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# Determinants of intention to use medical smartwatch-based dual-stage SEM-ANN analysis

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ABSTRACT

The current study is based on an integrated research model developed by combining constructs from the Technology Acceptance Model (TAM) and other features affecting smartwatch effectiveness, such as content richness and user satisfaction (SAT). TAM is used to locate factors influencing the adoption of the smartwatch (ASW). Most importantly, the current study focuses on factors influencing smartwatch acceptance and use in the medical area, facilitating and enhancing the effective role of doctors and patients. The present study's conceptual framework examines the close association between two-term TAM variables of perceived ease of use (PEU) and perceived usefulness (PU) and the constructs of user satisfaction and content richness. It also incorporates the flow theory (EXP) to measure the effectiveness of the smartwatch. The study also uses the flow theory to assess involvement and control over ASW. The study used a sample of 489 respondents from the medical field, including doctors, nurses, and patients. The study employed a hybrid analysis method combining Structural Equation Modeling (SEM) and an Artificial Neural Network (ANN) based on deep learning. The study also used Importance-Performance Map Analysis (IPMA) to determine the relevance and performance of the variables influencing ASW. Based on the ANN and IPMA analyses, user satisfaction is the most crucial predictor of intention to use a medical smartwatch. Applying the structural equation model to the sample shows that SAT, PU, PEU, and EXP significantly influence intention to use a medical smartwatch. The study also revealed that content richness is an important factor that enhances users' PU. The current study could enable healthcare provider practitioners and decision-makers to identify factors for prioritisation and to strategise their policies accordingly. Methodologically, this study indicates that a "deep ANN architecture" can determine the non-linear associations between variables in the theoretical model. Overall, the study finds that smartwatches are in high demand in the medical field and are useful in information transmission between doctors and their patients.

## 1. Introduction

The rapid development of the Internet of Things (IoT) has allowed users to access information without location or time restrictions. One of the evolutions in IoT is developing wearable technology, particularly smartwatches. The growth in demand and use of wearable technology has also allowed various stakeholders to access physical activity and medical information without time and location restrictions [1–3].

The development and sales of smartwatches have been increasing due to the advantages they provide in information access for users. The ability of smartwatches to link with mobile phones enables many people to adopt smartwatch technology and allows users to access different mobile phone features, get notifications, change watch faces, and monitor the time as they carry out different activities [4–6]. The demand for this technology has grown considerably in the medical field. Currently, smartwatch users can monitor their physical wellbeing, including blood pressure, blood glucose level, blood oxygen content, and level of physical activities [7,8]. The increase in health awareness and the demand for technology that can help people monitor medical-specific features has led to increased research and smartwatch development and innovation.

This study employs the integrated and innovative research model to investigate factors determining the adoption of smartwatches (ASW). Specifically, the integrated and innovative research model combines the

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Technology Acceptance Model (TAM) [9], the diffusion of innovation (DOI) model [10], and the flow model [11] to evaluate ASW predictors and the role of increased adoption of this technology. This model also contributes to investigating the direct and indirect effects of ASW antecedents. The current study is mainly aimed towards assessing ASW success in the medical area because adoption of that technology is vital for patients and doctors. ASW depends not only on individual users' decisions but also on the community's exchange of related information that is capable of diffusing attitudes and behaviours within a network of patients and doctors. The current research also joins previous smartwatch studies that have included external factors as determinants of ASW. Previous studies such as [12,13] have examined the impact of external variables, such as availability and mobility, on ASW. However, the current study assesses external factors, such as degree of satisfaction, content richness, and innovations, as the main external factors influencing ASW. While various studies have examined the acceptance of smartwatches, the current study is the first to evaluate ASW within the medical field using an integrated model.

The main issue of most researchers in Taiwan, Malaysia, and Korea has been ASW, and researchers have used surveys to collect information from participants. However, the difference between studies on ASW performed in Taiwan, Korea, and Malaysia has been the factors used in the studies. Studies such as [12,13] evaluated the impact of different external factors on ASW; the former evaluated mobility and availability effects, while the latter assessed novelty and social dimension on ASW. However, a study by Ref. [14] in Taiwan focused on other factors, including design aesthetics, relative advantage, and complexity. The study by Ref. [12] showed that ASW might have psychological implications, and thus the study's external factors were different from those used in other studies. Similar research by Ref. [15] examined availability and attitude as the main external factors influencing ASW.

Recently, studies have examined the difference in factors affecting smartwatches among users. One of these studies focused on the effectiveness of smartwatches by evaluating the attitudes of users from different countries. The study's comparative analysis indicated that the effect of availability on ASW differs between France and Thailand. The study also showed that the impact of trust in ASW differed between France and China. Studies [16,17] analysed wearable devices and indicated that external factors such as mobility, trust, cost, usefulness, and enjoyment played a considerable role in wearable device adoption.

Previous studies [12–26] on ASW have used questionnaires and TAM as key parts of their models [20–22]. However, a study by Ref. [19] differed from previous studies because it used UTAUT2 as an extended model. The TAM model is widely used in ASW studies because of its effect on ASW. The model affects ASW in two ways. Firstly, the model indicates that ASW may be affected by PU. However, PU is also affected by various extended factors. Secondly, the TAM model indicates that PEU influences the adoption and acceptance of smartwatches. Based on this model, PEU is a decisive element in external factors, such as fashion and innovativeness [20–22].

The available literature indicates no adequate empirical research supporting smartwatch use in the UAE medical sector. The available literature shows that the inadequacy in implementing smartwatches in the medical field is due to insufficient knowledge of smartwatch use and adoption factors. Most studies on ASW have employed the SEM approach to assess the theoretical models. Thus, the current research is based on two main aims. First, the study intends to assess factors influencing ASW by using the TAM [27,28] and Flow models [29]. The study also offers a solution to the previous ASW studies that used SEM in a single-stage linear analysis [30], meaning they could only assess the linear association among factors in the theoretical model, making it difficult to estimate the complicated process involved in decision making [31]. Even though some studies have suggested that the application of the ANN method to analyse data in the second stage [32–34] could solve the problem, such a proposal is limited because it involves a single hidden layer or shallow ANN [35]. The study by Ref. [36] proposed that the solution to the difficulties in predicting the complex decision-making process is to use a deep ANN and not a shallow ANN, because a deep ANN uses more than one hidden layer and can improve the accuracy of non-linear models. The current study uses a hybrid SEM-ANN method based on deep ANN. The objective is to offer deep learning based on the recommendations. Therefore, while previous studies have used the TAM model to investigate factors influencing ASW, the current study assesses the adoption and acceptance of smartwatches using a hybrid conceptual model.

The study contributes to the ASW literature because its framework focuses on the close link between the TAM constructs of PU and PEU and the constructs of content richness and user satisfaction. The study also includes other external factors that assess smartwatch effectiveness. The integration of flow theory also includes the degree of involvement and control over smartwatch dimensions in the study. Lastly, the current research examines the inherent motivation for ASW in the medical field, where smartwatches are needed to enhance doctors' effectiveness and their communication with patients.

## 2. Research model and hypotheses development

### 2.1. Content richness

Content richness consists of timeliness, relevance, and adequacy [37]. Sufficient or adequate content richness arises when users have access to various information. Timely (timeliness or correctness) content richness is the extent to which users can access up-to-date information [38,39]. Timelines are essential because outdated information is not useful; therefore, technological information is regarded as time-critical [40]. Relevance content richness arises when the information provided meets users' needs [41]. The link between content richness and PU was covered by Refs. [42,43]. Technology has high-quality content when it meets the user's needs. Thus, the study hypothesises as follows:

**H1**. Sufficiency (SUF) positively influences smartwatch PU.

**H2**. Timeless (TIM) positively influences smartwatch PU.

**H3**. Relevance (REL) positively influences smartwatch PU.

### 2.2. User satisfaction

User satisfaction arises when users' emotions regarding specific prior experiences match their expectations. Satisfaction influences users' negative or positive user reactions to technology. Users tend to prefer user-friendly and useful technology for their everyday operations. In such cases, users' intrinsic and extrinsic motivations are activated. Users' self-efficacy and personal innovativeness dominate their expectations. Thus, users feel satisfied when their expectations are met [44–46]. Since expectations influence satisfaction, user satisfaction can predict the adoption and use of technology. The more a technology meets the users' expectations, the more satisfied the user becomes and the higher the level of that satisfaction. Researchers have identified the close association between adoption and use of technology and user satisfaction, with user satisfaction as the primary predictor of the technology use [47–49]. Thus, based on user satisfaction, the study hypothesises as follows:

**H4**. User satisfaction (SAT) positively influences ASW.

### 2.3. TAM model

TAM has been widely used in the existing literature to investigate technology adoption and use in various fields [50,51]. Specifically, the current study focuses on two TAM constructs related to ASW: PU is the user's attitude towards the usefulness of the smartwatch, and PEU assesses the effort required to use technology and its user-friendliness [9,52]. Based on the TAM model, the study hypothesises as follows:

**H5**. PU positively affects ASW.

**H6**. PEU positively influences ASW.

### 2.4. Flow theory

Flow refers to a sense of involvement, control, and enjoyment. Users will accept, adopt, and consistently use technology when they feel it offers enjoyment. Consequently, activation of users' thought, attention, and behavioural repertoire leads to increases in positive feelings, which result in increased intention (the flow experience) to use technology [11, 53,54]. Time elapses faster when users experience flow and become inherently motivated. The consistent use of technology can be defined as continuous interactivity when users are pleased with, are enjoying, and are immersed in technology [55,56]. Research has showed that flow experience is a major predictor of the adoption of IT systems, including e-learning and entertainment. Thus, the flow experience is users' unconscious emotions when using technology [57]. Therefore, flow theory can predict the adoption and acceptance of technology. Based on the flow model, the study hypothesises as follows:

**H7**. Flow experience (EXP) positively influences ASW.

## 3. Methodology

Deductive research based on a cross-sectional design was employed in this study. The study administered online questionnaires to gather data from United Arab Emirates (UAE) healthcare providers. The study was conducted at healthcare centres in Dubai. The data collection was administered at five hospitals and seven primary healthcare clinics between December 15, 2020, and January 15, 2021. The official mail and social platforms, including WhatsApp, of the healthcare providers, which included administrative staff and clinical staff, were used to circulate the questionnaire link. The data collected was trustworthy because it was collected from a healthcare setting [58]. Information on healthcare practices is best collected from a healthcare facility. Furthermore, the target population was chosen as the unit of analysis for the study based on recommendations from healthcare service management studies [59–62]. The sample used had adequate knowledge of their organisation's practices and health quality, as recommended by Ref. [62]. The study also used non-probability sampling, especially the convenience sampling procedure, because the lists of workers in the selected or sampled hospitals and primary clinics were challenging to access. Healthcare organisations in Dubai have policies that protect the private information of staff. Thus, information such as the list of workers and their details are difficult to access. Convenience sampling was also employed because it is cheap, consumes less time, and enables access to a large sample [63].

The study evaluated the theoretical model using the PLS-SEM and ANN algorithm. PLS-SEM was used because of its ability to offer concurrent analysis to measure the structural model, enhancing the precision of the results [64,65]. The study also used the deep ANN method in SPSS software to assess the conceptual model's predictors. A deep ANN algorithm will significantly contribute to the present research on information systems (IS) as a complementary multi-analytical approach. The current study will be among the few that have used ANN to investigate ASW in the medical arena. Despite showing the influence of various factors ASW, the study's main contribution is its use of a framework emphasising the close association between two-term TAM variables of PU and PEU and the variables of content richness and user satisfaction. The study also employed flow theory to assess the user's control over and involvement in smartwatches. The present study shows factors that influenced people to use smartwatches in a medical environment, where smartwatches are essential in enhancing patients' and doctors' roles.

### 3.1. Data collection

In the present study, 11 out of the 500 randomly distributed questionnaires were rejected because they had missing values. Thus, only 489 (98%) questionnaires were completed and ready for analysis. The 489 questionnaires were distributed based on the sample size stipulated in Ref. [66]. Based on that study, a sample of 306 questionnaires would be appropriate for a population of 1500 persons. Since the sample size was 489 respondents (higher than the 306), SEM was used to verify the hypothesis [67]. Even though the hypotheses were created based on existing models, they were structured based on the ASW framework. SEM was used in the present study to evaluate the model and the final path model.

### 3.2. Personal/demographic information

Table 1 shows the study participants' demographics. The table shows that the sample respondents were of different genders, ages, educational qualifications, and experience and working in various sectors. Based on the table, the respondents comprised 51% females and 49% males. The table also indicates that respondents aged 18 to 29 were 39% of the sample, while those above 29 years were 61%. The demographic data also shows that most of the participants were well educated. Based on Table 1, 73% of the participants had bachelor's degrees, 15% had master's degrees, 11% had attained doctoral education level, and the rest had diploma qualifications. The study employed a purposive sampling approach [68] because participants were voluntarily participating in the study.

### 3.3. Instrument of the study

Table 2 shows the survey instruments that the study used to verify the hypotheses. The table comprises 21 items measuring the eight constructs located in the questionnaire. The study revised and redesigned questions from previous studies before using them in the questionnaire. The objective of revising and redesigning the questions was to improve the generalisability of the study.

### 3.4. Pilot study of the questionnaire

The study employed a pilot study to determine the questionnaire items' reliability. The study included 50 participants randomly chosen from the total sampled participants. The sample was 10% of the total sample of 500 respondents. IBM statistics version 23 was used to test items' internal reliability. Specifically, the reliability was tested using Cronbach's alpha. A Cronbach's alpha coefficient of 0.7 is sufficient for a questionnaire item [73] based on social science studies. The result shows that the measurement items were adequate. The result of the Cronbach's alpha for seven scales of measurement are shown in Table 3.

**Table 1**
The profile of respondents.

| Variables | Categories | Frequency | Percent |
|---|---|---|---|
| Gender | Female | 251 | 51% |
| | Male | 238 | 49% |
| Age | 18–29 | 191 | 39% |
| | 30–39 | 196 | 40% |
| | 40–49 | 63 | 13% |
| | 50–59 | 39 | 8% |
| Education | Diploma | 6 | 1% |
| | Bachelor's | 359 | 73% |
| | Master's | 72 | 15% |
| | Doctorate | 52 | 11% |

**Table 2**
Measurement items.

| Constructs | Items | Instrument | Sources |
|---|---|---|---|
| Adoption of Smartwatch | ASW1 | Using a smartwatch is recommended within a medical environment. | [52,69,70] |
| | ASW2 | Using a smartwatch with my patients and peers helps me in my career. | |
| PEU | PEU1 | Doctors and patients find it easy to use a smartwatch. | [27,28] |
| | PEU2 | A smartwatch can substitute for other technology because of its ease of use. | |
| | PEU3 | Mental effort is needed because a smartwatch is a complicated technology. | |
| PU | PU1 | Technical abilities can improve with smartwatch use. | [27,28] |
| | PU2 | Smartwatches improve users' desire to get new regular information. | |
| | PU3 | Doctors and patients can depend on a smartwatch as a good source of medical information. | |
| Relevance | REL1 | Smartwatches provide adequate content. | [38] |
| | REL2 | As a patient or doctor, I consider a smartwatch as a valuable source of information. | |
| | REL3 | Smartwatches provide acceptable content that meets my needs. | |
| Sufficiency | SAF1 | Smartwatches offer adequate medical information. | [38] |
| | SAF2 | A smartwatch offers adequate information when I use it. | |
| | SAF3 | Smartwatches cannot offer the information I need for personal use. | |
| Timeliness | TIM1 | Smartwatches provide updated medical information. | [38] |
| | TIM2 | Smartwatches do not offer updated medical information. | |
| User satisfaction | SAT1 | As a patient/doctor, I have satisfactory experience with smartwatches. | [44] |
| | SAT2 | A smartwatch will satisfy all my needs as a patient/doctor. | |
| | SAT3 | A smartwatch did not offer a satisfactory experience. | |
| Flow Experience | EXP1 | A smartwatch allows me to be fully engaged. | [11,71,72] |
| | EXP2 | My attention is only placed on the smartwatch when I am using it. | |

**Table 3**
The pilot study's Cronbach's alpha values.

| Constructs | Cronbach's Alpha. |
|---|---|
| ASW | 0.888 |
| PEU | 0.856 |
| PU | 0.757 |
| SAT | 0.795 |
| CONT | |
| REL | 0.783 |
| TIM | 0.869 |
| SUF | 0.799 |
| EXP | 0.759 |

### 3.5. Structure of the survey

The questionnaires were distributed to 500 participants (N = 500) among the United Arab Emirates (UAE) medical centre, including the primary healthcare sector [68]. The survey included the following sections:

- Participant's Personal data
- Adoption of Smartwatch Questions
- Items (19) related to SAT, EXP, PEU, and PU CONT (TIM, SUF, and REL)

A 5-point Likert scale (1 = strongly disagree … 5 = strongly agree) was used to measure 21 items.

### 3.6. Common method Bias (CMB)

The study carried a Harman's single-factor with seven factors to ensure that the data were free of CMB [73]. The seven factors were then loaded into a single factor. The newly created factor (single factor) explained 23.21% of the variation (largest variance) based on the analysis. However, 23.21% of the variation was below the required 50% threshold value [73]. Thus, the Harman's single-factor result indicates that the collected data was free of CMB.

## 4. Findings and discussion

### 4.1. Data analysis

The present study differs from prior studies because it employed a hybrid SEM-ANN methodology created with deep learning to assess the hypothesized association among variables in the research model. Previous studies have used a single-stage analysis through SEM. The hybrid SEM-ANN used in the present study involves two phases. In the first phase, the study uses partial least squares-SEM (PLS-SEM) using SmartPLS to evaluate the proposed research model [74]. The absence of prior related research and the theoretical model's exploratory nature motivated the use of PLS-SEM in the present research. The study also adhered to the general procedures for using PLS-SEM in research involving information systems [75]. Specifically, it applied a two-step method involving measurement and structural models to assess the research model proposed in previous literature [76]. The study also utilised IPMA to investigate the relevance and usefulness of the model's constructs. In the second phase, the study adopted ANN to investigate, authenticate and complement PLS-SEM analysis and identify the efficacy of predictors on predicted variables. As an instrument of function approximation, ANN is applicable where there is complex collaboration between input(s) and output(s) and the collaboration is non-linear. It involves three main dimensions: network architecture, learning rules, and transfer functions [76]. These three mechanisms are further divided into subgroups including but not limited to recurrent network and feed-forward multilayer perceptron (MLP) network [31]. The most applied approach in ANN is the MLP neural network. The MLP consists of many layers, including input and output layers that are linked using hidden nodes. The neurons or predictor variables in the input layer transport unprocessed data to the hidden layers in synaptic weights. The chosen activation function influenced each hidden layer output. One of the most-used activation functions is the sigmoidal function [77,78]. Thus, the proposed model was tested using the MLP neural network.

### 4.2. Convergent validity

A Cronbach's alpha test and composite reliability were employed for measurement model reliability. The study also tested the model's discriminant and convergent validity [79]. A Cronbach's alpha coefficient in Table 4 lies between 0.716 and 0.897 (more than the 0.7 threshold) [80]. Table 4 also indicates that the composite reliability (CR) value ranges between 0.735 and 0.904, which also exceeds the 0.7 threshold [81]. The results show that the constructs are reliable and free of error.

The convergent validity was measured using average variance extracted (AVE) and factor loading [79]. The factor loading values in Table 4 are more than the 0.7 threshold value. However, the 0.539 to 0.799 AVE values cross the 0.5 threshold value. The results indicate that each construct in the study satisfied the convergent validity.

**Table 4**
Constructs reliability.

| Constructs | Items | Factor Loading | Cronbach's Alpha | CR | AVE |
|---|---|---|---|---|---|
| Adoption of smartwatch | ASW1 | 0.756 | 0.840 | 0.739 | 0.765 |
| | ASW2 | 0.943 | | | |
| Users' satisfaction | SAT1 | 0.742 | 0.716 | 0.847 | 0.539 |
| | SAT2 | 0.839 | | | |
| | SAT3 | 0.741 | | | |
| Flow experience | EXP1 | 0.775 | 0.858 | 0.798 | 0.799 |
| | EXP2 | 0.729 | | | |
| Perceived ease of use | PEU1 | 0.900 | 0.897 | 0.758 | 0.554 |
| | PEU2 | 0.728 | | | |
| | PEU3 | 0.779 | | | |
| Perceived usefulness | PU1 | 0.889 | 0.828 | 0.776 | 0.682 |
| | PU2 | 0.827 | | | |
| | PU3 | 0.876 | | | |
| Relevance | REL1 | 0.839 | 0.847 | 0.886 | 0.754 |
| | REL2 | 0.884 | | | |
| | REL3 | 0.846 | | | |
| Timeliness | TIM1 | 0.828 | 0.889 | 0.735 | 0.629 |
| | TIM2 | 0.855 | | | |
| Sufficiency | SUF1 | 0.899 | 0.844 | 0.904 | 0.610 |
| | SUF2 | 0.798 | | | |
| | SUF3 | 0.748 | | | |

### *4.3. Discriminant validity*

Discriminant validity is the measure of the degree of variance between one construct of the research model and the rest of the constructs [82]. Discriminate validity was evaluated in three ways: the cross-loading scale, Fornell-Larcker criterion, and Heterotrait-Monotrait ratio (HTMT), which are required in discriminant validity measurement [79]. One of the methods involved evaluating the correlations between latent variable measurements and measurement items. Discriminate validity can hence be evaluated by comparing various constructs or measures. Each measure must exhibit higher loading than the cross-loading, implying that the loading of measures for the hypothesized construct must exceed that for the research model constructs.

The study involved a computation of the average variance extracted (AVE) to ensure that each of the model constructs showed a higher variance with its own measures than the variance between a specific construct and the rest of the latent constructs in the research model. Each construct must yield a value of the square root of its AVE as higher than the threshold (0.5) and at the same time greater than the variance between that specific construct and the rest of the model constructs [83]. If the AVE of a construct exceeds 0.5, then at least 50% measurement variance is explained by the construct. The value of the discriminate was estimated by applying Partial Least Squares (SmartPLS ver. 3.2.6). The values of the loadings and cross-loadings are tabulated in Table 5. The values of the loadings and cross-loadings showed that the measurement items had greater loading on their own latent constructs compared to their loading on other constructs [84].

Table 6 tabulates the outcomes of the AVE analysis. The bold diagonal part in the table gives an account of the square roots of the AVE values. The offload diagonal constituents in the table indicate the correlations among constructs. The square roots evaluated for the AVE values were found between 0.792 and 0.923, which exceed the recommended value of 0.5, as seen in the table. There is a significant difference between the AVE values and their corresponding correlations with the construct [85]; hence, it can be stated that all constructs showed greater variance with their specific measures as compared to their variance with other model constructs, therefore indicating the Fornell-Larcker criterion.

Recently, a criterion referred to as the heterotrait-monotrait ratio of correlations (HTMT) was proposed to evaluate the discriminate validity [86]. HTMT is statistically defined as the mean value of the heterotrait-heteromethod correlations compared to the average value of the monotrait-heteromethod correlations [86]. The HTMT method can be used for model analysis in PLS-SEM through the evaluation of discriminate validity. In the absence of a discriminate validity evaluation, the accuracy of the hypothesized structural paths is not certain, which may either be attributed to inaccurate results or to statistical discrepancies. The HTMT technique has clearly outperformed other techniques of determining the discriminate validity, including the Fornell-Larcker criterion [83] and (partial) cross-loadings, since a distinguishing feature of the HTMT technique is identifying the lack of discriminate validity [87]. HTMT values below 1 must suggest a distinct correlation between two constructs, while HTMT values greater than the threshold indicate a lack of discriminate validity. Some researchers have proposed an HTMT threshold value of 0.85 [88], whereas others have considered 0.90 as the threshold [89]. The heterotrait-monotrait ratio of the correlations (HTMT) values obtained are shown in Table 7, which indicates discriminate validity since a higher variance was found between the constructs and their individual measures and a lower variance of the construct with the rest of the model constructs.

**Table 5**
Cross-loading scale.

| | ASW | SAT | EXP | PEU | PU | REL | TIM | SUF |
|---|---|---|---|---|---|---|---|---|
| ASW1 | **0.756** | 0.647 | 0.102 | 0.400 | 0.264 | 0.045 | 0.211 | 0.062 |
| ASW2 | **0.943** | 0.443 | 0.274 | 0.102 | 0.677 | 0.018 | 0.564 | 0.184 |
| SAT1 | 0.353 | **0.742** | 0.459 | 0.239 | 0.451 | 0.647 | 0.218 | 0.119 |
| SAT2 | 0.449 | **0.839** | 0.618 | 0.290 | 0.428 | 0.239 | 0.011 | 0.185 |
| SAT3 | 0.454 | **0.741** | 0.264 | 0.421 | 0.111 | 0.216 | 0.442 | 0.052 |
| EXP1 | 0.181 | 0.156 | **0.775** | 0.077 | 0.507 | 0.293 | 0.439 | 0.091 |
| EXP2 | 0.245 | 0.419 | **0.729** | 0.490 | 0.647 | 0.339 | 0.350 | 0.185 |
| PEU1 | 0.018 | 0.365 | 0.511 | **0.900** | 0.650 | 0.133 | 0.108 | 0.089 |
| PEU2 | 0.223 | 0.305 | 0.599 | **0.728** | 0.259 | 0.076 | 0.018 | 0.145 |
| PEU3 | 0.599 | 0.443 | 0.154 | **0.779** | 0.647 | 0.022 | 0.211 | 0.366 |
| PU1 | 0.551 | 0.286 | 0.599 | 0.399 | **0.889** | 0.159 | 0.366 | 0.135 |
| PU2 | 0.319 | 0.677 | 0.623 | 0.283 | **0.827** | 0.335 | 0.639 | 0.211 |
| PU3 | 0.321 | 0.243 | 0.551 | 0.373 | **0.876** | 0.647 | 0.405 | 0.018 |
| REL1 | 0.581 | 0.563 | 0.449 | 0.391 | 0.094 | **0.839** | 0.001 | 0.482 |
| REL2 | 0.473 | 0.635 | 0.455 | 0.336 | 0.758 | **0.884** | 0.347 | 0.091 |
| REL3 | 0.491 | 0.545 | 0.500 | 0.512 | 0.420 | **0.846** | 0.691 | 0.185 |
| TIM1 | 0.559 | 0.557 | 0.539 | 0.455 | 0.533 | 0.233 | **0.828** | 0.123 |
| TIM2 | 0.153 | 0.156 | 0.490 | 0.421 | 0.555 | 0.564 | **0.855** | 0.594 |
| SUF1 | 0.449 | 0.419 | 0.501 | 0.360 | 0.257 | 0.600 | 0.233 | **0.899** |
| SUF2 | 0.450 | 0.395 | 0.612 | 0.518 | 0.187 | 0.420 | 0.297 | **0.798** |
| SUF3 | 0.585 | 0.300 | 0.401 | 0.442 | 0.094 | 0.087 | 0.105 | **0.748** |

**Table 6**
Fornell-larcker scale.

| | ASW | SAT | EXP | PEU | PU | REL | TIM | SUF |
|---|---|---|---|---|---|---|---|---|
| ASW | **0.923** | | | | | | | |
| SAT | 0.621 | **0.792** | | | | | | |
| EXP | 0.454 | 0.445 | **0.827** | | | | | |
| PEU | 0.325 | 0.555 | 0.385 | **0.896** | | | | |
| PU | 0.346 | 0.567 | 0.543 | 0.379 | **0.887** | | | |
| REL | 0.570 | 0.631 | 0.657 | 0.234 | 0.451 | **0.845** | | |
| TIM | 0.649 | 0.698 | 0.545 | 0.440 | 0.328 | 0.441 | **0.882** | |
| SUF | 0.478 | 0.528 | 0.268 | 0.659 | 0.298 | 0.459 | 0.539 | **0.859** |

**Table 7**
Heterotrait-monotrait ratio (HTMT).

| | ASW | SAT | EXP | PEU | PU | REL | TIM | SUF |
|---|---|---|---|---|---|---|---|---|
| ASW | | | | | | | | |
| SAT | 0.336 | | | | | | | |
| EXP | 0.211 | 0.628 | | | | | | |
| PEU | 0.138 | 0.436 | 0.202 | | | | | |
| PU | 0.255 | 0.269 | 0.259 | 0.679 | | | | |
| REL | 0.318 | 0.330 | 0.651 | 0.789 | 0.461 | | | |
| TIM | 0.344 | 0.425 | 0.743 | 0.584 | 0.470 | 0.356 | | |
| SUF | 0.461 | 0.567 | 0.732 | 0.573 | 0.615 | 0.204 | 0.267 | |

### *4.4. Model fit*

The model fit in PLS-SEM is based on SmartPLS measures such as Chi-Square, squared Euclidean distance (d_ULS), RMS theta, NFI, SRMR, and geodesic distance (d_G) [90]. The SRMR evaluates how the observed and model correlations differ [90]. Usually, if SRMR exceeds 0.08, the model is a good fit [87], while a good fit model has an NFI of more than 0.90 [91]. The NFI is derived as the ratio of the chi-square of the proposed and benchmark models [92]. Thus, the larger the chi-square value, the larger the NFI. Hence, NFI is preferred in measuring model goodness of fit [90]. The d_ULS and d_G measure the deviation between the empirical covariance matrix and composite factor model covariance matrix [90,93]. Reflective models employ RMS theta to evaluate the correlation of the outer model residuals [92]. A good fit PLS-SEM model has an RMS theta value close to zero. Specifically, a 0.12 RMS value is considered a good fit, while other values indicate that the model is not a good fit [94]. Based on [90], the association between construction in a model is assessed using the saturated model. However, total effect and model structures are assessed under the estimated model. The RMS theta of 0.073 in Table 8 indicates that the PLS-SEM model had enough goodness-of-fit.

### *4.5. Hypotheses testing*

The present study used a machine learning classification algorithm and PLS-SEM to evaluate the proposed model. The study aimed to enrich and enhance the existing studies on information systems by using a complementary multi-analytical approach. It employed the machine learning classification algorithm to investigate factors influencing ASW. PLS-SEM can predict ASW and validate a conceptual model using existing theories [95], while the machine learning classification algorithm can predict ASW using predictive constructs [96]. The classification algorithm includes neural networks and decision trees, among others. The present research shows that the decision tree performance is better than other machine learning classification algorithms. The study used the decision tree (parametric) to classify numerical and categorical variables by subdividing the sample into homogeneous subsamples based on the highest significance predictor variables [97]. However, the nonparametric test (PLS-SEM) was applied in the present study to assess the significance of the coefficients.

**Table 8**
Model fit indicators.

| | Complete Model | |
|---|---|---|
| | Saturated Model | Estimated Model |
| SRMR | 0.042 | 0.041 |
| d_ULS | 0.788 | 1.295 |
| d_G | 0.628 | 0.620 |
| Chi-Square | 582.292 | 582.292 |
| NFI | 0.792 | 0.799 |
| Rms Theta | 0.073 | |

#### *4.5.1. Hypotheses testing using PLS-SEM*

A coefficient of determination ($R^2$) and path coefficients were employed to evaluate the structural model [2]. $R^2$ is important in assessing model predictive accuracy [85,99,100]. The path analysis coefficients, *p*-value, and *t*-values for all the hypotheses are shown in Table 9. Table 10 shows that the empirical data analysis supports all the hypotheses (H1 to H7) (see Fig. 1).

The coefficient of determination ($R^2$) was employed to assess the structural models obtained by squaring the correlation between the dependent variable predicted and the actual values [98]. Thus, $R^2$ shows the dependent construct degree of variation. An $R^2$ greater than 0.67 indicates a high coefficient value, while a moderate coefficient value falls between 0.33 and 0.67. Weak values fall between 0.19 and 0.33, while a coefficient value below 0.19 is inadmissible [82]. As illustrated in Table 10 and Fig. 2, the $R^2$ of 0.701 and 0.712 show that the structural model has a high prediction of PU and ASW. Specifically, it explains 70% and 71% of the changes in PU and ASW, respectively.

The results show that SUF, TIM, and REL significantly affected PU ($\beta = 0.521$, $p < .001$), ($\beta = 0.492$, $p = .007$), and ($\beta = .567$, $p < .001$), respectively (see Table 10). Thus, the results support H1, H2, and H3. The results also show that SAT, PU, PEU, and EXP significantly influenced ASWA ($\beta = 0.646$, p $< .001$), ($\beta = .249$, $p = .032$), ($\beta = 0.553$, $p < .001$), and ($\beta = 0.798$, $p = .028$), respectively (see Table 10).

**Table 9**
$R^2$ of the endogenous latent variables.

| Constructs | $R^2$ | Result |
|---|---|---|
| ASW | 0.712 | High |
| PU | 0.701 | High |

 

**Table 10**
Hypotheses-testing of the research model.

| Hypothesis | Relationship | Path coefficient | *t*-value | *p* value | Remarks |
|---|---|---|---|---|---|
| H1 | SUF -> PU | 0.521 | 19.825 | 0.000 | Supported** |
| H2 | TIM -> PU | 0.492 | 3.836 | 0.018 | Supported* |
| H3 | REL -> PU | 0.567 | 17.328 | 0.000 | Supported** |
| H4 | SAT -> ASW | 0.646 | 15.679 | 0.000 | Supported** |
| H5 | PU -> ASW | 0.249 | 3.272 | 0.043 | Supported* |
| H6 | PEU -> ASW | 0.553 | 11.644 | 0.000 | Supported** |
| H7 | EXP -> ASW | 0.798 | 4.523 | 0.019 | Supported* |

#### 4.5.2. ANN results

SPSS was employed to carry out the ANN analysis, which relies on only significant independent constructs created by the PLS-SEM results. Thus, the ANN analysis only included SUF, PU, PEU, EXP, TIM, and SAT factors. Figs. 3 and 4 show that the ANN model comprises output neuron (ASW) and many input neurons (SUF, PU, PEU, EXP, TIM, and SAT). The deep ANN approach (two-layered) allowed deeper learning for each output neuron node [101,102]. The study used the sigmoid function as the activation function for the output and hidden neurons. The study also standardised the neurons (input and outputs) between [0, 1] to complement the proposed research model [103]. The present research also employed a tenfold cross-validation method (r = 80:20) for testing and data training to avoid ANN model overfitting [77]. The root means square of the error (RMSE) is recommended to evaluate the accuracy of the ANN. The ANN model's RMSE value for training was 0.1389, and the RMSE value for the testing data was 0.1416. The little variances among RMSE values and the standard deviation for data training and testing (i.e., 0.0047 and 0.009) indicate that the research model has high precision in applying ANN.

#### 4.5.3. Sensitivity analysis

Table 11 shows the mean and normalized usefulness of the independent constructs used in the ANN model. Table 11 shows that SAT is the primary predictor of ASW, followed by PU, PEU, REL, SUF, EXP, and TIM. The goodness of fit ($R^2$) was used to authenticate and validate ANN model performance and accuracy [104]. Based on the results, the predictive power of the ANN analysis ($R^2$ = 83%) exceeded the predictive power of PLS-SEM ($R^2$ = 71.2%). The findings show that the ANN approach is better at elucidating the endogenous constructs than the PLS-SEM approach. The power of the deep learning ANN in predicting the associations (non-linear) between constructs led to the difference in the predictive power of the two models.

#### 4.5.4. Importance-Performance Map Analysis

In this study, IPMA was used in PLS-SEM to assess the factors affecting ASW. According to Ref. [105], IPMA leads to a better understanding of the PLS-SEM approach. As an alternative path coefficients tester (importance measure), IPMA also consists of the latent constructs and their measures of performance [105]. The IPMA in this study showed the total effects of the usefulness and performance of each construct in the ASW framing. The IPMA result in Fig. 5 shows the importance and performance of the constructs used in the model. Based on the figure, SAT has the highest importance and performance, followed by PU and PEU, and then REL in third place. EXP reported the lowest usefulness and performance.

## 5. Discussion and conclusion

The present research was an empirical examination of ASW effectiveness in the medical area. The study adopted an integrated model that combines external factors and TAM variables to validate ASW. These external factors consisted of personal innovativeness, content richness, and flow theory along with user satisfaction. The study found a positive relationship between content richness and ASW. Specifically, the study showed that content richness can result in a high ASW by considering timeliness, relevancy, and sufficiency. The research also showed that content richness influences increased smartwatch use through PU, and content richness has a positive and significant effect on PU and, subsequently, ASW. The present study supports previous findings showing that quality content affected PEU and PU [22,106,107]. Like the present study, previous ASW studies have showed that content richness was an external factor that significantly influenced PU [22,108]. Personal

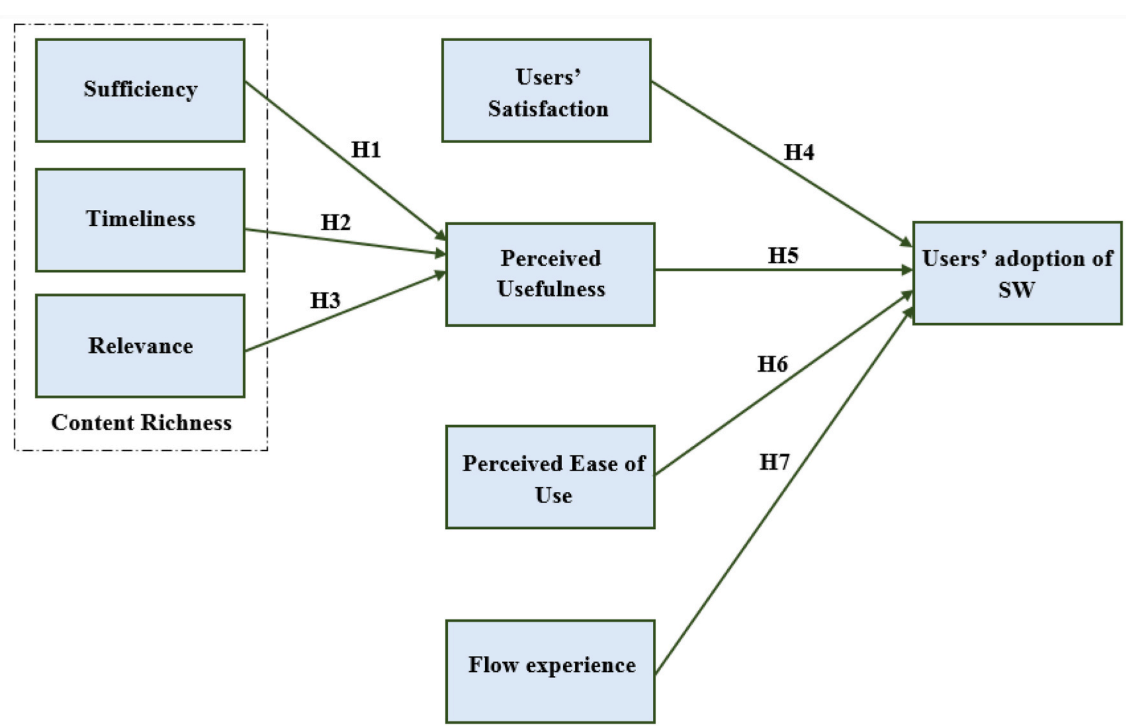


**Fig. 1.** Research model.

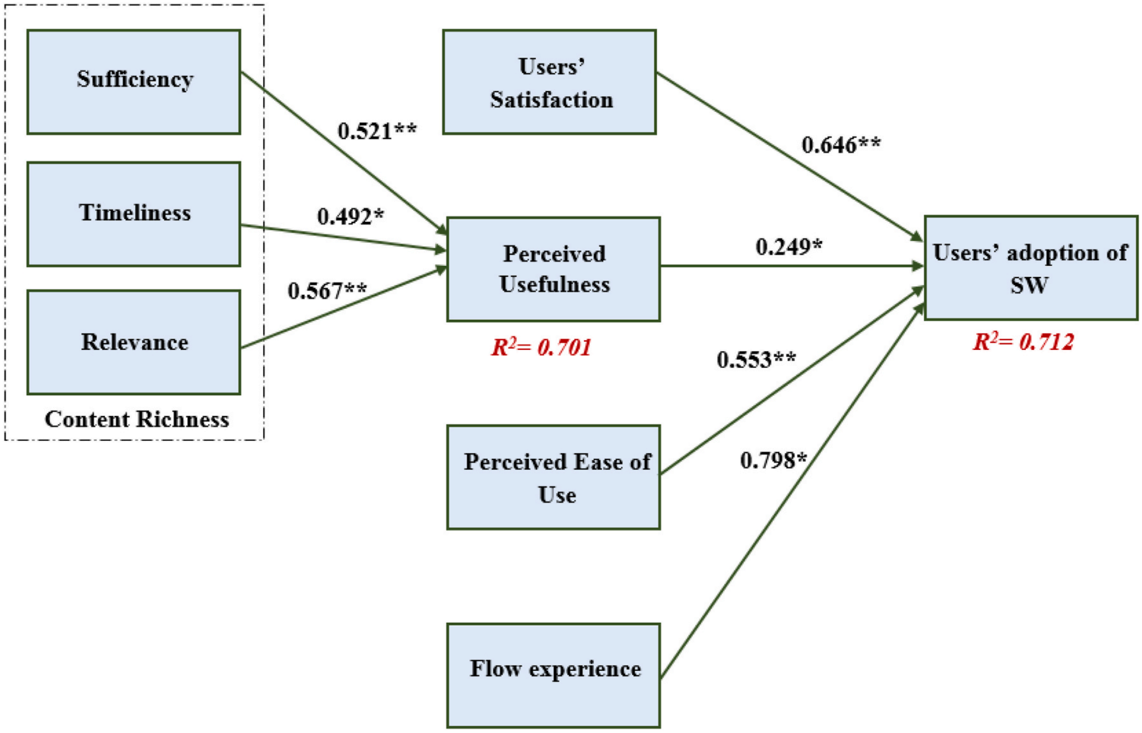


**Fig. 2.** Path test of the research model.

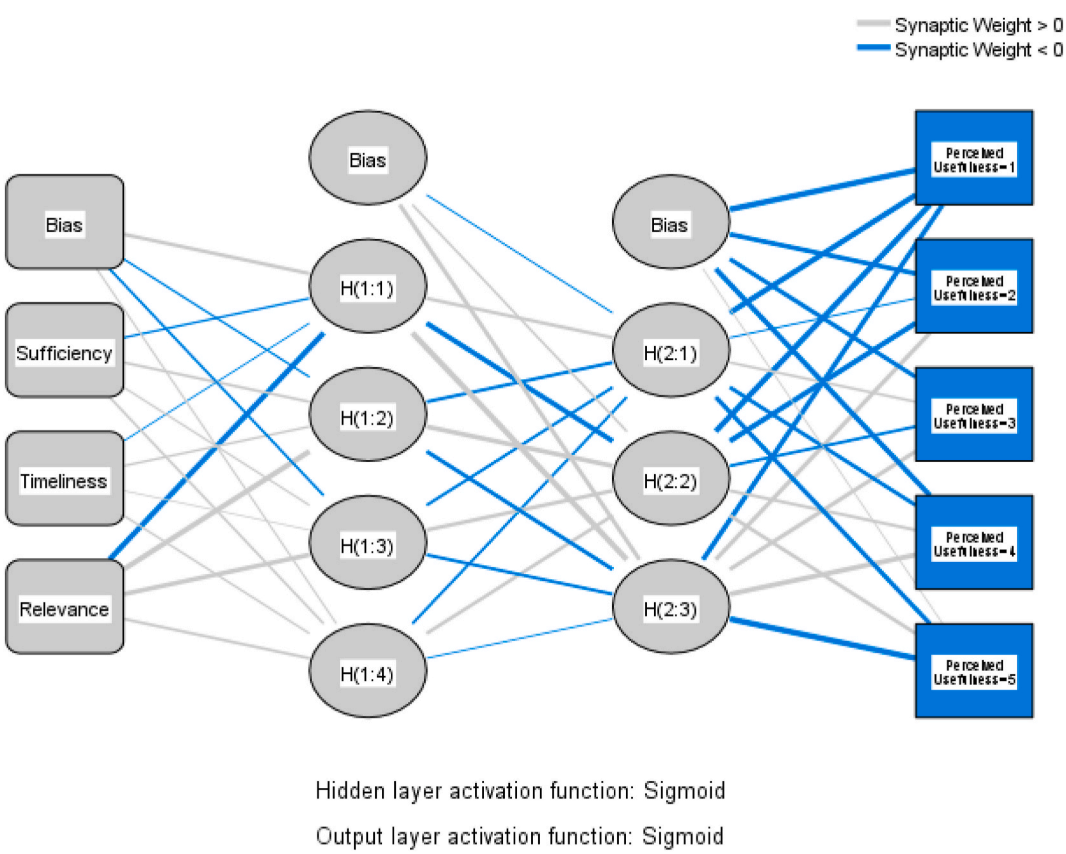


**Fig. 3.** ANN model (part one).

innovativeness is closely associated with individual characteristics. Thus, persons with a higher level of innovativeness are enthusiastic about using the technology. The present study further revealed that PU significantly influences PEU and PU to a lesser degree. These results support prior findings that innovativeness has a significant influence on the use of technology [102,103]. Personal innovativeness is closely

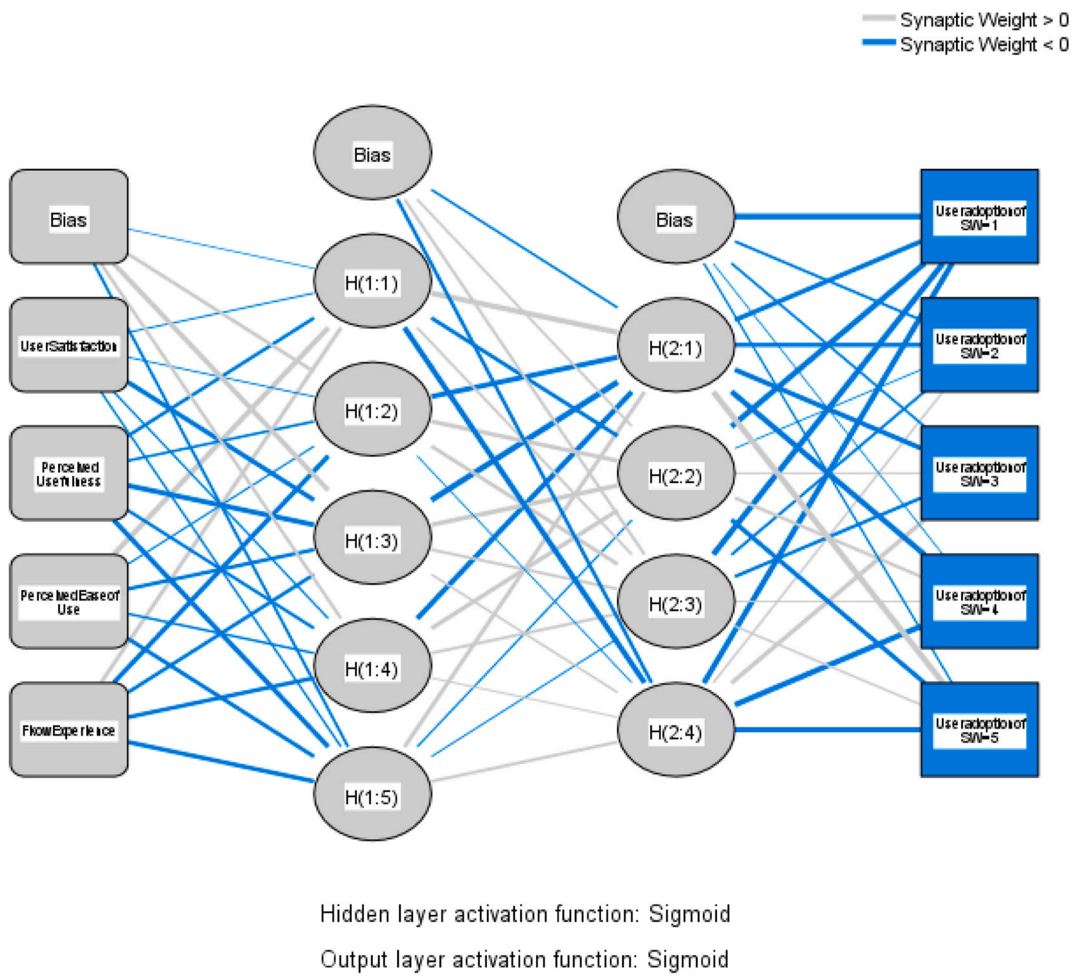


**Fig. 4.** ANN model (part two).

**Table 11**
Independent variable importance.

| | Importance | Normalized Importance |
|---|---|---|
| **EXP** | .092 | 45.2% |
| **SAT** | .455 | 99.8% |
| **PEU** | .158 | 82.4% |
| **PU** | .194 | 89.6% |
| **REL** | .199 | 62.8% |
| **TIM** | .101 | 35.7% |
| **SUF** | .159 | 53.6% |

linked to personality traits. Innovativeness is also closely associated with enjoyment, because users' personal innovativeness increases with an increase in the level of enjoyment [109].

The study also found that the TAM constructs significantly and directly influence ASW, and the PEU and PU positively and significantly affect ASW. Users in academic and non-academic environments tend to highly demand technology that is free of effort and that is useful [110,111]. Previous studies' findings on technology adoption in the medical field support the present study's findings because they revealed that nurses, patients, and doctors were eager to adopt technology because it was useful and easy to use [112,113].

The study also employed a flow model and found that flow significantly influences technology adoption. User-level engagement can have a negative or positive impact on their technology adoption. User engagement increases with the use of the smartwatch. The increased engagement has, in turn, led to increasing adoption. The present study findings support previous studies that have showed that flow experience drives users' behaviour intention [114,115].

External variables such as PEU and PU tend to affect users' satisfaction. The current research found that satisfied users who adopted technology rated the smartwatch as valuable and free of effort. Previous studies have arrived at similar findings by showing that technology users who evaluated the perceived value as significant had a higher satisfaction level [116,117]. Thus, users' satisfaction positively impacts users' behavior intention. Satisfied technology users also tend to consider technology as free of effort.

### 5.1. Practical impact in medicine

The present research contributes significantly to wearable technology literature in the medical field. The study showed that wearable technology developers should focus on satisfying user-specific needs in the medical area. Thus, developers of wearables, especially smartwatches, should be aware of how this technology could meet doctors' and patients' needs. Such knowledge is essential, because technology developers will be adding technology features that meet doctors' needs and that will therefore improve doctors' and patients' willingness to adopt and accept the technology. Specific smartwatch features or functions may influence users' adoption of the technology [118,119]. The current study also shows that the need for correct information at the right time may increase users' adoption and use of wearable technology. When developers update and create features that meet doctors' and patients' needs, those users will increase their demand for wearable technology, especially smartwatches.

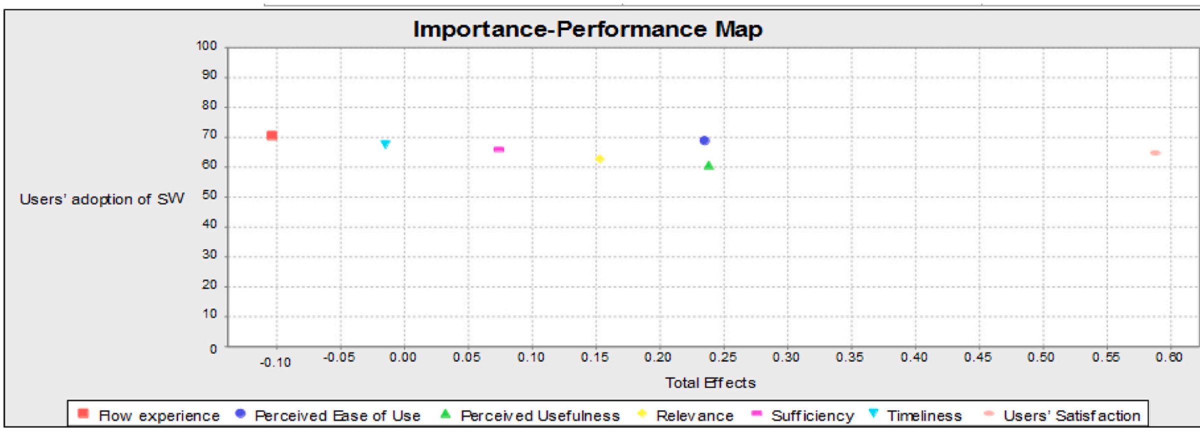


**Fig. 5.** IPMA results.

Designing wearable technology functions (updating and creating more features) to meet users' needs in the medical field will result in increased demand, adoption, and acceptance of wearable technology within the medical area. Thus, compatibility between users' needs and wearable technology can contribute to achieving the long-term goal of developing wearable technology.

### 5.2. Managerial impact in the field of medicine

The study recommends that hospital administration and management adopt wearable technology in their operations. A policy in hospitals to use wearable technology in different departments would enhance the adoption of wearable technology and promote other related applications. The study also recommends that patients use smart wearable technology with phone-based applications. Based on the present research, wearable technology has a considerable impact on doctors and patients. For instance, smartwatches can help doctors and patients monitor their physical activity, oxygen content in the blood, heart rate, and blood glucose level. Thus, developers must continue to enhance their wearable devices by adding features beneficial to patients and doctors [120,121].

This study could guide doctors, physicians, and practitioners toward more use of smartwatches and other wearable devices for different medical needs. Specifically, users' adoption of wearable technology may increase due to external factors, including satisfaction, flow experience, and content-richness. Thus, doctors should be conversant with medical features in wearable devices so that they can make wise use of those devices while also encouraging patients to use them.

An adequately designed wearable technology should have many medical-specific features, such as the ability of users to read their blood glucose or blood oxygen content, among other physical data [7,8]. Previous literature has showed that users' demand for wearable technology increases when user-friendly features are present [122]. Therefore, wearable technology developers should understand doctors' and hospital managers' needs and develop or upgrade wearable devices in the medical field to meet the medical requirements.

### 5.3. Theoretical implications

The current study's methodology is also a contribution to the existing research. Unlike prior studies, which have mostly used SEM analysis, the present study employed the hybrid SEM-ANN method built on deep learning. The results show that the predictive power of the ANN model is better than the PLS-SEM model. The high ANN predictive power is due to the incorporation of the deep learning ANN in identifying the non-linear association between the variables in the theoretical model.

### 5.4. Limitations of the study

Despite its contributions to the existing literature, the present study bears certain limitations that should be considered in future research. The generalisability of the current study may be limited because it only included frontline healthcare providers. The study did not involve other healthcare providers because it was beyond its scope. The time and cost-related constraints limited the study to data obtained from a single governmental service sector, which is a unique service culture. The lack of private-sector data may limit the generalisability of the findings to additional sectors or even to other service sectors. Though the present study used a cross-sectional design using a survey questionnaire in data collection over a short time period, a longitudinal research design could have allowed for extended supervision to reveal the overtime health effects of COVID-19 mental health over time. Thus, future studies should use longitudinal research designs to enable longer supervision. Lastly, the study data was obtained from employees using a survey questionnaire as the primary method. However, using different data collection methods such as interviews and observations to collect data from healthcare providers could have provided more insight into the pandemic.

The present study focused on factors influencing ASW. Future research should modify the variables to incorporate features of the newly developed smartwatches. The present study also employed the TAM model and flow theory. Future research should focus on other models based on different social and psychological factors. The present study only focused on the medical field; hence, future research should focus on academic and non-academic areas. Lastly, the present study has not highlighted the impact of gender differences, and, thus, future studies should assess the effect of gender differences.

## 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.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.imu.2022.100859.

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