Improving Healthcare with Wearables: Overcoming the Barriers to Adoption

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Abstract. Wearable technology devices (WTDs) record exercise activity and capture vital health statistics. These details can be shared with healthcare providers to monitor patients, manage chronic illness and save lives. The adoption of these devices continues to grow, but so does their abandonment. Within the context of healthcare, protection motivation theory (PMT) explains that individuals seek to protect themselves from health threats that they perceive to be severe. We combine this theory with the unified theory of adoption in order to investigate the factors that motivate individuals to adopt WTD to manage their health. The results of the quantitative study show that consumers need to be convinced that the data collected from these devices can lead to improved health outcomes.

Keywords: Wearables · PMT · UTAUT · Personalization · PLS

1 Introduction

Wearable technology devices (WTDs), such as smartwatches, FitBits, Nike, Jawbone, and others, are becoming increasingly popular. WTDs are small electronic devices that consist of one or more sensors with computational capabilities that provide information and entertainment for the wearer. These sensors are embedded into the WTDs which are attached to the body, for example, to the wrist or to the head. WTDs capture health data such as the number of steps taken in a day, duration of physical activity, calories burned, stress level, body temperature, number of hours that the individual sleeps, location, and even ECG measurements. For output, WTDs can showcase information through the flashing of LED lights on a wrist device to a complex display of data on a mobile app.

It is expected that WTDs will play a transformative role in fitness, health, and other medical applications [1]. Individuals are more inclined to self-monitor their health with this technology. There is a growing population of WTD users who are interested in personal analytics as a concept of self-discovery, a movement called the Quantified – Self (QS) [2]. As WTDs motivate people to exercise and walk, they are considered to be a preventative tool for chronic disease [3]. WTDs are often used to improve sleep, to increase productivity and to lose weight [1]. To increase user engagement, WTD manufacturers utilize different techniques such as the gamification of physical activity with competitions and challenges, while publishing the feedback of their performance on social media. WTDs such as FitBit, allow individuals to compete against their friends

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or strangers [4]. Social influence is used to alter beliefs, attitudes, motivations and intentions [5]. The prediction is that wearable computing market will reach more than $171.2 billion in 2021, with a compound annual growth rate (CAGR) of 50% [6].

WTDs collect health and fitness data. Up until recently, there was little value in sharing this information with the healthcare industry. Today, Google and Apple are linking the two with bridging applications. Apple recently launched ResearchKit, which is an open-software platform to create health apps and uses WTDs for medical research. They also launched CareKit, which is an open-software platform to create health apps that help people manage various medical conditions and share that information with their physicians [7]. Among the first four apps that were released by Apple were those that help manage diabetes, and track symptoms of depression [8]. This is Apple's step to accelerate integration of WTDs into healthcare. It is also predicted that other wearable manufactures will follow this approach, therefore making it easier for medical researchers and doctors to collect data and resolve issues regarding reliability and safety of WTDs. Another issue is that consumer surveys showed that more than 50% of WTD owners abandon their devices after only one year or less of using the technology [3]. Furthermore, according to research conducted by PwC (2014) [9] only half of those who own the technology wear them on a daily basis (n = 1000). Previous research has identified that most WTDs do not provide additional functionality other than the basic functions such as recording steps or heart rate [5]. Most consumers are unaware that WTDs can share their data with a health care provider, or that they can save their lives by sending data to their physician's office. While the adoption rate has increased, the abandonment rate is still high. Researchers also found that the technology might require too much effort in order to use it, which makes the experience unpleasant for the users [10].

Consumers fail to recognize the potential health benefits of WTDs beyond the counting of steps and the calories burned [11]. However, there are new improvements in WTDs such as the hands-free data collection of measurements of heart rate, blood flow and blood oxygen, which allow for a real-time view of personalized data by the healthcare provider [1]. These devices may also improve disease control and survival rates. For example, Apple watch was able to save a person who suffered a heart attack because the watch showed an abnormal heart rate. The patient was able to call an ambulance and the paramedics determined that he was having a heart attack. The doctors cleared the blockage prevented other occurrences and were able to save a life [12]. WTDs are an example of a protection technology whose efficiency is improved when they provide personalized feedback in order to protect users from unforeseen health conditions, such as heart attacks. As of today, they have not been widely adopted. This leads to our research question: *what motivates individuals to use wearable technology devices in order to protect themselves against unforeseen health related threats*?

Practitioners need to not only attract, but also to motivate users to continue using their WTDs. In order to provide customized feedback, WTDs collect health data by implicitly monitoring individuals' behaviours and vital signs. According to Park [13], personalization increases adoption and continued use of an IT innovation. Extant studies of WTDs have determined that feedback, information display, and specific design principles all play a role in keeping the user engaged with the technology [11]. This suggests that personalization could have an impact on behavioural intention to use WTDs. Studies of user adoption of WTDs have combined theories of acceptance and use of technology with Protection Motivation Theory (PMT) [14]. WTDs can be considered as protective technology, as they have been designed to protect users against health fears and concerns. None of the studies have been conducted in North America. We address this gap in the literature by proposing the theoretical foundation of Protection Motivation Theory (PMT) and extending it with the construct of personalization together with behavioural antecedents from the unified theory of acceptance and use of technology (UTAUT) [15].

The remainder of this paper is organized as follows. The next section is the review of the literature, which includes our development of the hypotheses and concludes with the research model. The third section of this paper describes the methodology. The results are then discussed, followed by conclusion that includes implications for the practitioners, limitations and suggestions for future studies.

2 Literature Review

WTDs can be considered a protective technology. Features such as the measurement of blood glucose level and heart rate can protect users from potential unforeseen health risks, such as heart attacks, and help to recognize disease symptoms. Because our investigation is in the context of healthcare, we develop a theoretical framework which includes health information technology (HIT) [16].

We chose Protection Motivation Theory (PMT) as our theoretical foundation as WTDs have the potential to protect individuals against a threat (such as managing a disease) or a fear (such as a heart attack) by providing personalized feedback. Our model of PMT resembles that of the Fear Appeals Model (FAM) from the study by Johnston and Warkentin (2010) [17] where researchers applied the theory to the adoption of spyware. In this section, we provide a background on PMT and its constructs [17, 18]. We also describe personalization which is added to the model and we add further information on UTAUT [15], which was included in our theoretical framework.

2.1 Protection Motivation Theory (PMT)

PMT is one of the leading theories of health behaviour [19, 20]. Researchers have used PMT to predict behaviours that promote health as well as those which compromise health [21]. PMT was developed by Rogers [18] in 1975 to identify the key factors in fear appeals and their cognitive mediation [21]. In other words, Rogers [18] theorized that motivation to protect oneself from potential harm is influenced by fear appeals. These fear appeals are composed of three components: 1. The magnitude of noxiousness of a depicted event; 2. The probability of that event's occurrence; and 3. The efficacy of protective response [22]. Protection motivation arises through this cognitive process, which produces an appropriate behavioural intention [23]. Since its inception in 1975, the theory has undergone a number of revisions and extensions.

PMT involves the appraisals of two components: threat and coping [24]. Health behaviour is induced by the threat appraisals and by the coping appraisals [18]. Threat appraisals include two constructs: perceived vulnerability and perceived severity. Coping appraisals focus on the coping responses that are available to the individual to deal with the threat: response efficacy, self-efficacy and response cost. An individual's cognitive processes evaluate the threat appraisals depending on the expectancy and the severity of exposure, and the actions that they take will depend upon their beliefs in the efficacy of the coping response. The PMT model used by Johnston and Warkentin [17] is shown in Fig. 1. Our research model (Fig. 2) is an adaptation of Johnston and Warkentin's model. Arrows in the model indicate directional associations and influences between variables, with positive (+) and negative (−) associations.

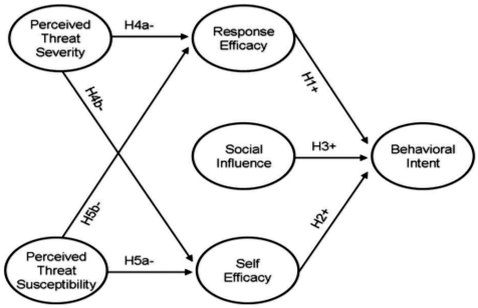

Fig. 1. Adapted PMT (Johnston and Warkentin 2010 [17])

2.1.1 Response Efficacy (RE)

Response efficacy refers to the beliefs that a recommended response will effectively protect a user from a threat [17, 18]. This is a measure of the individual's confidence in the effectiveness of the WTD in preventing a risk to health. In the context of our research, when individuals believe that using WTDs can enable them to reduce threats to their health because of the personalized feedback, they are more likely to adopt and use the technology. The effectiveness of the technology can be regarded as the degree to which the device can help them monitor their daily physical conditions, make personal healthcare plans, and reduce health related threats. For example, a user may decide to monitor their heart rate because of a previous heart attack, or a family history of heart attacks. To reduce the risks of having a heart attack (the threat), the user may monitor the data collection and later review the results with their health care provider (the response). PMT predicts that RE would have a positive relationship with behaviour intention and this positive relationship is widely supported in PMT [18]. Therefore, we hypothesize:

H1: Response Efficacy is positively associated with intention to use wearable device

2.1.2 Self-Efficacy (SE)

Self-efficacy is defined as the level of confidence of individual in their ability to perform the coping behavior. In the case of WTDs, they must be confident that they are able to monitor their health correctly. When individuals are confident of their competency to use the technology, they are more likely to use the technology. According to Bandura (1977) [25], self-efficacy is a strong predictor of behaviour intention.

However, previous PMT research found that self-efficacy does not significantly influence user intention to adopt technology, but it has been suggested that self-efficacy would have a greater importance in intention to use technology in health-related fields [14, 26]. For example, WTD users can use technology to self-monitor their physical conditions with personalized feedback, but the determinant factor is their belief that they are competent to deploy the functionality of the WTDs. This positive relationship between self-efficacy and intention behaviour to adopt technology has been well established in previous technology acceptance studies as verified by Venkatesh et al. (2003) [15] and other extant studies [14, 17, 26]. Hence, we hypothesize:

H2: Self-Efficacy is positively associated with intention to use wearable devices

2.1.3 Perceived Vulnerability (PV)

Perceived vulnerability refers to the assessment of the likelihood that individuals will encounter a threat to their health [18]. Perceived vulnerability is an important element that impacts one's reaction to a threat appeal [17]. According to the theory, when the probability of encountering a threat is high, an individual adopts new health information technology (HIT) in order to reduce or avoid health threats [19]. Previous PMT research found that individuals appear to make decisions that are predictable based on the assessment of their perceived health risks [17, 26]. Researchers identified that in instances where perceived vulnerability was high, users' become increasingly concerned with their knowledge and ability to respond to the threat [19]. For example, a person who has a history of heart attacks in the family, feels that they will increase the probability of a heart attack is high if they live an unhealthy life style (eg. smoking, lack of exercise). Hence, they consider themselves to be highly vulnerable to the threat. As the fear of a heart attack rises, they feel more vulnerable and their self-confidence to use the technology correctly decreases. Therefore, we hypothesize:

H3a: Perceived vulnerability will negatively influence perceptions of response efficacy.

H3b: Perceived vulnerability will negatively influence perceptions of self-efficacy

2.1.4 Perceived Severity (PS)

Perceived Severity refers to the degree of physical harm that may arise from unhealthy behaviour [18]. Several studies showed that users are more likely to adopt health technology when the threat to their health is severe [14, 26]. However, PMT also defines the threat severity perception as the ability to influence the strength of the response to the health threat. For example, in medical practice, if someone suffers a heart attack, they are aware of the probability of it being followed by another. When the patient goes home and understands the possible consequence, their fear of a severity of the threat increases. This causes an emotional response to the threat. In the context of our study, when the perception of the severity of suffering another heart attack is high, it decreases their confidence in the WTD and their own ability to use the WTD successfully to address the threat [17]. Accordingly, we hypothesize:

H4a: Perceived severity will negatively influence perception of response efficacy.
H4b: Perceived severity will negatively influence perception of self- efficacy

2.1.5 Response Cost (RC)

Response cost refers to the extent to which individuals have adequate resources to perform a behaviour. Within the context of our research, response cost is associated with external resources such as money, time and effort, that are required in order to use WTDs. If a significant amount of money must be spent or it takes a large effort to learn to use the technology (these are examples of high response costs), individuals might be reluctant to use the technology, indicating a negative relationship between response cost and behavioural intention [18]. Hence, we hypothesize:

H5: Response Cost is negatively associated with intention to use wearable devices

2.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

Previous studies of technology acceptance in healthcare have built upon technology acceptance theories, such as the Unified Theory of Acceptance and Use of Technology (UTAUT) [26–29]. Studies in the past have investigated the professionals' technology acceptance rather than the patients' technology acceptance [14]. One of the interesting findings of these studies is that while they did find performance expectancy and facilitating conditions to have significant impact on IT use, effort expectancy and social influence were not significant [26, 30]. Therefore, further investigation is needed in the context of technology acceptance in healthcare.

In addition to using PMT to understand user behavioural intention of a health technology, we have also included constructs from UTAUT [15]. UTAUT is a widely used theory to explain technology acceptance [15, 26, 31]. In UTAUT, Venkatesh et al. (2003) [15] evaluated the most common adoption technology theories and proposed the Unified Theory of Acceptance and Use of Technology (UTAUT) by integrating elements from eight major user acceptance models. UTAUT has four key constructs that determine technology intention and behaviour usage. These are: performance expectancy, effort expectancy, social influence and facilitating conditions. From a number of empirical tests of UTAUT, the theory explained approximately 70% of the variance in behavioural intention and 50% in actual use of the technology [16].

We have extended our theoretical foundation of PMT with UTAUT because the model is easily extended, scales are readily available from extant literature and its core constructs have been validated across different disciplines, including HIT.

2.2.1 Performance Expectancy (PE)

Performance expectancy is defined as the degree to which an individual believes that using the system will help him or her attain gains in job performance" [15]. In the context of our research, where wearable technology is the technology of interest, its effectiveness is captured by the extent to which it can help users reduce the health-related threat, and hence Response Efficacy in PMT is s a proxy for PE [14, 26]. Therefore, we exclude the

Performance Expectancy construct from our model and substitute it with Response Efficacy from PMT.

2.2.2 Effort Expectancy (EE)

Venkatesh et al., (2003) [15] described effort expectancy as users' opinions of the level of ease related to the use of technology. Previous studies indicated a small significance of EE on intention to use [32]. WTD do not come with clear instructions on how to use the technology, and therefore their design should be easy to use. Hence, we hypothesize:

H6: Effort expectancy is positively associated with intention to use wearable devices.

2.2.3 Social Influence (SI)

Social influence is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" p. 451 [15]. Previous studies on professionals' health technology acceptance behaviour found that social influence is not significant in intended behaviour of users [33]. However, other studies of technology adoption in healthcare using UTAUT demonstrated that social influence is a significant factor to adoption intention [14, 26]. In the context of WTDs, individuals tend to make their decision based on the opinion and suggestions of others, since this is still a fairly new technology. We therefore hypothesize:

H7: Social influence is positively associated with intention to use a wearable device

2.2.4 Facilitating Conditions (FC)

According to UTAUT, facilitating conditions are derived from two sources: external and internal [15]. External control refers to the extent to which individuals believe that necessary resources are in place to perform an action, while internal control refers to their assessment of their own abilities to perform the action [26, 34].

In the context of this study, response cost (a construct previously described in PMT) is associated with external control because it describes the resources (such as monetary and effort) that are require in order to learn to use WTDs. Self-efficacy (another construct from PMT previously described) is associated with internal control because it refers to an individual's ability to learn to use WTDs.

Following the framework of UTAUT [15], facilitating conditions can be interpreted with self-efficacy and response cost [26]. Hence, we drop FC from our model and replace it with response cost and self-efficacy. This elimination and replacement of constructs have been confirmed in several HIT adoption studies [14, 26].

2.3 Personalization

New personalization technologies and applications are becoming increasingly popular [35]. Personalization involves customizing the feedback context to each of the user's needs. Personalization exists in many fields and has been previously defined in the literature [36]. Sun et al. (2015) [26] has defined personalization as delivering "the right content to the right person in the right format at the right time". In the context of WTDs, personalization is the delivery of appropriate health services for specific health conditions and preferences via a WTD. Park [13] identified that personalization increases adoption and continued use of IT. WTD's personalized services can efficiently increase effectiveness of the interaction of WTD provider, and hence could lead to higher satisfaction among users, and have a positive relationship with intention to use. We therefore hypothesize:

H8: Personalization positively affects intention to use a wearable device

3 Research Model

The research model is shown in Fig. 2.

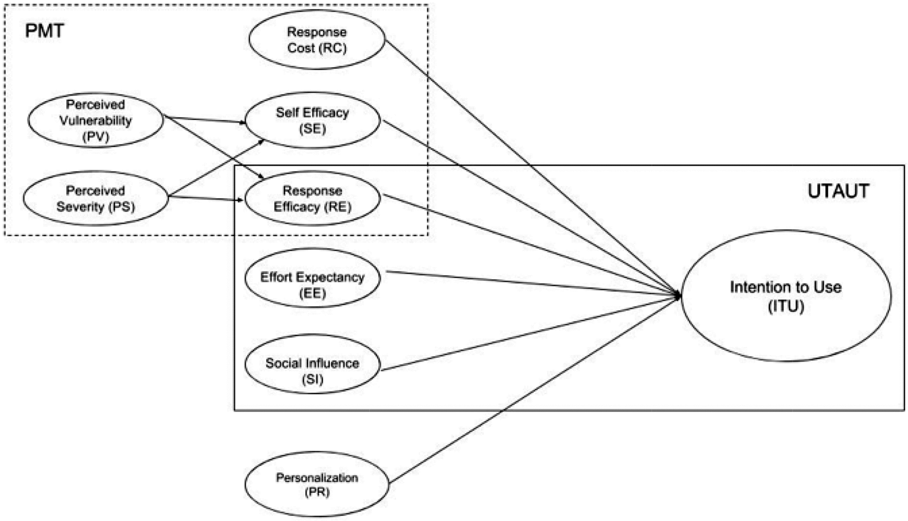

Fig. 2. Research model

4 Methodology

An online survey of the general public in United States of America was used as an instrument to gather the data. Items were measured on seven-point Likert scales with 1 being "strongly agree" and 7 being "strongly disagree". Initial consultation was done with survey experts to examine the logical consistency, contextual relevance, and question clarity of the measurements. The suggestions were incorporated into the next version of the questionnaire. In addition, a pilot study with 20 participants was conducted to collect more feedback to further improve the questionnaire. The comments and suggestions from participants were incorporated via minor modifications of the measurements, such as formatting of the questionnaire and clarity of the items. The main study was then launched after finalizing the questionnaire. The survey was sent to 239 participants, utilizing the service of an organization that offers an incentive to individuals who are willing to respond to questionnaires.

The statistical tool was PLS, which was selected for the development of a new theory. PLS is a suitable software for prediction and building theory [37]. PLS is used widely in the MIS field. SmartPLS was selected to analyze the data and provide various reports that tests the measurements of the model and the structural model in this study.

The structural model was tested via PLS algorithm that calculated the path coefficients and R^2 for the endogenous variables. The bootstrapping was used to calculate the t-values for this research by setting it to sample 5000.

5 Results

5.1 Descriptive Statistics

The survey was sent to 239 participants. Analysis was conducted on 141 responses (59.0%) that were completed. 49.6% were male and 50.3% were female. Average age was 48, oldest 77, while youngest was 18.

5.2 The Measurement Model

The outer loading for each construct was calculated through the SmartPLS algorithm. All indicators were convergent, as their correlation coefficients were greater than 0.708 [38].

The internal consistency of the model was confirmed by SmartPLS where Cronbach's alpha was greater than 0.8 [39]. Average Variance Extracted (AVE) was greater than 0.5 and Composite Reliability was greater than 0.6 [38].

Fornell Larckler scores [40] were also prepared by SmartPLS and the resulting table showed that the square root of AVE was greater than the correlation coefficient.

5.3 The Structural Model

The coefficient of determination, R^2 is the portion of the variance of the dependent variable that is explained by the independent variables. The intention to use, $R^2 = 0.784$, which is considered moderate [41].

For each path in the model, the t-values were calculated by bootstrapping with 5000 samples. A number of independent variables did not have a significant influence on intention to use: Perceived Severity, Response Cost, and Self Efficacy. All other hypotheses were supported with $p < 0.05$, and $p < 0.01$.

The effect size of each variable is measured by f-squared. Each construct is removed from the model and the change in R^2 is calculated. The value of f^2 is:

$$F^2 = (R^2\,\text{included} - R^2\,\text{excluded})/R^2\,\text{included}$$

where R^2 included is all constructs and R^2 excluded is when the selected construct is removed from the model.

The effect size is considered small if it is between 0.02 and 0.14, medium if it is between 0.15 and 0.34 and large if it is 0.35 and over [42]. Table 1 shows the effect size.

Table 1. Effect size.

Construct	Dependent variable	f^2	Effect size
Effort expectancy	Intention to use	0.038	Small
Perceived vulnerability	Response efficacy	0.100	Small
Perceived vulnerability	Self-efficacy	0.091	Small
Personalization	Intention to use	0.027	Small
Response efficacy	Intention to use	0.237	Medium
Social influence	Intention to use	0.391	Large

5.4 Wearable Technology Device Functions

The survey also provided a list of functions that could be useful for wearable technology devices. The most popular function was to record number of steps, track fitness activities, and recording of calorie burn. See Table 2.

Table 2. Wearable technology device functions ranked.

Function	Rank
Record number of steps	1
Track fitness activities	2
Record calorie burn	3
Monitor my heart rate	4
Track sleeping pattern/quality of sleep	5
Record change in behaviour/movement to monitor disease	6
Record my moods	7

5.5 Summary of Results

Six of the 10 hypotheses were supported. Table 3 shows the results.

Table 3. Summary of results

No.	Construct	Path coeff.	t-statistic	P value	Supported
1.	RE → ITU	0.370	4.982	0.000	$p < 0.01$
2.	SE → ITU	−0.010	0.117	0.907	
3a.	PV → RE	0.411	3.536	0.000	$p < 0.01$
3b.	PV → SE	0.418	3.067	0.002	$p < 0.05$
4a.	PS → RE	0.126	0.999	0.318	
4b.	PS → SE	−0.023	0.159	0.876	
5.	RC → ITU	−0.062	1.225	0.221	
6.	EE → ITU	0.135	1.895	0.047	$p < 0.05$
7.	SI → ITU	0.455	6.567	0.000	$p < 0.01$
8.	PR → ITU	0.117	1.955	0.051	$p = 0.051$

6 Discussion

Social influence was one of the main factors that influenced individual's intention to use WTDs to monitor their health. Individual's value the opinion of others in adoption of health information technology. In addition effort expectancy was significant. These results suggest that social influence and effort expectancy should be considered when investigating health technology acceptance. PMT assumes that people base their decision on their own evaluations, but the theory does not take into account that people might be influenced by others in their social circle, such as family members and friends. For example, Fitbit is successful partly because they encourage their users to compete against each other and share their fitness results online [4], hence influencing others to purchase the technology in order to participate with friends.

Because this technology is a protective technology, family members might influence those that are vulnerable to health threats, because of their unhealthy lifestyle (e.g. smoking). Since social influence can positively affect user behavior, companies should carry out certain promotion strategies to obtain more users through social influence (for example, through word of mouth). Another way to attract new users is through healthcare providers, as they have direct access to patients and can recommend WTDs and specific apps.

Response efficacy is a significant factor ($P < 0.01$). This is one of the important factors when deciding to use the technology, as users must feel confident in the effectiveness of the WTDs in preventing risks to their health. They must be confident that the technology is reliable and will function as designed.

In our study, self-efficacy was not significant, but effort expectancy was. WTDs are designed to be easy to use, and can be learned quickly. Perhaps because of the wide availability of apps in general, users are confident of their ability to use them and hence self-efficacy is a non-significant factor. However, given the significance of ease of use, companies should reinforce the simplicity of the apps. Simple instructions and online tutorials could make users aware of all the extra functions that WTDs offer. If the app has shortcuts and has valuable functionality, users will engage with the technology for a longer period of time.

The results of the structural model analysis confirm the negative relationships between perceived vulnerability on response efficacy ($p < 0.01$) and self-efficacy ($p < 0.05$). H3a and H3b are supported as perceived vulnerability has a significant effect on both perceptions of response efficacy and self-efficacy. These results are consistent with the Fear Appeals Model (FAM) [17]. In the context of health care, when users perceive that the probability of a threat (eg. suffering a heart attack) is high, their fear also increases. They might have experienced similar threats (eg. a previous heart attack) or they are might have knowledge of these threats (eg. family history of heart attacks). They are then influenced by their perceived probability of the outcome (eg. death or paralysis). Therefore, the perception of the WDTs to function effectively decreases. The perception of using the technology correctly also decreases. Users might experience fear or panic and loss of confidence that they can correctly use the technology and they may perceive that the technology has lost the potential to protect them from threats or their fears. Understanding this, practitioners need to emphasize that WTDs have the potential to save lives by identifying the symptoms early enough through data collection.

The results also indicate that the relationships between perceived severity and response efficacy and that of self-efficacy are not significant, thereby confirming that H4a and H4b are unsupported ($p > 0.05$). These results are inconsistent with FAM [17], but are consistent with previous PMT studies. FAM predicts that when individual's perceived severity is high, their confidence in using the technology decreases. However, this prediction is unsupported. An individual suffering from a preexisting health condition, such as heart condition, if they perceive that the threat to their health is severe (eg. previous heart attack), they are more likely to use WTDs to protect their health from malicious consequences. In order to keep consumers using WTDs providers should emphasize that the technology has capabilities to manage their disease or condition long term.

Personalization was also a significant influencing factor ($p = 0.05$). WTD users receive personalized feedback based on the data that they collect. This personalization might be related to response efficacy of the technology as individuals expect the technology to function effectively. For example, individuals that previously suffered a heart attack or those that use WTDs to record their vital signs to manage their disease expect reliable information based on their personal data. Personalization might be a factor for consumers who identify themselves as the qualified-self (QS) and use personalized feedback to better monitor their health. Healthcare providers might be successful in identifying these individuals and could recommend health apps based on their health needs.

Response Cost had no significance on intention to use ($p > 0.05$). Price, time and effort spent on using WTDs were not an issue for the participants. We predicted that if individuals must spend significant amount of money for the service or effort to learn to use the technology or the app, they might be reluctant to use WTDs. However, neither money nor effort were significant factors in decision making among consumers. Perhaps people believe if it is more expensive, then it must be better. Companies such as Apple and Fitbit, who sell WTDs in the higher price bracket, are still growing in the wearable sector.

7 Limitations and Future Research

We used the services of a professional research organization that recruits individuals who like to respond to survey questionnaires in return for a monetary reward. This does not represent a general population. Since WTD adoption is still in the early stage, the survey respondents are likely to be early adopters who are more self-motivated to purchase and experiment with this technology than are mainstream consumers. A further limitation is that the survey was only sent to United States consumers and therefore reflects their experience with the technology and excludes opinions of Canadian and Mexican markets, which would be a greater representation of North American markets. This research did not consider the potential influence of technology adoption among different cultures. Hence, testing whether the provided relationships are still held in other countries is necessary. Future researchers could extend this study by conducting a comparison of consumer acceptance between different cultures of different countries.

8 Conclusion

As the adoption of wearable technology devices is increasing, so does the abandonment of these devices. More people are monitoring their health with the use of technology in order to stay healthy or to manage disease. Today, software platforms, such as Apple's CareKit, are trying to close the gap between everyday wearables and the use of wearables in healthcare. This study provides an understanding of users' intentions to use of wearable technology in a healthcare setting.

Our study has contributed to the evaluation of PMT and UTAUT within a specific context, namely the use of WTDs. From a survey of 142 participants, our results indicate that in the current wearable device market, users are more affected by social influence and response efficacy when they decide to use a WTD to manage their health. It is also noted that in threat appraisals, perceived vulnerability has an effect on response efficacy and self-efficacy, while perceived severity showed to be not significant. The approach is applicable to adoption and intent to use of other health information technologies and we suggest that future researchers do a culture comparative study on adoption of WTDs.

For researchers, our study provides evidence that PMT as a foundation theory may be a valuable tool for understanding and explaining why individuals do or do not use protective technologies such as WTDs in the context of healthcare.

Practitioners should ensure that WTDs have useful functions to protect vulnerable users against health threats. Consumers also highly value the opinion of others, and perhaps look to their loved ones or their healthcare providers for advice.

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