EXPLORING THE FACTORS AFFECTING CONSUMER INTENTION TO USE WEARABLE MOBILE DEVICES TO TRACK HEALTH INFORMATION

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ABSTRACT

EXPLORING THE FACTORS AFFECTING CONSUMER INTENTION TO USE WEARABLE MOBILE DEVICES TO TRACK HEALTH INFORMATION

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The popularity and usage of wearable devices is increasing as a consequence of their increasing capabilities. These devices collect various types of health related data with increasing accuracy. Collected data is used by consumers to track their own health data in addition to being used by health professionals to support medical diagnosis and treatment. This research investigates the factors affecting the adoption of wearable devices to track health information. The UTAUT2 model was used as the basis for this study as it is focusing on the acceptance of technology from consumers' perspectives. The model was enhanced with the categorization of use construct and addition of three new constructs: Goal Clarity, Technology Stack Compatibility, and Perceived Risk. The UTAUT2 model addresses technology use only in terms of use frequency, and this is not sufficient to analyze wearable devices which lend themselves to varying degrees of passive and active use. It is proposed that wearable device usage should be analyzed in three categories:

- Type-1 Use: Users wear the device primarily out of habit with no significant focus on the data.
- Type-2 Use: Users check the collected data.
- Type-3 Use: Users take actions based on the collected data.

The results showed that each type of use is influenced by different factors with remarkably different intensities. Additionally it is found that, goal clarity for Type-3 use, and technology stack compatibility for all three types of use, are strong determinants of behavioral intention to use wearable devices with the purpose of tracking health related data.

Keywords: technology acceptance, wearable devices, mobile health, health data tracking

ÖZ

TÜKETİCİLERİN SAĞLIK VERİLERİNİ TAKİP ETMEK AMACIYLA GİYİLEBİLİR CİHAZLARI KULLANMA EĞİLİMİNİ ETKİLEYEN FAKTÖRLERİN ARAŞTIRILMASI

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Giyilebilir cihazların kullanımı artan yeteneklerinin bir sonucu olarak yaygınlık kazanmaktadır. Bu cihazlar sağlıkla ilgili çeşitli verileri artan doğrulukla toplamaktadır. Toplanan veriler sağlık profesyonelleri tarafından tıbbi teşhis ve tedaviyi desteklemek için kullanılmakta, bunun yanı sıra tüketiciler de kendi sağlık durumlarını takip etmek için bu verileri kullanmaktadır. Bu araştırma sağlık bilgilerini izlemek için giyilebilir cihazların benimsenmesini etkileyen faktörleri araştırmaktadır. UTAUT2 modeli teknolojinin tüketici bakış açısıyla kabulüne odaklandığı için bu çalışmanın temeli olarak kullanılmıştır. Bu model teknoloji kullanımının sınıflandırılması ve üç yeni yapının eklenmesiyle geliştirilmiştir: Hedef Netliği, Teknoloji Yığını Uyumluluğu ve Algılanan Risk. UTAUT2 modeli teknoloji kullanımını yalnızca kullanım sıklığı açısından ele almaktadır ancak bu yaklaşım değişen derecelerde pasif ve aktif kullanıma uygun olan giyilebilir cihazları analiz etmek için yeterli değildir. Giyilebilir cihaz kullanımının üç kategoride incelenmesi önerilmektedir:

- Tip 1 Kullanım: Kullanıcılar cihazı verilere odaklanmadan alışkanlık nedeniyle kullanırlar.
- Tip 2 Kullanım: Kullanıcılar toplanan verileri kontrol ederler.
- Tip 3 Kullanım: Kullanıcılar toplanan verileri temel alarak harekete geçerler.

Sonuçlar her bir kullanım türünün farklı faktörlerden kayda değer seviyede farklı yoğunluklarda etkilendiğini göstermiştir. Ek olarak, Tip-3 kullanımı için hedef netliği ve her üç kullanım türü için de teknoloji yığını uyumluluğu, sağlık verilerinin takibi amacıyla giyilebilir cihazları kullanmaya yönelik davranışsal niyetin güçlü belirleyicileri olarak bulunmuştur.

Anahtar Sözcükler: teknoloji kabulü, giyilebilir cihazlar, mobil sağlık, sağlık verisi takibi

To My Family

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LIST OF ABBREVIATIONS

AVE	Average Variance Extracted
BI	Behavioral Intention to Use
CA	Cronbach's Alpha
DOI	Diffusion of Innovation Theory
ECG	Electrocardiogram
EE	Effort Expectancy
FC	Facilitating Conditions
FOG	Freezing of Gait
GC	Goal Clarity
GSM	Global System for Mobile Communications
HM	Hedonic Motivation
HTMT	Heterotrait-Monotrait Ratio
MM	Motivational Model
MPCU	Model of PC Utilization
PDA	Personal Digital Assistant
PE	Performance Expectancy
PEOU	Perceived Ease of Use
PLS	Partial Least Squares
PR	Perceived Risk
PU	Perceived Usefulness
SCT	Social Cognitive Theory
SI	Social Influence
TAM	Technology Acceptance Model
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
TSC	Technology Stack Compatibility
UTAUT	Unified Theory of Acceptance and Use of Technology
UTAUT2	Extended Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflation Factor

CHAPTER 1

INTRODUCTION

Mobile Health (m-Health) is defined as the use of portable electronic devices with software applications to provide health services and manage patient information (Källander, 2013). Developments in sensors, communication technologies and advances in computing power enabled collecting and processing data from users. It is an emerging field in the intersection of medical informatics, public health and business, which utilizes information and communication technology to collect and transmit data (Eysenbach, 2001). One of the most important characteristics of mobile health is its availability anywhere, at any time and to anyone (de Moraes, de Souza, Pires, & do Prado, 2016).

Capabilities and penetration of mobile devices are increasing constantly, and collecting mobile health data is one of the most important issues related to these devices, especially smart bands. Use of wireless mobile devices can support continuous health monitoring and encourage healthy behaviors to prevent and reduce health problems (Roy, Zalzala, & Kumar, 2016). Wearable devices combine the benefits of self-monitoring with features increasing motivation (Patel, Asch, & Volpp, 2015). In 2017 (Lee & Lee, 2020), the global mobile healthcare market was predicted to grow to 90.4 billion USD in 2022 with a more than 40% increase in 10 years compared to 63.4 billion USD in 2013. These devices use multiple sensors to collect vital information via Body Area Network (BAN), whose importance in healthcare increases by providing home healthcare, remote patient monitoring and real-time tele-consultation (Vargaa, Bokora, & Takácsb, 2014).

The increase in the capabilities and accuracies of wearable devices is in line with the increasing market size and decreasing costs. Different audiences use wearable devices with different motivations. Health professionals use these devices to track their patients' health data, and consumers use these devices for tracking their own health status or physical activities. The interest of consumers in activity tracking, well-being and preventive health, triggered a paradigm shift in the healthcare to a more personalized approach (Lee D. , 2018). The control shifted to individuals, namely consumers from the healthcare professionals. Because of these, the distinction between consumer devices with health tracking functions and medical devices started to fade and the border became blurry.

Considering the expanding usage of wearable devices by consumers, the importance of understanding the mechanisms that drive adoption of these devices is increasing. However, this area, especially in case of using wearable devices for health tracking purposes, requires more research and investigation. This research aims to explore the factors affecting consumers' adoption of wearable device usage with the purpose of tracking health related data.

Remaining sections of this chapter presents background information about the research and the identified research gap and demonstrates the research problem. The phases of the research and the research approach as well as the outline of this thesis are also explained in this chapter.

1.1. Research gap and research problem

Developments in sensor technology increase the variety of collected data including but not limited to movement, sleep quality, heart rate, breath rate, skin temperature, skin moist level, body posture. Consumer's acceptance and adoption of wearable health products are expected to increase in near future based on technological advances (Nasir & Yurder, 2015). Adoption of wearable mobile devices by consumers in order to track health data is an important subject but there are not enough studies on the adoption of these devices (Lunney, Cunningham, & Eastin, 2016).

The majority of acceptance studies focusing on consumers' adoption of wearable devices use the Technology Acceptance Model (TAM). The TAM, which is the most prominent theory of acceptance, is especially successful in organizational settings. However, it is criticized for not being suitable for individuals, contrary to its success on analyzing technology adoption by organizations (McMaster & Wastell, 2005).

The Unified Theory Acceptance and Use of Technology (UTAUT2) which focuses more on how consumers adopt new technologies on individual level was developed (Venkatesh, Thong, & Xu, 2012) and used widely since 2012. Mobile health applications are proved to be very useful in preventive healthcare (Melzner, Heinze, & Fritsch, 2014) but there are not enough studies exploring how preventive healthcare can be applied in order to improve health status of consumers.

The UTAUT2 model considers constructs such as price, habit and hedonic motivation which were not included in previous models. Price is proposed as a positive predictor of consumer's intention to use a technology, which is not applicable to the most of the cases in organizational context. Similarly, hedonic motivation, the degree to which the technology is perceived to be enjoyable (Nordhoff, et al., 2020) predicts behavioral intention. Habit is linked to both behavioral intention and the actual usage. These three constructs increased the success and the popularity of the UTAUT2 model. Taking into account its success and focus on consumers perspective, the UTAUT2 model is seen as a prominent candidate to explore adoption of wearable devices in mobile-health domain.

However the distinct nature of wearable devices requires some enhancements in the model. Wearable devices are functioning and collecting data at any time as long as they are being worn. In this sense they are being used as long as the user is wearing them but when the user starts paying attention to the collected data and make use of this data then the nature of the use significantly changes. These particular characteristics of wearable devices make them significantly different than other technology domains that the UTAUT2 model was previously applied. In the original UTAUT2 model, the actual usage is measured as the frequency of using the device ranging from "never" to "many times a day". This kind of rating is enough to measure the usage for most of the applications, such as mobile internet, online banking or e-commerce when technology use is explicitly noticeable. However, this is not the case for wearable devices, which are worn/used continuously. Having the device worn does not mean that the device is being actively used to track health related data. Hence, the use construct needs a more refined definition and analysis.

Considering that wearable devices are multifunction consumer goods that are used for various purposes (tracking physical activity data, miscellaneous types of communication, stylish accessories etc.) generally together with other devices and services, the compatibility of the wearable devices with the existing technology ecosystem of the users is an important topic that needs to be analysed to precisely understand the determinants of adoption of these devices.

Privacy, is also an important aspect effecting technology acceptance, considering the sensitivity of health information collected by wearable devices and mobile applications (Jusob, George, & Mapp, 2016). Collected data is becoming diversified which increases the importance of privacy especially from consumer perspective (Pfleeger, 2014). UTAUT2 model, does not involve privacy related constructs and effect of privacy on consumer adoption of wearable devices is not studied in details.

This study starts with a comparison of previously developed models in order to determine the most suitable model to explore the dynamics of adoption of wearable devices to track and improve the health status of consumers. Following the selection of the model, the model was validated with the help of an online survey, as well as open-ended questions and interviews. Subsequently, the selected model was enhanced with additional constructs and validated using a new online survey. The results were analyzed and evaluated under the light of quantitative and qualitative analyses.

The primary purpose of this study is to identify the factors affecting consumers' adoption of wearable devices to track and improve health status.

1.2. Research approach and phases of research

This study was performed in five main phases with several steps. Below figure (Figure 1) shows these steps.

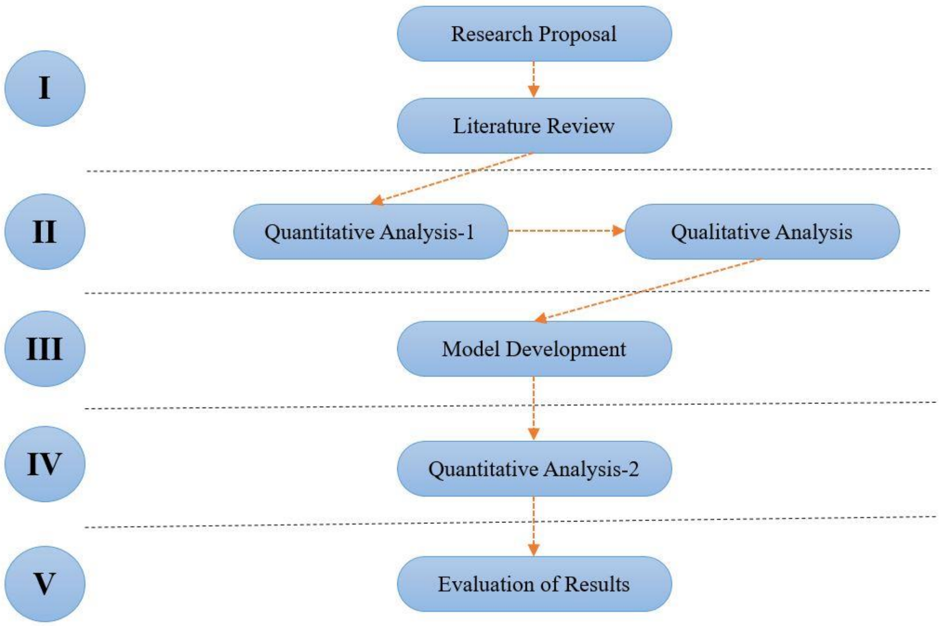

Figure 1: Research Phases

In the first phase, the research problem was clarified and the need for this research is justified with the help of the review of the existing literature.

In the second phase, an online survey based on original UTAUT2 constructs was held. The purpose of this initial quantitative analysis was to determine the strengths and weaknesses of original UTAUT2 model for the domain in question. This survey was completed by 1263 participants. Quantitative analysis was done using partial least squares method and results were summarized. In the qualitative part of this phase, a short survey with open-ended questions was used to gain a better understanding of users' intention. Analysis of these questions were used to devise the questions for the semi-structure one-to-one interviews. The findings from the interviews were used to formulate the extensions to the UTAUT2 model, which were proposed and tested in the third and fourth phases respectively.

The third phase of the study consists of the model development and hypotheses formulation. A new model based on the UTAUT2 model was devised using the findings from the preliminary survey, open-ended questions and the interviews from the second phase.

In the fourth phase, the newly devised model was validated through quantitative analysis based on an online survey which was completed by 683 participants. The results of the proposed model and the UTAUT2 model were comparatively analyzed for different user groups and hypotheses were tested.

The fifth phase provided an evaluation of the results and discussion of the findings.

1.3. Outline of the document

The following chapter presents a review of existing research on the topic, starting from mobile and wearable technologies in healthcare and then summarizes the prominent technology acceptance theories. The second chapter is concluded with existing literature on acceptance of wearable devices usage for health purposes.

Chapter 3, is dedicated to instruments of data collection and analysis. Results of the initial survey were also analyzed in this chapter.

Chapter 4 presents the qualitative analysis phase with the survey on open-ended questions and the interviews. A short discussion on the findings from qualitative analysis is presented in this chapter.

In the fifth chapter, the proposed model with extensions to the UTAUT2 model is explained. The updated survey with additional questions is also presented at chapter 5.

The sixth chapter presents the analysis of both models, the proposed model and the UTAUT2 model with the data from the second survey.

Seventh chapter is the discussion part, where findings from the qualitative and quantitative analysis were summarized.

Chapter 8 presents the summary and conclusion of the whole study with remarks on limitations of this current research with a guidance to future studies.

CHAPTER 2

LITERATURE REVIEW

A detailed literature review was conducted in order to understand the existing research and theories. The literature review consists of 3 parts. First part presents the overall status of “Mobile and Wearable Technologies in Healthcare”. An overview of the research on wearable devices is given in this section from a technological perspective, with a focus on developments on mobile technology, sensors and wearable devices. The second part presents the theories of technology acceptance and summarizes the evolution of acceptance models. Last part of this chapter presents existing research on wearable devices with a classification into two groups a) technology based studies and b) user based studies. This classification also points out the need for research on acceptance of wearable devices.

2.1. Mobile Health and Wearable Devices

Mobile health is an area that is continuously gaining importance and being examined from different perspectives of different stakeholders, including technology manufacturers, healthcare professionals, and policymakers. Wearable devices are electronic devices worn by patients/consumers tracking health or activity related data continuously (Nanjappan, Liang, & Wang, 2017). Market size of wearable devices increase continuously with the advances in technology, namely increase in capabilities and accuracy in measurement. As the penetration of these devices into our daily lives proceeds, the distinction between medical devices and consumer devices starts to disappear. Developments in sensors, communication technologies, and advances in computing power enables collecting and processing data from users. Mobile health is positioned as an emerging field in the intersection of medical informatics, public health, and business, which utilizes information and communication technology to collect and transmit data (Eysenbach, 2001). In parallel with improvements in sensor technology, power consumption, and manufacturing, the variety of available wearable devices is also increasing. Some of them directly target general consumers, whereas some are tailored for specific audiences such as the elderly population, users with postural disorders, or pregnant women. The capabilities and accuracy of mobile devices are constantly increasing, and collecting mobile health data is becoming an essential subject regarding wearable mobile devices, especially smart bands. The use of wireless mobile devices can support continuous health monitoring and encourage healthy behaviors to prevent and reduce health problems (Roy, Zalzala, & Kumar, 2016). Wearable devices combine the benefits of self-monitoring with features increasing motivation (Patel, Asch, & Volpp, 2015). Although wearable devices are not limited to wrist-worn devices, it is the most common wearable device type. Wrist-worn wearable devices, including smart watches and smart bands are widely used by consumers for both health and non-health related reasons (Dehghani, 2018).

2.2. Technology Acceptance

Mobile Health or mHealth is defined as the use of portable electronic devices including smart phones or wearable devices to provide health services and manage information such as health history or vital information (Källander, 2013). 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 (de Moraes, de Souza, Pires, & do Prado, 2016).

Wearable Medical Devices Market size was valued at over USD 9 billion in 2018 and is expected to witness 39.4% (Ugalmugle & Swain, 2020) compound annual growth rate (CAGR) from 2019 to 2025. Although wrist-worn devices like smart watches and smart bands constitute the majority of wearable devices as high as 95% (Richter, 2018) 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.

Previous research on wearable devices can be split into 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 amongst the most popular models. These models are applied in various domains or for various 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 continuously increasing. This leads to researches aiming to understand the motives behind individuals' and organizations acceptance of technology and adoption of new applications, tools and information systems. Technology Acceptance Model (TAM) (Davis, 1989) was proposed in the late 80s and dominated the area nearly two decades especially from the organizational perspective. TAM continued to be the leading model in technology acceptance domain (Malatjia, van Eck, & Zuva, 2020) and applied in various contexts which also revealed the limitations of the model (Ajibade, 2018).

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 8 models in order to obtain a stronger model, Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003). The new model provided better results on the acceptance of technology, but its focus was on organizational perspective too. 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 (Venkatesh, Thong, & Xu, 2012). 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.

2.2.1. Technology Acceptance Model (TAM)

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 (Ajzen & Fishbein, 1980) and Theory of Planned Behavior (Ajzen, 1991) contributed to TAM. These two theories used "Behavioral Intention" which is defined as a person's perceived likelihood to engage in a given behavior (Committee on Communication for Behavior Change in the 21st Century, 2002).

"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 (Figure 2).

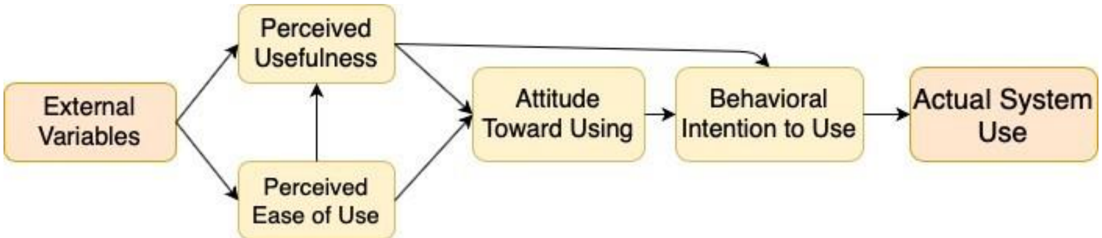

Figure 2: Technology Acceptance Model

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 (Lee, Kozar, & Larsen, 2003). 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 (King & He, 2006).

2.2.2. Technology Acceptance Model 2 (TAM2)

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" (Venkatesh & Davis, 2000). 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 (Figure 3) model includes the concepts of voluntariness and experience which were 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.

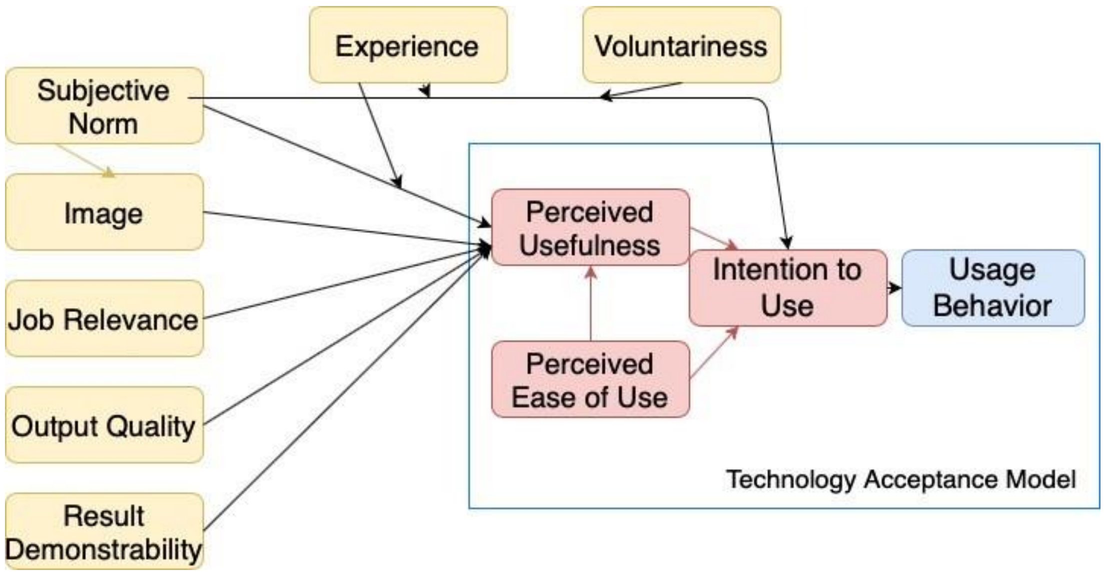

Figure 3: Technology Acceptance Model 2

2.2.3. Unified Theory of Acceptance and Use of Technology Model (UTAUT)

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. The UTAUT Model shows Root Constructs obtained from the previous theories (Figure 4).

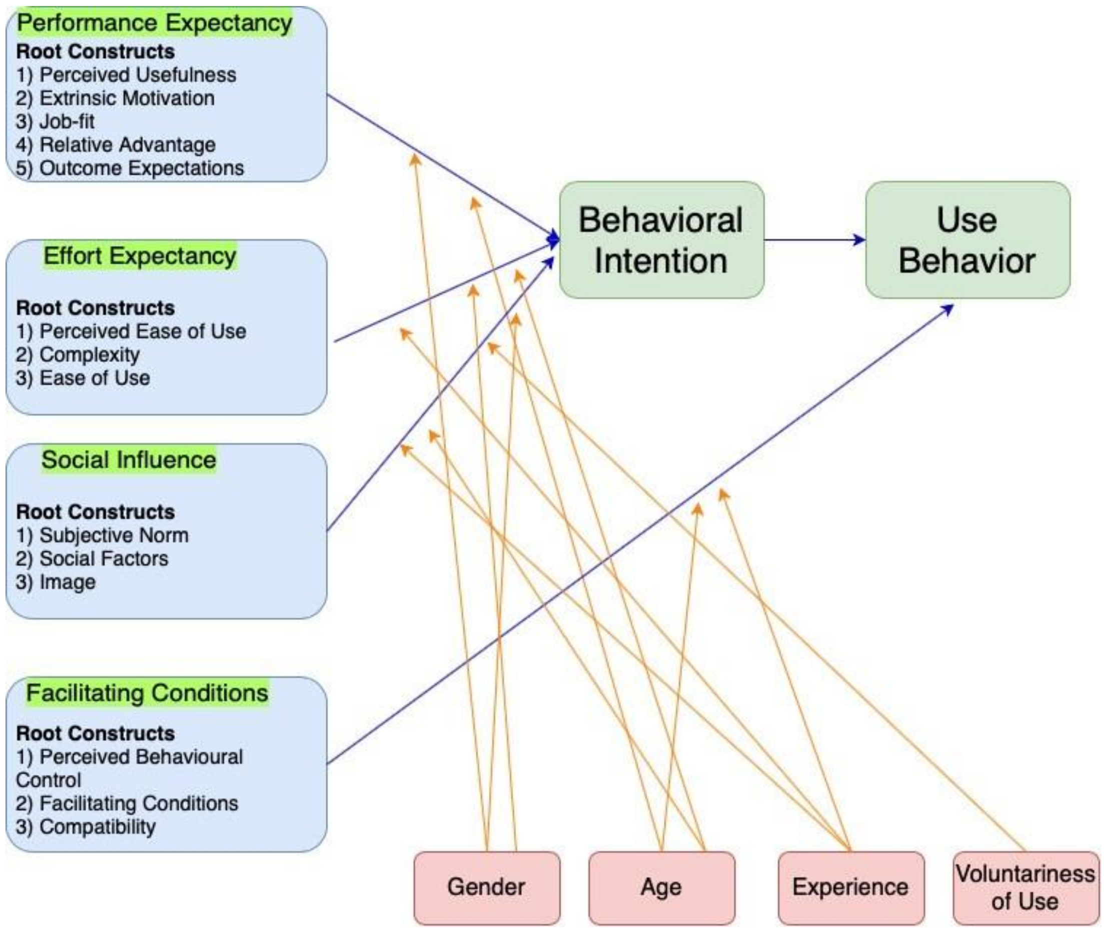

Figure 4: UTAUT Model

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.

2.2.4. Extended Unified Theory of Acceptance and Use of Technology Model (UTAUT2)

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 (Venkatesh, Thong, & Xu, 2012).

Four core constructs defined by UTAUT model were directly adopted (Brown & Venkatesh, 2005) (Venkatesh, Morris, Davis, & Davis, 2003) and listed below. Performance expectancy is defined as the "degree to which using a technology will provide benefits to consumers in performing certain activities" (Venkatesh, Morris, Davis, & Davis, 2003). Effort expectancy is defined as "Degree of ease associated with consumers' use of technology". 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 (Venkatesh, Morris, Davis, & Davis, 2003) 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 behaviour (Venkatesh, Morris, Davis, & Davis, 2003).

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 (Figure 5) 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 (van der Heijden, 2004).

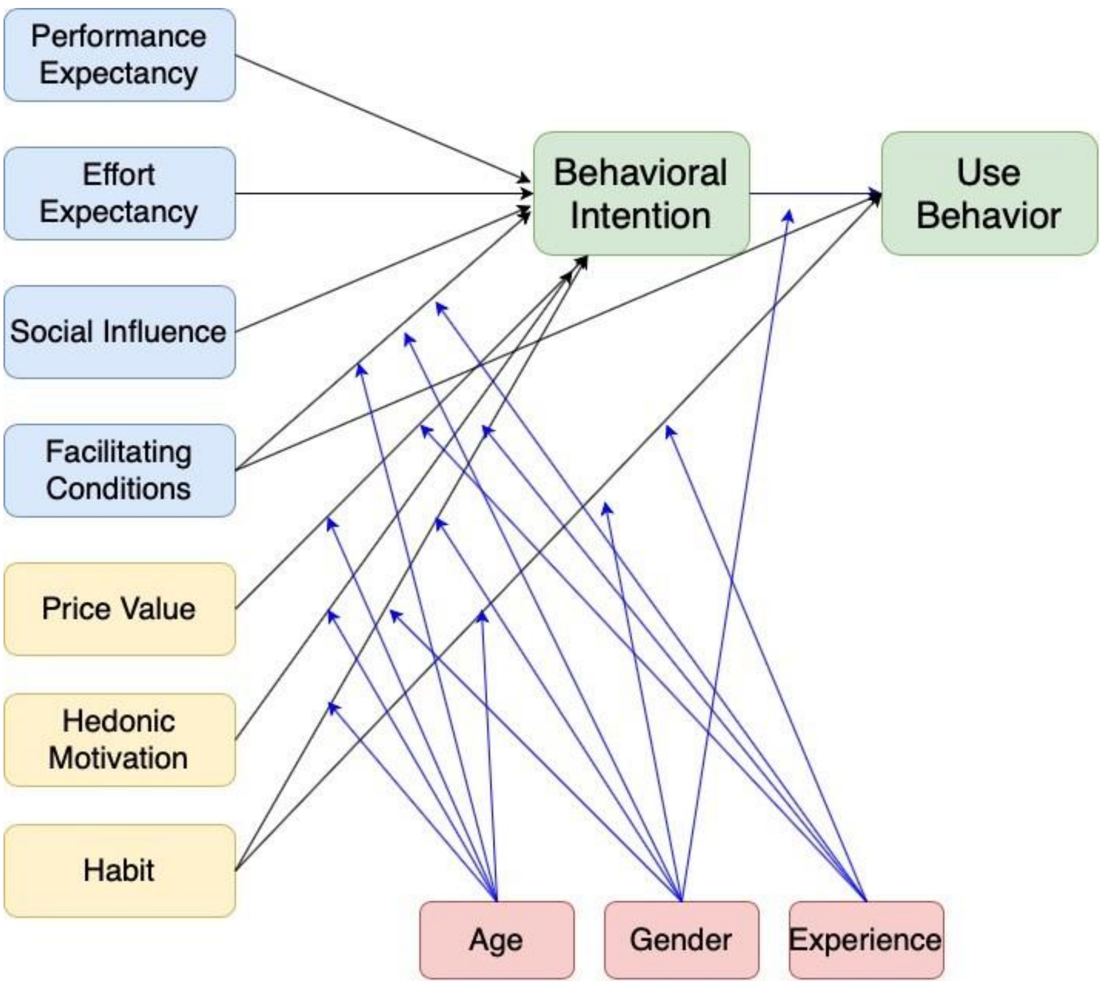

Figure 5: The UTAUT2 Model

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 (Chan, Gong, Xu, & Thong, 2008) (Brown & Venkatesh, 2005).

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 (Limayem, Hirt, & Cheung, 2007).

2.3.Previous Studies on Mobile Health and Wearable Devices

This part of the literature review checked the existing research on use of wearable devices for mobile health applications. A systematic review was conducted using Science Direct database for the articles published after 2005. During the literature survey, below queries were performed using Science Direct database and results were listed below.

On Science Direct database, 3 sets of keywords were used to search the articles based on “Title, Abstract and Keyword" attributes. The keyword sets are listed below. The first set was targeting all the articles having any one of these terms which are used interchangeably. The keywords given in the first set were combined with Boolean operator “OR”. Each of second and third set had a single keyword. During the searches, these 3 sets were combined with operator "AND" as shown below.

Keyword Set 1: “Mobile Health, M-Health, E-Health, eHealth, mHealth”

Keyword Set 2: “Wearable”

Keyword Set 3: “Acceptance

Search 1: Keyword Set 1

Search 2: Keyword Set 1 AND Keyword Set 2

Search 3: Keyword Set 2 AND Keyword Set 3

Search 4: Keyword Set 1 AND Keyword Set 2 AND Keyword Set 3

Search 5: Keyword Set 1 AND Keyword Set 3

Search 1 provided a general result set of 1271 articles, which were related to mobile health domain. Search 2-3-4-5 provided a narrower result set focusing on wearable devices and technology acceptance in mobile health domain. Each of the 123 unique articles returned by Search 2, Search 3, Search 4 and Search 5 were analysed to identify the relevance to the research topic. Yearly distribution of these 123 articles is given below (Table 1).

Table 1: Literature Search Results

	Search 1: Keyword Set 1	Search 2: Keyword Set 1 + Keyword Set 2	Search 3: Keyword Set 2 + Keyword Set 3	Search 4: Keyword Set 1 + Keyword Set 2 + Keyword Set 3	Search 5: Keyword Set 1 + Keyword Set 3
2006	34	0	0	0	1
2007	33	1	1	0	0
2008	32	1	0	0	1
2009	36	1	1	0	1
2010	36	1	0	0	0
2011	71	0	1	0	4
2012	77	1	4	0	1
2013	139	1	1	0	10
2014	182	5	3	1	14
2015	251	11	3	1	8
2016	341	16	12	0	19
2017	39	1	1	0	2
Total	1271	39	27	2	61
		123 unique articles			

Each article was checked for the relevance to the mobile health domain and two main focus areas were determined for each article. For example, if an article is focusing on how low power consumption sensors can increase the battery life but not dealing with user side, application areas, system design, user acceptance, it is classified in the technology domain and marked to be located in “Power Consumption” branch of the technology domain. On the other hand, if a research study is focusing on clinical studies of developed devices or how the user interacts with these devices, and not considering development of these devices, it is classified to be in the User Related Studies domain.

After removing 10 articles without full text, and after removing 1 article in French, remaining 112 articles were classified as shown below according to yearly distribution (Figure 6) and focus topics (Figure 7).

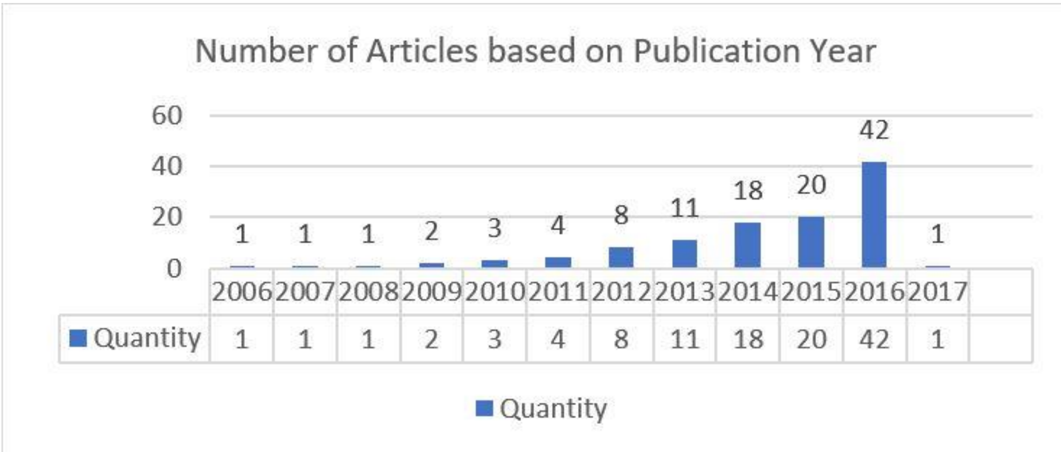

Figure 6: Yearly Article Distribution

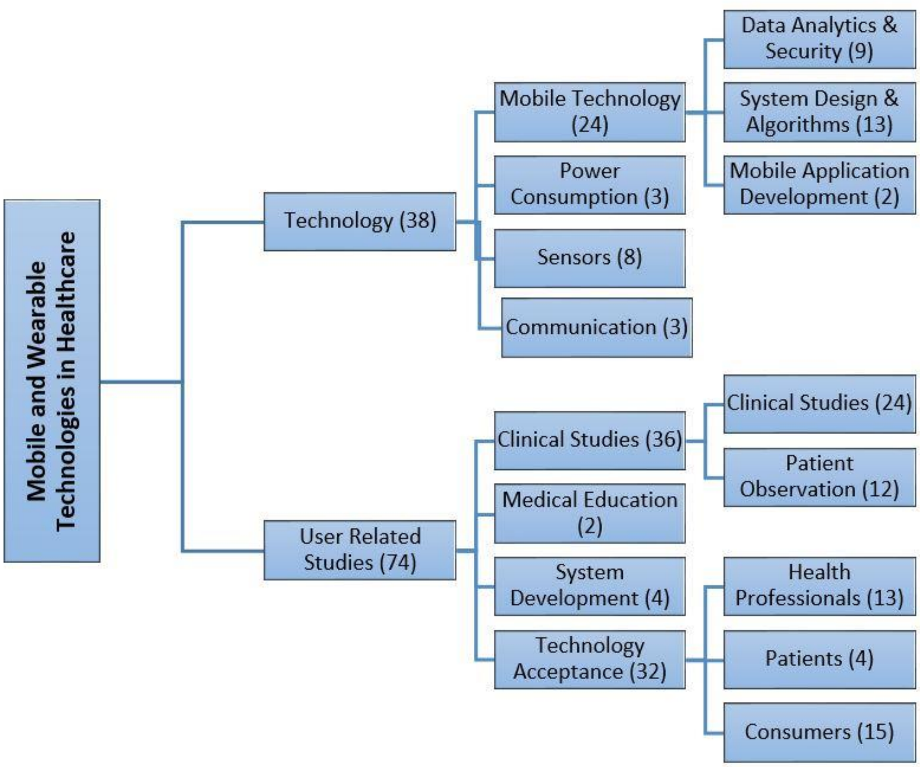

Figure 7: Article Classification

Figure 7 classifies existing research on mobile health domain for wearable devices into two main groups with sub-groups (Pancar & Ozkan-Yildirim, 2018). The yearly distribution of these studies is also listed based on publication year (Table 2).

Table 2: Distribution of publications by focus and year

		Technology				User Related Studies			
Year	Qty.	Communication	Mobile Tech.	Power Consumption	Sensors	Clinical Study	Medical Education	System Development	Technology Adoption
2006	1					1			
2007	1					1			
2008	1	1							
2009	2		1		1				
2010	3					2		1	
2011	4		1			1			2
2012	8		1		2	3			2
2013	11		2		2	3			4
2014	18	1	4	1		4		1	7
2015	20	1	4		2	6	2		5
2016	42		11	2	1	14		2	12
2017	1					1			
	112	3	24	3	8	36	2	4	32

It is reasonable to predict that the studies on mobile technology will continue increasing since the capabilities of mobile devices are increasing constantly and increasing capabilities of wearable devices will trigger the researches on technology and user related studies. As Table 2 lists, the studies for both groups are increasing since 2009, which supports the above prediction. Another important topic is the increase in user related studies, especially for Clinical and Technology Adoption studies. Wearable devices are getting more mature and more accessible, and they are not used only by early adopters anymore and started to be used by larger communities. The increase in usage and interaction with these devices created the need for technology adoption studies.

2.3.1. Technology

One of the major research areas related to the wearable devices for mobile health applications is the technology used in these devices. It is possible to classify these devices based on the communication technologies and protocols, power consumption and energy efficiency, sensor technologies and collected data and as a final group mobile health technology can be listed including data analytics, security and mobile application development. Following four sections will briefly mention the current status in these areas.

Communication

Advances in wireless communication technologies is a very important factor underpinnig the increasing popularity and usage of wearable devices. Wearable devices generally use Wi-Fi technology to collect data from remote sensors. Choosing best access point is an important issue (Norbert, Piri, & Bokor, 2015) to select the most suitable network environment (Wi-Fi, 3G, 4G, etc.). Depending on the purpose of the usage, these devices support Bluetooth, Wi-Fi or GSM connection. The communication type of the devices is directly related with power consumption (Seneviratne, et al., 2017).

Power Consumption

Power consumption of wearable sensors and devices is very important for the seamless operation of these devices, high power consumption and low energy efficiency will require recharging very often. Optimization of charging of wearable devices for heart rate measurement (Kiruthiga, Sharmila, Mahalakshmi, & Muruganandam, 2017) is an active research area which is open for new improvements. A review study (Rault, Bouabdallah, Challal, & Marin, 2017) lists previous researches on decreasing power consumption and increasing energy efficiency. Healthcare applications require continuous measurement which is draining the battery and the increase in healthcare applications will need energy-efficient approaches for wearable devices.

Sensors

Sensors technology is one of the most popular topic in technology area and there are previous literature reviews (Chan, Estève, Fourniols, Escriba, & Campo, 2012), (Appelboom, et al., 2014) focusing to the hardware or user interaction with sensors. The sensors make measurement of several data such as pulse, blood oxygen, or body temperature which depends on the type of the device and main usage purpose (Haghi, Thurow, & Stoll, 2017). There are also studies focusing on sensor requirements for wrist-worn wearable devices (Bieber, Haescher, & Vahl, 2013).

Mobile Technology

Studies in mobile health technology section contains data analytics (Wu, Li, Cheng, & Lin, 2016), (Leff & Yang, 2015). With the help of big data analytics (Hossain, Masud, Muhammad, Rawashdeh, & Hassan, 2014), huge amount of data collected via sensors can be analyzed in order to obtain meaningful results. Another important issue is data security (MayaMohan, Kavithadevi, & Prakash, 2016), since health data contains personal information (Moosavi, et al., 2015), security and authorization are of great importance. Several researches focus on information security during collection of data from remote sensors and storage and processing of this data in smart phones or application servers. Most of the wearable devices in the market works together with smart phones and development of these smart phone applications has a great effect on many aspects including user experience (Hussain, et al., 2015), user acceptance, security etc. (Liu, Zhu, Holroyd, & Seng, 2011).

2.3.2. User Related Studies

Second major area is user related studies which includes “Clinical Studies using wearable technologies in order to monitor and improve patient status”, “Medical Education using wearable technologies” and “Technology Adoption by different audiences (healthcare professionals, patients, consumers).

Clinical Studies

Advances in mobile technologies for rehabilitation purposes can be used to increase the availability and accessibility for treatments in order to increase effectiveness of treatments (Papi, Osei-Kuffour, Chen, & McGregor, 2015)and observation of patients outside of clinical environment as part clinical studies.

There are various usages of mobile technologies for clinical studies in order to monitor and improve patient status. Existing technologies can be combined with wearable sensors in order to monitor patients with heart failure (Mickelson, Wilis, & Holden, 2015). A glove functioning as finger flexion monitor can be used in order to observe hand dysfunction of patients by collecting how users perform daily activities that are very valuable to show the difference between clinical observation and daily usage (Simone, Sundarrajan, Luo, Jia, & Kamper, 2007).

Wearable technologies also have critical importance for Parkinson patients especially for Freezing of Gait (FOG) disorder, which is hard to study in clinical settings since it is not possible to detect when gait will occur (Factor, et al., 2014). Wearable sensors are used to collect data from patients in real-time with a smartphone-based architecture which enabled continuous data collection and analysis (Capecci, Pepa, Verdini, & Ceravolo, 2016), (Atallah, et al., 2012). As a consequence of aging population, fall detection and prevention also gains importance, for the older population falls are still leading causes for injury and death (Ferrari, et al., 2012). Development of algorithms with low computational complexity to improve performance (Benocci, et al., 2010), (Sannino, De Falco, & De Pietro, 2015), (Gao, Chen, Tang, Zhang, & Li, 2016).

Medical Education

As the usage and application of wearable mobile devices in health domain increases, training and education of health professionals also worth studying. As stated before, wearable technology is gaining importance and expected to have a disruptive effect in healthcare provision and education (Sultan, 2015). Wearable devices are used by medical students as part of their courses in order to enhance cardiovascular diseases (Vallurupalli, Paydak, Agarwal, Agrawal, & Assad-Kottner, 2013). The changes in personalized health and collection of data will cause a transformation in providing health service and will effect health professionals as well as patients, which will also effect nursing education by modification of learning environments and teaching methods (Hopia, Punna, Laitinen, & Latvala, 2015).

System Development

Articles in this category, approaches the topic from a broader perspective and focuses on development and deployment of these systems. Recently developed systems for community health care utilizes wearable devices to monitor user activity and collect data which can be used for various purposes, wearable devices can help predicting seasonal diseases by the data they collect over extended periods of time (Roy, Zalzala, & Kumar, 2016). Due to the changes in industry, most of the current business tasks are knowledge-intensive and ageing of global workforce and preventive healthcare systems using wearable technologies are gaining importance in order to collect health data from employees and predict possible illnesses (Nikayin, Heikkilä, de Reuver, & Solaimani, 2014).

Technology Adoption

Acceptance and adoption of technology by organizations and individuals is a well-studied area and there are many research studies applying previous models or proposing extensions to existing models. Some examples from selected studies using Technology Acceptance Model (TAM) are listed below (Table 3).

Table 3: Articles using Technology Acceptance Model

Article Name	Author/Year	Audience	Journal	Location
A study on Singaporean women's acceptance of using mobile phones to seek health information	(Lim, et al., 2011)	Consumer	International Journal of Medical Informatics	Singapore
Learning with mobile technologies – Students' behavior	(Briz-Ponce, Pereira, Carvalho, Juanes-Méndez, & García-Peñalvo, 2017)	Consumer, Patient	Computers in Human Behavior	Portugal
Tablet computers in support of rural and frontier clinical practice	(Anderson, Henner, & Burkey, 2013)	Health Professional	International Journal of Medical Informatics	United States
The underlying factors of the perceived usefulness of using smart wearable devices for disaster applications	(Cheng & Mitomo, 2017)	Consumer	Telematics and Informatics	Japan
Wearable technologies: The role of usefulness and visibility in smartwatch adoption	(Chuah, et al., 2016)	Consumer	Computers in Human Behavior	Malaysia

There are several studies using an extension of the TAM (Table 4). Some of them propose new constructs such as Perceived Importance (Dünnebeil, Sunyaev, Blohm, Leimeister, & Krcmar, 2012), Vanity and Need for Uniqueness (Choi & Kim, 2016) and Perceived Behavioral Control (Alaşehir, Sezgin, & Özkan, 2013) or use constructs from other models like Unified Theory of Acceptance and Use of Technology (UTAUT) or Theory of Planned Behavior (TPB).

Table 4: Articles using extensions of Technology Acceptance Model

Article Name	Author/Year	Audience	Journal	Location
A cross-sectional investigation of acceptance of health information technology: A nationwide survey of community pharmacists in Turkey	(Sezgin & Özkan-Yıldırım, 2016)	Health Professional	Research in Social and Administrative Pharmacy	Turkey
Consumers' and Physicians' Perceptions about High Tech Wearable Health Products	(Nasir & Yurder, 2015)	Consumer + Health Professional	Procedia - Social and Behavioral	Turkey
Determinants of physicians' technology acceptance for e-health in ambulatory care	(Dünnebeil, Sunyaev, Blohm, Leimeister, & Krcmar, 2012)	Health Professional	International Journal of Medical Informatics	Germany
Is the smartwatch an IT product or a fashion product? A study on factors affecting the intention to use	(Choi & Kim, 2016)	Patient	Computers in Human Behavior	Korea
The impact of post-adoption beliefs on the continued use of health apps	(Cho, 2016)	Consumer + Patient	International Journal of Medical Informatics	Korea
The Role of Gender in Pharmacists Attitudes Towards E-pharmacy Application	(Alaşehir, Sezgin, & Özkan, 2013)	Health Professional	Procedia - Social and Behavioral	Turkey
User acceptance of wearable devices: An extended perspective of perceived value	(Yang, Yu, Zo, & Choi, 2016)	Consumer	Telematics and Informatics	Korea
Wearable fitness technology: A structural investigation into acceptance and perceived fitness	(Lunney, Cunningham, & Eastin, 2016)	Consumer	Computers in Human Behavior	United States
Women's use of online resources and acceptance of e-mental health tools during the perinatal period	(Fonseca, Gorayeb, & Canavarro, 2016)	Patient	International Journal of Medical Informatics	Portugal
Work in Progress toward Adoption of an e-health Application by Healthcare Personnel: A Model Validation	(Sezgin, Alasehir, & Ozkan-Yildirim, 2014)	Health Professional	Procedia Technology	Turkey

Another point that is worth noting is the audience of acceptance articles. As discussed in the previous sections, the researches related to technology are mainly targeting the same audience, namely system developers, and clinical studies mainly focus on patients and physicians together. However, the studies about technology acceptance focus on one of the various target audiences such as consumers, health professionals or patients.

Besides TAM and TAM extension models, other models are also used by researches in order to examine the acceptance of wearable devices for health purposes. UTAUT model is used for a cross-country comparison from consumer perspective (Dwivedi, Shareef, Simintiras, Lal, & Weerakkody, 2016), and in order to evaluate an e-Health system in Australian context (Gajanayake, Iannella, & Sahama, 2016).

Among the selected articles, there are 3 literature reviews working on previous studies from health professional perspective (Sezgin, Alasehir, & Ozkan-Yildirim, 2014), ageing population (Peek, et al., 2014), and patients for home telemonitoring (Cruz, Brooks, & Marques, 2014).

CHAPTER 3

INSTRUMENTS OF DATA COLLECTION AND PRELIMINARY ANALYSIS

This chapter presents the instrument used for data collection and the results of the preliminary survey testing the UTAUT2 model in mobile health domain.

3.1. Survey Development

An online survey was prepared to collect data from users of wearable devices. Survey items used by Venkatesh (Venkatesh, Thong, & Xu, 2012) were modified to suit the wearable device usage in health domain. In addition to the items of the original UTAUT2 constructs, the survey also included questions regarding age, gender, experience with the technology and some open-ended questions to support the rating questions. These open ended questions are explained in the next chapter. The duration of using wearable devices and the technology affinity of users were asked to understand users' experience with the technology. The participants were asked to classify themselves as being an early adopter, early majority, late majority or laggards based on their experience with technology.

Survey questions of the preliminary survey are prepared in English and Turkish and are presented in (Appendix A, Appendix B).

3.2. Preliminary Survey

The preliminary survey with UTAUT2 items and open-ended questions was conducted between April and May 2018. Prior to distributing the questionnaire and collecting data, the Middle East Technical University's Human Subjects Ethics Committee application is completed and approval to apply the questionnaire is obtained. The approval document is provided (Appendix C). The survey was promoted with below methods to reach potential 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)

Below scale was used while preparing the results for analysis (Table 5):

- Questions with LIKERT scale are 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.

Table 5: Scale for Analyzing Survey Results

SCALE	**Answers**	**Usage**	**Gender**	**Age**	**Experience**
5	Strongly Agree	Many times per day		>54	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	<18	Do not remember

1357 participant completed the survey, 1285 of these participants declared they were currently using wearable devices. 22 of these results were excluded from the analysis because of having monotonously very high scores.

Demographic information about these 1263 participants are summarized in below tables. Age group and gender distribution (Table 6) and countries where the participants are located are shown (Table 7).

Table 6: Age and Gender Distribution

Age Group	Female	Male
<18	2	6
18-24	349	138
25-34	232	100
35-44	139	77
45-54	74	50
>55	38	58
Total	834	429

Table 7: Geographical Distribution

Country	Participant Qty.
USA	1171
The Netherlands	38
Germany	25
South Africa	10
Switzerland	7
Others	12
Total	1263

Most of the participants are from USA, which can be a reason of high usage of social media and the success in social network advertisements targeting correct user groups. Countries marked as "Other" have only 1 participant completing the survey. Number of female participants was higher than male participants in all age groups, which is an expected result for online surveys (Saleh & Bista, 2017).

Table 8: Distribution based on Usage Duration

Experience	Participant Qty.
Less than 1 month	62
6 months	294
1 year	343
3 years	425
5 years or more	124
I do not remember	15

The participants were asked to report about their experience with the technology. They selected usage duration starting from 1 month or less to 5 years or more (Table 8). They classified themselves based on technology affinity and selected one of the groups from early adopters to laggards (Table 9).

Table 9: Distribution based on Technology Affinity

User Type	Qty
Early Adopters	297
Early Majority	506
Late Majority	167
Laggards	26
I do not know	267

We analyzed the preliminary survey responses using original UTAUT2 model. 1357 participants completed the survey, and after eliminating the participants who were not using the wearable devices and the participants whose answers showed unrealistic or inconsistent distribution, the data from 1263 participants were used in quantitative analysis.

1257 of 1263 participants told that they were using smart bands or smart watches as wearable devices. One participant said he is using a smart ring and one participant said she is using an ovulation tracker. Five participant said they are using continuous glucose monitoring devices as part of their medical treatment. Although this study aims to analyze consumers' adoption of all kind of wearable devices, due to the popularity of smart bands/watches, more than %99 of participants are using wrist worn devices. There are other types of wearable devices on the market but since smart bands/watches are the most common type, it was not possible to access the users of other devices. This should be kept in mind while evaluating the survey responses.

Analysis of the Preliminary Survey

After preparing the survey responses for analysis, below steps were followed to examine the validity and reliability of measurement model and to evaluate the structural model.

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. 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 variable). In our models, BI and USE are endogenous latent variables and others are exogenous latent variables.

Measurement Model Analysis

- Criteria 1: Convergence

  - Iterations are expected to converge without reaching maximum number of iterations.

- Criteria 2: Reliability
  - Cronbach`s Alpha value:
    - Cronbach`s Alpha value greater than 0.7 assumes that all indicators of a construct are equally reliable (Henseler, Ringle, & Sinkovics, 2009), (Nunnally, 1978).
  - Composite Reliability:
    - Composite reliability, controls individual reliability of indicators and is expected to be greater than 0.7. Composite reliability varies from 0 to 1, and values over 0.6 are accepted as sufficient for exploratory studies (Chin, 1998), (Höck & Ringle, 2010) and values over 0.7 are adequate for confirmatory studies (Henseler, Ringle, & Sarstedt, 2012).
- Criteria 3: Validity:
  - Convergent validity:
    - Average Variance Extracted (AVE) should be greater than or equal to 0.5 (Segars, 1997).
  - Divergent validity:
    - Measured using Fornell Larcker criterion, square root of AVE is expected to be greater than correlation coefficient between structures. Fornell-Larcker's criterion was used to check discriminant validity. According to this criterion, the square root of AVE for a construct should be higher than the correlation with any other variables (Fornell & Larcker, 1981).
  - Check HTMT
    - HTMT is a new measure proposed in 2015, which is used to test discriminant validity.
    - It 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 (Henseler, Ringle, & Sarstedt, 2015).

- Criteria 4: Internal Consistency (Loadings):
    - Path loadings and cross-loadings should be checked to ensure internal consistency and discriminant validity.
    - In a good model, indicators are expected to have higher loadings on the intended constructs and lower loadings for other constructs (Garson, 2016). Path loadings are expected to be greater than 0.7.

Structural Model Analysis

Following the verification of the measurement model, we continued with the structural model analysis—this analysis aimed to explore the relationships between the constructs.

- Criteria 1: Structural Path Coefficients
    - Structural path coefficients show how factors are connected to other factors, higher path coefficients means stronger connection between latent variables.
- Criteria 2: R-Squared (Variance)
    - The coefficient of determination (R-Squared) was used to measure the explanatory power of the model.
    - R-Squared is the overall effect size measure for structural model. It is calculated only for endogenous latent variables.
    - Models with high R-Squared provide a precise prediction (Rasoolimanesh, Roldán, Jaafar, & Ramayah, 2017).
    - There are different threshold values proposed by researchers:
        - Comparison of R-Squared is done based on cutoff criteria of 0.67, 0.33 and 0.19 to be named as “substantial”, “moderate” and “weak” respectively (Chin, 1998).
        - R-Squared values up to 0.25 are considered weak, R-Squared values up to 0.50 are considered moderate, and values up to 0.75 are considered substantial (Henseler, Ringle, & Sinkovics, 2009).
- Criteria 3: Multicollinearity (Inner)

- Multicollinearity exists, when there is high intercorrelation between two or more independent variables (Garson, 2016).
- Variance inflation factor (VIF) is used to measure multicollinearity, where VIF values higher than 5 (higher than 4 for more strict cutoff) imply the existence of multicollinearity (Grewal, Cote, & Baumgartner, 2004).

- Criteria 4: f-Square (Change in Variance)
    - Change in R-Squared values when an exogenous latent variable is removed is called as the f-square value.
    - f-square values are classified as small, medium and high for 0.02, 0.15 and 0.35 (Cohen, 1988).
- Criteria 5: t-value testing
    - The significance of the paths (t-values) were checked (Gefen, Straub, & Boudreau, 2000). The relationships between constructs (paths) were checked for t-values and p-values and marked as supported or not supported.

3.3.1. Measurement Model Analysis Results

This section uses output of Smart PLS 3 software PLS Algorithm calculation. Results of UTAUT2 model are listed for each step. PLS Algorithm run with path weighting scheme for maximum 1000 iterations and with stop criteria 10-7.

- Checking Convergence and Reliability
    - Both models converged in 8 iterations.
    - Cronbach`s Alpha and Composite Reliability values are greater than 0.7 as expected (Table 10).

Table 10: Reliability Values

	Cronbach's Alpha	Composite Reliability
BI	0,858	0,914
EE	0,866	0,909
FC	0,708	0,820
HM	0,877	0,925
Habit	0,786	0,858
PE	0,819	0,879
Price	0,873	0,920
SI	0,947	0,966
USE	1,000	1,000

- Checking Validity (AVE, Discriminant validity and HTMT)
  - AVE is expected to be greater than 0.5 which is confirmed.
  - 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 criteria is also fulfilled (Table 11).
  - HTMT values are found to be lower than 0.9 (Table 12).

Table 11: Convergent & Discriminant Validity values

	AVE	BI	EE	FC	HM	Habit	PE	Price	SI	USE
BI	0,779	0,883								
EE	0,713	0,345	0,844							
FC	0,538	0,332	0,696	0,733						
HM	0,804	0,434	0,314	0,314	0,896					
Habit	0,603	0,548	0,347	0,329	0,456	0,777				
PE	0,647	0,576	0,388	0,410	0,490	0,490	0,804			
Price	0,794	0,327	0,307	0,299	0,284	0,262	0,349	0,891		
SI	0,904	0,195	-0,005	0,001	0,151	0,197	0,197	0,131	0,951	
USE	1,000	0,277	0,118	0,107	0,084	0,380	0,165	0,064	0,000	1,000

Table 12: HTMT Values

	BI	EE	FC	HM	Habit	PE	Price	SI
BI								
EE	0,399							
FC	0,420	0,859						
HM	0,498	0,354	0,393					
Habit	0,645	0,382	0,397	0,559				
PE	0,669	0,442	0,523	0,577	0,594			
Price	0,362	0,350	0,385	0,319	0,308	0,412		
SI	0,215	0,014	0,070	0,166	0,255	0,237	0,139	
USE	0,299	0,125	0,127	0,089	0,394	0,175	0,065	0,010

- Checking Internal Consistency (Loadings)
  - High loading and low cross-loading is expected, below tables shows these values.
  - Results for both models support high loading and low cross-loadings as shown below (Table 13).

Table 13: Loadings and Cross-Loadings

	BI	EE	FC	HM	Habit	PE	Price	SI	USE
BI1	0,865	0,330	0,313	0,362	0,433	0,471	0,240	0,121	0,234
BI2	0,870	0,259	0,250	0,390	0,494	0,487	0,308	0,244	0,241
BI3	0,912	0,326	0,316	0,395	0,518	0,562	0,314	0,149	0,258
EE1	0,254	0,813	0,546	0,221	0,247	0,283	0,230	-0,024	0,066
EE2	0,277	0,834	0,595	0,244	0,245	0,312	0,272	-0,003	0,090
EE3	0,312	0,862	0,601	0,298	0,322	0,362	0,290	0,002	0,131
EE4	0,315	0,867	0,606	0,288	0,347	0,345	0,243	0,005	0,106
FC1	0,282	0,644	0,843	0,267	0,287	0,344	0,283	-0,015	0,086
FC2	0,288	0,627	0,822	0,259	0,291	0,344	0,185	-0,016	0,091
FC3	0,197	0,337	0,607	0,152	0,159	0,209	0,196	-0,042	0,071
FC4	0,188	0,360	0,630	0,230	0,204	0,292	0,219	0,094	0,064
HM1	0,380	0,299	0,310	0,924	0,417	0,460	0,236	0,102	0,086
HM2	0,427	0,323	0,312	0,927	0,433	0,467	0,295	0,138	0,077
HM3	0,355	0,215	0,214	0,835	0,373	0,388	0,228	0,168	0,062
Habit1	0,468	0,341	0,334	0,326	0,829	0,407	0,210	0,110	0,388
Habit2	0,349	0,144	0,130	0,403	0,730	0,326	0,174	0,210	0,182
Habit3	0,339	0,146	0,139	0,346	0,674	0,349	0,214	0,260	0,140
Habit4	0,506	0,365	0,338	0,376	0,860	0,429	0,221	0,107	0,380
PE1	0,538	0,418	0,422	0,407	0,458	0,801	0,260	0,093	0,188
PE2	0,486	0,290	0,313	0,388	0,420	0,844	0,278	0,170	0,146
PE3	0,330	0,195	0,246	0,367	0,291	0,711	0,306	0,243	0,077
PE4	0,459	0,302	0,308	0,416	0,376	0,853	0,297	0,167	0,098
Price1	0,200	0,245	0,256	0,221	0,182	0,257	0,835	0,074	0,028
Price2	0,338	0,282	0,261	0,266	0,263	0,340	0,919	0,123	0,068
Price3	0,307	0,289	0,285	0,266	0,240	0,323	0,918	0,141	0,066
SI1	0,175	-0,001	0,005	0,146	0,176	0,189	0,142	0,937	-0,009
SI2	0,180	-0,004	0,007	0,139	0,197	0,181	0,108	0,961	-0,006
SI3	0,199	-0,008	-0,008	0,145	0,188	0,192	0,124	0,954	0,013
USE1	0,277	0,118	0,107	0,084	0,380	0,165	0,064	0,000	1,000

3.3.2. Structural Model Analysis Results

After both models were found as valid and reliable according to measurement model analysis, structural models were analyzed using Smart PLS 3 Bootstrapping algorithm. 1000 subsamples are produced using PLS Bootstrapping algorithm with significance level of 0.05.

- Resulting Path Coefficients & R-Squared values are shown below (Table 14). Performances of both models were compared for endogenous latent variables

Table 14: Path Coefficients and R-Squared values

	BI	USE
R Squared	0,446	0,152
R Squared Adjusted	0,443	0,150
BI	-	0,107
EE	0,057	

FC	0,010	-0,038
HM	0,089	
Habit	0,294	0,333
PE	0,323	
Price	0,085	
SI	0,049	

- Checking Multicollinearity
    - Multicollinearity exists if two or more independent variables are highly correlated, Variance Inflation Factor (VIF) is a commonly used test to check multicollinearity.
    - Inner VIF values are calculated in this step (Table 15), both models have VIF values lower than 5, stating that there is no multicollinearity for the inner model also.

Table 15: Inner VIF values

	BI	USE
BI		1,483
EE	2,054	
FC	2,056	1,164
HM	1,465	
Habit	1,496	1,480
PE	1,673	
Price	1,216	
SI	1,081	

- Checking f-square
    - f-square value is the difference in R-Squared when a specific construct is removed from the model, it is calculated by Smart PLS 3 program (Table 16).

Table 16: f-Square values

	f-Square
Habit ->Use	0,089
BI -> Use	0,009
FC -> Use	0,001
PE -> BI	0,112
Habit -> BI	0,104
Price -> BI	0,011
HM -> BI	0,010
SI -> BI	0,004
EE -> BI	0,003
FC -> BI	0,000

- t-Values:
    - t-values and p-values were used for testing. T-values below 1,96 are marked as not supported (Table 17).

Table 17: t-statistics for preliminary survey

Path Relationship	T Statistics	P Values	Test Result
BI -> USE	2,804	0,005	Supported
EE -> BI	1,817	0,070	Not Supported
FC -> BI	0,310	0,757	Not Supported
FC -> USE	1,053	0,293	Not Supported
HM -> BI	3,194	0,001	Supported
Habit -> BI	10,478	0,000	Supported
Habit -> USE	6,752	0,000	Supported
PE -> BI	10,273	0,000	Supported
Price -> BI	3,238	0,001	Supported
SI -> BI	2,467	0,014	Supported

It is seen that, two of the core constructs of the UTAUT2 model, effort expectancy and facilitating conditions do not have a significant effect on behavioral intention to use and actual usage.

As explained in previous sections, participants of the updated survey was divided into sub-groups, and each group was analyzed separately. This section compares path coefficients and R-Squared values for different user groups (Table 18).

Table 18: Sub-Groups for Analysis

Group Name	User Type	Qty
Group 1	Female	834
Group 2	Male	429
Group 3	<35	827
Group 4	>45	220
Group 5	Early Adopters	297
Group 6	Early Majority	506
Group 7	Late Majority + Laggards	193
Group 8	Exp 1-2 (Short Term users, less than 1 year)	356
Group 9	Exp 4-5 (Long Term users, 3+ years)	549

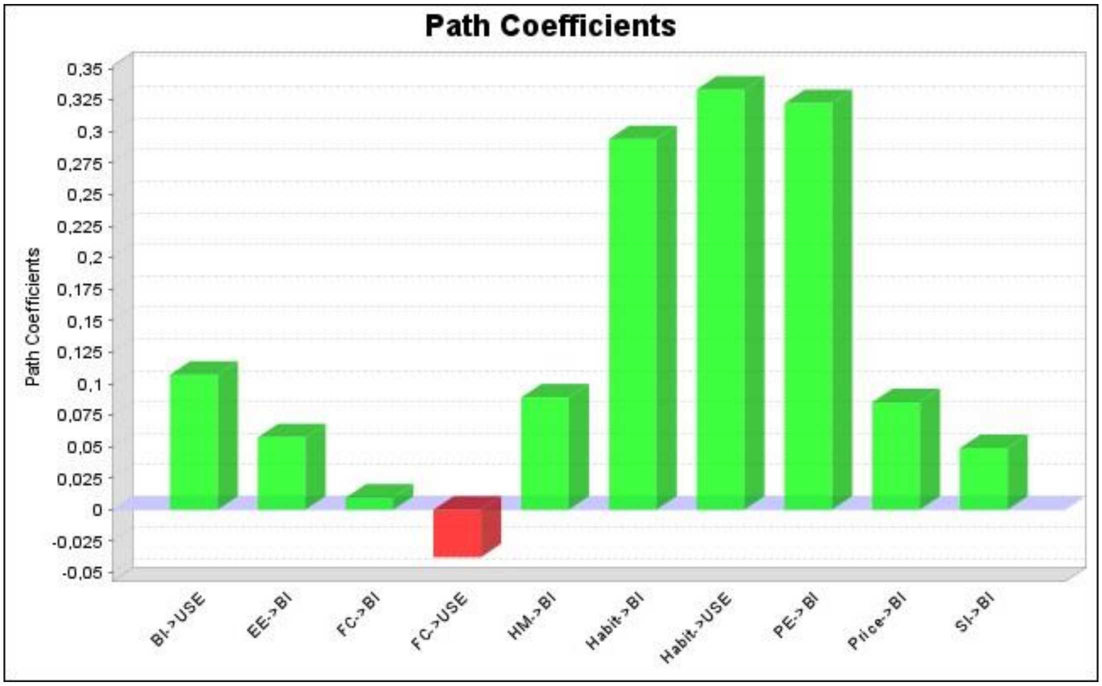

Figure 8: Preliminary Analysis (All Users)

Without any classification of users, habit and performance expectancy (PE) are seen as most significant factors in determining the behavioral intention. Similarly, habit is the most significant factor for use, followed by behavioral intention. Facilitating conditions has a little affect, low as 0,027. The R-Squared values are found as 0,444 and 0,288 for behavioral intention and use, respectively.

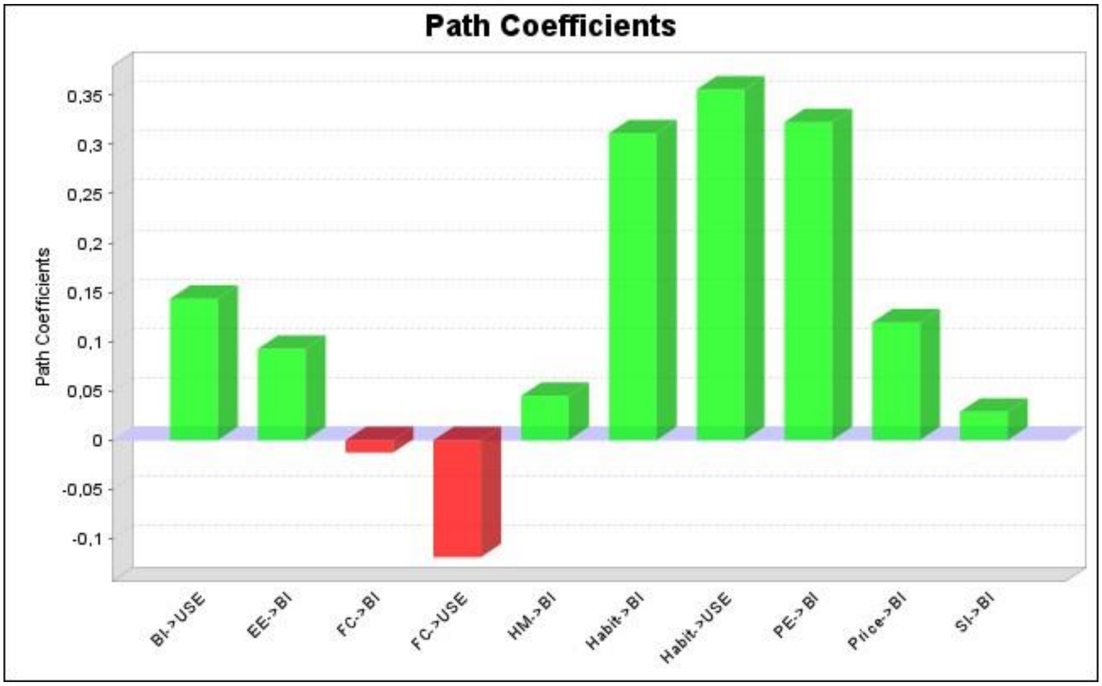

Figure 9: Preliminary Analysis (Female Users)

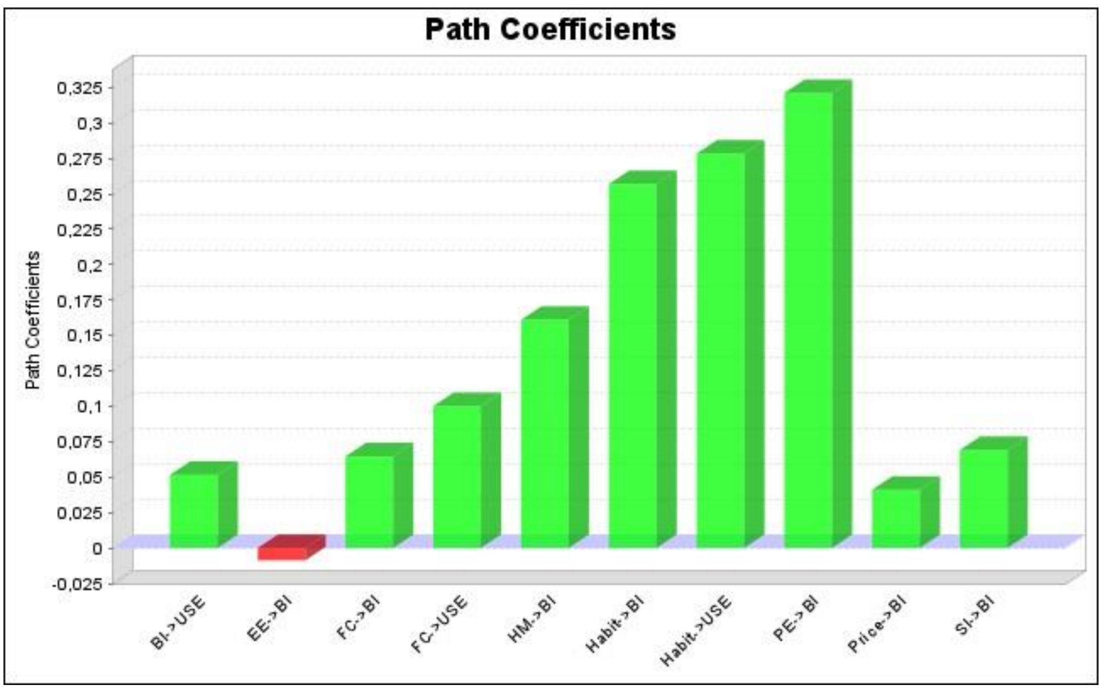

Figure 10: Preliminary Analysis (Male Users)

834 of the 1263 participants were female and 429 were male. The R-Squared values of behavioral intention between male and female users were similar (around 5% difference)

but the R-Squared values for actual usage for male users were 20% higher than female users.

Habit and Performance Expectancy were the most significant constructs. The effect of habit on usage was stronger for male users whereas the effect of habit on behavioral intention was stronger for female users. Hedonic Motivation was found to be more important for male compared to female users, although the value was not very significant.

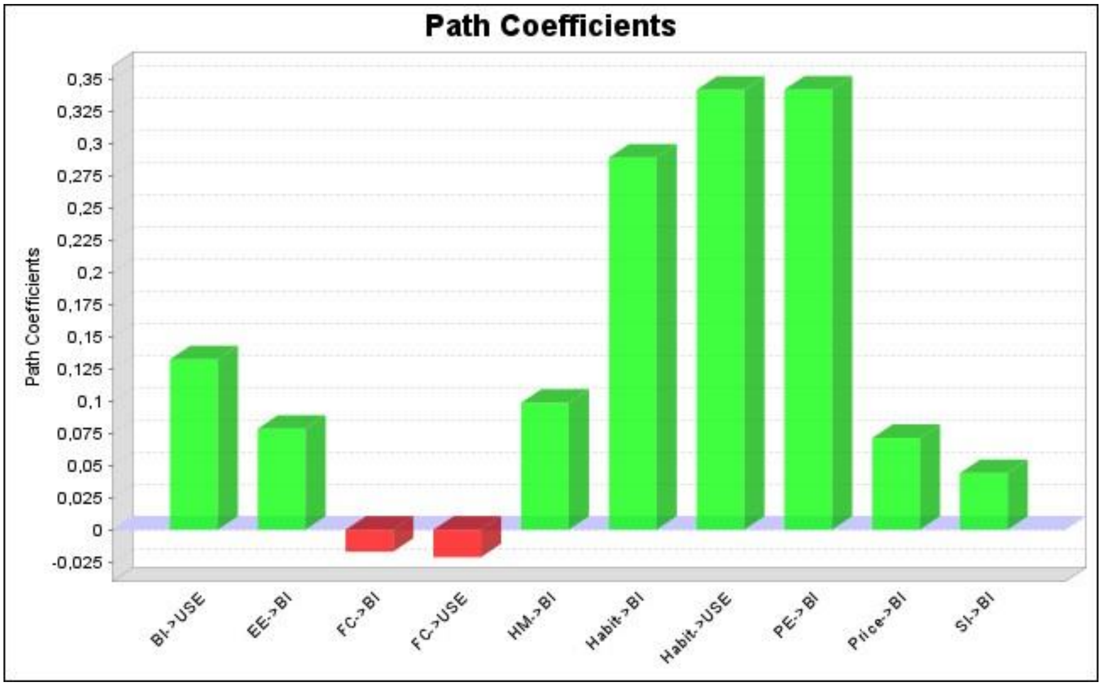

Figure 11: Preliminary Analysis (Younger Users)

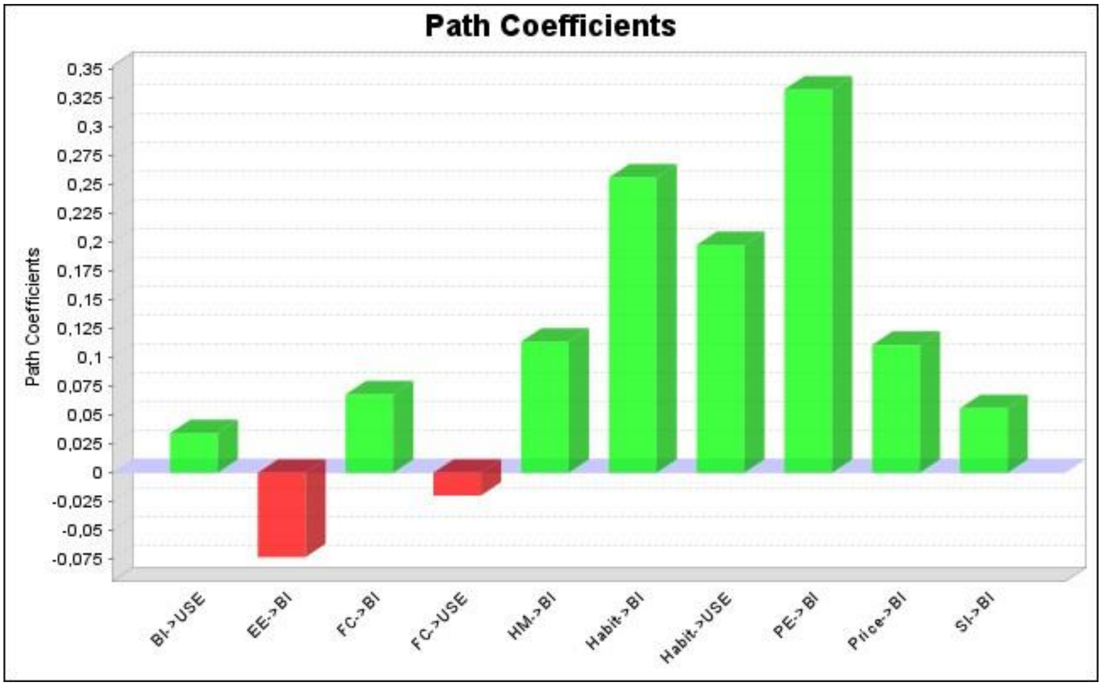

Figure 12: Preliminary Analysis (Older Users)

Comparing the results according to age of the participants, didn’t show a big difference, since the values were not very significant. 827 of the participants were younger than 35 years old and 220 of the participants were older than 45 years old. The R-Squared values for BI were almost same with that of all users, however the R-Squared values for Use were a little higher for younger users and a little lower for older users.

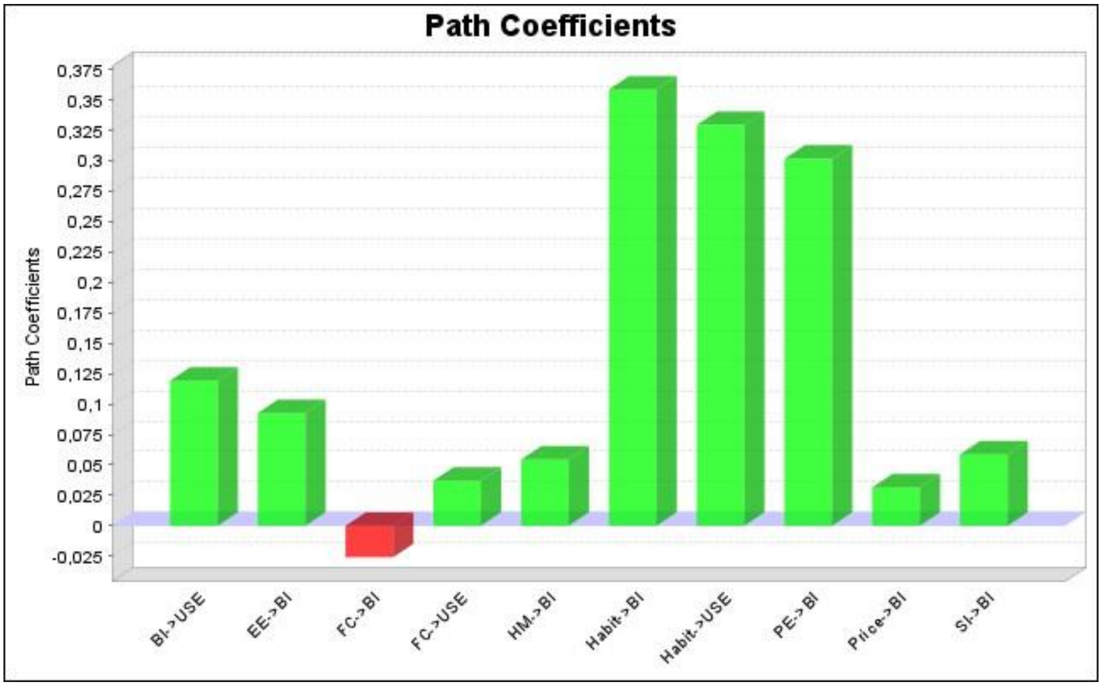

Figure 13: Preliminary Analysis (Early Adopters)

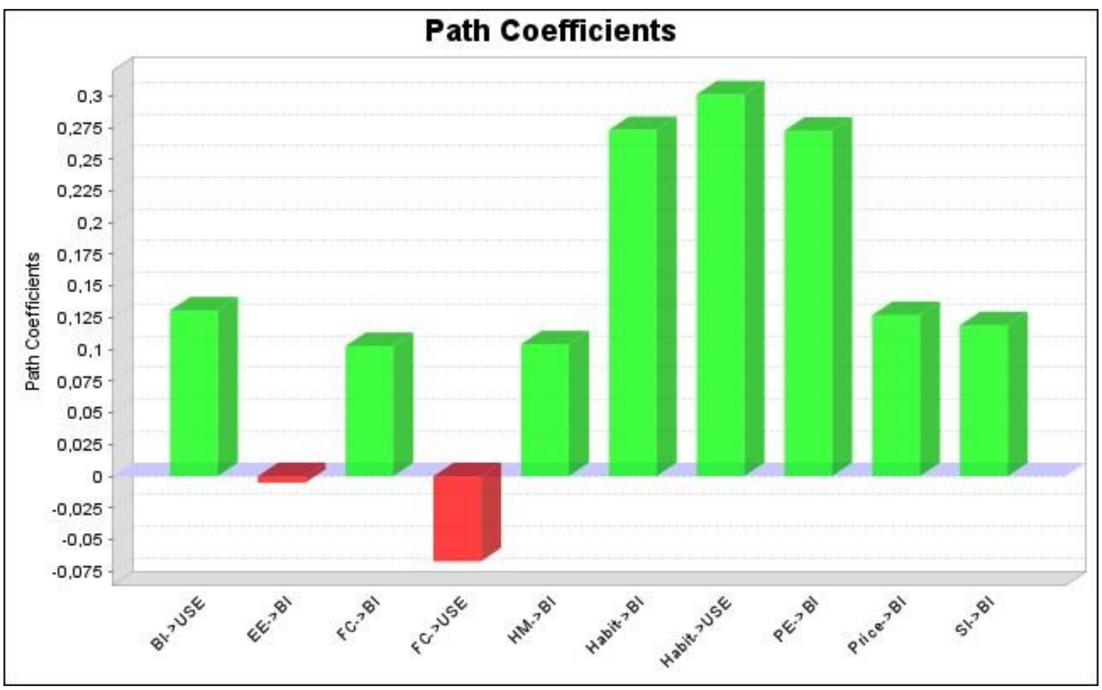

Figure 14: Preliminary Analysis (Early Majority)

The grouping based on self-reported technology affinity was the most interesting one. The model performed best for late majority and laggards with the highest R-Squared values for BI (0,524) and Use (0,445). The effect of habit on use was almost similar for early adopters, early majority and late majority & laggards with 0,434, 0,408 and 0,453.

The effect of effort expectancy was almost zero for early majority and around 0,1 for other groups. The effect of facilitating conditions was around 0,1 for early majority, and negative for other groups.

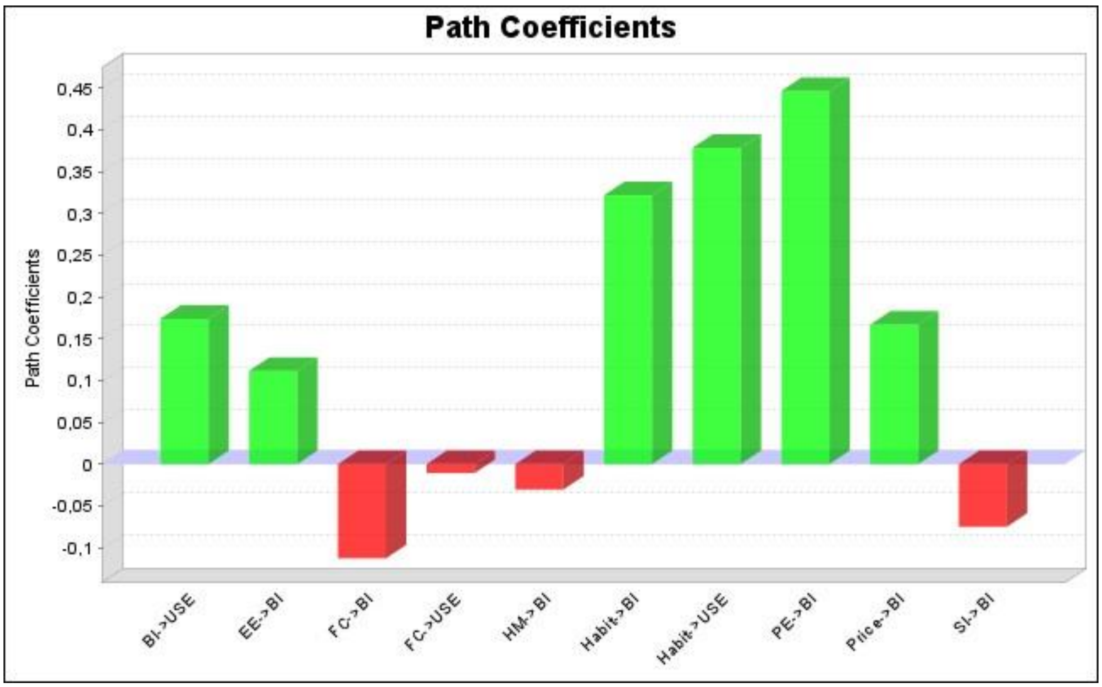

Figure 15: Preliminary Analysis (Late Majority & Laggards)

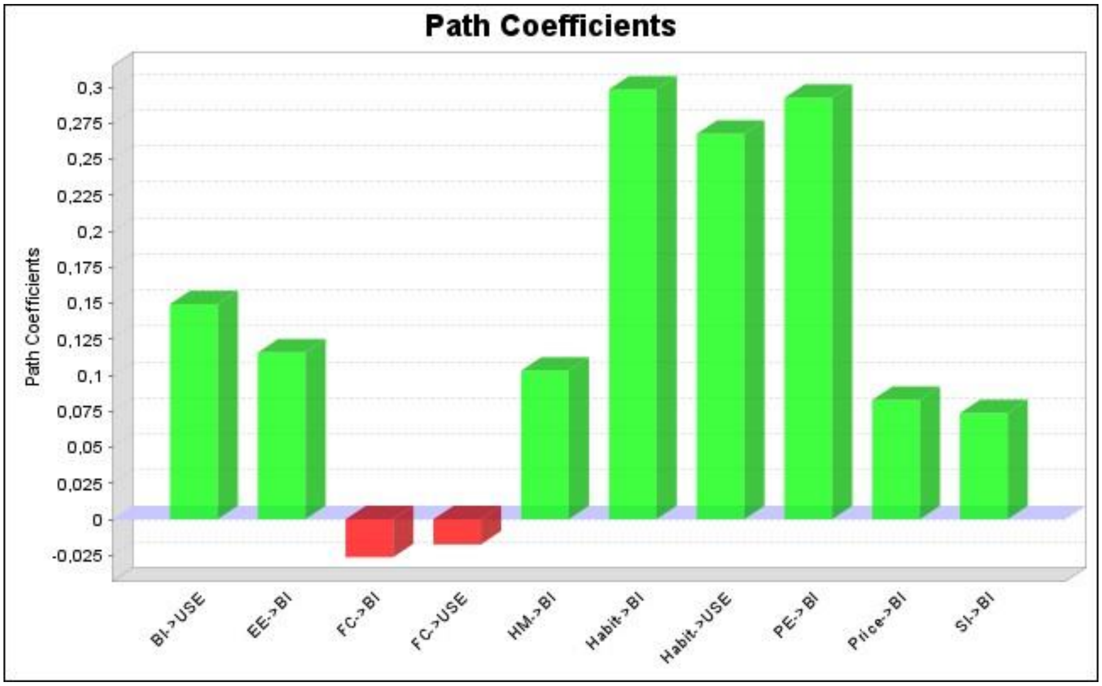

Figure 16: Preliminary Analysis (Short Term Users)

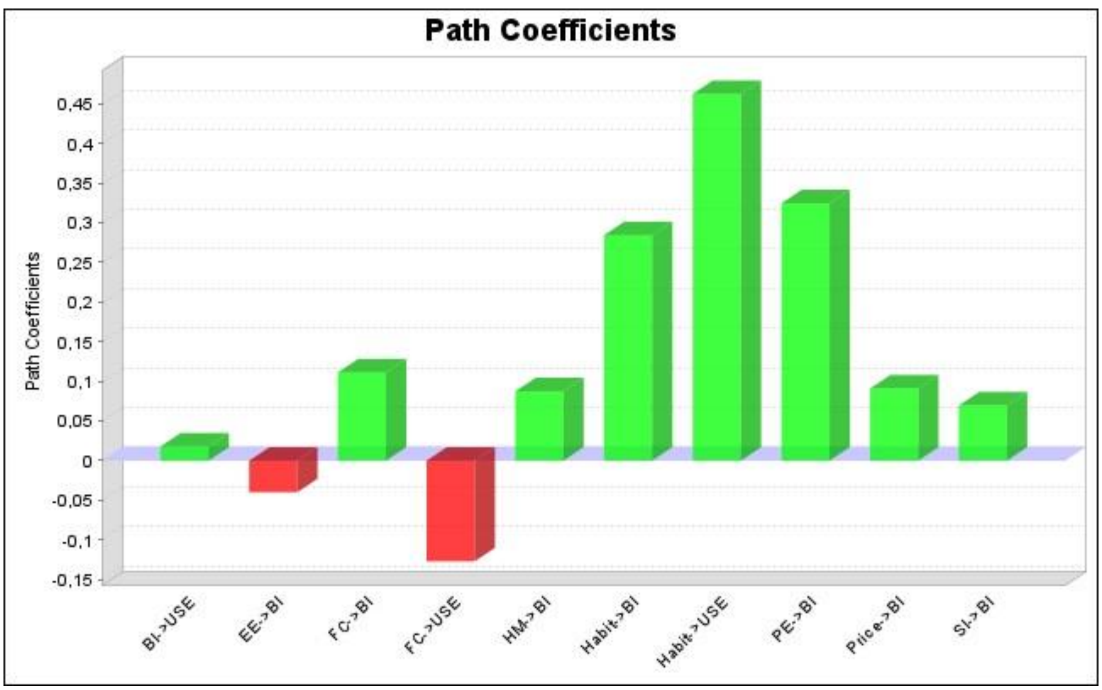

Figure 17: Preliminary Analysis (Long Term Users)

Considering the duration of wearable device usage, the effect of effort expectancy and facilitating conditions decreased. As the users gets more familiar with the devices, these factors become less important in determining the behavioral intention and use.

Habit and performance expectancy values increased for long-term users compared to short-term users who are using these devices for less than 1 year.

Below table summarizes the R-Squared and Path Coefficient values for different user groups (Table 19).

Table 19: Comparison of User Groups

Group		#1	#2	#3	#4	#5	#6	#7	#8	#9
Participant Qty	1263	834	429	827	220	297	506	193	356	549
Path	All	Female	Male	Age < 35	Age > 45	Early Ad.	Early Maj.	Late Maj. & Lag.	Short-Term User	Long Term User
BI (R Squared)	0,446	0,442	0,470	0,441	0,453	0,473	0,432	0,525	0,465	0,443
USE (R Squared	0,152	0,181	0,133	0,177	0,044	0,187	0,136	0,246	0,134	0,206
BI -> USE	0,107	0,143	0,052	0,133	0,034	0,119	0,131	0,174	0,149	0,018
FC -> USE	-0,038	-0,119	0,100	-0,021	-0,020	0,037	-0,067	-0,011	-0,017	-0,127
Habit -> USE	0,333	0,356	0,279	0,342	0,197	0,330	0,301	0,379	0,268	0,463
EE -> BI	0,057	0,093	-0,009	0,079	-0,073	0,093	-0,005	0,112	0,116	-0,040
FC -> BI	0,010	-0,013	0,065	-0,017	0,068	-0,026	0,103	-0,113	-0,026	0,111
HM -> BI	0,089	0,045	0,161	0,099	0,114	0,054	0,104	-0,030	0,103	0,087
Habit -> BI	0,294	0,311	0,257	0,289	0,256	0,359	0,273	0,322	0,299	0,284
PE-> BI	0,323	0,323	0,321	0,342	0,332	0,302	0,273	0,447	0,293	0,325
Price -> BI	0,085	0,119	0,041	0,071	0,111	0,032	0,127	0,167	0,083	0,091
SI -> BI	0,049	0,029	0,069	0,044	0,056	0,059	0,119	-0,075	0,074	0,070

Analysis of the results shows that Habit and Performance Expectancy (PE) are by far the most important factors on consumers' intention to use the wearable devices for health purposes and also on the actual usage.

Influence of Price and Hedonic Motivation (HM) on BI are higher than any construct except Habit and PE. Price is found to be almost 3 times more important for women in comparison to men. On the other hand hedonic motivation is found to be 4 times more important for men in comparison to women. Inverse relation between price and hedonic motivation is as expected. It is seen that, price is least important for early adaptors but it is important for late majority.

UTAUT2 constructs which are likely to influence the behavioral intention such as effort expectancy (EE) and facilitating conditions (FC) seem to be insignificant for wearable device users. This might be the due to the fact that, wearable devices which have large market share are very easy to use and do not require much effort to use. It is possible that EE and FC constructs are not able to measure this aspect of user perception successfully. In addition to battery time open-ended questions also show that significant number of users complain about skin irritation and discomfort while using wearable devices. Any of the UTAUT2 constructs successfully managed to measure these factors.

In-depth analysis of the survey data, pointed to an issue in the measurement of "Use" construct. It was seen that 1233 of the 1263 participants answered this question with 4 (Often) or 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 is 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. Addition of new questions to measure use of technology is expected to improve the model performance for wearable devices.

CHAPTER 4

QUALITATIVE ANALYSIS

Qualitative analysis was done in two parts. The first part is the analysis of responses to the open-ended questions which helped to have a better understanding compared to the rating questions in the survey. The second part is the semi-structured interviews which were conducted with 20 of volunteering survey participants. The interviews were done as online video calls and were recorded with the approval of the participants.

4.1. Open-ended Questions

At the end of the updated survey, there were 6 optional questions, which enabled participants to explain their feelings and thoughts about wearable devices in a more detailed way.

Although these questions were optional, almost half of participants answered all 6 questions (Table 20).

Table 20: Open-Ended Questions

1	Why do you use a wearable device? (If you are not using now, when do you think you will start using a wearable device?)
2	What is the main benefit you get from your wearable device? (If you are not using now, what kind of benefit do you expect from a wearable device?)
3	What is the most negative aspect of wearable devices? (in general or of the one that you are using)
4	Why do you think that some of your friends are using wearable devices? (consider the ones using wearable devices)
5	Why do you think that some of your friends are not using wearable devices? What prevents them from using such devices? (consider the ones not using any wearable device)
6	Would you like to add anything? Please write your comments about wearable devices such as why do you use them, what are your expectations, how did you start using them?

Detailed analysis of responses to each question resulted in a classification of users answers based on most common responses. Below table summarizes these groups with number of responses in each group (Table 21).

Table 21: Distribution of Responses to Open-Ended Questions

	Question	**Classified /Answered**	**Popular Answers**
1	Why do you use a wearable device? (If you are not using now, when do you think you will start using a wearable device?)	**846/1131**	Activity Tracking (**683**) Health Improvement (**100**) Motivation (**30**) Lose Weight (**28**) Manage Phone (**5**)
2	What is the main benefit you get from your wearable device? (If you are not using now, what kind of benefit do you expect from a wearable device?)	**940/1121**	Activity Tracking (**664**) Motivate (**132**) Manage Phone (**99**) Learning Time (**22**) Convenience (**10**) Health (**6**) Insurance (**5**) Socializing (**2**)
3	What is the most negative aspect of wearable devices? (in general or of the one that you are using)	**857/1087**	Battery (**314**) Skin Irritation (**66**) Cost (**60**) Addiction (**57**) Not Fashionable (**51**) Not comfortable (**49**) Accuracy (**47**) Not Waterproof (**33**) Privacy (**28**) Durability (**28**)
4	Why do you think that some of your friends are using wearable devices? (consider the ones using wearable devices)	**905/1065**	Activity Tracking (**281**) Health (**264**) Fashionable (**64**) Social Influence (**50**) Fitness (**44**) Manage phone (**42**) Trendy (**38**) Weight Loss (**23**)
5	Why do you think that some of your friends are not using wearable devices? What prevents them from using such devices? (consider the ones not using any wearable device)	**895/1074**	Cost (**720**) No interest/need (**69**) Not tech savvy (**27**) Privacy (**23**) Not health conscious (**21**) Fashionable (**15**)
6	Would you like to add anything? Please write your comments about wearable devices such as why do you use them, what are your expectations, how did you start using them?	**410**	The question was very general, and it was not possible to classify the answers.

It is surprising that, as the most negative aspect of wearable devices only 60 participant showed cost of these devices. However, when they are asked “Why do you think that some of your friends are not using wearable devices?”, 720 participant mentioned cost as the most important factor.

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 (DellaVigna & Malmendier, 2002). Participants reported battery/charging as the most negative aspect of wearable devices. Battery/charging could be evaluated as part of facilitating conditions for the case of wearable devices. However, analysis of the survey showed that Facilitating Conditions was not a significant factor for the participants. Wearable devices are becoming part of 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.

4.2. Interviews

In order to gain additional insights and verify the findings of quantitative analysis, online interviews were conducted with a small subset of survey participants. All sessions were recorded with the approval of participants and were completed between 20 and 30 minutes. 20 participants joined online interviews (10 male and 10 female). The age range was between 18 and 44 for males and between 29 and 46 for female interviewees. 17 of 20 participants named themselves as early adopters or early majority and told that they are following new technologies and products. It is seen that users who are relatively more interested in technology also showed more interest in the interviews, which might affect the interview findings.

Responses were analyzed for:

1. Device Acquisition
2. Habit (& usage duration)
3. Performance Expectancy
4. Effort Expectancy

5. Social Influence & Interaction
6. Physical Comfort
7. Price
8. Privacy
9. Visual Appearance
10. Type of Use
11. Used devices until now

On one hand the interviews provided new insights that were not revealed through the pilot survey, on the other hand they confirmed some of the findings of the survey-based analysis.

Although not seen from the survey results, as speculated previously, **price** is a significant factor for adopting wearable devices, and interviews strongly confirmed the importance of price. One of the participants stated that price affected her decision to select the wearable device, "Price is an important factor in selecting the device. Depending on what features you want from it, some of the models can be very pricey. I look at what my top priority is as far as what I want it to do and how much was I willing to pay for it. So I choose a lower price model, which may be did not have as many features." Another participant said "Price is definitely important, no doubt about it. Part of the reason I did not buy it for myself until I get it as a birthday gift." One of the interviewees said, "I was hesitant about purchasing a wearable device because the price was fairly high, even though it does have a lot of functionality." For many interviewees, the price was the main barrier before acquiring the first device and the main determinant of the type and brand of the wearable device that they are using currently and a critical factor for their device upgrade decisions.

Performance expectancy was identified as a very important factor in the survey-based analysis. Interviews are also confirming this. Furthermore, interviews add more details about the performance expectancy. It seems that the feature set of the device is the primary performance factor for the users. The accuracy of the functionality, although double-checked by many users, does not seem to be an issue for the majority of the users. Moreover, additional functionalities of wearable devices (functionalities other than data collection purposes such as email notifications, smartphone assistance) are very important for the users and their performance evaluation.

Quantitative analysis of the survey highlighted **Habit** as a very important factor. Interview findings are also in line with this. The majority of the interviewees mentioned that it is a daily habit for them, and rarely do they forget to wear these devices. One of the participants said, "I only remove it for charging, I wear it every single day, it is a part of me." Another participant stated, "Using it almost every day for last 5 years, I feel weird if I forget to put it on."

In the survey, **effort expectancy** was found to be almost irrelevant to the use of wearable devices, and almost all interviewees confirmed this, mentioning that wearable devices are straightforward to use and there is almost no learning curve.

According to the quantitative analysis of the survey, **social influence** is not a significant factor for the use of wearable devices. Interview results are mostly confirming this. Users are not very much influenced by people who are important to them. However, interviews showed that there is a significant social aspect driving wearable device use. People are setting collective challenges, making friendly competitions, and sometimes checking each other's activities and comparing this to their data even when there is no competition. This can be named more as social interaction rather than social influence. One of the participants said, "My previous device did not have a social network and competitive events, I have many friends and families and can find many people to compete on daily steps basically," and social network functions affected her switching decision. Another participant stated that challenges with friends helped her to increase movement.

Privacy was not mentioned as an important factor for most of the interviewees. They stated that other devices such as smart assistants they are using at home have access to more sensitive information, and they do not see a higher risk to privacy related to their wearable device usage, or it is an acceptable level of risk. One of the participants said that "It is something that I think about, but I do not necessarily have concerns, just because so much more of my information everywhere else, that this is a minor thing. The data is rather anonymized, and it does not bother me if my anonymized data is shared." Another participant said, "I have always operated under the belief that anything I do is possibly being recorded somewhere. So at least now I am getting some benefit from it." A similar comment came from another participant "Using these devices can create a risk of security, smart speakers and assistants or similar devices also have risks, risks created by the watch is not bigger than this." Generally, it can be said that participants are aware of the information they are sharing. However, most of them think that the benefits they receive from the wearable devices outweigh the risks created by using these devices. As stated earlier, most of the interviewees defined themselves as early adopters, which are more open to new technologies; this may have had an impact on why privacy is not seen as an important factor.

A significant number of interviewees mentioned that they are using multiple bands to fit their clothing. A participant said, "I change the band when I go out, if I go to the gym, it is just the rubber band, and if I go out I use the stainless one. It is very easy to switch the bands." That means the visual appearance of the wearable devices is somewhat crucial for them. On the other hand, nobody mentioned it as a very important factor.

The majority of the interviewees mentioned that they are taking actions and making changes in their life based on the data collected by wearable devices, and some of them are even sharing it with their doctor or health insurance providers.

Interview results showed that users had different approaches to checking their devices and taking actions. One of the participants said that "I was curious about how many steps I was getting in a day, I was really trying to get as many steps as possible as I could do, and that was the main reason. The fact that I could record or keep track of my sleeping was another reason. If I cannot meet the goals, I try to complete them by not using an elevator or having a short walk". Another participant stated, "My wearable devices provide feedbacks and give goals to reach. I can check my progress and compare with previous days/weeks."

Interviews revealed the importance of the wearable device's compatibility with the user's existing technology stack or technology ecosystem. Users are preferring devices fitting their existing smartphones, computers, etc. This can be considered some sort of facilitating conditions; however, existing UTAUT2 questions are far from detecting this type of facilitating conditions. Most of the participants declared that compatibility with other devices they are using is an important factor. A participant said, "I am pretty much into the ecosystem. It works with my phone, syncs without problem, it is important to be compatible with other devices." Another participant mentioned that she was a long-term user of the brand and said, "I have been using smartphones from the same company for more than 10 years, it is compatible with my other devices from the same brand, and it is easy to use, and I feel secure since I trust the brand".

These interviews also showed that some participants had a clear goal regarding what they want to achieve by using the device or what they expect from their device. In contrast, some others are have more diverse expectations and reasons for the usage of the wearables. One participant said, "I use it to keep track of my heart rate, workout, and steps, and new features such as menstrual tracking and ECG were added in time." Another participant said, "Primarily, it is for physical activity monitoring. I think that is the main use I did, I think initial adoption was probably more because of novelty, but now I use it to track physical activity." Sometimes the initial usage had external motivations as "my doctor recommended I start using a tracker, and I use that as a way of encouraging me to become more active." This goal can also change "It has become that I use it a lot for activity tracking, but when I first got it was mostly like getting notifications on my wrist." The reason for using can also change with new functionalities added to the wearable devices. "I started using it trying to track how far I was actually walking and just loved it very much. I recently updated to another version to get more out of which provides additional functionality, such as recording workouts and support notifications from a smartphone". Some users also told that they were mainly using their device for its smart features, "Predominantly about the organization, activity, weather, to-do list, upcoming appointments, and notifications."

Considering from a health-tracking perspective, some users just wear the device on their wrists and do not check their health data. Some check the data regularly (daily or weekly), and some users monitor their data, compare with previous data and take action.

CHAPTER 5

RESEARCH MODEL DEVELOPMENT AND QUANTITATIVE ANALYSIS

This chapter presents the modifications to the UTAUT2 model and explains why these modifications are needed based on the results of the preliminary survey and the interviews.

5.1.Model Definition and Hypotheses Formulation

As seen from the quantitative analysis of the pilot survey and the interviews, the UTAUT2 model can be a valuable tool to understand factors affecting the use of wearable devices for health purposes. However, it is also seen that there is room for improvement.

The previous chapter explained the steps in the analysis of the original UTAUT2 model and presented the findings. This chapter will focus on enhancing the UTAUT2 model to better understand the determinants of technology acceptance in wearable devices.

Wearable devices are becoming more and more popular as their capabilities, accuracy, and types increase. Due to the variety of use cases, consumers have different motivations and ways of utilizing these devices. Some use accessories or a complementary device to their smartphones, whereas others track their fitness workouts. Some are tracking health data and adjusting their behaviors to keep and improve their health. As explained in previous sections, existing technology acceptance models and especially the UTAUT2 model are used in several studies to explore the adoption of these devices by consumers. Considering the characteristics of wearable devices and the insights gained from the interviews, we hypothesized that the original USE construct of UTAUT2 cannot adequately cover various types of technology use in this particular domain. Unlike some other cases of technology use (e.g., use of online banking services or e-commerce services), wearable devices:

- have a physical aspect (user acquire a device, wear it on their body, connect it with other devices, charge it, etc.)

- are part of the users' daily routine (the distinction between using and not using the wearable device is blurry, active and passive types of use are conceivable)

• are typically multifunction and multipurpose tools (the same device accomplishes various related and unrelated tasks for its user)

The combination of these 3 characteristics makes varying degrees of passive and active use of wearable devices possible. UTAUT2 model measures actual usage with a single construct by asking the usage frequency, and this can be sufficient to measure the acceptance of technology in many domains. However, in the case of wearable devices, this approach is not enough to address the various types of technology use. In this study, we propose that wearable device usage should be analyzed in 3 categories:

Type 1 Use: This type of usage can be considered as passive use of technology. The device is sporadically or regularly worn, but the usage is mostly habitual, and there is no significant focus on the data collected by the device. This type of use is very prevalent in the case of wearable devices.

Type 2 Use: In this type of use, the users focus on the collected data. They check the data, the statistics, and the trends (e.g., checking the number of steps at the end of the day, checking sleep cycles weekly or every morning).

Type 3 Use: This is the type of usage in which users are using their devices, checking the data, and actually take actions based on the data provided by these devices (e.g., check the daily step count and try to reach a milestone every day, try to keep the heart rate in a defined interval.)

It can be said that type 1 use covers type 2 use and type 2 use covers type 3 use, but it is not correct in the reverse direction (Figure 18).

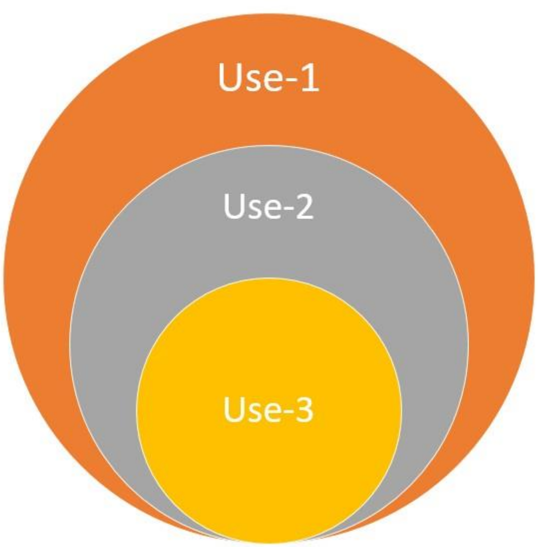

Figure 18: Use Types

In addition to the three categories of use explained above, we are also proposing three additional constructs, goal clarity, perceived risk, and technology stack compatibility, to improve the model's explanatory power.

Goal Clarity (GC): Models resting on an intention → behavior linkage (e.g., TAM, TRA, TPB) treat behavior as a terminal goal and fail to consider that many actions are taken not so much as ends in and of themselves but rather as a means to more fundamental ends or goals (Bagozzi, 2007). In the case of mobile health, improving health or keeping good health is particularly important and not necessarily a direct consequence of every type of technology use. Wearing the device the whole day without paying attention to the collected data or simply checking the collected data without any behavioral change is unlikely to result in concrete health benefits. That is why we classify the use of technology and study each type separately. Previous research also state that goal clarity can significantly impact human behaviors (Wang, Rajan, Sankar, & Raju, 2014). The effect of goal setting and performance is examined in various contexts such as online games (Sweetser & Wyeth, 2005), organizational performance (Erez & Kanfer, 1983), or learning with serious games (Wang, Rajan, Sankar, & Raju, 2014). There are numerous researches on the implications of goal setting to task performance (Anderson & Stritch, 2016), which show that when the users have a clear goal, they perform better (Locke & Latham, 1991). The effects of having a clear goal are also investigated in health-related studies. In dietary behavior change, having a clear goal supported the users' nutritional behavior change (Cullen, Baranowski, & Smith, 2001). Also, in a study aiming to help healthy aging (Nelis, Thom, Jones, Hindle, & Clare, 2018), goal setting was found to be beneficial. We believe that having a clear goal also significantly influences the acceptance of technology. We propose "goal clarity" as a new construct to test this hypothesis. This construct is not about what the goal is; instead, it is about whether the user has a clear and concrete expectation from the technology in question. Having a clear goal (such as losing weight or being more active) and concrete expectations from wearable device usage can influence consumers' acceptance of technology, especially for the third type of usage, which is about users taking actions based on the data their devices provided.

Perceived Risk (PR): The ubiquitous nature of wearable devices enables them to collect data continuously, and as the diversity of the collected data increases (i.e., daily activity, heart rate, sleep cycles, fertility), these data may constitute a risk. There are many risks associated with the use of wearable devices (Lee, Egelman, Lee, & Wagner, 2015), ranging from financial to medical risks. As stated in previous studies (Chellappa & Sin, 2005), privacy affects consumers' acceptance of new technologies due to the sensitivity of the collected data. In the organizational context, privacy is considered an organizational issue, and the users do not need to deal with privacy. However, at the individual level, and especially as a consumer, the users need to consider the risk of tracking their vital data, including storing and sharing these data. How and where this data will be stored, how this data is evaluated, and who has ownership and access to the data are essential questions that the consumers may ask. Perceived risk is an important concept for consumers, including but not limited to online purchase (Hong & Yi, 2012) and all kinds of technology usage. Perceived risk is proposed as a new construct that includes the privacy aspect and other possible risks concerned with the use of wearable devices.

Technology Stack Compatibility (TSC): Wearable devices, especially wrist-worn ones such as smartwatches or smart bands, usually provide additional features like displaying notifications, controlling messages, or even voice call functions. These devices are generally coupled with applications on smartphones. This coupling with the smartphone and users' other devices (pc, tablet, virtual assistants in the form of smart speakers) and online services (e.g., social networks) is mentioned various times in the interviews. The compatibility of electronic devices is defined as the wearable medical device's being consistent with the user's existing preferences and habits (Degerli & Ozkan Yildirim, 2020). In addition to preferences and habits, having a wearable device compatible with other technology devices you own (e.g., smartphone, smart speaker, etc.) is also an important factor. Product compatibility is a strategic decision for device manufacturers (Wu, Li, Lin, & Zheng, 2017) that can affect consumers' decisions on their purchase of a device. We name the compatibility of the wearable devices with other devices and services used by the user as technology stack compatibility and propose it as a new construct to the UTAUT2 model.

The main hypotheses of this study are:

H1: The usage of wearable devices can be analyzed in three categories and each type of use is influenced by different factors with different intensities.

H2: Goal Clarity positively affects behavioral intention for type-1 use (BI1).

H3: Goal Clarity positively affects behavioral intention for type-2 use (BI2).

H4: Goal Clarity positively affects behavioral intention for type-3 use (BI3).

H5: Perceived Risk negatively affects behavioral intention for type-1 use (BI1).

H6: Perceived Risk negatively affects behavioral intention for type-2 use (BI2).

H7: Perceived Risk negatively affects behavioral intention for type-3 use (BI3).

H8: Technology Stack Compatibility positively affects behavioral intention for type-1 use (BI1).

H9: Technology Stack Compatibility positively affects behavioral intention for type-2 use (BI2).

H10: Technology Stack Compatibility positively affects behavioral intention for type-3 use (BI3).

The proposed model with 3 separate constructs for actual usage of technology and behavioral intention to use and the three additional constructs is shown below (Figure 19).

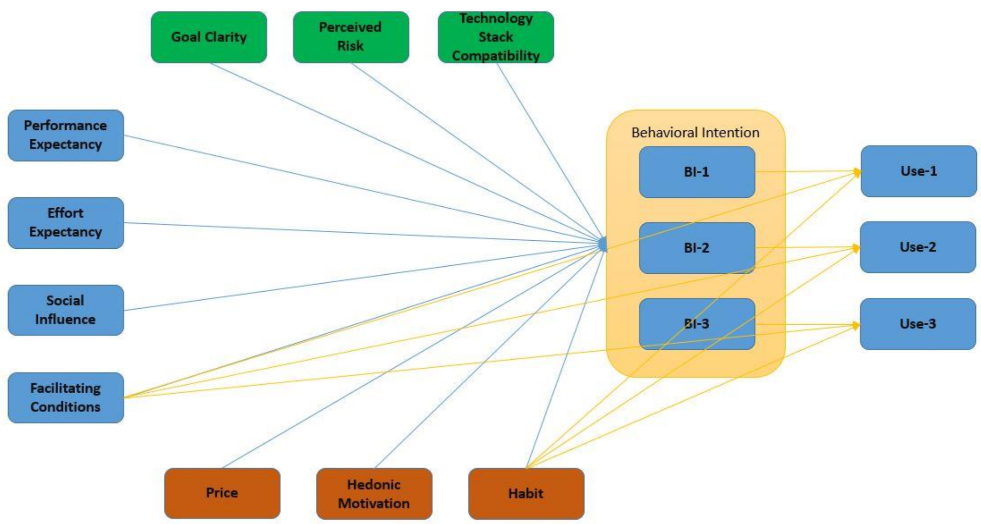

Figure 19: Proposed Model

In order to test the proposed model and compare the results with the original UTAUT2 model, we applied another online survey. The following sections explain this new survey and the analysis of results.

5.2. Updated Survey

The updated survey included all questions from the previous survey together with the questions for the newly added constructs (Goal Clarity, Perceived Risk and Technology Stack Compatibility). The Use construct was separated to three (Use-1, Use-2 and Use-3) to reflect the three level usage explained in previous section. The BI construct was also separated into three (BI-1, BI-2 and BI-3) to match corresponding Use constructs.

Similar to the preliminary survey, we got the ethics committee approval for the updated questionnaire. The second approval document is given in Appendix D. The updated survey is shown in Appendix E.

740 participants between October-November 2020 completed the updated survey. 57 of these participants were eliminated due to data quality issues (e.g., missing response, same response for all questions).

The remaining 683 users were classified for their purpose of use and asked whether they are using their devices mainly for health-related purposes (e.g., physical well-being, fitness, physical activity, weight loss, heart rate tracking, sleep duration, etc.) or other purposes (smart features, accessory, calls, notifications).

624 participants reported that they are using their wearable devices mainly for health purposes. Similar to the preliminary survey participants, wrist worn devices, namely smart bands/watches are the most common type of wearable devices as reported in survey responses. These participants were split into sub-groups based on their gender, age, and experience with technology to increase the granularity of the analysis (Table 22).

Table 22: User Distribution (age, gender, experience)

		Gender		Age			Experience	
	All	**Female**	**Male**	**18-34**	**35-44**	**Over 45**	**Up to 1 Year**	**3 years or more**
Total	683	405	278	268	177	238	358	314
For Health	624	378	246	245	162	217	330	283

Similar to the interviews, the participants were also asked to classify themselves based on their technology affinity (Table 23). According to this self-declared grouping, which has a similar distribution to the interviews with more than half of the participants naming themselves an early adopter or early majority.

Table 23: User Distribution (technology affinity)

User Groups	**Early Adopter**	**Early Majority**	**Late Majority**	**Laggards**	**Do not know**
Quantity	120	210	125	30	139

As in this study, our principal focus is the use of wearable devices in the mobile health domain; all further analysis were done for the participants who reported health-related items as their main purpose of wearable device use.

5.3. Analysis of Updated Survey

Survey data was analyzed using SmartPLS (Ringle, Wende, & Becker, 2015) software in the same way as explained in the pilot study. Both models (UTAUT2 and Proposed model) were analyzed with the main data set of 624 participants who have reported health tracking as their main purpose of use. Quantitative analysis of the measurement model and structural model was done for both the whole set (624 participants) and for sub-groups based on gender, age, and experience with the technology.

Cronbach's Alpha value, Composite Reliability, and Average Variance Extracted (AVE) were calculated and found inside the acceptable limits (Table 24).

Table 24: Reliability and Validity Values

	Proposed Model			UTAUT2		
	Cronbach's Alpha	**Composite Reliability**	**AVE**	**Cronbach's Alpha**	**Composite Reliability**	**AVE**
BI				0,875	0,923	0,801
BI1	0,875	0,923	0,801			
BI2	0,935	0,958	0,885			
BI3	0,915	0,947	0,855			
EE	0,894	0,926	0,757	0,894	0,926	0,758
FC	0,735	0,835	0,562	0,735	0,834	0,561
GC	0,946	0,961	0,861			
HM	0,888	0,931	0,818	0,888	0,931	0,818
Habit	0,766	0,847	0,581	0,766	0,841	0,572
PE	0,835	0,890	0,670	0,835	0,889	0,667
PR	0,922	0,945	0,810			
Price	0,907	0,942	0,844	0,907	0,942	0,844
SI	0,946	0,965	0,903	0,946	0,965	0,903
TSC	0,733	0,849	0,652			
Use1	1,000	1,000	1,000			
Use2	1,000	1,000	1,000			
Use3	1,000	1,000	1,000			
USE				1,000	1,000	1,000

In addition to the above-listed values testing construct reliabilities and validities, both models were checked for discriminant validity according to Fornell and Larcker's criterion, and the square root of AVE values were found to be greater than the correlation with any other variables. Cross loadings were confirmed to have higher loadings within the constructs and lower cross-loadings as expected (Appendix F).

R-Squared values (Table 25) and path coefficients (Table 28) for both models are listed.

Table 25: R-Squared Values

	For Health 624 All	**R-Squared**	**R-Squared Adjusted**
Proposed Model	BI1	0,519	0,511
	BI2	0,261	0,249
	BI3	0,463	0,454
	Use1	0,196	0,192
	Use2	0,224	0,220
	Use3	0,300	0,297
UTAUT2	BI	0,498	0,492
	USE	0,207	0,203

Similar to the analysis of the preliminary survey, t-statistics were used to check for the path significance. The values for the UTAUT2 model (Table 26) and the proposed model are calculated with remarks on each relationship as supported or not supported.

Table 26: t-statistics for UTAUT2 Model

Path Relationship	T Statistics	P Values	Test Result
BI -> USE	1,929	0,054	Not Supported
EE -> BI	2,779	0,006	Supported
FC -> BI	1,256	0,209	Not Supported
FC -> USE	0,988	0,323	Not Supported
HM -> BI	2,632	0,009	Supported
Habit -> BI	5,878	0,000	Supported
Habit -> USE	4,688	0,000	Supported
PE -> BI	4,863	0,000	Supported
Price -> BI	2,205	0,028	Supported
SI -> BI	0,793	0,428	Not Supported

The t-statistics table for the proposed model also contains the quantitative analysis results for the proposed hypotheses. The hypotheses for the new constructs Goal Clarity are supported for BI-2 and BI-3, and for Perceived Risk are supported for BI-1 and BI-2, whereas for Technology Stack Compatibility behavioral intention constructs for all three types of use are supported Table 27.

Table 27: t-statistics for the proposed model

Related Hypothesis	Path Relationship	T Statistics	P Values	Test Result
	BI1 -> Use1	2,235	0,026	Supported
	BI2 -> Use2	6,992	0,000	Supported
	BI3 -> Use3	12,699	0,000	Supported
	EE -> BI1	2,871	0,004	Supported
	EE -> BI2	1,569	0,117	Not Supported
	EE -> BI3	1,010	0,313	Not Supported
	FC -> BI1	0,600	0,548	Not Supported
	FC -> BI2	0,040	0,968	Not Supported
	FC -> BI3	0,298	0,766	Not Supported
	FC -> Use1	1,029	0,304	Not Supported
	FC -> Use2	0,335	0,738	Not Supported
	FC -> Use3	0,102	0,919	Not Supported
	HM -> BI1	2,144	0,032	Supported
	HM -> BI2	0,684	0,494	Not Supported
	HM -> BI3	0,843	0,399	Not Supported
	Habit -> BI1	5,696	0,000	Supported
	Habit -> BI2	1,988	0,047	Supported
	Habit -> BI3	4,876	0,000	Supported
	Habit -> Use1	4,349	0,000	Supported
	Habit -> Use2	3,317	0,001	Supported
	Habit -> Use3	2,488	0,013	Supported
	PE -> BI1	3,575	0,000	Supported
	PE -> BI2	2,520	0,012	Supported
	PE -> BI3	5,133	0,000	Supported
	Price -> BI1	1,425	0,154	Not Supported
	Price -> BI2	0,824	0,410	Not Supported
	Price -> BI3	1,074	0,283	Not Supported
	SI -> BI1	0,767	0,443	Not Supported
	SI -> BI2	0,676	0,499	Not Supported
	SI -> BI3	1,845	0,065	Not Supported
H2	GC -> BI1	1,155	0,248	Not Supported
H3	GC -> BI2	3,023	0,003	Supported
H4	GC -> BI3	5,768	0,000	Supported
H5	PR -> BI1	3,784	0,000	Supported
H6	PR -> BI2	2,255	0,024	Supported
H7	PR -> BI3	1,206	0,228	Not Supported
H8	TSC -> BI1	3,467	0,001	Supported
H9	TSC -> BI2	4,091	0,000	Supported
H10	TSC -> BI3	3,115	0,002	Supported

Path coefficients for the participants who are using their wearable devices for health purposes are shown below.

Table 28: Path Coefficients for all users with health purpose

	Proposed Model						UTAUT2	
For Health 624 All	**BI1**	**BI2**	**BI3**	**Use1**	**Use2**	**Use3**	**BI**	**Use**
BI								0,137
BI1				0,154				
BI2					0,397			
BI3						0,498		
EE	0,145	0,091	-0,047				0,147	
FC	0,032	0,002	0,014	0,058	0,015	-0,004	0,073	0,057
GC	0,048	0,137	0,253					
HM	0,088	0,034	0,037				0,103	
Habit	0,281	0,113	0,198	0,308	0,147	0,093	0,293	0,335
PE	0,178	0,149	0,285				0,237	
PR	-0,106	0,077	0,035					
Price	0,055	0,031	0,038				0,088	
SI	0,021	0,026	0,060				0,022	
TSC	0,142	0,178	0,109					

The R-Squared values for both models for different user groups were calculated and listed (Table 29).

Table 29: R-Squared values for User Groups

		Female Users (378 Participant)	Male (246 Participant)	Younger Users (245 Participant)	Older Users (217 Participant)	Short Term Users (330 Participant)	Long Term Users (283 Participant)
Proposed Model	BI1	0,524	0,540	0,509	0,538	0,555	0,517
	BI2	0,208	0,366	0,241	0,394	0,252	0,305
	BI3	0,469	0,464	0,427	0,590	0,507	0,445
	Use1	0,242	0,160	0,243	0,155	0,237	0,158
	Use2	0,219	0,244	0,289	0,147	0,165	0,325
	Use3	0,280	0,334	0,287	0,421	0,266	0,368
UTAUT2	BI	0,500	0,522	0,489	0,516	0,523	0,508
	USE	0,249	0,178	0,254	0,160	0,247	0,168

The path coefficients for user groups, based on gender (female-male) (Table 30, Table 31) , age (users between ages 18 and 34 as younger users and users over 45 years old as older users) (Table 32, Table 33, and experience with the technology (users up to 1-year experience as short term users and users more than 3 years experience as long term users) are shown in below tables. These user groups were explained with the number of participants in each group previously. 3 constructs with the highest coefficients for behavioral intention (BI1, BI2, and BI3) and use (Use1, Use2, and Use3) are highlighted in below tables.

Table 30: Path Coefficients for Female Users

	Proposed Model						UTAUT2	
	BI1	BI2	BI3	Use1	Use2	Use3	BI	Use
BI								0,160
BI1				0,171				
BI2					0,414			
BI3						0,483		
EE	0,151	0,073	-0,041				0,149	
FC	0,036	-0,010	0,024	0,005	-0,013	0,007	0,086	0,003
GC	0,077	0,125	0,221					
HM	0,052	0,050	-0,014				0,055	
Habit	0,278	0,102	0,201	0,370	0,133	0,081	0,296	0,387
PE	0,145	0,090	0,337				0,219	
PR	-0,113	0,062	0,033					
Price	0,077	0,053	0,040				0,105	
SI	0,053	0,019	0,039				0,063	
TSC	0,132	0,178	0,100					

Table 31: Path Coefficients for Male Users

	Proposed Model						UTAUT2	
	BI1	BI2	BI3	Use1	Use2	Use3	BI	Use
BI								0,087
BI1				0,117				
BI2					0,345			
BI3						0,513		
EE	0,093	0,117	-0,028				0,096	
FC	0,074	0,029	0,013	0,149	0,071	-0,029	0,108	0,149
GC	0,005	0,154	0,279					
HM	0,126	0,021	0,109				0,156	
Habit	0,305	0,139	0,178	0,238	0,201	0,133	0,302	0,286
PE	0,238	0,219	0,205				0,288	
PR	-0,098	0,094	0,042					
Price	0,002	0,013	0,055				0,047	
SI	-0,038	0,037	0,109				-0,043	
TSC	0,163	0,176	0,107					

Table 32: Path Coefficients for Younger Users

	Proposed Model						UTAUT2	
	BI1	BI2	BI3	Use1	Use2	Use3	BI	Use
BI								0,179
BI1				0,193				
BI2					0,466			
BI3						0,499		
EE	0,107	0,162	-0,027				0,111	
FC	0,107	0,050	0,055	0,051	-0,053	-0,066	0,142	0,053
GC	0,092	0,153	0,210					
HM	0,113	0,051	0,040				0,136	
Habit	0,280	0,004	0,235	0,344	0,205	0,089	0,277	0,365
PE	0,165	0,175	0,258				0,228	
PR	-0,097	0,120	0,091					
Price	0,017	-0,085	0,007				0,054	
SI	0,066	0,081	0,091				0,071	
TSC	0,111	0,108	0,088					

Table 33: Path Coefficients for Older Users

	Proposed Model						UTAUT2	
	BI1	BI2	BI3	Use1	Use2	Use3	BI	Use
BI								0,151
BI1				0,160				
BI2					0,272			
BI3						0,593		
EE	0,183	-0,098	-0,082				0,185	
FC	-0,047	0,119	0,023	0,024	0,095	0,021	0,019	0,024
GC	0,065	0,141	0,364					
HM	-0,008	-0,015	0,053				-0,015	
Habit	0,316	0,148	0,027	0,261	0,102	0,091	0,333	0,274
PE	0,183	0,175	0,330				0,258	
PR	-0,104	0,018	0,001					
Price	0,107	0,120	0,044				0,148	
SI	0,017	0,074	0,105				0,027	
TSC	0,155	0,222	0,138					

The path coefficients for users based on their experience with the technology is also presented (Table 34, Table 35), similar to the above tables for gender and age groups.

Table 34: Path Coefficients for Short Term Users

	Proposed Model						UTAUT2	
	BI1	BI2	BI3	Use1	Use2	Use3	BI	Use
BI1				0,105				0,089
BI2					0,311			
BI3						0,446		
EE	0,090	0,027	-0,006				0,109	
FC	-0,003	0,004	-0,020	0,123	0,090	0,028	0,041	0,130
GC	0,096	0,186	0,226					
HM	-0,016	-0,055	0,068				-0,001	
Habit	0,296	0,140	0,197	0,359	0,121	0,103	0,304	0,377
PE	0,284	0,216	0,291				0,368	
PR	-0,137	0,003	0,008					
Price	0,041	-0,006	0,017				0,068	
SI	0,065	0,046	0,072				0,061	
TSC	0,136	0,119	0,137					

Table 35: Path Coefficients for Long Term Users

	Proposed Model						UTAUT2	
	BI1	BI2	BI3	Use1	Use2	Use3	BI	Use
BI1				0,255				0,239
BI2					0,503			
BI3						0,567		
EE	0,154	0,131	-0,132				0,135	
FC	0,112	-0,011	0,074	-0,047	-0,069	-0,066	0,153	-0,061
GC	0,009	0,124	0,281					
HM	0,180	0,117	-0,038				0,196	
Habit	0,239	0,054	0,170	0,219	0,188	0,108	0,255	0,255
PE	0,126	0,120	0,339				0,154	
PR	-0,075	0,154	0,072					
Price	0,056	0,068	0,078				0,094	
SI	-0,057	-0,022	-0,004				-0,053	
TSC	0,118	0,230	0,094					

The results of the quantitative analysis clearly show that breaking down the technology use into 3 types provides new insights. For example, goal clarity is an important factor for type 3 use (path coeff.: 0,253), however, it has almost no significance for type 1 use (path coeff.: 0,048). A reverse pattern is seen for effort expectancy, which seems to be somewhat important in type 1 use (path coeff: 0.145) and negligible for type 3 use (path coeff.: -0.047). It is also seen that the performance of newly proposed constructs Technology Stack Compatibility (TSC) and Goal Clarity (GC) clearly deserves further attention. Our analysis shows that TSC is an important factor for any use type and GC is a very important factor for type 2 and type 3 usage.

Furthermore, user group analysis provides interesting results showing how the significance of factors varies between user groups. For example, technology stack is found to be significantly more important for older users in comparison to younger users. Detailed interpretation of the quantitative analysis is given in the next section.

CHAPTER 6

DISCUSSION

As seen from the interviews, wearable devices are used in various ways. Some users are simply wearing the devices and once in a while checking the statistics regarding their daily physical activities, whereas some others are using these devices to make concrete changes in their daily lives. This is not a surprising observation considering the nature of wearable devices which allow varying degrees of passive and active use. Moreover, even for a single user, the boundary between using the device and not using it is not always clear. Wearable devices are functioning and collecting data at any time as long as they are being worn. In this sense they are being used as long as the user is wearing them but when the user starts paying attention to the collected data and make use of this data, then the nature of the use significantly changes. This is the reason why we proposed the categorization of the technology use, and our quantitative analysis shows that this distinction is useful to provide new insights in regards to the determinants of wearable device usage for health purposes. As seen in below (Table 36), the most significant constructs are PE, Habit, and EE. For type 1 use, goal clarity seems to have almost no significance. However, in the case of type 2 and type 3 use, goal clarity turns out to be one of the most important factors and even more important than habit. This is a very striking observation enabled by categorization of the use type.

Similarly, effort expectancy, which is somewhat important for type 1 use, is negligible in case of type 2 and type 3 use. It can be thought that the effort is insignificant for the users when they use the wearable devices more actively. When we check the user groups, again, we see that the factors influencing the behavioral intention to use the technology are highly dependent on the type of use. For the group of users who has long experience with technology, the top 3 most important factors for type 1 use are found as Habit, HM and EE, whereas for type 3 use the top 3 most important factors are found as PE, GC and Habit. For the same group, the importance of HM is 0.18 for type 1 use and it shrinks to 0,117 -0,038 for type 2 and type 3 use, respectively. For male users, the importance of TS is 0,176 for type 2 use and significantly less (0.107) for type 3 use. Similar to the effort expectancy, in the case of the technology stack, we can think that, the more active use of the wearable devices outweighs the importance of compatibility issues and opportunities. Focusing more on the outcome of technology use leads to less consideration of the compatibility with the existing technology ecosystem of the user (Pancar & Ozkan-Yildirim, 2021).

The most significant factors (with path coefficients greater than 0.1) for each BI and Use constructs are shown in descending order of significance (Table 36).

Table 36: Most significant factors for BI and Use

BI1	BI2	BI3	BI (UTAUT2)	Use1	Use2	Use3	Use (UTAUT2)
Habit (0,281)	**TS** (0,178)	**PE** (0,285)	**Habit** (0,293)	**Habit** (0,308)	**BI2** (0,397)	**BI3** (0,498)	**Habit** (0,335)
PE (0,178)	**PE** (0,149)	**GC** (0,253)	**PE** (0,237)	**BI1** (0,154)	**Habit** (0,147)		**BI** (0,137)
EE (0,145)	**GC** (0,137)	**Habit** (0,198)	**EE** (0,147)				
TS (0,142)	**Habit** (0,113)	**TS** (0,109)	**HM** (0,103)				
PR (-0,106)							

Categorization of use type is important because the determinants of the technology acceptance are highly dependent on use types. Another reason is its establishing the connection between the use of technology and the intended goals behind the technology use. In the area of mobile health, keeping the health status or improving it has the highest importance. However, when we talk about multi-function consumer devices, the link between technology use and the intended outcome of the technology use is not that straightforward. To explore this connection a bit more, we proposed goal clarity (GC) as a new construct in our extended UTAUT2 model. As wearable devices are multifunction and multipurpose consumer devices, the users have various expectations from them and these expectations vary even for the same user over the time. Some users have their wearable devices for a particular purpose, whereas some other users are not focused on a particular functionality but enjoy the various benefits of these devices at varying degrees. With GC construct we tracked whether the users' having clear and concrete expectations from their wearable devices has a significant impact on their behavioral intention to use these devices. The answer is yes. If users have clear goals then they are using the wearable devices more actively (Pancar & Ozkan-Yildirim, 2021). As mentioned previously, GC seems to have no significance for type 1 use but it is very important for type 2 and type 3 use. That means when users have clear expectations from their wearable device use, they actively check the data collected by these devices and adjust their daily routines based on these data. This is an important finding especially for mobile health studies as health benefits will not materialize unless the users make concrete changes in their daily lives, and having a clear goal seems to be a key factor in this regard. In other words, we can also say that goal clarity drives users from type 1 use towards type 3 use.

As seen from the interviews, the compatibility of the wearable devices with the users' existing technology ecosystem is a very important factor. As wearable devices are part of the users' daily life, it is very natural that users are looking for a good fit for their existing devices and services while deciding on a new wearable device. Moreover, once bought, the level of compatibility is likely to play an important role on how much and how frequently these devices are utilized. Our quantitative analysis confirms this hypothesis. According to the path coefficients, the technology stack is an important factor for all 3 types of use in our extended UTAUT2 model. For type 2 use, TS is the most important 3rd factor. For type 1 and type 3 use, it is the most important fourth factor. Moreover, in all user groups and for all use types, TS is always within the top 5 most important factors and in some cases it is the most important factor such as type 2 use for female users, old users, and long-term technology users.

As wearable devices extensively collect various personal data, we proposed perceived risk as a new construct to the UTAUT2 model. However, neither the interviews nor the survey-based quantitative analysis that we made point to perceived risk as an important factor. Perceived Risk (PR) construct which also measures privacy concerns did not perform well although 5% of the participants mentioned privacy in their replies to open ended questions. The type of the devices used by the participants and their current capabilities might have led the users not to focus too much on privacy risks. However, we would expect that importance of privacy would increase in parallel to the improvements in tracking capabilities of wearable devices. It seems that, as of now the benefits received from wearable devices outweigh the risks created by using these devices. It is also very likely that the importance of perceived risk is not revealed due to the fact that vast majority of the participants that we reached for our survey and interview are using general purpose consumer devices such as smartwatches and smart bands rather than specialized wearable devices collecting more sensitive health information. Depending on the type of wearable device, PR might play an important role in the adoption of wearable devices for health purposes. However, in this study, we were not able to validate this hypothesis.

During the interviews, we identified price as a very important factor for users, but our quantitative analysis does not confirm this observation. According to both the original UTAUT2 model and our extended UTAUT2 model, price is observed as an insignificant factor. This finding is in line with a previous study which states that "once the wearable device is acquired, it does not have any significant impact on the use frequency." (Ozkan-Yildirim & Pancar, 2021). We believe that price is an important factor for the adoption of wearable devices; however, the UTAUT2 model including our extended version, is far from detecting this factor. In this study, we enriched the UTAUT2 model by introducing the type of use categorization. The next step is to enrich the model by focusing on the distinction between acquiring a wearable device and using the wearable device. In the case of wearable devices, adoption of technology is comprised of 2 stages:

- acquisition of the device (initial acquisition & upgrade)

- use of the device (use frequency & type of use)

We hypothesize that different sets of factors influence these 2 stages of technology adoption. Analysis of this hypothesis remains as a future work. Technology adoption of wearable devices can be grouped in terms of in terms of acquisition and actual usage (Figure 20).

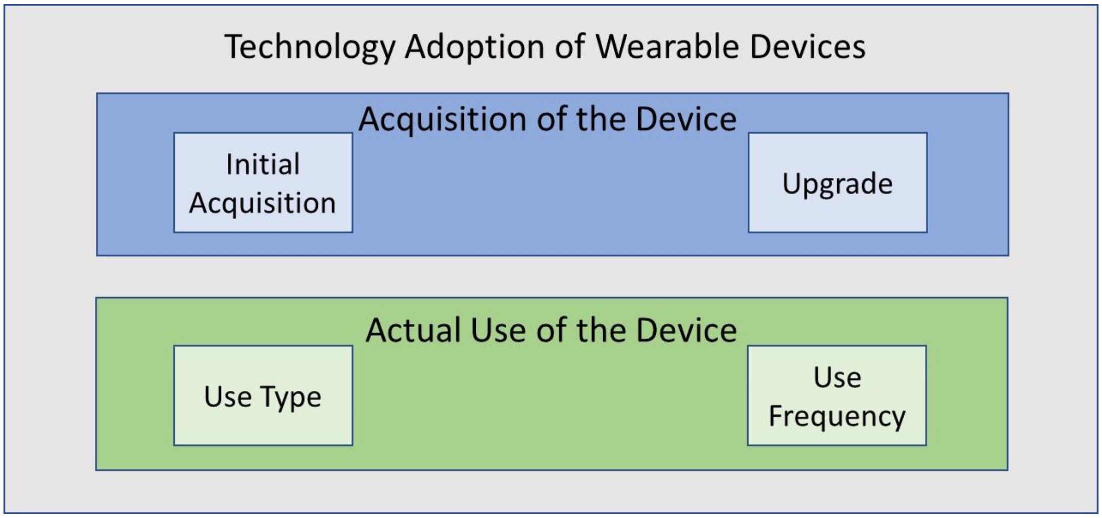

Figure 20: Technology Adoption of Wearable Devices

The new concept of technology use categorization and 2 newly proposed constructs improved the overall performance of the UTAUT2 model. As seen from table 10, the variance explained in technology use was 20% in the original UTAUT2 model. In the extended model, the variance explained in technology use is 22% for type 2 use and 30% for type 3 use. Variance explained in behavioral intention was 50% in the original UTAUT2 model. In the extended model, it is 52% for behavioral intention for type 1 use (BI-1). For BI-2 and BI-3, explained variance is 20% and 46%, respectively. Reduced explained variance for BI-2 can be attributed to a relatively low habit construct for type 2 use. Performance Expectancy, Habit, Goal Clarity, and Technology Stack Compatibility are the most important factors affecting the adoption of wearable devices to track health information. 2 out of these top-performing 4 constructs are newly proposed constructs in our extended model. Although this study focuses on the acceptance of wearable devices in the mobile health domain, we believe that these 2 new constructs (GC and TSC) are likely to be important factors for the acceptance of wearable devices by consumers in other domains.

CHAPTER 7

SUMMARY AND CONCLUSION

Wearable devices are gaining importance as supplementary devices in our daily lives. Each year more and more people are using wearable devices for various reasons, and health is one of the most important reasons. Users are trying to track their health status and adopt healthier daily life practices with the help of wearable devices. This research study used the UTAUT2 model as a basis to investigate consumers' adoption of wearable devices. We applied a pilot survey using the original UTAUT2 model, asked open-ended questions and conducted one-to-one interviews. Based on the findings from the pilot survey and the interviews, we enhanced the UTAUT2 model with the concept of technology use categorization.

Additionally, we proposed three new constructs (Goal Clarity, Perceived Risk, and Technology Stack Compatibility) to enhance the model. Breaking down the technology use into categories and newly proposed Goal Clarity helped us understand how goals can influence the adoption of wearable device usage, and brought us closer to establishing the connection between technology use and the intended goals behind the technology use. The Technology Stack Compatibility construct was found to be a significant factor for the adoption of wearable device usage, and we believe its importance is not limited to the health domain (Pancar & Ozkan-Yildirim, 2021). It is seen that two of the original UTAUT2 constructs, namely Performance Expectancy and Habit, are strong determinants of wearable device acceptance in the health domain and Effort Expectancy is somewhat important for all user groups. All other original UTAUT2 constructs have almost no significance. The newly proposed Perceived Risk construct was not identified as an important factor for wearable device use for health tracking purposes. This result might be due to one of the known limitations of our study. The majority of users who have completed the survey were using general-purpose wearable devices. It was not possible to reach enough participants using health-specific wearable devices (such as glucose meters, fertility tracker, etc.). As explained in previous sections, this study mains covers acceptance of smart bands/watches, not all types of wearable devices. For other types of wearable devices, different factors could be important. Considering the increase in technology, it is expected to have different wearable devices to track health and accomplish other tasks. The mechanisms of acceptance for these devices could be different than the existing ones, especially of the wrist worn devices and this model may not be totally adaptable. A potential future study that would complement this study could be investigating and comparing the factors affecting the adoption of different categories of wearable devices, such as multi-purpose vs single-purpose or devices with health vs predominantly non-health focused functionalities. Additionally, the participants who volunteer for online surveys and interviews generally have higher technology affinity. These two factors may have weakened the importance of the perceived risk construct.

In this study, we did not investigate factors influencing the acquisition of wearable devices. However, we think this is an important topic deserving further attention as the acquisition of the device is the first stage of the adoption of wearable devices.

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APPENDICES

APPENDIX A

PRELIMINARY SURVEY IN TURKISH

ARAŞTIRMAYA GÖNÜLLÜ KATILIM FORMU

Bu araştırma, ODTÜ Enformatik Enstitüsü Bilişim Sistemleri Bölümü öğretim elemanlarından Prof. Dr. Sevgi Özkan Yıldırım ve Doktora programı öğrencisi Tansu Pancar tarafından yürütülen bir çalışmadır. Bu form sizi araştırma koşulları hakkında bilgilendirmek için hazırlanmıştır.

Çalışmanın Amacı Nedir: Araştırmanın amacı tüketicilerin sağlık bilgilerini takip etmek amacıyla giyilebilir cihazları kullanma eğilimini ve bu cihazları kullanma kararı verme nedenlerini anlamaktır. Araştırmaya katılmayı kabul ederseniz, çevrimiçi olarak yöneltilecek anket sorularını yanıtlamanız beklenmektedir. Bu çalışmaya katılım ortalama olarak 20 dakika sürmektedir.

Bize Nasıl Yardımcı Olmanızı İsteyeceğiz: Size çevrimiçi ortamda sunulan anketleri doldurmanız beklenmektedir.

Sizden Topladığımız Bilgileri Nasıl Kullanacağız: Araştırmaya katılımınız tamamen gönüllülük temelinde olmalıdır. Ankette, sizden kimlik veya kurum belirleyici hiçbir bilgi istenmemektedir. Cevaplarınız tamamıyla gizli tutulacak, sadece araştırmacılar tarafından değerlendirilecektir. Katılımcılardan elde edilecek bilgiler toplu halde değerlendirilecek ve bilimsel yayımlarda kullanılacaktır. Sağladığınız veriler gönüllü katılım formlarında toplanan kimlik bilgileri ile eşleştirilmeyecektir.

Katılımınızla ilgili bilmeniz gerekenler: Çalışma katılımcılar açısından herhangi bir risk içermemektedir ve katılım tamamen isteğe bağlıdır. Katılım sırasında sorulardan ya da herhangi başka bir nedenden ötürü kendinizi rahatsız hissederseniz cevaplama işini yarıda bırakabilirsiniz.

Araştırmayla ilgili daha fazla bilgi almak isterseniz: Bu çalışmaya katıldığınız için şimdiden teşekkür ederiz. Araştırma hakkında daha fazla bilgi almak için Enformatik Enstitüsü Bilişim Sistemleri Bölümü doktora öğrencisi Tansu Pancar (E-posta: tansu.pancar@metu.edu.tr) ile iletişime geçebilirsiniz.

	Anket Maddeleri	**1**	**2**	**3**	**4**	**5**
Performance Expectancy	PE1. Günlük hayatımda giyilebilir cihazları sağlık bilgilerimi takip etmek icin kullanışlı buluyorum.					
	PE2. Giyilebilir cihazları kullanmak, sağlığım için önemli olan şeyleri elde etme şansımı arttırıyor.					
	PE3. Giyilebilir cihazları kullanmak, işleri daha çabuk halletmeme yardımcı oluyor.					
	PE4. Giyilebilir cihazları kullanmak sağlık bilgilerimi takip etme konusunda verimliliğimi arttırır.					
Effort Expectancy	EE1. Sağlık bilgilerimi takip etmek için giyilebilir cihazları kullanmayı öğrenmek benim için kolaydır.					
	EE2. Sağlık bilgilerimi takip etmek için giyilebilir cihazlarla olan etkileşimim açık ve anlaşılırdır.					
	EE3. Giyilebilir cihazların sağlık bilgilerimi takip etmek icin kullanımını kolay buluyorum.					
	EE4. Sağlık bilgilerimi takip etmek için giyilebilir cihazların kullanımında ustalık kazanmak benim için kolaydır.					
Social Influence	SI1. Benim için önemli olan kişiler, sağlık bilgilerimi takip etmek için giyilebilir cihazları kullanmam gerektiğini düşünüyor.					
	SI2. Davranışlarımı etkileyen kişiler, sağlık bilgilerimi takip etmek için giyilebilir cihazları kullanmam gerektiğini düşünüyor.					
	SI3. Görüşlerine değer verdiğim kişiler, sağlık bilgilerimi takip etmek için giyilebilir cihazları kullanmamı tercih ederler					
Facilitating Conditions	FC1. Giyilebilir cihazları kullanarak sağlık bilgilerini takip etmek için gerekli kaynaklara sahibim.					
	FC2. Giyilebilir cihazları kullanarak sağlık bilgilerini takip etmek için gerekli bilgiye sahibim.					
	FC3. Giyilebilir cihazlar, kullandığım diğer teknolojilerle uyumludur.					
	FC4. Sağlık bilgilerimi takip etmek için giyilebilir cihazları kullanırken güçlük çektiğim zaman diğerlerinden yardım alabilirim.					

Hedonic Motivation	HM1. Sağlık bilgilerini takip etmek için giyilebilir cihazları kullanmak eğlencelidir.					
	HM2. Sağlık bilgilerini takip etmek için giyilebilir cihazları kullanmak keyiflidir.					
	HM3. Sağlık bilgilerini takip etmek için giyilebilir cihazları kullanmak eğlendiricidir.					
Price Value	PV1. Sağlık bilgilerini takip etmek için kullanılan giyilebilir cihazların fiyatları makuldur.					
	PV2. Sağlık bilgilerini takip etmek için kullanılan giyilebilir cihazlar verilen paraya değer.					
	PV3. Mevcut fiyatlar göz önünde bulundurulduğunda, sağlık bilgilerini takip etmek için kullanılan giyilebilir cihazlar fiyatına göre iyi bir değer sağlar.					
Habit	HT1. Sağlık bilgilerimi izlemek için giyilebilir cihazları kullanmak benim için bir alışkanlık haline geldi.					
	HT2. Sağlık bilgilerimi izlemek için giyilebilir cihazları kullanmak benim için bir bağımlılık haline geldi.					
	HT3. Sağlık bilgilerimi izlemek için giyilebilir cihazları kullanmalıyım.					
	HT4. Sağlık bilgilerimi izlemek için giyilebilir cihazları kullanmak benim için doğal bir hale geldi.					
Behavioral Intention	BI1. Gelecekte sağlık bilgilerimi takip etmek için giyilebilir cihazları kullanmaya devam etmek niyetindeyim					
	BI2. Günlük yaşamımda, sağlık bilgilerimi takip etmek için her zaman giyilebilir cihazları kullanmaya çalışacağım.					
	BI3. Sağlık bilgilerimi takip etmek için sıklıkla giyilebilir cihazları kullanmayı planlıyorum.					
Use	Lütfen sahip olduğunuz giyilebilir cihazlar için kullanım sıklığını seçin: **Not:** Kullanım sıklığı "hiçbir zaman" ile "günde bir çok kez" arasında değişecektir.					
General Information	Yaş					
	Cinsiyet					
	Konumunuz					
	Sağlık bilgilerinizi takip etmek için ne kadar zamandır giyilebilir cihaz kullanıyorsunuz?					
	Giyilebilir cihazınızın türü ve markası hakkında bilgi verebilir misiniz?					

APPENDIX B

PRELIMINARY SURVEY IN ENGLISH

	Survey Items	1	2	3	4	5
Performance Expectancy	PE1. I find wearable devices useful in my daily life to track health information					
	PE2. Using wearable devices increases my chances of achieving things that are important for my health.					
	PE3. Using wearable devices helps me accomplish things more quickly.					
	PE4. Using wearable devices increases my productivity for tracking my health information.					
Effort Expectancy	EE1. Learning how to use wearable devices to track health information is easy for me.					
	EE2 My interaction with wearable devices to track health information is clear and understandable.					
	EE3. I find wearable devices easy to use to track my health information					
	EE4. It is easy for me to become skillful at using wearable devices to track health information.					
Social Influence	SI1. People who are important to me think that I should use wearable devices to track my health information					
	SI2. People who influence my behavior think that I should use wearable devices to track my health information.					
	SI3. People whose opinions that I value prefer that I use wearable devices to track health information.					
Facilitating Conditions	FC1. I have the resources necessary to use wearable devices to track health information					
	FC2. I have the knowledge necessary to use wearable 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 devices to track my health information.					
Hedonic Motivation	HM1. Using wearable devices to track health information is fun.					
	HM2. Using wearable devices to track health information is enjoyable.					
	HM3. Using wearable devices to track health information is very entertaining					
Price Value	PV1.Wearable devices which are used to track health information are reasonably priced.					
	PV2. Wearable devices which are used to track health information are a good value for the money.					
	PV3. At the current price, wearable mobile devices which are used to track health information provides a good value.					
Habit	HT1. The use of wearable devices to track health information has become a habit for me.					
	HT2. I am addicted to using wearable devices to track my health information.					
	HT3. I must use wearable devices to track my health information.					

	HT4. Using wearable devices to track health information has become natural to me.					
Behavioral Intention	BI1. I intend to continue using wearable devices to track health information in the future					
	BI2. I will always try to use wearable devices to track health information in my daily life.					
	BI3. I plan to continue to use wearable 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."					
General Information	Age					
	Gender					
	Location					
	How long have you been using a wearable device to track your health information					
	Can you give information about type and brand of your wearable device?					

APPENDIX C

METU HUMAN SUBJECTS ETHICS COMMITTEE APPROVAL for PRELIMINARY SURVEY

UYGULAMALI ETİK ARAŞTIRMA MERKEZİ
APPLIED ETHICS RESEARCH CENTER

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10 EKİM 2017

Konu: Değerlendirme Sonucu

Gönderen: ODTÜ İnsan Araştırmaları Etik Kurulu (İAEK)

İlgi: İnsan Araştırmaları Etik Kurulu Başvurusu

Sayın Doç.Dr. Sevgi ÖZKAN YILDIRIM ;

Danışmanlığını yaptığınız doktora öğrencisi Tansu PANCAR'ın **"Kullanıcıların sağlık bilgisini takip etmek amacıyla giyilebilir mobil cihazları kullanma eğilimini etkileyen faktörlerin araştırılması"** başlıklı araştırmanız İnsan Araştırmaları Etik Kurulu tarafından uygun görülerek gerekli onay **2017-FEN-056** protokol numarası ile **15.10.2017 – 30.09.2018** tarihleri arasında geçerli olmak üzere verilmiştir.

Bilgilerinize saygılarımla sunarım.

Prof. Dr. Ş. Halil TURAN
Başkan V

Prof. Dr. Ayhan SOL
Üye

Prof. Dr. Ayhan Gürbüz DEMİR
Üye

BULUNAMADI

Doç. Dr. Yaşar KONDAKÇI
Üye

Doç. Dr. Zana ÇITAK
Üye

Yrd. Doç. Dr. Pınar KAYGAN
Üye

Yrd. Doç. Dr. Emre SELÇUK
Üye

APPENDIX D

METU HUMAN SUBJECTS ETHICS COMMITTEE APPROVAL for the MAIN SURVEY

UYGULAMALI ETİK ARAŞTIRMA MERKEZİ
APPLIED ETHICS RESEARCH CENTER

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03 OCAK 2019

Konu: Değerlendirme Sonucu

Gönderen: ODTÜ İnsan Araştırmaları Etik Kurulu (İAEK)

İlgi: İnsan Araştırmaları Etik Kurulu Başvurusu

Sayın Doç. Dr. Sevgi Özkan YILDIRIM

Danışmanlığını yaptığınız Tansu PANCAR'ın **"Kullanıcıların sağlık bilgisini takip etmek amacıyla giyilebilir mobil cihazları kullanma eğilimini etkileyen faktörlerin araştırılması"** başlıklı araştırması İnsan Araştırmaları Etik Kurulu tarafından uygun görülerek gerekli onay **2017-FEN-056** protokol numarası ile araştırma yapması onaylanmıştır.

Saygılarımla bilgilerinize sunarım.

Prof. Dr. Tülin GENÇÖZ
Başkan

Prof. Dr. Ayhan SOL
Üye

Prof. Dr. Ayhan Gürbüz DEMİR
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Prof.Dr. Yaşar KONDAKÇI (4.)
Üye

Doç. Dr. Emre SELÇUK
Üye

Doç. Dr. Pınar KAYGAN
Üye

Dr. Öğr. Üyesi Ali Emre TURGUT
Üye

APPENDIX E

MAIN SURVEY in ENGLISH

Wearable Devices Survey

Dear participant,

This survey is prepared as part of a research study and you will be asked questions about wearable devices.

Answering all questions will take around 20 minutes and throughout the survey personal information will not be

collected.

You can find brief information about wearable devices below.

What is a Wearable Device

Wearable devices are smart electronic devices which can be incorporated into clothing or worn on the body as accessories. A wearable device is often used for tracking a user's vital signs or pieces of data related to health and fitness, location or even his/her biofeedback indicating emotions.

Wearable devices are expected to be capable of taking all the measurements shown in the figure below, with additional features and extended benefits to the user.

Smart bands, smart watches and activity trackers are most popular and well-known types of wearable devices. However there are various types of wearable devices which are used for preventive healthcare such as:

- sweat, body temperature and heart rate tracking body patches to avoid heat related injuries during physically demanding activities
- ovulation tracking bracelet providing insights regarding fertility and pregnancy
- posture tracking device providing real-time feedback to improve the user's posture
- blood alcohol level tracking wrist band to avoid alcohol related accidents and injuries

This survey is part of an academic research and does not have any commercial relation with wearable device producers

Perfect Wearable Device of Future

	Survey Items	1	2	3	4	5
Performance Expectancy	PE1. I find wearable mobile devices useful in my daily life.					
	PE2.Using wearable mobile devices increases my chances of achieving things that are important for me.					
	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 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 provides a good value.					
Habit	HT1.The use of wearable mobile devices to track health information has become a habit for me					
	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.					
Goal Clarity (*)	I have a goal that I am trying to achieve and I am using my wearable device for this purpose.					
	I have a clear goal and my wearable device usage is related to this goal.					
	I know what I want to achieve and my use of wearable devices is related to this.					
	I have a personal goal and my wearable device usage is related to this goal.					
Perceived Risk (*)	Using wearable devices has some risks. My personal information might be used without my knowledge.					
	My use of wearable devices might cause me to lose control over my private data.					
	I see some risks in using wearable devices.					
	Using wearable devices increases the risk of losing control of my digital privacy.					
Technology Stack Compatibility (*)	Wearable devices are generally compatible with my other technology tools (mobile phone, computer, etc).					
	It is important for me that my wearable device is well integrated with my other tech devices.					
	It is important for me that my wearable device is well integrated with online services that I am using.					
Behavioral Intention-1	BI11 I intend to continue using wearable devices to track my health information in the future.					
	BI12 I will always try to use wearable devices to track my health information in my daily life.					
	BI13 I plan to continue to use wearable devices to track my health information frequently.					

Behavioral Intention-2 (*)	BI21 I intend to continue checking the data collected by my wearable device.					
	BI22 I will always try to check the data collected by my wearable device.					
	BI23 I plan to continue checking the data collected by my wearable device.					
Behavioral Intention-3 (*)	BI31 I intend to continue taking actions (making some changes in my daily life etc) based on the data collected by my wearable device.					
	BI32 I will always try to take actions (make some changes in my daily life etc) based on the data collected by my wearable device.					
	BI33 I plan to continue taking actions (making some changes in my daily life etc) based on the data collected by my wearable device.					
Use-1	How often do you wear (carry on your arm, wrist or body, depending on type of wearable device you are using) your wearable device?					
Use-2 (*)	How often do you check the data collected by your wearable device?					
Use-2 (*)	How often do you take actions (make some changes in your daily life etc) based on the data collected by your wearable device?					
Previous Experience with Technology	Which of the below categories do you think you belong to based on your technology affinity? Early Adopters (1) Early Majority (2) Late Majority (3) Laggards (4) I do not know (5)					
General Information	Age					
	Gender					
	Location					
	How long have you been using a wearable device to track your health information					
	Can you give information about type and brand of your wearable device?					

- Survey questions including the additional constructs are shown above, participants were asked to give ratings ranging from 1 (Strongly Disagree) to 5 (Strongly Agree)
- Additional questions and constructs are marked with an asterisk (*)
- Original UTAUT2 questions are derived from (Ozkan Yildirim & Pancar, 2021)

APPENDIX F

CROSS LOADINGS of the MAIN SURVEY

Cross loadings for the proposed model for 624 participants.

	BI1	BI2	BI3	EE	FC	GC	HM	Habit	PE	PR	Price	SI	TS	Use1	Use2	Use3
BI11	0,873	0,426	0,458	0,469	0,478	0,264	0,412	0,449	0,484	-0,168	0,313	0,141	0,411	0,297	0,195	0,211
BI12	0,869	0,452	0,550	0,385	0,279	0,369	0,478	0,540	0,541	-0,251	0,370	0,264	0,333	0,298	0,175	0,302
BI13	0,941	0,524	0,546	0,437	0,395	0,328	0,426	0,546	0,512	-0,211	0,339	0,188	0,429	0,357	0,225	0,251
BI21	0,513	0,929	0,537	0,296	0,269	0,282	0,292	0,305	0,394	-0,027	0,235	0,174	0,340	0,217	0,393	0,281
BI22	0,491	0,946	0,569	0,322	0,279	0,349	0,297	0,338	0,400	-0,018	0,258	0,167	0,331	0,217	0,436	0,331
BI23	0,476	0,947	0,574	0,273	0,260	0,315	0,259	0,318	0,391	0,007	0,222	0,163	0,329	0,218	0,443	0,338
BI31	0,531	0,563	0,901	0,293	0,301	0,432	0,339	0,454	0,547	-0,061	0,292	0,223	0,343	0,255	0,320	0,473
BI32	0,550	0,567	0,943	0,265	0,258	0,478	0,408	0,462	0,575	-0,042	0,297	0,263	0,328	0,201	0,286	0,504
BI33	0,529	0,524	0,931	0,278	0,261	0,470	0,366	0,422	0,538	-0,065	0,309	0,246	0,349	0,193	0,306	0,525
EE1	0,333	0,182	0,194	0,827	0,602	0,256	0,264	0,266	0,333	-0,116	0,244	0,052	0,268	0,190	0,147	0,150
EE2	0,414	0,306	0,289	0,891	0,628	0,322	0,336	0,333	0,352	-0,141	0,283	0,092	0,324	0,209	0,186	0,190
EE3	0,491	0,334	0,281	0,881	0,567	0,276	0,333	0,384	0,359	-0,150	0,307	0,111	0,283	0,262	0,198	0,177
EE4	0,405	0,247	0,266	0,880	0,657	0,280	0,299	0,325	0,375	-0,113	0,273	0,074	0,336	0,247	0,179	0,194

FC1	0,338	0,229	0,226	0,565	0,787	0,268	0,208	0,254	0,295	-0,110	0,228	-0,005	0,270	0,207	0,160	0,104
FC2	0,364	0,235	0,211	0,647	0,823	0,214	0,233	0,263	0,288	-0,118	0,178	-0,055	0,296	0,236	0,152	0,082
FC3	0,321	0,201	0,258	0,516	0,778	0,217	0,285	0,261	0,285	-0,111	0,261	0,063	0,445	0,142	0,135	0,215
FC4	0,248	0,195	0,187	0,335	0,588	0,156	0,288	0,214	0,277	-0,011	0,205	0,154	0,245	0,067	0,072	0,127
GC1	0,294	0,268	0,441	0,299	0,238	0,922	0,208	0,243	0,433	-0,048	0,230	0,158	0,236	0,130	0,270	0,439
GC2	0,314	0,300	0,440	0,300	0,263	0,935	0,206	0,259	0,463	-0,061	0,243	0,143	0,233	0,169	0,279	0,417
GC3	0,368	0,301	0,467	0,329	0,286	0,931	0,252	0,310	0,505	-0,092	0,229	0,154	0,236	0,195	0,248	0,390
GC4	0,349	0,369	0,495	0,287	0,279	0,925	0,247	0,289	0,474	-0,022	0,232	0,157	0,212	0,184	0,287	0,432
HM1	0,442	0,262	0,359	0,338	0,324	0,220	0,919	0,418	0,481	-0,162	0,384	0,236	0,277	0,120	0,125	0,230
HM2	0,493	0,285	0,390	0,369	0,317	0,227	0,937	0,483	0,537	-0,183	0,419	0,274	0,314	0,181	0,152	0,251
HM3	0,388	0,267	0,338	0,255	0,255	0,226	0,855	0,412	0,468	-0,152	0,339	0,302	0,257	0,089	0,134	0,227
Habit 1	0,442	0,231	0,296	0,331	0,292	0,167	0,203	0,737	0,357	-0,122	0,130	0,069	0,245	0,423	0,239	0,165
Habit 2	0,332	0,171	0,309	0,138	0,131	0,187	0,438	0,725	0,376	-0,055	0,194	0,219	0,134	0,159	0,129	0,211
Habit 3	0,341	0,242	0,374	0,178	0,118	0,283	0,460	0,741	0,422	-0,045	0,278	0,319	0,159	0,152	0,189	0,326
Habit 4	0,568	0,352	0,460	0,430	0,387	0,265	0,410	0,839	0,469	-0,128	0,268	0,125	0,285	0,443	0,281	0,301
PE1	0,542	0,343	0,428	0,455	0,433	0,362	0,417	0,463	0,745	-0,133	0,282	0,087	0,404	0,276	0,240	0,257

PE2	0,484	0,368	0,533	0,337	0,323	0,523	0,416	0,438	0,835	-0,120	0,278	0,149	0,347	0,291	0,249	0,387
PE3	0,416	0,315	0,500	0,272	0,227	0,382	0,498	0,439	0,847	-0,066	0,389	0,364	0,319	0,201	0,204	0,389
PE4	0,424	0,343	0,493	0,261	0,250	0,379	0,468	0,410	0,844	-0,082	0,332	0,298	0,306	0,196	0,213	0,392
PR1	-0,188	0,001	-0,039	-0,116	-0,084	-0,013	-0,097	-0,088	-0,076	0,874	-0,140	0,041	-0,117	-0,142	-0,029	-0,045
PR2	-0,203	-0,013	-0,027	-0,119	-0,106	-0,036	-0,159	-0,077	-0,078	0,912	-0,144	0,060	-0,098	-0,150	-0,016	0,018
PR3	-0,212	-0,029	-0,079	-0,156	-0,141	-0,083	-0,234	-0,138	-0,149	0,883	-0,184	-0,005	-0,145	-0,150	-0,042	-0,075
PR4	-0,239	-0,005	-0,065	-0,148	-0,110	-0,074	-0,163	-0,128	-0,132	0,931	-0,145	0,046	-0,136	-0,153	-0,066	-0,067
Price 1	0,303	0,209	0,261	0,259	0,241	0,198	0,338	0,204	0,289	-0,133	0,888	0,295	0,264	0,077	0,090	0,237
Price 2	0,374	0,241	0,311	0,315	0,271	0,242	0,435	0,297	0,396	-0,168	0,933	0,322	0,324	0,140	0,110	0,272
Price 3	0,367	0,246	0,315	0,305	0,281	0,248	0,385	0,284	0,379	-0,166	0,934	0,318	0,296	0,146	0,103	0,269
SI1	0,220	0,166	0,243	0,098	0,043	0,156	0,280	0,214	0,252	0,003	0,339	0,943	0,161	-0,005	0,063	0,210
SI2	0,204	0,175	0,262	0,089	0,034	0,158	0,278	0,202	0,254	0,063	0,313	0,957	0,176	-0,048	0,058	0,201
SI3	0,208	0,168	0,247	0,092	0,036	0,156	0,292	0,220	0,263	0,044	0,319	0,950	0,180	-0,034	0,057	0,220
TS1	0,371	0,279	0,318	0,352	0,437	0,197	0,280	0,250	0,346	-0,116	0,312	0,114	0,772	0,209	0,155	0,213
TS2	0,341	0,263	0,220	0,236	0,316	0,136	0,184	0,168	0,284	-0,094	0,176	0,098	0,842	0,162	0,185	0,102
TS3	0,341	0,310	0,338	0,247	0,263	0,252	0,285	0,258	0,381	-0,123	0,278	0,219	0,807	0,151	0,208	0,201

USE1	0,356	0,231	0,233	0,264	0,226	0,184	0,146	0,416	0,297	-0,165	0,134	-0,031	0,217	1,000	0,376	0,229
USE2	0,222	0,452	0,328	0,206	0,177	0,292	0,152	0,288	0,278	-0,044	0,110	0,062	0,227	0,376	1,000	0,503
USE3	0,285	0,338	0,542	0,205	0,174	0,452	0,261	0,332	0,436	-0,049	0,283	0,221	0,218	0,229	0,503	1,000

Cross loadings for the UTAUT2 model for 624 participants.

	BI	**EE**	**FC**	**HM**	**Habit**	**PE**	**Price**	**SI**	**USE**
BI11	0,875	0,469	0,478	0,413	0,464	0,496	0,313	0,142	0,297
BI12	0,868	0,385	0,278	0,478	0,533	0,542	0,370	0,264	0,298
BI13	0,941	0,436	0,397	0,427	0,557	0,519	0,340	0,188	0,357
EE1	0,333	0,832	0,609	0,265	0,277	0,342	0,244	0,052	0,190
EE2	0,414	0,887	0,630	0,337	0,343	0,359	0,283	0,092	0,209
EE3	0,491	0,881	0,570	0,334	0,396	0,370	0,307	0,111	0,262
EE4	0,405	0,881	0,663	0,300	0,334	0,382	0,274	0,075	0,247
FC1	0,339	0,565	0,800	0,209	0,272	0,305	0,228	-0,005	0,207
FC2	0,364	0,648	0,842	0,234	0,278	0,298	0,178	-0,055	0,236
FC3	0,321	0,515	0,760	0,285	0,266	0,290	0,261	0,064	0,142
FC4	0,248	0,335	0,565	0,288	0,211	0,282	0,205	0,154	0,067
HM1	0,442	0,337	0,321	0,921	0,403	0,481	0,384	0,237	0,120
HM2	0,493	0,369	0,313	0,940	0,471	0,538	0,419	0,274	0,181
HM3	0,387	0,254	0,248	0,849	0,391	0,465	0,339	0,302	0,089
Habit1	0,442	0,331	0,295	0,203	0,779	0,364	0,130	0,070	0,423
Habit2	0,331	0,138	0,125	0,437	0,687	0,373	0,195	0,218	0,159
Habit3	0,340	0,177	0,113	0,459	0,689	0,416	0,279	0,319	0,152
Habit4	0,568	0,430	0,389	0,411	0,855	0,477	0,269	0,126	0,443
PE1	0,543	0,456	0,433	0,418	0,473	0,773	0,282	0,087	0,276
PE2	0,484	0,337	0,323	0,416	0,435	0,831	0,278	0,149	0,291

PE3	0,416	0,272	0,223	0,498	0,427	0,833	0,389	0,364	0,201
PE4	0,424	0,261	0,247	0,468	0,400	0,830	0,333	0,298	0,196
Price1	0,302	0,259	0,235	0,338	0,197	0,286	0,887	0,296	0,077
Price2	0,374	0,314	0,266	0,435	0,288	0,396	0,934	0,323	0,140
Price3	0,367	0,305	0,279	0,385	0,276	0,378	0,934	0,319	0,146
SI1	0,220	0,097	0,036	0,280	0,198	0,244	0,339	0,946	-0,005
SI2	0,203	0,089	0,027	0,277	0,186	0,246	0,313	0,955	-0,048
SI3	0,207	0,092	0,029	0,291	0,203	0,255	0,319	0,949	-0,034
USE1	0,355	0,264	0,230	0,147	0,434	0,301	0,135	-0,030	1,000

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