

Smart Wearable Technology for Health Tracking: What Are the Factors that Affect Their Use?



Sevgi Ozkan-Yildirim and Tansu Pancar

1 Introduction

Wearable devices are rapidly gaining importance in parallel with their increasing capabilities. Wearable devices are able to collect very diverse vital information about users such as daily step count, sleep duration, heart rate and blood pressure with the help of various sensors, they conveniently provide this data to users, and users are making use of this data in numerous ways [1]. In such an area where variety is constantly increasing, it is important to understand which factors influence consumers' intention to use wearable mobile devices. Technology acceptance models such as TAM and UTAUT and their variants are powerful tools for understanding these factors. Among various acceptance models, although TAM is the most popular one, UTAUT2 is more suitable for wearable devices as it has a focus on consumers. This study explores the factors affecting consumers' decision of using these devices based on UTAUT2 model, newly proposed additional constructs and open-ended questions.

A survey with 366 participants was conducted, and the results were quantitatively analyzed. In addition to the survey with multiple-choice questions dedicated to constructs in UTAUT2 model, another survey with open-ended questions was also completed. This second survey included six questions allowing the participants to further explain their usage of wearable devices. Responses to these questions revealed valuable insights regarding the expectations of users from wearable devices.

S. Ozkan-Yildirim (✉) · T. Pancar
Informatics Institute, Middle East Technical University, Ankara 06800, Turkey
e-mail: sevgiozk@metu.edu.tr

T. Pancar
e-mail: tansu.pancar@metu.edu.tr

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This chapter aims to understand important factors affecting consumers' acceptance of wearable devices to track health information. UTAUT2 model is extended with new constructs and both models are tested, and results are presented and compared. The main contribution of this chapter is showing that factors affecting acceptance of wearable devices usage vary significantly depending on age, gender, and experience with the technology.

It is seen that habit and performance expectancy are by far the most dominant factors influencing behavioral intention to use, and hence, further breakdown of these factors is likely to provide better insights. Effect of performance expectancy (PE) on behavioral intention (BI) was found to be more important for males. Furthermore, it is observed that both UTAUT2 and the proposed model perform much better for male users. Another relevant finding is that the answers to open-ended questions emphasize the importance of price although quantitative analysis did not highlight price as an important factor. This indicates the importance of hybrid approaches in technology acceptance studies which supports the findings from quantitative analysis with qualitative data from interviews or open-ended questions. It is seen that side-benefit expectancy (in our case wearable device's being fashionable and stylish) is the most important fourth factor after performance expectancy, effort expectancy, and habit. Not surprisingly, SBE is found to be relatively more important for younger users compared to other user groups. Neither the quantitative analysis nor the open-ended questions show that privacy is an important factor for the wearable device users. This might be due to the limitation of our study and reaching users with some particular devices (fertility trackers, and neurological monitors) may reveal the importance of privacy in acceptance of wearable devices in health domain.

This chapter is organized as follows; next section briefly presents fundamental models on user acceptance. In Sect. 3, proposed modifications to the UTATU2 model and the research gap are presented. Section 4 contains the detailed analysis of the survey and open-ended questions. Section 5 is dedicated to the interpretation of the findings from Sect. 4. Section 6 summarizes the whole study and the findings with remarks and limitations.

2 Literature and Background Information

Mobile health or mHealth is defined as the use of portable electronic devices including smartphones or wearable devices to provide health services and manage information such as health history or vital information [2]. Mobile health applications enabled by wearable devices are increasing in the consumer devices market. The diversification in sensor types and increasing accuracy helped these devices to provide better measurements and more detailed health data. Due to the ubiquitous nature of mobile devices, mobile health is also available anywhere, at any time [3].

Wearable medical devices market size was valued at over USD 9 billion in 2018 and is expected to witness 39.4% [4] compound annual growth rate (CAGR) from 2019 to 2025 The global mHealth market size is expected to reach USD 316.8 billion

by 2027 [5]. Although wrist-worn devices like smartwatches and smart bands constitute the majority of wearable devices as high as 95% [6], the variety of device types and usage purposes increases. Understanding users' main purpose to use these devices is an important step to evaluate the adoption mechanism.

It is possible to separate previous research on wearable devices in two main categories, technology-related studies and user-related studies. The first group contains studies related to technology including power consumption, sensors, mobile technologies, communication, and connectivity-related research. The second group includes studies related to users, which can be listed as clinical studies, development of systems for health professionals or medical education and technology acceptance studies.

Acceptance and adoption of new technologies by organizations and individuals is a well-studied and established area. There are many research studies applying previous models or proposing extensions to existing models with additional constructs or modifications. Technology acceptance model (TAM) and unified theory of acceptance and use of technology (UTAUT) can be listed among the most popular models. These models are applied in different domains or with different target audiences. Extended unified theory of acceptance and use of technology (UTAUT2) model focuses more on individuals rather than organizations and promises to be more useful at understanding consumer's adoption of technology. These models will be explained briefly in the following pages.

In parallel with the advances in technology, the role of technology in our lives is increasing continuously. This leads to researches having the aim of understanding the motives behind individuals' and organizations acceptance of technology and adoption of new applications, tools and information systems. Technology acceptance model (TAM) [7] was proposed in the late 80 s and dominated the area nearly two decades especially from the organizational perspective. TAM continued to be the leading model in technology acceptance domain and applied in various contexts which also revealed the limitations of the model.

In 2000, Davis and Venkatesh improved the model with new core constructs, which was named as TAM2 model. In 2003, Venkatesh proposed a new model, combining previous eight models in order to obtain a stronger model, unified theory of acceptance and use of technology (UTAUT) [8]. The new model provided better results on the acceptance of technology, but it also focused on organizational perspective. As technology solutions are rapidly increasing their share in every aspect of daily life, the boundaries between technology and non-technology domains are fading away. This trend is causing the acceptance of new technologies by consumers to be impacted by non-technology factors like fashion, environment concerns, and social acceptance.

With the increase of information systems usage by consumers, the UTAUT model turned out to be insufficient and an extension to UTAUT model, UTAUT2 was developed by Venkatesh in 2012 which strengthened existing model with three new constructs specifically added for individuals [9]. Three new constructs, "Hedonic Motivation", "Price", and "Habit" were added, and "Voluntariness" is removed.

In below sections, TAM, TAM2, UTAUT, UTAUT2, and an extended version of UTAUT2 model will be explained briefly.

2.1 TAM Model

Davis suggested two main constructs in the first version of technology acceptance model (TAM), perceived usefulness and perceived ease of use. Psychological theories aiming to understand behavior, theory of reasoned action [10], and theory of planned behavior [11] contributed to TAM. These two theories used “Behavioral Intention” which is defined as a person’s perceived likelihood to engage in a given behavior [12].

“The degree to which a person believes that using a particular system would enhance his or her job performance” is defined as “Perceived Usefulness (PU)” by Davis and “the degree to which a person believes that using a particular system would be free of effort” is defined as “Perceived Ease of Use (PEOU)”. Davis suggested a link between perceived ease of use and perceived usefulness. The relationship between these two constructs and their effect to actual system usage is shown in Fig. 1.

Perceived usefulness (PU) is both used as a dependent variable (due to being predicted by PEOU) and as an independent variable directly predicting behavioral intention (BI).

TAM is widely used in various contexts since 1989, and several studies were published as validations and extensions of TAM model. In 2003, Lee analyzed the evolution of TAM and divided it into four periods, introduction, validation, extension, and elaboration [13]. Many studies used TAM as a base model and proposed extensions and new constructs for various domains, user groups, and contexts. In a meta-analysis study, 88 TAM studies were evaluated and stated TAM measures to be robust and reliable [14].

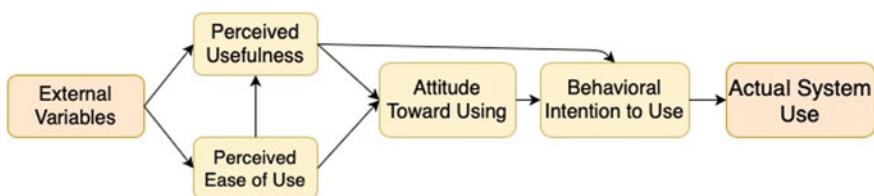


Fig. 1 Technology acceptance model

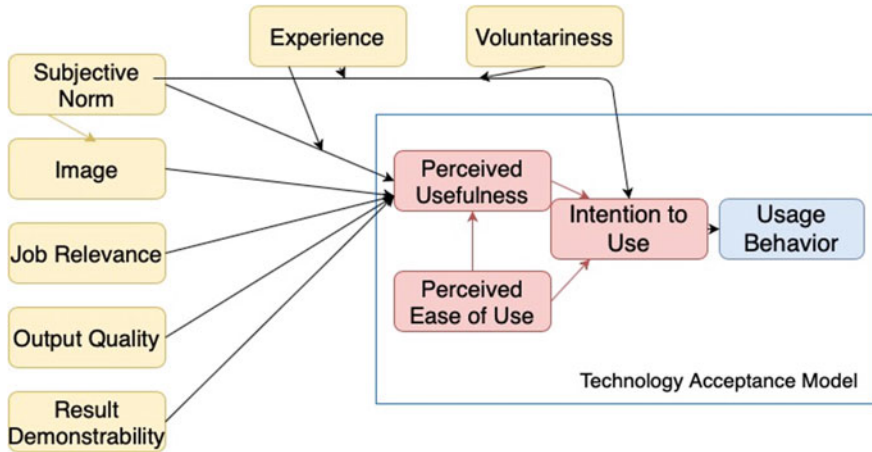


Fig. 2 TAM2

2.2 TAM2 Model

In 2000, Venkatesh and Davis modified TAM model and included new core constructs which can be listed under two groups, social influence processes (subjective norm, voluntariness, and image) and cognitive processes (job relevance, output quality, and result demonstrability) besides “Perceived Usefulness” and “Perceived Ease of Use” [15]. By adding, social influence processes, TAM2 enabled to keep record of individual’s connections (i.e., managers or peer workers) with the construct subjective norm (SN). The TAM2 model is shown in Fig. 2. This model includes the concepts of voluntariness and experience which was not explicitly mentioned in original TAM model, in order to have a better understanding of technology adoption in organizations. TAM2 model proved to work well in both voluntary and mandatory scenarios, where subjective norm is effective in mandatory cases but not effective in voluntary cases.

2.3 UTAUT Model

In 2003, Venkatesh summarized prior theories in order to obtain a better performing result and listed core constructs of these theories and examined their importance on behavioral intention and use behavior. The UTAUT model is proposed with four main constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions. Figure 3 shows the UTAUT model with root constructs obtained from the previous theories.

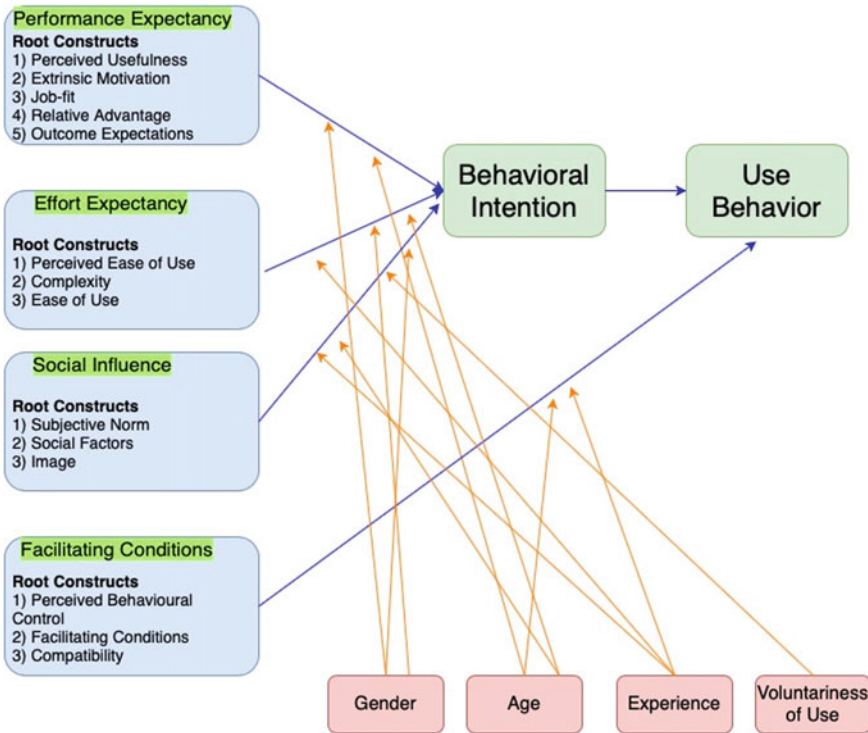


Fig. 3 UTAUT model

Besides main constructs, there are also four moderating variables such as gender, age, experience, and voluntariness of use. Similar to TAM and TAM2, UTAUT model also focuses on the use of technology in organizations.

2.4 UTAUT2 Model

The unified theory of acceptance and use of technology (UTAUT2) model was developed in order to customize the previous UTAUT model for individuals, especially consumers [9].

Four core constructs defined by UTAUT model were directly adopted [16, 8] and listed below. Performance expectancy is defined as the “degree to which using a technology will provide benefits to consumers in performing certain activities” [8]. Effort expectancy is defined as “degree of ease associated with consumers’ use of technology” [8]. The extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology is named as social influence [8]. The fourth and the last core construct is facilitating conditions which is

defined as consumers’ perceptions of the resources and support available to perform a behavior [8].

One of the moderators in UTAUT model, “voluntariness”, is removed because it is valid for organizations, where new technology is mainly proposed by the management, but for the case of consumers, intention to use the new technology is mostly voluntary.

The UTAUT2 model proposed three new constructs (hedonic motivation, price, and habit) in addition to the four existing constructs in UTAUT model. Hedonic motivation, which can be defined as the enjoyment of using new technology, is conceptualized as perceived enjoyment [17].

In the organizational context, employees do not care about the cost of new technology, and previous models did not include any construct related to cost and price of using new technology. However, from consumers’ perspective, price is an important parameter since users are responsible for the costs [18, 16].

Habit, the third construct added to the former model, is defined as the extent to which people tend to perform behaviors automatically because of learning [19] The Venkatesh’s UTAUT2 model is shown in Fig. 4.

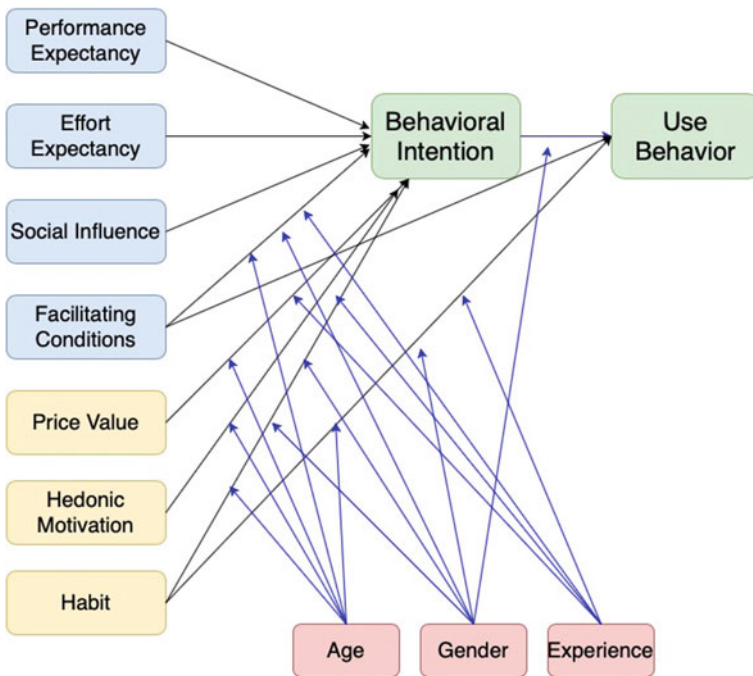


Fig. 4 UTAUT2 model

3 Proposed Model

3.1 *Research Gap*

Mobile health applications are proved to be very useful in preventive healthcare [20] and publications on wearable devices technology for mobile health research show an increasing trend in the last 10 years period. Technology-related topics dominate the area, and most of the publications focus on technology such as sensors, battery, communication technology or data analytics. Although the same trend is valid for publications on user-related topics including technology acceptance studies, they are few in numbers and constitute less than 10% of all publications between 2010 and 2019 [21].

In previous sections, technology acceptance models were examined including TAM, UTAUT, and UTAUT2 models. It is seen that TAM model, which is criticized for not being suitable for individuals, contrary to its success on analyzing technology adoption by organizations [22], is still the most dominant theory on technology adoption in mobile health and wearables area. The extended unified theory of acceptance and use of technology (UTAUT2) [9] which focuses on how consumers adopt new technologies on an individual basis seems to be under-appreciated in mobile health and wearables studies. Furthermore, there are several factors such as privacy, current health status, health expectancy which are not covered by UTAUT2 but worth analyzing to see how they influence the adoption of technology in the mobile health area.

3.2 *Proposed Model and Modifications*

In our research, we applied UTAUT2 model in its original form and also with proposed modifications which will be explained in the following paragraphs. Five new constructs (side-benefit expectancy, privacy, perceived health status, future health expectancy, and mere exposure) were added to the original model. Side-benefit expectancy is proposed as a new construct to extend UTAUT2 model in order to understand the users' expectancy from new technology besides its main purpose. For example, a smart wrist band, which is used to track the number of steps and heartbeat, can also be used as a stylish accessory. Being stylish does not affect the performance of the wrist band but can affect the user's decision to use or not. Fashion is likely to be an important aspect of wearable device adoption [23]. There are many studies examining the link between visual attributes to users' emotional attachment to these products, and how this link effects user acceptance [24, 25]. Furthermore, environmental friendliness (e.g., green-products) or symbolizing high social status can also be examined as side-benefits expected from the technology.

Privacy is an important concept regarding consumers' acceptance of new technologies [26] especially on an individual level. Privacy is defined as the willingness

of consumers to share information over the Internet [27], and the privacy concept can also be defined as an individual's right to isolate their information from other people [28]. The importance of privacy is also related to the sensitivity of health information collected by wearable devices and mobile applications [29]. Individual's identifiable information should not be available to third parties including other individuals, companies or organizations, and in case this data is used by others, the owner of this data should have control over the use of this data. Previous models mainly worked on the organizational perspective, and the privacy of users was mainly related with trust in the organization. However, from consumer perspective, information on acceptance of new products and services can be used for various purposes (ranging from targeted advertisements to pricing of insurance). The addition of privacy construct to UTAUT2 model is expected to improve the overall performance of the existing model. Two new domain-specific constructs focusing on healthcare are proposed:

- Perceived health status
- Future health expectancy.

Measuring users' perception of his or her own health status is critical in understanding the intention to use these devices. Newly introduced construct, perceived health status, aims to understand how healthy the user feels himself or herself. Perceived health status is defined as the degree to which a person rates his or her own health status. Being healthy means not only the absence of disease or injury, but also includes overall physical, mental and social well-being [30].

Besides, perceived health status, it is also important to learn the user's expectancy for his or her future health status. The expectancy of future health may provide valuable information regarding the intention to use wearable mobile devices to track and improve the user's health status. Future health expectancy is defined as the degree to which a person believes that his or her health status will be in the future compared to his or her current health status [31].

Repeated exposure of an individual to a stimulus object enhances his attitude toward it [32]. The authors believe mere exposure is one of the important factors on acceptance of technology from consumer perspective, and hence, we propose it as a new construct to the UTAUT2 model. Better-than-average (BTA) effect is the phenomenon that people rate themselves more favorably than an average peer on most trait dimensions [33–35]. Due to BTA effect, under mere exposure to new technology through other people, individuals are likely to have the over-confidence regarding effort expectancy and facilitating conditions. The proposed model is shown in Fig. 5.

4 Survey and Analysis

The data was collected through an online survey which was active between December 2017 and May 2018. The completion rate of the survey was around 30 percent. After

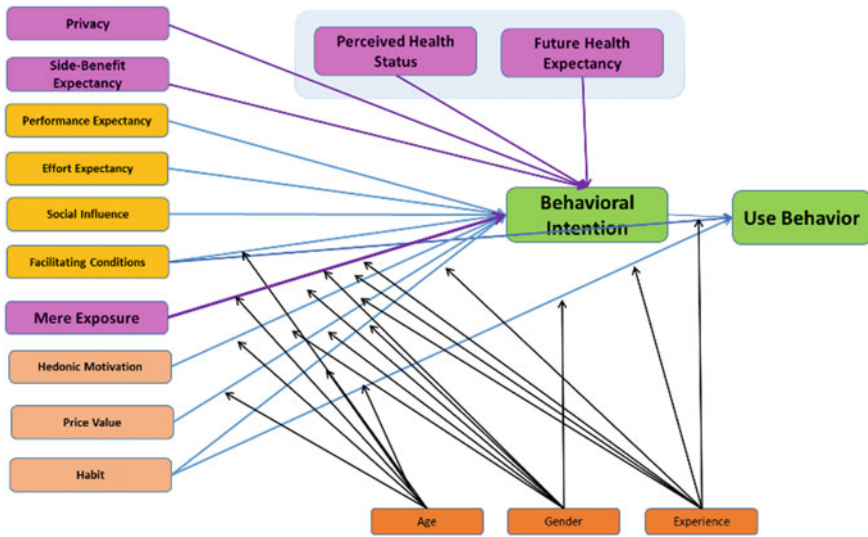


Fig. 5 Modified UTAUT2 model

the elimination of incomplete responses, remaining 366 responses were included in the analysis.

Below methods were used to reach survey participants:

- Personal network to reach known users of wearable devices
- User groups and fan pages of wearable devices on social media (mainly through Facebook)
- Reaching influencers on wearable devices (mainly through LinkedIn and Twitter)
- Using paid advertisements targeting wearable device users (mainly through Facebook and LinkedIn).

Demographic information about these 366 participants is summarized in below tables. Table 1 presents age group and gender distribution, and Table 2 presents countries where the participants are located. Most of the participants are from the

Table 1 Participant Qty. based on age and gender

Age group	Gender	
	Female	Male
18–24	19	14
25–34	76	53
35–44	67	40
45–54	38	15
>55	30	14
Total	230	136

Table 2 Participant Qty. based on country

Country	Participant quantity
USA	275
Turkey	47
Germany	16
Switzerland	8
Canada	5
UK	5
The Netherlands	2
Others	8
Total	366

USA, which can be due to high usage of social media and the success in social network advertisements targeting correct user groups. Countries marked as “Other” have only one participant who completed the survey. Number of female participants was higher than male participants in all age groups, which is an expected result for online surveys [36].

Below scale was used while preparing the results for analysis (Table 3):

- Questions with LIKERT scale were automatically converted to 1–5 scale.
- For gender, 0 is used for female, and 1 is used for male participants.
- For age, 1 is used for the youngest participant group, and 5 is used for oldest participant group.
- For experience, 1 is used for the minimum experience, and 5 is used for usage of more than 5 years.
 - Eight users who did not remember their usage duration were omitted from this analysis.

Survey items used by Venkatesh [9] were modified to suit the wearable device usage in health domain. These items and survey items for the newly proposed constructs are listed in Table 4. In addition to the items listed in Table 4, the survey

Table 3 Scale for analyzing survey results

Scale	Answers	Usage	Gender	Age	Experience
5	Strongly agree	Many times a day		>55	5 years or more
4	Agree	Often		45–54	3 years
3	Neither agree nor disagree	Sometimes		35–44	1 year
2	Disagree	Rarely		25–34	6 months
1	Strongly disagree	Never	Male	18–24	1 month
0			Female		

Table 4 Survey questions with new constructs

Performance expectancy	PE1. I find wearable mobile devices useful in my daily life to track health information
	PE2. Using wearable mobile devices increases my chances of achieving things that are important for my health
	PE3. Using wearable mobile devices helps me accomplish things more quickly
	PE4. Using wearable mobile devices increases my productivity
Effort expectancy	EE1. Learning how to use wearable mobile devices to track health information is easy for me
	EE2. My interaction with wearable mobile devices to track health information is clear and understandable
	EE3. I find wearable mobile devices easy to use
	EE4. It is easy for me to become skillful at using wearable mobile devices to track health information
Social influence	SI1. People who are important to me think that I should use wearable mobile devices to track health information
	SI2. People who influence my behavior think that I should use wearable mobile devices to track health information
	SI3. People whose opinions that I value prefer that I use wearable mobile devices to track health information
Facilitating conditions	FC1. I have the resources necessary to use wearable mobile devices to track health information
	FC2. I have the knowledge necessary to use wearable mobile devices to track health information
	FC3. Wearable mobile devices are compatible with other technologies I use
	FC4. I can get help from others when I have difficulties using wearable mobile devices to track health information
Hedonic motivation	HM1. Using wearable mobile devices to track health information is fun
	HM2. Using wearable mobile devices to track health information is enjoyable
	HM3. Using wearable mobile devices to track health information is very entertaining
Price	PV1. Wearable mobile devices to track health information are reasonably priced
	PV2. Wearable mobile devices to track health information are a good value for the money
	PV3. At the current price, wearable mobile devices to track health information provide a good value
Habit	HT1. The use of wearable mobile devices to track health information has become a habit for me

(continued)

Table 4 (continued)

	HT2. I am addicted to using wearable mobile devices to track health information
	HT3. I must use wearable mobile devices to track health information
	HT4. Using wearable mobile devices to track health information has become natural to me
Behavioral intention	BI1. I intend to continue using wearable mobile devices to track health information in the future
	BI2. I will always try to use wearable mobile devices to track health information in my daily life
	BI3. I plan to continue to use wearable mobile devices to track health information frequently
Use	Please choose your usage frequency for the wearable devices you own Note: Frequency ranged from “never” to “many times per day.”
Privacy*	PRI1. My use of wearable mobile devices to track health information would cause me to lose control over the privacy of my information
	PRI2. Using wearable mobile devices to track health information would lead to a loss of privacy for me because my personal information could be used without my knowledge
	PRI3. Others (people or organizations) might take control of my information if I use wearable mobile devices to track health information
Side-benefit expectancy*	SBE1. Visual appearance of wearable mobile devices is important for me
	SBE2. Wearable mobile devices can be used as stylish accessories
	SBE3. Wearable devices used for tracking health information have many other useful functions
Future health expectancy*	FHE1. I feel healthy compared to one year ago
	FHE2. I will not have any major health problem in next 5 years
	FHE3. I have to take actions to stay healthy in next 5 years
Perceived health status*	PHS1. I have no problems doing my usual activities
	PHS2. I am not anxious or depressed
	PHS3. I feel healthy today
Mere exposure*	ME1. I know many people using wearable devices
	ME2. I have several friends using wearable devices to track their health status
	ME3. There are many people around me interested in wearable devices
	ME4. Number of people around me using or interested in wearable devices is increasing

Constructs and questions which were added in the proposed model are marked with an *

also included questions regarding age, gender, experience with the technology, and location of the participant.

4.1 Analysis of Results

4.1.1 Criteria of Evaluation

After preparing the survey results for analysis, validity and reliability of the measurement model were examined, and then, the structural model was evaluated. The measurement model is explained as the relationship of indicator variables to their related constructs. Indicator variables are the questions for each construct and connected to their respective factors by the paths constructed in the model. The measurement model is also called as “Outer Model”.

Structural model, which is also called as “Inner Model”, is the relationship between latent variables. Latent variables are classified as exogenous and endogenous latent variables. Exogenous variables are defined as not being an effect of any other latent variable (there are no incoming arrows from other latent variables). A latent variable is endogenous if it is an effect of one or more other latent variables (there is at least one incoming arrow from other latent variables). In our models, BI and Use are endogenous latent variables, and others are exogenous latent variables. Table 5 shows important criteria for evaluating measurement and structural models with widely used limits for each criterion.

4.1.2 Measurement Model Analysis

This section uses output of Smart PLS 3 software PLS algorithm calculation. Results of the proposed model are listed for each step. PLS algorithm is run with path weighting scheme for maximum 1000 iterations and with stop criteria 10–7.

- Checking Convergence
 - The proposed model converged in seven iterations.
- Checking Reliability:
 - Cronbach’s alpha and composite reliability values are greater than 0.7 as expected, except 1 construct in the proposed model (SBE, which is also not very low).

Table 6 shows the Cronbach’s alpha and composite reliability values. Checking Validity (AVE, discriminant validity, and HTMT)

- AVE is expected to be greater than 0.5 which is confirmed to be true.

Table 5 Evaluation criteria for measurement and structural models

	Criteria	Explanation
Measurement model criteria	Convergence	Iterations are expected to converge without reaching the maximum number of iterations
	Cronbach's alpha	Cronbach's alpha value is a good measure to estimate internal consistency and therefore reliability of the scale. Cronbach's alpha value greater than 0.7 assumes that all indicators of a construct are equally reliable [37, 38]
	Composite reliability	Composite reliability controls individual reliability of indicators and is expected to be greater than 0.7
	Convergent validity	Average variance extracted (AVE) should be greater than 0.5
	Divergent validity	Measured using Fornell Larcker criterion, square root of AVE is expected to be greater than correlation coefficient between structures
	HTMT	HTMT stands for heterotrait-monotrait ratio which is calculated as the ratio of geometric mean of heterotrait-heteromethod correlations and average of monotrait-heteromethod correlations HTMT is expected to be lower than 0.9 for a well-fitting model [39]
	Path loadings	Path loadings and cross-loadings should be checked to ensure internal consistency and discriminant validity
	Cross-loadings	High loading and low cross-loading values are expected. Path loadings are expected to be greater than 0.7

(continued)

Table 5 (continued)

	Criteria	Explanation
Structural model criteria	Structural path coefficients	Structural path coefficients show how factors are connected to other factors, and higher path coefficients mean stronger connection between latent variables
	Coefficient of determination (variance)	<i>R</i> -square is the overall effect size measure for structural model, which is also called as coefficient of determination. It is calculated only for endogenous latent variables. <i>R</i> -square will have a value between 0 and 1. A value near 1 indicates that most of the variation of the response data is explained, and a value near 0 indicates that the variation is explained very little by the input values [40]
	Multicollinearity (inner VIF)	Inner VIF values should be lower than 5 to ensure there is no multicollinearity between latent variables
	f-square (change in variance)	Change in <i>R</i> -square values when an exogenous latent variable is removed is called the f-square value f-square values are classified as small, medium, and high for 0.02, 0.15, and 0.35 [41]
	Residuals	Analyzing residuals can be used as a way to identify outliers in our result data Residuals greater than 1.96 imply outliers at the 0.05 significance level for a normally distributed data set

- Fornell Larcker criterion is used to test discriminant validity, which states square root of AVE (diagonal entries) to be greater than non-diagonal entries. This criterion is also confirmed.
- HTMT value is calculated and found to be lower than 0.9.

AVE and discriminant validity values are presented in Table 7. For each construct, diagonal entries are higher than the non-diagonal entries listed below the related construct.

HTMT values are calculated for the proposed model and presented in Table 8.

Table 6 CA and CR for proposed model

Proposed model		
	Cronbach's alpha	Composite reliability
BI	0.872	0.922
EE	0.861	0.906
FC	0.762	0.847
FHE	0.866	0.934
HM	0.881	0.927
Habit	0.774	0.846
ME	0.852	0.899
PE	0.76	0.848
PHS	0.762	0.855
Price	0.831	0.894
Privacy	0.889	0.911
SBE	0.61	0.767
SI	0.915	0.946
Use	1	1

- Checking Internal Consistency (Loadings)
 - High loading and low cross-loading is expected.
 - Results supported high loading and low cross-loadings.

Measurement model analysis confirms the healthiness of the model in terms of convergence, reliability, validity, internal consistency, and multicollinearity. Results of the proposed model are similar to the results of UTAUT2 model, and both are inside the generally accepted limits for partial least squares analysis [42].

4.1.3 Structural Model Analysis

After confirming the model to be valid and reliable according to measurement model analysis, structural model was analyzed using Smart PLS 3 Bootstrapping algorithm. In total, 1000 subsamples were produced using PLS Bootstrapping algorithm with a significance level of 0.05.

- Resulting path coefficients and *R*-square values are shown in below tables. Performances of both models were compared for endogenous latent variables, which are behavioral intention (BI) and use for the proposed model.

It is seen that, the proposed model provides a slight increase in predicting BI, but the value for predicting use behavior was the same for both models.

The *R*-square values and path coefficients for use were calculated and presented for both UTAUT2 and the proposed model in Table 9.

Table 7 Convergent and discriminant validity values for proposed model

Proposed model															
	AVE	BI	EE	FC	FHE	HM	Habit	ME	PE	PHS	Price	Privacy	SBE	SI	Use
BI	0.798	0.893													
EE	0.706	0.538	0.840												
FC	0.586	0.480	0.597	0.765											
FHE	0.877	0.149	0.195	0.149	0.936										
HM	0.809	0.533	0.494	0.439	0.138	0.900									
Habit	0.583	0.736	0.453	0.405	0.227	0.528	0.763								
ME	0.691	0.384	0.314	0.397	0.144	0.422	0.407	0.831							
PE	0.585	0.677	0.569	0.551	0.156	0.561	0.596	0.346	0.765						
PHS	0.666	0.296	0.362	0.256	0.445	0.318	0.268	0.190	0.309	0.816					
Price	0.739	0.292	0.317	0.326	0.168	0.398	0.308	0.267	0.327	0.171	0.860				
Privacy	0.773	-0.106	-0.106	-0.092	0.017	-0.033	-0.044	-0.028	-0.099	0.044	-0.107	0.879			
SBE	0.535	0.342	0.311	0.282	0.186	0.365	0.272	0.235	0.323	0.277	0.231	0.039	0.731		
SI	0.854	0.217	0.011	0.139	0.068	0.187	0.259	0.223	0.201	-0.028	0.226	0.083	0.103	0.924	
Use	1.000	0.478	0.337	0.343	0.026	0.366	0.460	0.280	0.372	0.220	0.133	-0.152	0.222	0.005	1.000

Table 8 HTMT values for proposed model

Proposed model													
	BI	EE	FC	FHE	HM	Habit	ME	PE	PHS	Price	Privacy	SBE	SI
EE	0.614												
FC	0.570	0.703											
FHE	0.164	0.223	0.175										
HM	0.607	0.559	0.520	0.159									
Habit	0.842	0.482	0.455	0.280	0.607								
ME	0.429	0.346	0.492	0.170	0.474	0.493							
PE	0.827	0.691	0.696	0.189	0.684	0.724	0.421						
PHS	0.334	0.421	0.297	0.519	0.364	0.302	0.201	0.388					
Price	0.319	0.354	0.411	0.211	0.430	0.352	0.295	0.388	0.186				
Privacy	0.099	0.103	0.087	0.057	0.045	0.078	0.041	0.078	0.062	0.110			
SBE	0.407	0.363	0.375	0.243	0.420	0.318	0.324	0.435	0.350	0.239	0.108		
SI	0.242	0.051	0.203	0.079	0.214	0.359	0.251	0.255	0.066	0.258	0.090	0.119	
Use	0.512	0.358	0.380	0.023	0.387	0.465	0.294	0.418	0.225	0.127	0.150	0.242	0.007

Table 9 Comparison for Use

Use		
	UTAUT2	Proposed model
<i>R</i> -square	0.267	0.267
Adj <i>R</i> -square	0.261	0.261
BI	0.253	0.253
FC	0.132	0.132
Habit	0.220	0.220

Table 10 Comparison for BI

BI		
	UTAUT2	Proposed model
<i>R</i> -square	0.647	0.657
Adj <i>R</i> -square	0.640	0.645
EE	0.123	0.112
FC	0.045	0.035
HM	0.057	0.032
Habit	0.470	0.473
PE	0.272	0.256
Price	-0.024	-0.031
SI	0.028	0.035
FHE		-0.062
ME		0.023
PHS		0.041
Privacy		-0.053
SBE		0.075

Similar to the comparison for use, Table 10 presents the *R*-square values and path coefficients for behavioral intention for both models.

Table 11 Inner VIF for proposed model

	BI	Use
BI		2.384
EE	2.022	
FC	1.848	1.309
FHE	1.300	
HM	1.910	
Habit	1.854	2.197
ME	1.384	
PE	2.189	
PHS	1.477	
Price	1.307	
Privacy	1.053	
SBE	1.244	
SI	1.196	

- Checking Multicollinearity
 - Multicollinearity exists if two or more independent variables are highly correlated, variance inflation factor (VIF) is used to test multicollinearity.
 - Inner VIF values are calculated in this step, the VIF values were lower than 5, stating that there is no multicollinearity for the inner model also.

Inner VIF values for behavioral intention and Use are presented in Table 11. Checking f-square

- f-square measures the strength of each predictor variable in explaining the endogenous variables.
 - The ranges 0.02, 0.15, and 0.35 are considered as weak, moderate, and substantial, respectively (Chin 1998). f-square can also be defined as the difference in R-square when a specific construct is removed from the model.
 - It is calculated by Smart PLS for the endogenous variables, which are BI and use in our case.

The f-square values for the proposed model are presented in Table 12.

4.2 User Group Analysis

We conducted a further analysis based on various user groups that are identified by gender, age, and experience (duration of wearable device usage) attributes. Data is separated into six subsets for user group analysis. The participant numbers in each group and a basic description of the groups is presented in Table 13.

Table 12 f-square values proposed model

Proposed model	
	Sample mean (M)
BI → Use	0.040
EE → BI	0.024
FC → BI	0.007
FC → Use	0.024
FHE → BI	0.011
HM → BI	0.005
Habit → BI	0.363
Habit → Use	0.036
ME → BI	0.004
PE → BI	0.089
PHS → BI	0.007
Price → BI	0.005
Privacy → BI	0.014
SBE → BI	0.018
SI → BI	0.006

Table 13 User groups for 366 participants

Group name	Group information
Age 1–2 (young)	162 participants (between 18 and 34 years)
Age 4–5 (old)	97 participants (over 45 years)
Exp 1–2 (short term)	106 participants (up to 6 months usage)
Exp 4–5 (long term)	128 participants (3 years and more usage)
Female	230 participants
Male	136 participants

For user group analysis, first, we removed the least significant paths (paths with coefficients less than 0.05) from both models and reran both models and saw that R^2 decreased by less than 1 percent. For the sake of simplicity, we used both models with reduced paths while doing the user group analysis. The least significant paths are highlighted in bold Table 14.

After the removal of insignificant paths, structural analysis calculation was done for user groups based on gender, age, and experience. Although the path coefficient between HM-BI is lower than 0.05 for the proposed model, it was higher than 0.05 for the UTAUT2 model and not removed from the model in order to make a comparison between the models, which was presented in Table 15 at the end of this section. Figure 6 presents the updated models after eliminating the insignificant paths.

Table 14 Proposed model

Proposed Model		
	BI	Use
BI		0.253
EE	0.112	
FC	0.035	0.132
FHE	-0.062	
HM	0.032	
Habit	0.473	0.220
ME	0.023	
PE	0.256	
PHS	0.041	
Price	-0.031	
Privacy	-0.053	
SBE	0.075	
SI	0.035	

Paths FC-BI, Price-BI, SI-BI, ME-BI, and PHS-BI were removed from the proposed model. This caused the removal of price, social influence, mere exposure, and perceived health status constructs from the model. Although these constructs are not included in the user group-based analysis, their effect is also discussed in the following sections. Analysis according to user groups was done with these simplified models. Path coefficients for the proposed model after deleting the insignificant paths for all 366 participants are presented in Fig. 7.

4.2.1 Age Group-Based Comparison

This study contains data from 366 participants whose ages lie in the range 18 and 65. Participants with age 35 or below were labeled as young users, and participants with age 45 and above were labeled as old users. Participants between 35 and 44 years were omitted from the analysis to achieve a clearer division between these two user groups. Figure 8 shows the path coefficients for the younger users, and Fig. 9 shows the path coefficients for the older users, based on above classification.

The proposed model shows a stronger relation for habit on use for older (Habit → Use = 0.395) users compared to younger (Habit → Use = 0.183) users. This finding is in line with a previous study on older users’ acceptance of Internet banking, in which habit was found to be an important factor of use behavior [43]. On the other hand, performance expectancy was found to be more important for younger (PE → BI = 0.298) users than older (PE → BI = 0.117) users. This shows us that, two most important factors (Habit and PE) on adoption of wearable devices are significantly influenced by age. Additionally, it was found that facilitating conditions have a stronger link with use for younger users (FC → Use = 0.192) compared to older

Table 15 Comparison of user groups

	Participant Qty.	366	162	97	106	128	230	136
Model	Path	All	Young	Old	New user	Experienced	Female	Male
UTAUT2	BI (R-square)	0.644	0.680	0.579	0.659	0.685	0.609	0.719
UTAUT2	Use (R-square)	0.268	0.225	0.331	0.296	0.175	0.183	0.384
UTAUT2	BI → Use	0.253	0.183	0.171	0.087	0.277	0.129	0.435
UTAUT2	FC → Use	0.135	0.192	0.089	0.127	0.065	0.172	-0.003
UTAUT2	Habit → Use	0.220	0.183	0.395	0.411	0.123	0.230	0.227
UTAUT2	EE → BI	0.132	0.125	0.149	0.158	0.103	0.140	0.107
UTAUT2	HM → BI	0.057	0.040	0.108	-0.021	0.176	0.133	-0.013
UTAUT2	Habit → BI	0.475	0.472	0.540	0.479	0.436	0.510	0.403
UTAUT2	PE → BI	0.286	0.298	0.117	0.331	0.249	0.150	0.470
Proposed model	BI (R-square)	0.653	0.695	0.594	0.662	0.697	0.621	0.728
Proposed model	Use (R-square)	0.268	0.225	0.331	0.296	0.175	0.183	0.384
Proposed model	BI → Use	0.253	0.183	0.170	0.087	0.277	0.130	0.435
Proposed model	FC → Use	0.135	0.192	0.089	0.127	0.065	0.172	-0.003
Proposed model	Habit → Use	0.220	0.183	0.395	0.411	0.123	0.229	0.227
Proposed model	EE → BI	0.123	0.113	0.149	0.137	0.094	0.118	0.093
Proposed model	FHE → BI	-0.047	-0.026	-0.076	0.023	-0.100	-0.044	-0.013
Proposed model	HM → BI	0.040	0.032	0.085	-0.015	0.157	0.121	-0.031
Proposed model	Habit → BI	0.483	0.476	0.550	0.473	0.458	0.526	0.398
Proposed model	PE → BI	0.272	0.262	0.097	0.317	0.241	0.139	0.447
Proposed model	Privacy → BI	-0.046	-0.063	-0.046	-0.037	-0.023	-0.094	0.052
Proposed model	SBE → BI	0.080	0.117	0.096	0.037	0.069	0.058	0.105

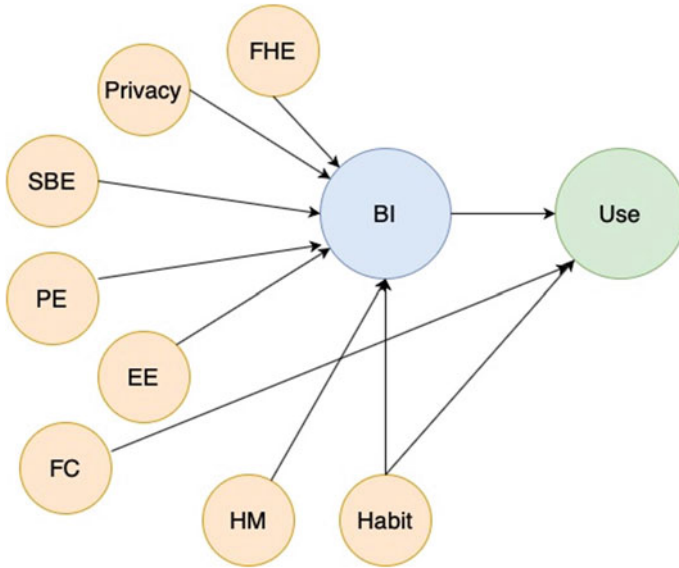


Fig. 6 Proposed model (insignificant paths removed for simplicity)

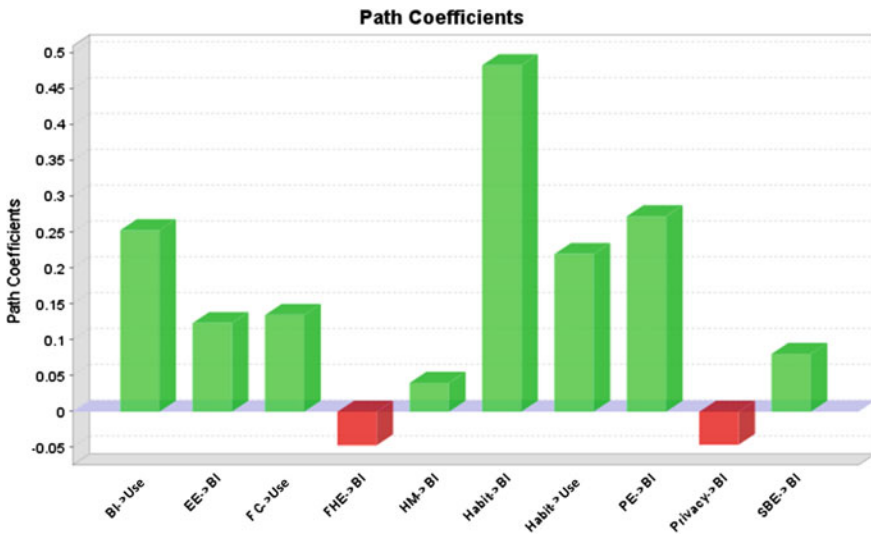


Fig. 7 Proposed model (for all participants)

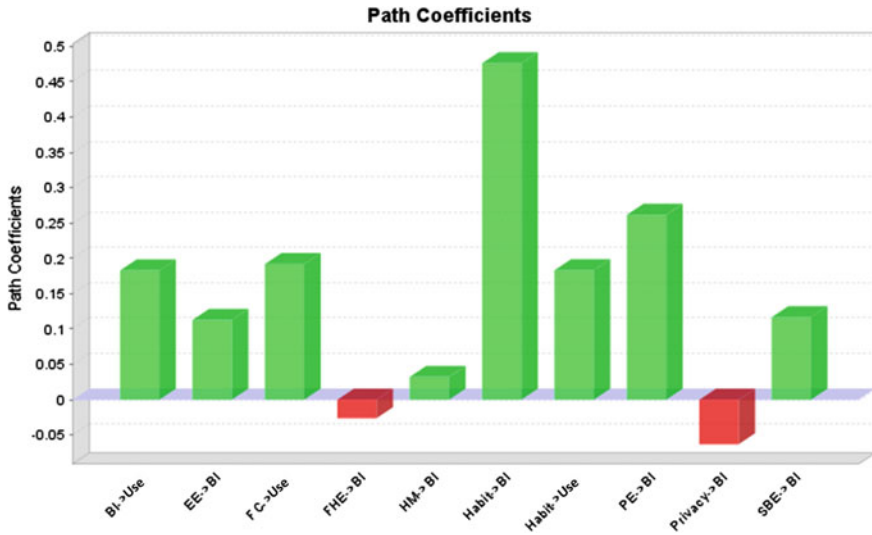


Fig. 8 Proposed model (for young users)

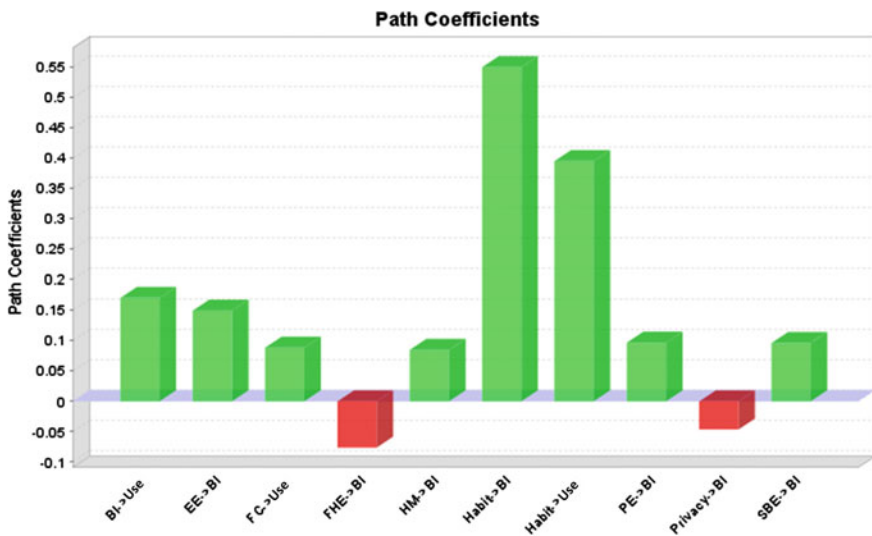


Fig. 9 Proposed model (for older users)

users ($FC \rightarrow Use = 0.89$). As we expect younger users to be more tech-savvy, this finding is somewhat counter-intuitive and requires further analysis.

Other parameters did not lead to a significant difference between user groups.

- For both models, FC-Use almost halved (0.192–0.89) from younger to older.

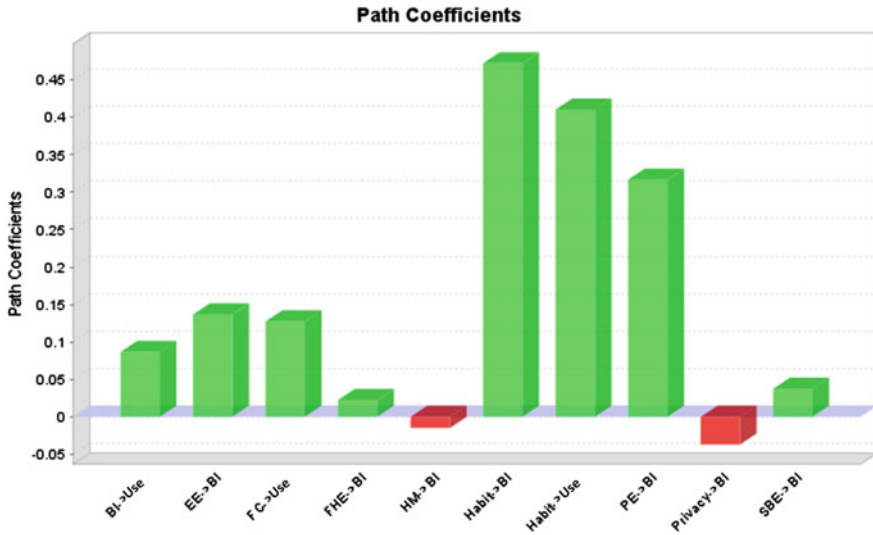


Fig. 10 Proposed model (for new users)

- For both models, Habit-Use almost doubled (0.183–0.265) from younger to older.
- For both models, PE-BI decreased more than half from younger to older.

4.2.2 Usage Duration-Based Comparison

Users were classified based on their experience with the technology. One hundred and six participants who have been using wearable devices for 6 months or less were classified as new users. One hundred and twenty-eight participants who have been using wearable devices for 3 years or more were classified as experienced users. New users had a weaker connection between behavioral intention and use (BI → Use) compared to experienced users with an increase of more than two times (0.087–0.277). As expected, facilitating conditions are less important for experienced users. The relationships between facilitating conditions and use are halved from new users to experienced users. Figures 10 and 11 show the path coefficients for new and experienced users, respectively, based on usage duration and experience with the technology.

4.2.3 Gender-Based Comparison

Among 366 participants, 230 were female, and 136 were male. Figures 12 and 13 present the differences between female and male users according to the proposed model.

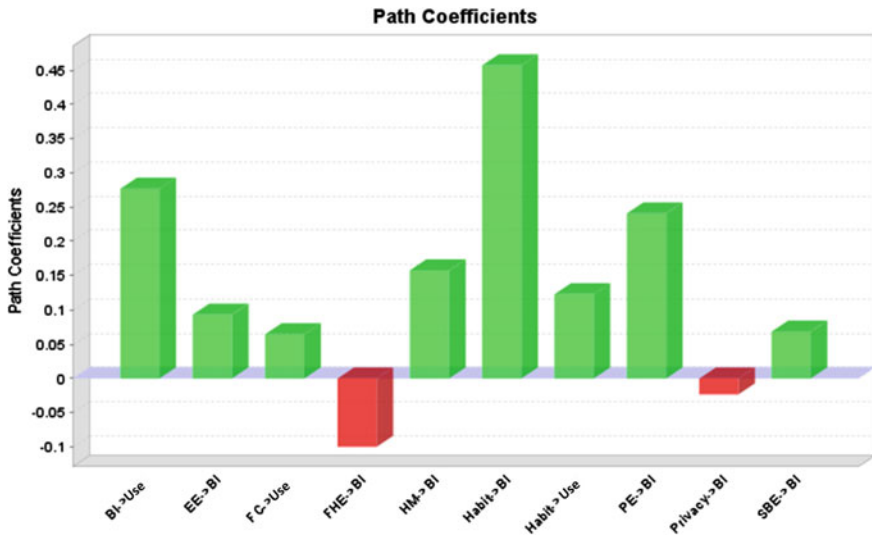


Fig. 11 Proposed model (for experienced users)

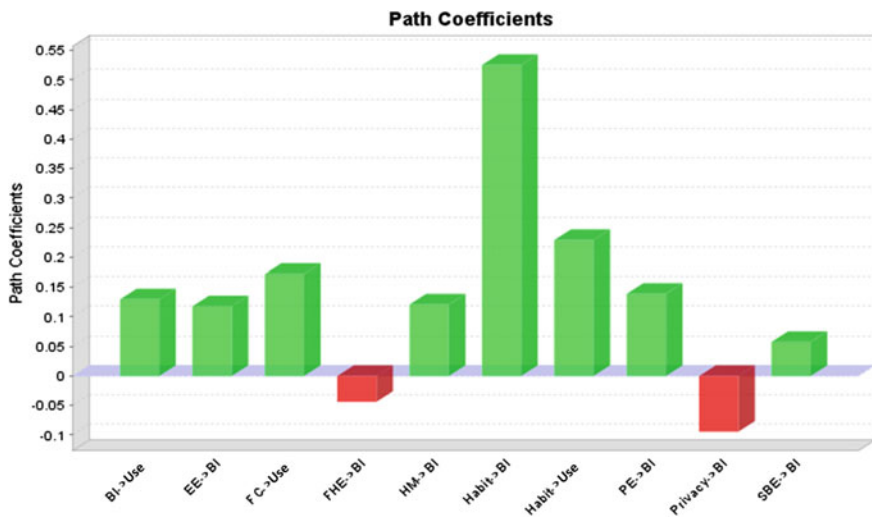


Fig. 12 Proposed model (for female users)

The R^2 value for behavioral intention is slightly higher (around 15%) for male users, and R^2 value for actual usage is a lot higher (almost 2 times) for male users compared to female users. This difference in R^2 values based on gender is clearly visible in the proposed model. The relationship between behavioral intention and use ($BI \rightarrow Use$ 0.13 for females and 0.435 for males) and the relationship between

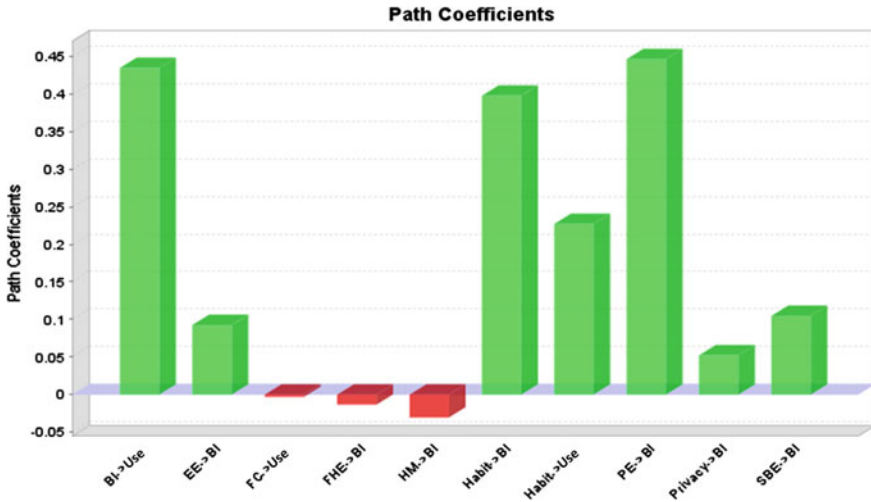


Fig. 13 Proposed model (for male users)

performance expectancy and behavioral intention (PE → BI) is almost tripled for male users compared to female users (0.150 for females and 0.47 for males). It is clear that both models perform significantly better for male users.

Table 15 presents a summary of path coefficients and *R*-square values for both models for all 366 participants as well as the six user groups explained above.

It is seen that not only *R*-square values significantly vary among different user groups but also the influence of each construct on behavioral intention (BI) and use is different for each user group. These findings are further explained in Sect. 5.

4.3 Open-Ended Questions

In total, 50 participants completed the survey with open-ended questions. The aim of the open-ended questions was to understand the main reason of wearable device usage. The participants were not only asked about their own opinion and experience but also about their perception on why their friends use or do not use these devices. Answers to these questions were grouped, and the mostly given answers were listed in the below table. Table 16 shows these questions and corresponding mostly given answers.

The survey showed that participants think that cost is the most important reason preventing their friends from using wearable devices, but very few (only 3) mentioned cost as the most negative aspect of their devices. The reason for this could be related to the one-time payment nature of these devices, especially for the long-term users, the importance of cost seems to fade away [44]. Participants reported battery/charging as the most negative aspect of wearable devices. Wearable devices are becoming part of

Table 16 Open-end questions and answers

	Question	Mostly given answers
1	What is the main purpose of using your wearable device?	Track physical activity Increase physical activity Track sleeping Track heart rate Easy access to phone Track daily workouts Set reminders Track steps
2	What is the main benefit you get from your wearable device?	Sleep pattern Being healthy Being multipurpose (track activity, integrate with phone, reminders) Motivate to walk more Check heart rate
3	Considering your friends who are using wearable devices. What may be their main reason to use wearable devices?	Being healthy Tracking steps Lose weight Ease of use Being trendy
4	Considering your friends who are not using wearable devices. What may be their main reason for not using wearable devices?	Price/being expensive Do not make exercise Privacy
5	What can you do motivate your friends to use wearable devices?	Show them my results Explain them how to use Give incentives Promote health
6	What is the most negative aspect of wearable devices?	Battery/charging Accuracy Outdated too quickly Cost Not very fashionable/stylish Privacy

users' daily routine, and users rely on many services provided by these devices such as receiving notifications, checking step count, sleep duration or even just checking the time more and more. Any interruption to these services leads to significant discontent. When the participants were asked about the main purpose of their wearable device usage, most of the participants stated "tracking" as the main reason. Some are using wearable devices to track daily physical activity and exercises, whereas others are tracking sleep duration and heart rate. Tracking proves to be useful only after a relatively longer and consistent usage, and this aspect explains the strong performance of habit construct in the quantitative analysis.

5 Interpretation of Results

Results of measurement and structural model were analyzed in detail and explained in above sections. Measurement model analysis confirms the healthiness of the model in terms of convergence, reliability, validity, internal consistency, and multicollinearity. Results of the proposed model are inside the generally accepted limits for partial least squares analysis. How much of the variance in behavioral intention and use can be explained using these models is the main criteria for evaluating model performance. Models with high R^2 provide a precise prediction [45], and R^2 values up to 0.25 are considered weak, R^2 values up to 0.50 are considered moderate, and values up to 0.75 are considered as substantial [42]. It is seen that proposed model explained substantial variance of behavioral intention ($R^2 = 0.657$). The model explained moderate variance of use behavior ($R^2 = 0.267$). These results show that proposed model can be used in the domain of wearable devices, but the newly proposed constructs did not provide any significant added value regarding the explanatory power of the model. An in-depth analysis of the survey data pointed to an issue in the measurement of “Use” construct. It was seen that 323 of 366 participants answered this question with 4 (often) and 5 (many times a day). It is likely that having almost a constant distribution negatively influenced the prediction of “Use” construct. Original UTAUT2 survey asks users the frequency of their use of a technology, which can be answered based on how often that specific technology is used. In our survey, the same question was used. With hindsight, it is seen that the question used in original UTAUT2 study could not adequately reflect the use of technology in case of wearable devices because it does not differentiate between active and passive usage. Using a wearable device to track health information is a continuous activity, and wearing that device and controlling the data collected by the sensors and taking actions based on the feedback of the device are different things. The addition of new questions for better addressing the nature of wearable device usage is likely to improve the model performance for wearable devices.

In a previous research on adoption of Internet banking, habit was found to be a stronger predictor of behavioral intention to use [43]. Our research also shows that habit is a strong determinant of technology adoption. Furthermore, our research shows that especially for older users the habit-use intention relation is significantly stronger. In addition to habit, we also found that performance expectancy is a very strong predictor of behavioral intention to use wearable devices for health status tracking. Habit and performance expectancy are by far the most dominant factors influencing behavioral intention to use, and hence, further breakdown of these factors may provide better insights and improve the success of proposed model.

The answers to open-ended questions emphasize the importance of price; however, quantitative analysis of the model shows that price has a very low impact (path coefficient less than 0.03) on behavioral intention to use wearable devices. It seems that once the wearable device is acquired, it does not have any significant impact on the use frequency. In a similar way, the answers to open-ended questions indicate to battery/charging problem but neither original UTAUT2 constructs nor any of the

newly proposed constructs is able to detect this factor. Current technology adoption models and theories do not include effect of batteries and charging to users' adoption of wearable devices [46]. Observations from the open-ended questions regarding price and battery/charging are important factors which cannot be addressed with existing constructs. This indicates the importance of hybrid approaches in technology acceptance studies which supports the findings from quantitative analysis with qualitative data from interviews or open-ended questions.

The effect of performance expectancy (PE) on behavioral intention (BI) was found to be more important for males, in a study on electronic document management systems, since males are more result-oriented than females [47], and our study confirms this finding for adoption of wearable devices. BI-Use and PE-BI have a stronger relation for male users compared to female users.

Our study also shows that impact of social influence to behavioral intention to use technology and impact of price to behavioral intention (BI) is stronger for older users compared to young users. On the other hand, performance expectancy seems to be much more important for young users in comparison with older users as seen from PE-BI relation.

Habit-Use has a weaker relation for experienced users compared to new users, whereas relation between BI-Use is stronger for experienced users in comparison with new users. However, BI-Use relation needs a further study with a focus on use type (active, passive) as explained above.

It is seen that social influence which is defined as the extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology [8] is not a very important factor on the use of wearable devices for health purposes.

Facilitating conditions, which are defined as consumers' perceptions of the resources and support available to perform a behavior [9], seem to be influential on the use of the wearable devices, but interestingly, it has less impact on the behavioral intention to use wearable devices. Our study shows a weaker FC-Use relation for male users compared to female users, which is in compliance with previous findings [47]. Furthermore, as expected, facilitating conditions were found to be less important for experienced users.

Side-benefit expectancy (in our case, wearable device's being fashionable and stylish) is found to be the most important fourth factor after performance expectancy, effort expectancy, and habit. However, its influence is significantly lower in comparison with other better performing three constructs. It is also seen that SBE is relatively more important for younger users compared to other groups.

Neither the quantitative analysis nor the open-ended questions show that privacy is an important factor for the wearable device users. It is very likely that, this result is due to the fact that most of the users who participated in the study use fitness trackers and smartwatches and the data collected by these devices seems to be less important in regard to privacy. In case of some other devices (fertility trackers and neurological monitors), privacy may emerge as an important factor.

An interesting finding of the overall study is that moderating effects such as gender, age, and experience affect almost all factors. Furthermore, it is also seen

that proposed model performance is significantly higher for male users compared to female users.

6 Conclusion

This study proposed some new generic and domain-specific constructs in addition to original UTAUT2 constructs and empirically tested both models in mobile health domain, in order to understand factors affecting consumers' adoption of wearable devices for health status tracking. The results were analyzed both to verify the model fitness and to see how the effect of each construct differs for different user groups based on moderating factors age, gender, and experience with technology. User group-based comparison of path coefficients showed that factors affecting acceptance of wearable devices usage vary significantly depending on age, gender, and experience (duration of wearable device usage). Results from the analysis showed that proposed model could be used as a tool to analyze factors affecting technology adoption of consumers. However, it is also seen that there is a room for improvement. This work is part of a broader study and will be extended with new quantitative analyses and interviews in order to collect deeper insights from consumers of wearable devices. All research studies have some limitations, and our work is not an exception. On the one hand, wearable device users who are not active in social media might be underrepresented in our study due to the fact that social media was the main element to reach survey participants. On the other hand, there are many different wearable devices in the market collecting various health information, and it turned out that most of our survey participants use fitness trackers and smartwatches. This might limit the explanatory power of our study to these devices. Reaching the users of innovative high-tech wearables which do not have a significant market share yet is a challenging target for our future work.

Finally, conducting interviews with different user groups is likely to bring additional value to this study by enhancing quantitative findings from the survey.

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