physicians and patients [123,124]. The findings suggest providing guidelines for consultants, physicians, and doctors to make successful use of wearable technology for various medical purposes. In particular, the external factors of content richness, satisfaction, and flow of experience are likely to convince users of technology to accept and adopt it; therefore, doctors must adopt such features to convince patients to use wearable technology devices.

An efficient wearable technology must have various medical-specific features that support medical evaluations like the entry of insulin units, blood glucose, and carbohydrates; viewing of all necessary previously reported values, monitoring of essential physical activities, etc. [6,7]. It is evident from earlier research that the level of use of such technology in the future is likely to be elevated if it is perceived as user-friendly [125]. Hence, doctors and hospital managers should collaborate with technology designers and identify highly beneficial medical aspects of technology such as smartwatches so that specific features can be improved or developed to cater to user needs.

6.3. Limitations of the study

This research has some limitations that need to be borne in mind during future research. The generalizability of the study was affected by the involvement of only frontline healthcare providers. Additionally, it was also not within the research scope to include other healthcare providers. Beyond this, only a specific service in the governmental medical sector was reflected in the study, which provided the only data collected for this study because of time and budget limitations. Furthermore, considering that the information was gathered from only one service industry, it may be problematic to generalize the findings to other service industries.

Moreover, this study followed a cross-sectional design using a survey questionnaire to collect data, and the duration of data collection was limited. Thus, it is likely that the results could have been better if a longitudinal research design had been used, which would have enabled more extensive supervision and better understanding of the benefits of smartwatch technology and apps. Finally, the required information in this study was only collected from staff by using a survey questionnaire.

It is also advised that future studies use multiple means of data collection or methods of data triangulation, like interviews and observation, to provide healthcare professionals with more comprehensive understanding of smartwatch adoption. Relevant external variables that enhance smartwatch visibility were the subject of the current study. Considering the ever-evolving features and uses of smartwatches, the external variables to be considered in future research may vary from the current ones.

In addition, the current study focused on flow theory along with the TAM model, but other researchers may concentrate on other models that may serve different psychological and social factors. This study was also restricted to the domain of medicine, so future studies could involve other environments, whether academic or non-academic. Finally, in the current research, no attention was paid to gender differences, so future research could bridge this gap and dig deeper to highlight the impact of gender differences.

7. Conclusion

A variety of studies have been conducted on the usage of various technologies in the medical profession, but there is a gap in studies on doctors, patients, and nurses' employment and privacy constraints. The goal of this research was to fill this gap in relation to content richness, constructs of user satisfaction, and innovativeness variables in consumer utilization of smartwatches for medical reasons. We feel that emphasizing this subject assists in further studies in this field because of the special attributes of this technology and the level of self-collected data in its usage.

The present research's findings revealed that the model's primary constructs influence smartwatch adoption in distinct ways. The content richness and personal innovativeness according to the study premise are essential aspects that enhance perceived usefulness. Additionally, perceived ease of use was found to be a strong predictor of personal innovativeness. Altogether, the data indicate that smartwatches are a great product in the medical field and that it could be utilized as a shared medium between doctors and their patients, which could improve the function of information sharing between users.

Declarations of interest

None.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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