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Abstract

Purpose – The purpose of this paper is to investigate the factors associated with consumer's intention to adopt wearable technology in healthcare, and to examine the moderating effects of product type on consumer's adoption intention.

Design/methodology/approach – An integrated acceptance model was developed based on unified theory of acceptance and use of technology 2 (UTAUT2), protection motivation theory (PMT), and privacy calculus theory. The model was tested with 462 respondents using a survey.

Findings – Consumer's decision to adopt healthcare wearable technology is affected by factors from technology, health, and privacy perspectives. Specially, fitness device users care more about hedonic motivation, functional congruence, social influence, perceived privacy risk, and perceived vulnerability, but medical device users pay more attention to perceived expectancy, self-efficacy, effort expectancy, and perceived severity.

Originality/value – This study is among the first to investigate healthcare wearable device from behavioral perspective. It also helps to comprehensively understand emerging health information technology (HIT) acceptance from technology, health, and privacy perspectives.

Keywords Healthcare, Wearable technology, Adoption intention, Fitness wearable device, Medical wearable device

Paper type Research paper

1. Introduction

The electronic technology that is incorporated into accessories that can be directly worn on the body is widely known as wearable technology (Tehrani *et al.*, 2014). According to Analysis Mason[1], the wearable device market will generate $22.9 billion in revenue by 2020. The market is predicted to grow at a CAGR of 50 percent between the years of 2014 and 2020. The popularity of wearable technology not only can promote physiolytics efficiency by linking them with data analytics (Wolff, 2013), but also can provide more opportunities for back-end players such as App developers (Maisto, 2013).

Recently, a large number of wearable devices, ranging from smart glass such as Google glass, smart watch including Geak Watch, iWatch, and Samsung Galaxy Gear, to smart bracelet such as Jawbone, Fitbit, and Goodon, etc., are available for public users. Wearable devices are primarily used in the field of military technology (Tehrani *et al.*, 2014). However, they are more like fashionable accessories in the early stage for

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the public. Up to now, the largest application of wearable devices is in the healthcare and medicine fields as wearable technology exhibits natural advantages in healthcare field (Chan *et al.*, 2012). The healthcare data can be continuously collected and transformed since users generally wear the device 24 hours a day. In addition, depending on the capacities on providing unseen scanning and sensory features, wearable devices have potentials to improve the quality of patients' healthcare seeking and doctor-patient communications (Maisto, 2013).

There are two main kinds of healthcare wearable devices in the current market. The first is fitness wearable devices, which help users to track and monitor their daily fitness conditions such as steps, distance, calories burned, sleep, and diet. These fitness wearable devices such as Fitbit, Jawbone, and 360 Kids Guardian, are more suitable for the young and the healthy users. On the contrary, medical wearable devices are more likely to be adopted by the elder and the unhealthy users. Wearable medical devices are generally designed for certain disease such as diabetes and cancer. Various firms, including Google, Apple, and Samsung, etc., are making efforts on researching various kinds of medical wearable devices. For instance, although Google has several patents of medical wearable devices, it still researches other related technologies like genetic testing. Apple has shown interest in researching medical sensor-laden devices that can analyze glucose levels via a person's tear. In addition, Samsung have announced a project joint with medical professionals to create new medical sensors at the University of California, San Francisco.

In addition to develop these amazing technologies, how to attract and keep their users is also an important issue for business managers. However, pioneering extant studies about user's adoption of healthcare wearable devices just have conceptually stated some critical factors or empirically examined a limited number of important roles from technology perspective (Claes *et al.*, 2015; Steele *et al.*, 2009; Fraile *et al.*, 2010). An integrated framework that can comprehensively explain individual's adoption of wearable device in healthcare is needed. Thus, we are going to fill this research gap by proposing and validating an integrative model to explain individual's adoption of healthcare wearable device from multiple perspectives. Since healthcare wearable devices continuously collect user's personal health information in real time, and individual's personal health information is more sensitive than other types of information such as demographic and general transaction information (Bansal *et al.*, 2010), healthcare wearable devices should not only be treated as an application of emerging technology in healthcare, but also should be regarded as a high privacy concern product. Therefore, we develop an integrative framework that consists of technology, healthcare, and privacy perspectives to examine user's decisions to adopt healthcare wearable devices. Furthermore, given that fitness and medical wearable devices have different targeted user groups and functions, we also investigate the moderating effect of product type on consumer's adoption intention.

The proposed model was tested by analyzing data collected from 462 respondents through a survey conducted at three large social network groups related to healthcare wearable devices. Most hypotheses were validated by the empirical data. This study is believed to present both theoretical and practical contributions. Theoretically, by developing and validating an integrated framework that consists of technology acceptance, health behavior, and privacy context, this study not only provides a more comprehensive understanding of consumer's acceptance of healthcare wearable device, but also has potentials to provide theoretical foundations for future healthcare wearable device adoption research. Practically, both wearable device managers and

social planners are guided by this study to conduct better strategies or policies to promote wearable technology adoption in healthcare sector.

The remainder of this paper is organized as follows. The next section reviews some related literatures about healthcare wearable devices and health information technology (HIT) acceptance. The integrated research model and hypotheses are provided in Section 3, which is followed by the research methodology in Section 4. Section 5 shows the data analysis and results of this study. Finally, we show the conclusions, implications, limitations, and future research in Section 6.

2. Literature review

This research is mostly related to extant studies that investigated user's acceptance of healthcare wearable devices. Extant literatures proved that users usually exhibit positive attitude toward the product of healthcare wearable devices (Steele *et al.*, 2009; Fraile *et al.*, 2010). Specially, Hensel *et al.* (2006) demonstrated that perceived ease of use is more important in determining consumer's adoption of healthcare wearable devices. Claes *et al.* (2015) claimed that elder users' purposes of adopting healthcare wearable devices is to independently and safely live at home for a long time. However, these studies only have conceptually stated the factors that would affect individual's adoption of healthcare wearable devices or just empirically examined a limited number of critical factors from technology perspective. An integrated framework to explain individual's adoption of healthcare wearable devices has not been merged and validated. Therefore, we are going to empirically examine consumer's adoption of wearable technology in healthcare from multiple perspectives. We hope to provide theoretical foundations for future healthcare wearable devices adoption research.

Given that healthcare wearable device is a kind of HIT product, we believe that extant literatures about HIT adoption would provide theoretical foundation for this work. Extant related studies have investigated consumer's acceptance of different kinds of HIT such as clinical decision support systems (Johnson *et al.*, 2014), mobile health services (Wu *et al.*, 2011; Sun *et al.*, 2013), electronic health record (Angst and Agarwal, 2009; Maillet *et al.*, 2015), and biometrics (Miltgen *et al.*, 2013). Most of these studies have investigated the adoption issue from technology perspective (Hung *et al.*, 2014; Johnson *et al.*, 2014; Wu *et al.*, 2011) by applying the main technology acceptance models such as technology acceptance model (TAM), theory of planned behavior (TPB), and unified theory of acceptance and use of technology (UTAUT). Besides, there are also some studies try to explain individual's adoption of HIT from healthcare perspective (Mishra *et al.*, 2012) by revising the health behavior models such as protection motivation theory (PMT), health behavior model (HBM), and subjective expected utility theory (SEU). Different from these two main perspectives, the factors from privacy perspective are also examined in prior studies (Angst and Agarwal, 2009; Li *et al.*, 2014). However, some researchers also argue that explaining user's HIT acceptance from single perspective cannot provide a comprehensive way to understand this complicated issue. Thus, Miltgen *et al.* (2013) developed a framework to investigate user's acceptance of biometrics by integrating technology acceptance theories with privacy context. Sun *et al.* (2013) studied the adoption of mobile health services by integrating technology acceptance theories (TAM, TPB, and UTAUT) and health behavior model (PMT).

Given that healthcare wearable device is an application of emerging technology in healthcare, both technological and healthcare factors are expected to significantly affect individual's adoption decision. In addition, potential consumers would also exhibit a high

level of privacy concern as healthcare wearable devices collect user's personal healthcare data in real time. Therefore, we are going to develop an integrated framework that consists of technology acceptance, health behavior, and privacy context to explain consumer's acceptance of healthcare wearable devices. This study not only has potentials to provide theoretical foundation for future healthcare wearable device adoption research, but also supplies a holistic picture to understand consumer's adoption intention toward emerging HIT.

3. Model development and hypothesis

To comprehensively understand consumer's adoption of healthcare wearable devices, we developed an integrated framework that combines technology acceptance, health behavior, and privacy calculus theories. We choose unified theory of acceptance and use of technology 2 (UTAUT2), PMT, and privacy calculus theories as the theoretical foundations of our proposed model. Considering the specific attributes of healthcare wearable devices, we propose our research model as shown in Figure 1. The reasons why we choose these theories and why we make these hypotheses are given in the following space.

3.1 Technology perspective

Among all technology acceptance models, UTAUT2 is the most comprehensive one to explain consumer's technology acceptance and use (Wong *et al.*, 2014). UTAUT2 has seven direct factors that affect consumer's intention to adopt the new technology,

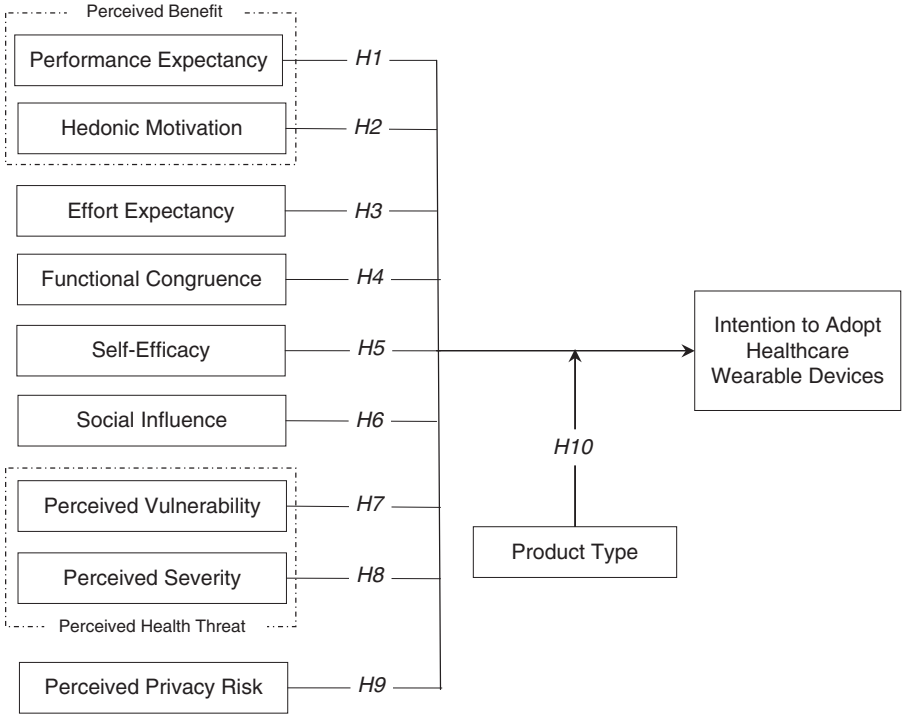

Figure 1.
The conceptual model

including performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit (Venkatesh *et al.*, 2012). We employ this framework to investigate user's adoption of wearable technology in healthcare from technology perspective. Given that healthcare wearable device consumers have not formed any habit related it as it still at its very early stage (Wei, 2014), we remove the factor of habit from the framework. The detail explanations of these factors are given as follows.

Performance expectancy is defined as the degree to which adopting a technology will bring effectiveness to users in performing certain activities (Venkatesh *et al.*, 2003, 2012). In the context of healthcare wearable devices, the effectiveness can be regarded as the degree to which the device can help consumers to monitor daily physical conditions, make personal healthcare plans, and reduce health-related threat, etc. This term of perceived expectancy also can be treated as response efficacy in PMT theory (Sun *et al.*, 2013) and perceived benefit in privacy calculus theory (Sharma and Crossler, 2014). When consumers believe that adopting healthcare wearable devices can enable them to increase these kinds of healthcare effectiveness, they are more likely to adopt the technology. This positive relationship is widely supported in UTAUT2 (Venkatesh *et al.*, 2012), PMT (Rogers, 1975), and privacy calculus model (Dinev and Hart, 2006). Therefore, we hypothesize that:

H1. Performance expectancy is positively associated with individual's intention to adopt healthcare wearable devices.

Another important factor in UTAUT2 is hedonic motivation, which refers to the pleasure or enjoyment derived from adopting and using a technology (Venkatesh *et al.*, 2012). Prior studies have shown the importance of hedonic motivation in determining individual's acceptance of a technology (Brown and Venkatesh, 2005). According to the summary of Venkatesh *et al.* (2012), hedonic motivation (also known as perceived enjoyment) directly affects individual's technology adoption intention in different contexts. Specially, in healthcare wearable device context, individuals would pay more attention to the enjoyment of the products since wearable device is different from other types of health IT products in terms of usage methods and functions. Users can directly wear the sensor and continuously check physical conditions such as sleep and diet (Wei, 2014). These attributes let wearable devices like a special "toy" more than just a healthcare device. Therefore, we make the hypothesis that:

H2. Hedonic motivation positively affects individual's intention to adopt healthcare wearable devices.

Effort expectancy is widely known as the degree of ease related to consumer's use of technology (Venkatesh *et al.*, 2012). In healthcare wearable device context, effort expectancy is introduced to measure consumer's perceived ease of using wearable devices in healthcare. Most recent related studies claimed that the new technology's ease of use are no longer the barriers of modern user's acceptance of technology since they usually have enough computer experience and technology ability (Wang *et al.*, 2014). However, in healthcare wearable device context, some studies also prove that effort expectancy positively affects consumer's intention to adopt wearable technology in healthcare (Hensel *et al.*, 2006). Other than other emerging technologies, the operations of healthcare wearable devices are generally more complicated, since they require users to continuously wear them and use other devices such as mobile phone at the same time.

Thus, effort expectancy is expected to positively influence consumer's adoption intention toward wearable devices in healthcare. We therefore hypothesize that:

H3. Effort expectancy is positively related to individual's intention to adopt healthcare wearable devices.

In UTAUT2, the factor of price value is developed to represent consumers' cognitive tradeoff between the perceived benefits and the monetary cost as consumers usually have to bear the cost of adopting a technology (Venkatesh *et al.*, 2012). This factor measures a dimension of quality that can be observed or experienced by consumers before purchase the products. Given that wearable device is generally combined by a physical sensor and an incorporated software (Wei, 2014), and users are required to wear the sensor 24 hours a day so that to monitor personal physical conditions in real-time (Tehrani *et al.*, 2014), the ergonomic design (i.e. material, buttery, and comfort) issue is more important for healthcare wearable devices than other technologies (Chan *et al.*, 2012). Thus, only the price reasonability is not enough to determine individual's observed quality. Hence, we introduce an integrated term of functional congruence, a factor adapted from self-congruency theory, to represent the perceived suitability of a product to fulfill the functional and basic product-related needs (Huber *et al.*, 2010). If consumers observe higher product quality in terms of comfort, buttery duration, and price reasonability (refers to functional congruence), they are more likely to purchase the healthcare wearable device. Therefore, we hypothesize that:

H4. Functional congruence has positive effect on individual's intention to adopt healthcare wearable devices.

In addition, the factor of facilitating conditions was developed to represent consumer's perceptions of necessary supports and resources available to perform the behavior in UTAUT2 (Venkatesh *et al.*, 2012). Different from UTAUT, UTAUT2 have theoretically hypothesized and tested the positive impacts of facilitating conditions on consumer's behavioral intention (Venkatesh *et al.*, 2012). In healthcare wearable device context, although users can personalize and self-monitor their physical conditions through the adoption of healthcare wearable devices, whether they have enough abilities and knowledge to enjoy these fantastic functions would challenge their possibilities of adopting the products. Thus, we introduce the factor of self-efficacy on self-monitoring and self-managing physical conditions (denote as self-efficacy) to measure the influence of consumers' capacities on effectively using the wearable device to self-monitor and self-manage their own physical conditions from facilitating conditions perspective. Extant studies have widely proved the positive impacts of self-efficacy on individual's adoption intention toward emerging technologies (Sun *et al.*, 2013; Johnston and Warkentin, 2010). In line with these studies, we also acknowledge that the consumer with higher level of self-efficacy is more likely to adopt wearable devices in healthcare. Therefore, we hypothesize that:

H5. Self-efficacy has positive influence on individual's intention to adopt healthcare wearable devices.

Furthermore, we also consider the effect of social influence on individual's adoption intention toward healthcare wearable devices. This relationship is also hypothesized and proved in UTAUT2 (Venkatesh *et al.*, 2012). Social influence refers to the extent to which user's decision making is influenced by others' perceptions (Venkatesh *et al.*, 2003; Sun *et al.*, 2013). Previous studies have empirically proved that social influence positively

affects individual's intention to adopt different kinds of HIT, such as biometrics (Miltgen *et al.*, 2013) and mobile health services (Sun *et al.*, 2013). In healthcare wearable device context, most users tend to make their adoption decisions reliant on others' suggestions since this kind of product is totally new for them. Therefore, we hypothesize that:

H6. Social influence is positively related to individual's intention to adopt healthcare wearable devices.

3.2 Healthcare perspective

In addition to technology acceptance of healthcare wearable devices, we also should add factors related to health behaviors to understand consumer's adoption intention (Sun *et al.*, 2013). Among all the theories that explain health behavior, PMT is regarded as a better theory than others (Prentice-Dunn and Rogers, 1986; Weinstein, 1993) to investigate individual's behaviors toward HIT. PMT considers two categories according to user's decision-making stages: first, the coping appraisal that includes response efficacy, response cost, and self-efficacy; and second, the threat appraisal that includes perceived vulnerability and perceived severity (Floyd *et al.*, 2000). According to Sun *et al.* (2013), response efficacy is reflected by perceived expectancy, and facilitating conditions can represent the response cost and self-efficacy. Since we have explained the expected effect of perceived expectancy on user's adoption of healthcare wearable device, we only need to add perceived vulnerability and perceived severity into our integrated model.

Perceived vulnerability refers to the possibility that one will experience health threat, while perceived severity represents the extant of threat from unhealthy behaviors (Rogers, 1975). Consumers are expected to adopt new HIT to reduce or avoid health threats when they are more likely to suffer the threat (Prentice-Dunn and Rogers, 1986). Prior related studies have empirically tested and proved the positive relationship between the health threat appraisal (that includes perceived vulnerability and perceived severity) and intention to adopt health technology (Sun *et al.*, 2013; Mishra *et al.*, 2012). Accordingly, we hypothesize that:

H7. Perceived vulnerability is positively associated with individual's intention to adopt healthcare wearable devices.

H8. Perceived severity has positive influence on individual's intention to adopt healthcare wearable devices.

3.3 Privacy perspective

Compared with other type of information such as demographic features and general transaction information, personal health information is more sensitive for individuals (Bansal *et al.*, 2010). Thus, considering the influences of privacy factors on consumer's acceptance of healthcare wearable device is necessary. Generally, individuals would perform risk-benefit analysis that accounts for drivers and inhibitors of information disclosure when they are requested to provide personal information to organizations, which is widely known as privacy calculus (Awad and Krishnan, 2006). Since HIT may aggravate individual's privacy concerns over the potential misuse of personal health information (Li *et al.*, 2014), consumers' decisions to adopt healthcare wearable technology would involve a highly salient privacy calculus in which users may face the tradeoff between perceived benefits and perceived privacy risks (Xu *et al.*, 2009). Thus, privacy calculus theory is more suitable to be merged in our theoretical framework.

When user's perception of benefit exceeds the privacy risk loss, he/she would choose to adopt healthcare wearable technology. Otherwise, the technology would not be accepted (Li *et al.*, 2014). Since the perceived benefit of adopting healthcare wearable device has been measured by perceived expectancy and hedonic motivation (Sharma and Crossler, 2014), we only need to consider the effect of perceived privacy risk in determining consumer's adoption intention. Consistent with prior studies about privacy calculus, we hypothesize that:

H9. Perceived privacy risk negatively affects individual's intention to adopt healthcare wearable devices.

3.4 The moderating effect of product type

Considering the differences of functions and targeted user groups between fitness and medical wearable devices, consumer's acceptance of various wearable devices would be differently affected by various antecedent factors. Fitness wearable device is designed for the young and the healthy users to monitor their daily fitness conditions such as steps, sleep, and diet (Chan *et al.*, 2012). Thus, consumers are more likely to have higher perceptions on the enjoyment, comfort, and buttery duration of the device. As for the health threat appraisal, the young and the healthy users would care more about the possibilities of health threat, since they pay more attention to prevention than the treatment of diseases. Therefore, we hypothesize that:

H10a. Hedonic motivation, functional congruence, and perceived vulnerability have stronger influences on individual's intention to adopt fitness wearable devices than medical devices.

On the contrary, medical wearable device is designed for the elder and the unhealthy users to monitor their physical conditions such as blood sugar and gene (Chan *et al.*, 2012). Medical device consumers thus should have more perceptions on the effectiveness and the perceived ease of use of the device. In addition, since this group of users laid more emphasis on the severity of health threat since most of them already have suffered certain disease, perceive severity is more important for medical wearable device user's adoption intention. Moreover, compared with personal fitness information, users usually are more sensitive on their personal medical information (Bansal *et al.*, 2010). Perceived privacy risk thus plays a more important role in determining consumer's acceptance of medical wearable devices. Furthermore, given that medical device users (generally the elderly and the unhealthy users) generally exhibits lower level of knowledge on technologies and self-monitoring, self-efficacy is expected to have more influence on consumer's intention to adopt medical wearable devices. Therefore, we make the hypothesis that:

H10b. Perceived expectancy, effort expectancy, self-efficacy, social influence, perceived severity, and perceived privacy risk have stronger influences on individual's intention to adopt medical wearable devices than fitness devices.

4. Research methodology

4.1 Item development

To test the hypothesized model, we conduct a survey that includes items for all constructs involved in the conceptual model. All items (see the Appendix) were adapted from previous published studies with minor modifications in wording to fit into healthcare

wearable device context. Each item was measured on five-point Likert scales with 1 being "strongly disagree" to 5 being "strongly agree." We have invited three professional researchers in management information systems (MIS) field to examine the logical consistency, terminology, contextual relevance, and question clarity of the measurements. In addition, a pilot study with 32 undergraduate and MBA students at MIS department was conducted for collecting more feedback to improve the questionnaire. The comments and suggestions from experts and the analysis of data collected from pilot study leads to some minor modifications of the measurements, including the formatting of the questionnaire, the clarity of the items, and the deletion of certainties. We launched the main study after finalizing the questionnaire.

4.2 Study design and procedure

The survey was administrated in three large social network groups associated with healthcare wearable devices. A document with description of the definition, sample products, and application in healthcare of both fitness and medical devices was first presented to each participant. To guarantee the respondents are the actual users of healthcare wearable devices and effectively divide them into two groups, the participants then were asked two questions: first, whether they have used wearable devices in healthcare, and second, which type of products have they used. We have totally distributed about 1,300 invitations, and 483 qualified participants were involved in the survey. Finally, a total of 462 usable responses (248 females and 214 males) were used in data analysis. The age of the participants ranges from 17 to 61 with an average of 32. In total, 83 percent of them have four or more years of internet experience. Our sample is expected to be representative for investing healthcare wearable technology adoption.

5. Data analysis and results

We employ a two-step approach (Anderson and Gerbing, 1988) to analysis the empirical data collected from the survey. We examined the measurement model at the first step, and the structural model was tested at step two. Considering the unique advantages of partial least square (PLS) method as indicated in prior studies (Xu *et al.*, 2011; Li *et al.*, 2014; Chan *et al.*, 2015), we employ PLS approach to analyze the research model in this study.

5.1 Measurement model

The quality of a measurement model is generally evaluated by its validity and reliability. We first examine the validity of the model, which includes the content validity and construct validity. Content validity measures the degree that how much the measurements can represent the corresponding construct (Dinev *et al.*, 2013). Our model is expected to show a satisfactory content validity, since all items were adapted from previous published works before an item-by-item review by related experts.

Construct validity is tested by examining the convergent validity and discriminant validity. The degree to which the measurements are related to the measured construct is known as convergent validity (Chan *et al.*, 2015). To achieve an acceptable convergent, each item's loading should be higher than 0.7, and its cross-loading should be lower than 0.3 (Dinev *et al.*, 2013). As shown in Table I, all values satisfy the requirement.

Discriminant validity refers to the extent to which the item does not reflect other constructs (Fornell and Larcker, 1981; Sharma and Crossler, 2014). Discriminant validity is examined by checking whether the square root of average variance

Constructs	Full ($n = 638$)	Fitness ($n = 341$)	Medical ($n = 297$)
Performance expectancy (PE)			
PE1	0.864	0.856	0.877
PE2	0.861	0.890	0.830
PE3	0.856	0.795	0.901
Hedonic motivation (HM)			
HM1	0.843	0.815	0.828
HM2	0.870	0.861	0.869
HM3	0.880	0.879	0.868
Effort expectancy (EE)			
EE1	0.876	0.896	0.854
EE2	0.850	0.899	0.823
EE3	0.862	0.818	0.906
Functional congruence (FC)			
FC1	0.862	0.823	0.894
FC2	0.893	0.886	0.896
FC3	0.806	0.811	0.783
Self-efficacy (SE)			
SE1	0.873	0.866	0.859
SE2	0.871	0.878	0.852
SE3	0.905	0.901	0.889
Social influence (SI)			
SI1	0.825	0.820	0.821
SI2	0.865	0.837	0.886
SI3	0.889	0.868	0.907
Perceived vulnerability (PV)			
PV1	0.862	0.806	0.906
PV2	0.835	0.837	0.856
PV3	0.858	0.885	0.826
Perceived severity (PS)			
PS1	0.826	0.835	0.816
PS2	0.856	0.814	0.886
PS3	0.874	0.880	0.846
Perceived pricy risk (PPR)			
PPR1	0.875	0.848	0.870
PPR2	0.867	0.821	0.908
PPR3	0.831	0.843	0.791
Behavioral intention (BI)			
BI1	0.825	0.826	0.808
BI2	0.817	0.766	0.830
BI3	0.839	0.804	0.846

Table I.
Loadings of measures in different samples

extracted (AVE) for each construct is higher than all the correlations between the construct and other constructs (Fornell and Larcker, 1981; Chan *et al.*, 2015). The results in Table II show that the discriminant validity of this model is satisfactory, since each construct's square root of AVE is greater than the correlations between the construct and the other constructs.

Table II.
Discriminant validity of constructs

	PE	HM	EE	FC	SE	SI	PV	PS	PPR	BI
Full sample ($n = 462$)										
PE	*0.860*									
HM	0.075	*0.864*								
EE	0.138	0.146	*0.863*							
FC	0.041	0.162	0.045	*0.854*						
SE	0.194	0.100	0.188	0.064	*0.883*					
SI	0.134	0.038	0.054	0.131	0.111	*0.860*				
PV	0.036	0.244	0.109	0.163	0.118	0.128	*0.852*			
PS	0.188	0.161	0.149	0.144	0.066	0.072	0.108	*0.852*		
PPR	0.042	−0.121	−0.031	0.002	0.044	0.126	−0.014	0.018	*0.858*	
BI	0.194	0.234	0.213	0.276	0.196	0.167	0.230	0.206	−0.164	*0.827*
Fitness sample ($n = 232$)										
PE	*0.848*									
HM	−0.051	*0.852*								
EE	0.148	0.171	*0.872*							
FC	0.056	0.145	0.000	*0.841*						
SE	0.182	0.083	0.120	0.063	*0.882*					
SI	0.161	−0.097	0.018	0.062	0.126	*0.842*				
PV	0.032	0.230	0.187	0.147	0.120	0.043	*0.843*			
PS	0.207	0.082	0.092	0.114	0.061	0.095	0.179	*0.843*		
PPR	−0.066	−0.314	−0.129	−0.116	−0.096	−0.054	−0.132	−0.085	*0.837*	
BI	0.149	0.376	0.175	0.252	0.333	0.073	0.287	0.123	−0.294	*0.799*
Medical sample ($n = 230$)										
PE	*0.870*									
HM	0.197	*0.855*								
EE	0.125	0.118	*0.862*							
FC	0.039	0.188	0.092	*0.859*						
SE	0.213	0.123	0.258	0.051	*0.867*					
SI	0.106	0.173	0.088	0.200	0.103	*0.872*				
PV	0.050	0.268	0.044	0.158	0.100	0.221	*0.863*			
PS	0.173	0.241	0.205	0.169	0.068	0.052	0.036	*0.850*		
PPR	0.139	0.068	0.059	0.108	0.175	0.295	0.099	0.115	*0.858*	
BI	0.244	0.092	0.256	0.290	0.058	0.263	0.163	0.285	−0.039	*0.828*

Note: The square root of AVE is denoted in italic

Then, we examine the reliability of the measurement model. Generally, it is determined by the values of Cronbach's α, composite reliability (CR), and AVE. To achieve a satisfactory reliability, Cronbach's α should be higher than 0.7, CR should be at least 0.6, and AVE should be no less than 0.6 (Hair *et al.*, 1998; Dinev *et al.*, 2006). Table III exhibits the results of reliability test, which indicates that all values are higher than the recommended thresholds. Put all these tests together, we conclude that the measurement model demonstrates satisfactory validity and reliability.

5.2 Hypothesis testing

We tested the structural model after assessing the quality of the measurement model so that to make adjustments about the hypotheses. We adopted the software of AMOS 6.0 to examine the degree to which the model can represent the empirical data. We summarize the indices of model fit for each sample as shown in Table IV. All indices in the table are within the commonly accepted thresholds. Thus, the model is reasonably fitted to the empirical data.

Construct	Cronbach's α	Composite reliability	AVE
Full sample ($n = 462$)			
Performance expectancy (PE)	0.844	0.8952	0.7402
Hedonic motivation (HM)	0.851	0.8987	0.7473
Effort expectancy (EE)	0.849	0.8972	0.7443
Functional congruence (FC)	0.836	0.8901	0.7300
Self-efficacy (SE)	0.839	0.9140	0.7799
Social influence (SI)	0.865	0.8949	0.7397
Perceived vulnerability (PV)	0.836	0.8880	0.7255
Perceived severity (PS)	0.834	0.8883	0.7263
Perceived pricy risk (PPR)	0.831	0.8931	0.7360
Behavioral intention (BI)	0.832	0.8665	0.6840
Fitness sample ($n = 232$)			
Performance expectancy (PE)	0.829	0.8845	0.7190
Hedonic motivation (HM)	0.855	0.8882	0.7261
Effort expectancy (EE)	0.852	0.9046	0.7600
Functional congruence (FC)	0.820	0.8783	0.7067
Self-efficacy (SE)	0.858	0.9129	0.7775
Social influence (SI)	0.814	0.8795	0.7088
Perceived vulnerability (PV)	0.822	0.8806	0.7111
Perceived severity (PS)	0.819	0.8808	0.7114
Perceived pricy risk (PPR)	0.817	0.8756	0.7013
Behavioral intention (BI)	0.825	0.8411	0.6385
Medical sample ($n = 230$)			
Performance expectancy (PE)	0.860	0.9031	0.7566
Hedonic motivation (HM)	0.850	0.8909	0.7314
Effort expectancy (EE)	0.852	0.8962	0.7425
Functional congruence (FC)	0.850	0.8940	0.7384
Self-efficacy (SE)	0.872	0.9006	0.7514
Social influence (SI)	0.858	0.9049	0.7606
Perceived vulnerability (PV)	0.845	0.8976	0.7453
Perceived severity (PS)	0.848	0.8862	0.7222
Perceived pricy risk (PPR)	0.851	0.8927	0.7357
Behavioral intention (BI)	0.838	0.8675	0.6858

Table III. The reliability of the measurement model

The results of hypothesis testing in each sample are shown in Table V. Almost all the hypothesized relationships are supported. For the full model, all the hypotheses from *H1* to *H9* are statistically supported. Among all factors that affect individual's intention to adopt healthcare wearable devices, social influence ($\beta = 0.171$, $p < 0.001$), and perceived privacy risk ($\beta = -0.215$, $p < 0.001$) are the most significant predictors. This result indicates that in current healthcare wearable device market, consumers are more affected by others' behaviors and privacy issues when they decide to adopt a proper device to manage their health conditions. In addition, effort expectancy ($\beta = 0.145$, $p < 0.005$), self-efficacy ($\beta = 0.125$, $p < 0.005$), perceived vulnerability ($\beta = 0.130$, $p < 0.005$), and perceived severity ($\beta = 0.116$, $p < 0.005$) also positively affect consumer's acceptance of wearable technology in healthcare. Furthermore, compared with these factors, the impacts of perceived expectancy ($\beta = 0.128$, $p < 0.01$), hedonic motivation ($\beta = 0.107$, $p < 0.01$), and functional congruence ($\beta = 0.122$, $p < 0.01$) are less significant. The intuition is that the whole group of potential users

Table IV.
The summary of model fit indices

Index	Observed value Full	Fitness	Medical	Recommended-value	References
χ^2/df	1.868	1.581	1.658	Less than 3	Fornell and Larcker (1981)
GFI	0.896	0.835	0.833	Greater than 0.80	Hair *et al.* (1998)
AGFI	0.878	0.806	0.804	Greater than 0.80	Hair *et al.* (1998)
NFI	0.890	0.827	0.836	Greater than 0.80	Fornell and Larcker (1981)
IFI	0.946	0.929	0.928	Greater than 0.90	Hair *et al.* (1998)
CFI	0.946	0.928	0.927	Greater than 0.90	Fornell and Larcker (1981)
RMSEA	0.043	0.050	0.054	Less than 0.08	Hair *et al.* (1998)

Table V.
The table summary

Path	Path coefficient Full	Fitness	Medical	Comparison (*t*-value) Fitness vs medical[a]
PE→BI	0.128*	0.086^{ns}	0.166***	−12.831***
HM→BI	0.107*	0.239***	0.098^{ns}	27.487***
EE→BI	0.145**	0.072^{ns}	0.169*	−16.814***
FC→BI	0.122*	0.314***	0.032^{ns}	44.805***
SE→BI	0.125**	0.031^{ns}	0.252***	−38.617***
SI→BI	0.171***	0.188**	0.138**	9.536***
PV→BI	0.130**	0.172*	0.116^{ns}	9.626***
PS→BI	0.116**	0.037^{ns}	0.222***	−35.187***
PPR→BI	−0.215***	−0.163*	−0.226**	9.974***

Notes: [a]The equation for *t*-value calculation is given as:

$$t = \frac{\beta_1 - \beta_2}{\sqrt{e_1^2 \cdot \frac{N_1 - 1}{N_1 + N_2 - 2} + e_2^2 \cdot \frac{N_2 - 1}{N_1 + N_2 - 2}} \cdot \sqrt{\frac{1}{N_1} + \frac{2}{N_2}}}$$

where β_i and e_i is the coefficient and standard error of each relationship in the structural model of group i, and N_i represents the sample size of data set for group i .*$p < 0.01$; **$p < 0.005$; ***$p < 0.001$; $^{ns}p > 0.01$ (ns)

cares less about the enjoyment, usefulness, and ergonomic design of healthcare wearable devices, since most devices in the current market does not exhibit high quality in terms of these aspects.

Then, we separately tested the fitness and medical subsample to investigate the moderating effect of product type. Within fitness subgroup, perceived expectancy, effort expectancy, self-efficacy, and perceived severity are no longer significant predictors for individual's adoption intention. Besides, although social influence, perceived vulnerability, and perceived privacy risk also have significant effects on individual's adoption intention, the relationships are not as strong as the results in full sample. In addition, the impacts of hedonic motivation and functional congruence are more significant than the corresponding results in the whole sample. Within medical subgroup, hedonic motivation, functional congruence, and perceived vulnerability do not exhibit significant impacts on individual's adoption intention. In addition, the influences of effort expectancy, perceived privacy risk, and social influence on individual's intention to adopt medical wearable devices are also less significant than the full sample. However, perceived expectancy, self-efficacy, and perceived severity has more significant influence on consumer's adoption intention.

Furthermore, *t*-tests were conducted to compare the results between fitness and medical wearable devices users. The results as shown in Table V indicate that there exist significant differences between the determinations of individual's intention to adopt fitness and medical wearable devices. Consistent with our predictions, potential fitness wearable device users pay more attention to hedonic motivation, functional congruence, and perceived vulnerability when they make decisions about whether to adopt the devices or not, while medical wearable device users lay more emphases on perceived expectancy, effort expectancy, self-efficacy, and perceived severity in their decisions to adopt the devices. However, fitness wearable devices users care more about social influence and perceived privacy risk than medical wearable devices consumers, which is different from our original hypothesis (i.e. *H10b*). The intuition is that the younger and the healthy users generally have more interests to purchase fitness wearable devices, and they care more about their social networks and privacy protection than the elder and the unhealthy consumers. Although this result not statistically supports the whole hypothesis of *H10*, the significant difference between the two groups of users is existed. Therefore, the moderating effects of product type on the hypothesized relationships are also proved.

6. Conclusions and discussions

Based on UTAUT2, PMT, and privacy calculus theory, this paper developed an integrative model that examines the antecedents of adoption intention toward healthcare wearable devices from technology, healthcare, and privacy perspectives. How these factors differently affect consumers' intention to adopt various kinds of healthcare wearable devices (i.e. fitness devices and medical devices) is also compared. The proposed conceptual model was empirically tested through a survey. The majority of the hypothesized relationships were supported by the data. To the best of our knowledge, this study is among the first to comprehensively investigate healthcare wearable technology issue from behavioral perspective, which has potentials to provide theoretical foundations for future research in this field. This research also helps to comprehensively understand consumer's acceptance of emerging HIT. Both business managers and social planners are guided by this study to conduct better policies and strategies to promote wearable technology adoption in healthcare.

This study has two main aspects of findings. First, our results show that all factors from technology acceptance, health behavior, and privacy context perspectives would significantly affect consumer's decision to adopt wearable technology in healthcare. Thus, we should pay attention to all these factors in each perspective when we design a specific healthcare wearable device. The other aspect of results deals with the difference between the acceptance of fitness and medical wearable devices. Our findings suggest that fitness wearable device users pay more attention to hedonic motivation, functional congruence, social influence, perceived privacy risk, and perceived vulnerability in their acceptance of wearable technology in healthcare, since they have more perceptions on the enjoyment, comfort, and pricing reasonability of the products. However, medical wearable device users care more about the factors such as perceived expectancy, effort expectancy, self-efficacy, and perceived severity when they decide to adopt a medical wearable device.

6.1 Theoretical implications

This study provides several theoretical implications for prior related literatures. First, this research is among the first to empirically investigate consumer's acceptance of wearable technology in healthcare. After observing the distinctive advantages of wearable technology in reducing healthcare cost and improving healthcare efficiency, extant related literatures have developed various kinds of specific wearable technologies to be applied in healthcare sector (Zheng *et al.*, 2014; Moran *et al.*, 2013). However, how to attract consumers to adopt these fantastic technologies is also crucial for information systems researchers. Pioneering studies about user's adoption of healthcare wearable devices just have conceptually stated some critical factors or empirically examined a limited number of important factors from technology perspective (Claes *et al.*, 2015; Steele *et al.*, 2009; Fraile *et al.*, 2010). Different from these works, this study comprehensively explores factors that affect consumer's intention to adopt wearable technology in healthcare from technology, healthcare, and privacy perspectives, which is expected to provide theoretical foundations for future emerging HIT (such as healthcare wearable devices) research from behavioral perspective.

In addition, a unified theory of individual's acceptance of emerging technologies in healthcare has been developed in this research. After reviewing a large number of literatures about HIT adoption and considering the unique characteristics of healthcare wearable devices, we merge three theoretical models to show how consumer's adoption intention toward healthcare wearable devices is affected. Compared with other HIT adoption references (Hung *et al.*, 2014; Johnson *et al.*, 2014; Sun *et al.*, 2013), it is believed that our integrated model will provide a more comprehensive understanding of consumer's decision to adopt emerging HIT. Our model indicates that further empirical studies about HIT adoption should consider factors from multiple perspectives such as technology, healthcare, and privacy perspectives, etc.

Furthermore, we highlight the differences between various groups (i.e. fitness and medical devices users) of consumers' acceptance of healthcare wearable devices, which overcomes the disadvantages of extant e-health behavioral studies that only focus on single type of products or consumers (Johnson *et al.*, 2014; Mishra *et al.*, 2012; Li *et al.*, 2014). Such kind of comparative study approach provides an excellent example (it also can be regarded as theoretical foundation in some degree) for future behavioral studies to investigate the differences between multiple groups of users in a unified framework.

6.2 Practical implications

Besides, this study also exhibits several practical implications. Both healthcare wearable devices managers and social planners are guided to conduct better strategies and policies to promote the adoption of wearable technology in healthcare. First, all the proposed factors from technology, healthcare, and privacy perspectives are proved to significantly affect consumer's intention to adopt wearable technology in healthcare. Managers and social planners thus should consider all these three aspects to increase the adoption of healthcare wearable devices. For instance, in order to promote the adoption of wearable devices in healthcare, managers and social planners not only should try to improve the usefulness, ease of use, functional congruence, and enjoyment of healthcare wearable devices, but also should consider consumer's healthcare behaviors and enhance privacy protection.

Second, the moderating effect product type (i.e. fitness wearable devices and medical wearable devices) on consumer's adoption intention toward healthcare wearable devices is significant. Hence, the product providers and social planners should lay emphasis on different aspects when managing various types of healthcare wearable devices. In detail, providers and social planners should pay more attention to the enjoyment and ergonomic design issues when researching or marketing fitness wearable devices. On the contrary, they should care more about the product's usefulness, consumer's self-efficacy on self-managing physical conditions, and consumer's perceived severity when managing the medical wearable devices.

6.3 Limitations and future research

Although this study provides several theoretical and practical contributions, there are still some limitations in this work. First of all, the empirical data used for hypothesis testing is collected at a single point in time. But retrospective analysis is more likely to be involved in the measurement of emerging HIT adoption. Thus, an alternative way to improve this study is to make a longitudinal investigation to obtain more convincing explanations about consumer's acceptance of healthcare wearable technology. Besides, the survey is only conducted in the country of China, which has not considered the potential influence of cultural and technological differences between different countries. Hence, testing whether the proved relationships are still held in other countries would be necessary. Another alternative way to extend this research is to conduct a comparative study of consumer's acceptance of healthcare wearable technology between countries with different form of cultures.

Note

1. The information was accessed on October 3, 2015 at www.analysysmason.com/Research/Content/Reports/Smart-wearables-forecast-Sep2014-RDMD0/

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Appendix. Measurement items

Performance expectancy (PE) adapted from Maillet *et al.* (2015)
- PE1: I find the healthcare wearable device useful in my daily life.
- PE2: using healthcare wearable device helps accomplish things more quickly.
- PE3: using healthcare wearable device improves the quality of my daily healthcare seeking.

Hedonic motivation (HM) adapted from Venkatesh *et al.* (2012)
- HM1: using healthcare wearable device is fun.
- HM2: using healthcare wearable device is enjoyable.
- HM3: using healthcare wearable device is entertaining.

Effort expectancy (EE) adapted from Venkatesh *et al.* (2012)
- EE1: learning how to use healthcare wearable device is easy for me.
- EE2: I find healthcare wearable device easy to use.
- EE3: It is easy for me to become skillful at using healthcare wearable devices.

Social influence (SI) adapted from Wu *et al.* (2011)
- SI1: people who are important to me would think that I should use healthcare wearable device.
- SI2: people who influence me would think that I should use healthcare wearable device.
- SI3: people whose opinions are valued to me would prefer that I should use healthcare wearable devices.

Functional congruence (FC) adapted from Huber *et al.* (2010)
- FC1: wearable devices are expected to be comfortable.
- FC2: wearable devices are expected to be fashionable.
- FC3: wearable devices are expected to be priced appropriately considering their quality.

Self-efficacy (SE) adapted from Sun *et al.* (2013)
- SE1: it is easy for me to self-monitor my physical conditions by using wearable devices.
- SE2: I have the capability to use wearable devices to self-monitor my physical conditions.
- SE3: I am able to use wearable devices to self-monitor my physical conditions without much effort.

Perceived vulnerability (PV) adapted from Sun *et al.* (2013)

Please answer the following questions in terms of these problems: having little knowledge about self-care; monitoring personal daily healthcare; and suffering medical diseases.
- PV1: I am at risk for suffering the stated problems.
- PV2: it is likely that I will suffer the stated problems.
- PV3: it is possible for me to suffer the stated problems.

Perceived severity (PS) adapted from Sun *et al.* (2013)

Please answer the following questions in terms of these problems: having little knowledge about self-care; monitoring personal daily healthcare; and suffering medical diseases.
- PS1: if I suffered the stated problems, it would be severe.
- PS2: if I suffered the stated problems, it would be serious.
- PS3: if I suffered the stated problems, it would be significant.

Perceived pricy risk (PPR) adapted from Li *et al.* (2014)

- PPR1: it would be risky to disclose my personal health information to vendors providing wearable devices.
- PPR2: there would be high potential for loss associated with disclosing my personal health information to vendors providing wearable devices.
- PPR3: there would be too much uncertainty associated with giving my personal health information to vendors providing wearable devices.

Behavioral intention (BI) adapted from Wixom and Todd (2005)

- BI1: I intend to use healthcare wearable device in the future.
- BI2: I intend to use healthcare wearable device at every opportunity in the future.
- BI3: I plan to increase my use of healthcare wearable device in the future.

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