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Health monitoring through wearable technologies for older adults: Smart wearables acceptance model

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ABSTRACT

In the context of a fast aging population, ubiquitous usage of smart wearable systems can alleviate the social burden caused by the increasing need of older adults for healthcare and assistance. To facilitate and encourage the use of smart wearable systems among older adults, this study investigated the factors that contribute to the acceptance of such systems, and smart wearables acceptance model for older adults was developed using structural equation modeling. The model was validated using 146 survey samples collected from adults aged 60 years and above. The results indicated that perceived usefulness, compatibility, facilitating conditions, and self-reported health status significantly and positively affect older adults' intention to use such technologies. Useful implications and insights were provided to future researchers and practitioners to enhance older adults' acceptance of smart wearable systems.

1. Introduction

The aging population entails an increasing need for healthcare and assistance through wearable health monitoring technologies to address impairments in cognitive ability, mobility, and psychosocial functioning of older adults (Erber, 2013; Chen and Chan, 2011). With the advent of a range of smart wearable systems, older adults are able to obtain immediate feedback on their vital signs, such as heart rate and blood pressure, thereby receiving real-time healthcare by transmitting physical condition data to a medical center through wireless sensor networks. As indicated by McCann et al. (2011), health technologies would provide older adults access to continuing healthcare. Wearable systems can be used at home, thereby reducing physical checkup cost and decreasing the risk of hospital admission. Therefore, facilitating the healthcare delivery process and mitigating the social burden by ubiquitous usage of smart wearable systems for older adults are critically important.

In a recent study by Abdullah et al. (2015), a patient monitoring system was designed for recording and notification of the vital signs of older adults, which enabled transmission of the physical signs to a remote clinic for possible diagnosis and rapid response by medical professionals. Services in e-health and telecare would enable older adults to connect to medical professionals or caregivers by accomplishing home-based healthcare, thereby reducing their back-and-forth travel costs (Murnane et al., 2016; Stowe and Harding, 2010; Niemela et al., 2007).

A smart wearable system supported by technologies, such as wireless sensor networks and electronic care surveillance devices, can be implemented by using sensors, actuators, and smart fabrics for health evaluation and decision support. Current applications of smart wearable systems mainly work in monitoring vital signs, body movement, location, and fall prevention (Li et al., 2016; Rosenbloom, 2016; Chan et al., 2012; Fraile et al., 2010). Table 1 shows the important physical signs that can be measured though smart wearable systems.

Several academic projects have developed a number of applications of smart wearable systems for health monitoring, including smart clothes, implantable devices, skin devices, and other wearable gadgets (Rault et al., 2017; Hakonen et al., 2015). For example, equipped with a wireless sensor network, a smart wearable device can be used to obtain ECG data, monitor current activity with a three-axis accelerometer sensor (Ehmen et al., 2012; Lee and Chung, 2009), and detect real-time human falls (Lin et al., 2007). However, despite the advancement of wearable systems, low-level acceptance of health technology by older adults was frequently reported in previous studies (Alaiad and Zhou, 2014; Postema et al., 2012; Liddy et al., 2008). Spagnolli et al. (2014) measured user acceptance for three devices separately, but research measuring elderly user acceptance for variety of health monitoring smart wearables as a whole is necessary even though acceptance for wearables, from simple to more complicated ones, might have some differences. User acceptance of smart wearables should be investigated

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Table 1
Vital physical signs measured by smart wearable systems.

Vital physical signs	Sensors	Observations
Electrocardiograph (ECG)	Skin electrodes	Heart rate, heart rate variability
Electroencephalogram (EEG)	Scalp-placed electrodes	Electrical activity of brain, brain potential
Electromyography (EMG)	Skin electrodes	Muscle activity
Blood pressure	Cuff pressure sensor	Status of cardiovascular system, Hypertension
Blood glucose	Glucose meter	Amount of glucose in blood
Galvanic skin response	Woven metal electrodes	Skin electrical conductivity
Respiration	Piezoelectric sensor	Breathing rate, physical activity, inspiration and expiration
Temperature	Temperature probe	Skin temperature, health state
Activity, mobility, and fall	Accelerometer	Body posture, limb movement

in depth to enable technology to serve older adults better. To date, few studies have specifically focused on the acceptance of smart wearable systems among older adults. This study aims to fill the research gap by understanding the attitudes of older adults toward wearable technologies and exploring influential factors that may contribute to the adoption of smart wearable systems. The findings will help to facilitate the ubiquitous use of smart wearable systems of older adults and then practically benefit older adults with complex needs.

2. Research model and hypotheses

With regard to technology adoption, Davis et al. (1989) developed the technology acceptance model (TAM), and Venkatesh et al. (2003) formulated the unified theory of acceptance and use of technology (UTAUT), which are widely used to understand organizational and individual adoption behaviors. TAM primarily confirmed the determinants of perceived usefulness and ease of use of computer systems within organizational settings; while UTAUT unified several previous models and theories, including TAM, and identified four determinants, i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions. UTAUT was tested with higher percentage of variance in intention explained than previous ones in organizational context. Chen and Chan (2014) developed the senior technology acceptance model, which examined the acceptance of gerontechnology from 4 domains, namely housing, communication, health, and education & recreation technologies. However, measurement items of health technology domain that their research covered mentioned no smart wearable health monitoring devices, leading to a lack of tailored factors for smart wearables acceptance study. Factors like attitude towards use in STAM were confirmed having non-significant influence on usage behavior, therefore those variables are not involved here. In the present study, factors concerning the uniqueness of smart wearables including compatibility, perceived social and performance risk, and health status, were considered to specifically predict the acceptance of smart wearable systems by older adults. The following section discusses potential influencing factors and corresponding hypotheses on smart wearable system acceptance.

2.1. Perceived ease of use, perceived usefulness, and intention to use

Perceived ease of use (PEOU) reflects the efforts that a participant demonstrates when trying to adopt smart wearable systems, while perceived usefulness (PU) reflects the benefits that a participant gains from using such systems. In addition, intention to use (IU) measures individual willingness to use the smart wearable systems. In previous technology acceptance models, PEOU and PU were widely adopted to predict technology adoption behaviors and assumed to exert significant effects on behavior intention (Yang et al., 2016; Park and Kim, 2012; Or et al., 2010; Ryu et al., 2009). Related to the present study, PEOU reflects the user's self-efficacy toward wearable health monitoring systems, whereas PU evaluates the benefits and values of using such systems. Moreover, IU directly reflects the intrinsic motivation of older adults to accept smart wearable systems. Thus, hypotheses related to PEOU, PU, and IU are developed as follows:

H1a–H1b. : PEOU has significant positive effects on PU and IU.

H2. PU has significant positive effects on IU.

2.2. Facilitating conditions

According to Venkatesh et al. (2003), facilitating conditions (FC) refer to the degree to which existing technical infrastructure and favorable conditions in the environment would motivate an individual to use information systems. Ma et al. (2016) pointed out that lack of access to information technology could be an explicit factor that affects the acceptance of smartphones for old adults. Additionally, Pan et al. (2010) concluded that FC for older adults also included the cost and availability of technical support.

With regard to smart wearable systems, the FC may be more important to predict IU considering that the systems may rely on the support of wireless networks from the community and network operators to transmit ubiquitous health monitoring data. Therefore, hypotheses related to FC in the smart wearables acceptance model (SWAM) are as follows:

H3a–H3c. FC has significant positive effects on customer PEOU, PU, and IU.

2.3. Compatibility

Compatibility (COM) refers to the degree to which a technology complies with the technical functionalities of other existing products (e.g., smartphones and tablets) and with the needs and lifestyles of users (Yang et al., 2016; Pagani, 2004). Compatibility was identified to significantly affect intention to use mobile learning and Web 2.0 services (Cheng, 2015; Corrocher, 2011). For smart wearable systems, technical compatibility with existing devices (e.g., smartphones, PCs, and wireless sensor network) is considered to measure the degree to which the monitored information can be transferred to remote devices. Besides, the compatibility with user lifestyle is posited to significantly affect adoption behaviors as well. Thus, the hypotheses related to COM are as follows:

H4a–H4c. COM has significant positive effects on PEOU, PU, and IU.

2.4. Social influence

Social influence (SI) refers to the degree to which family members or important peers believe that the participant should accept a technology (Or and Karsh, 2009; Venkatesh et al., 2003; Thompson et al., 1991). SI occurs when the emotions, opinions, and behaviors of an individual are affected by important persons such as family members and friends. In previous studies, SI was identified as a strong antecedent for intention to use of Internet and perceived usefulness of consumer health information technology (Chen and Chan, 2014; Pan and Maryalice, 2010; Or and Karsh, 2009). In terms of wearable health monitoring systems, SI measures the effects of important family members and peers, and commercial advertisements. Therefore, the following hypotheses are developed:

H5a–H5c. : SI has significant positive effects on customer PEOU, PU, and IU.

2.5. Perceived social risk and performance risk

Adopting smart wearable systems among older adults may lead to potential risks, such as perceived social risk (PSR) and performance risk (PR) (Chan et al., 2012; Fraile et al., 2010). PSR measures the degree to which health monitoring device users perceive stigmatization and humiliation by adopting smart wearable systems (Fensli et al., 2010). Perceived stigmatization might be a crucial issue because some users try to shield their health monitoring wireless sensors from being visible to others (Fensli and Boisen, 2008).

Considering that smart wearable health monitoring systems have not been widely accepted by older adults, such systems are likely to meet unanticipated risks. Therefore, PR refers to the degree to which users believe the technology may bring unanticipated risks, such as safety risk, functionality risk, and privacy violation (Chatterjee; Price, 2009). Specifically, PR may involve radiation, electric shock, or invasion when using smart wearable systems. Electronic circuits embedded in the wearable devices enable the system to perform minimally invasive diagnostic tests such as glucose level monitoring (Valdastri et al., 2004). However, these electronic circuits may lead to the concern for safety when elderly people use these wearable devices. Therefore, PSR and PR are considered as possible determinants that affect IU among older adults. The study posits the following hypotheses:

H6a–H6c. PSR negatively affects customer PEOU, PU, and IU.

H7a–H7c. PR negatively affects customer PEOU, PU, and IU.

2.6. Health conditions

Wearable systems help older adults maintain their health and safety. Self-reported health conditions (Health) reflects the current health status and conditions (e.g., hypertension, cardiovascular disease, and diabetes) and biophysical characteristics (e.g., visual and auditory ability, mobility, and cognitive ability) of respondents. Significant influence of health conditions on acceptance and usage of technology were reported in previous studies (Chen and Chan, 2014; Or et al., 2010). In the current study, target participants are adults aged 60 years or above, whose impaired health status may at some point influence the acceptance of smart wearable systems. Thus, hypotheses related to self-reported health status are developed as follows:

H8a–H8c. : Health negatively affects customer PEOU, PU, and IU.

Meng et al. (2011) explored some user requirements for the acceptance of wearable healthcare systems, but no further analysis on those factors was performed in their study. The present study aims at investigating the degree to which influential factors affect the intention to use smart wearables. Therefore, with preceding hypotheses, SWAM was proposed to examine the interrelationships among those factors (see Fig. 1).

3. Research methods

3.1. Study design and procedures

A cross-sectional questionnaire with close-ended questions was employed to investigate the intentions of participants toward using smart wearable systems. Knowing that older adults may be unfamiliar with wearable systems and have difficulties in understanding technological terms, the interviewer showed a group of images of representative wearable devices (e.g., smart shirt, waist band, smart watch, mECG, and band-aid-like devices), and impartially introduced their respective measuring functions to research participants. When the participants had gained a rough idea of smart wearable systems, informed consents were obtained prior to formal interview. A face-to-face interview rather than self-administered reporting was adopted for synchronous communication with participants and completion of the questionnaire. Correctness of responses was confirmed by repeating the answers of interviewees. Each one-on-one assessment of participants takes around 30 min. To maintain the consistency of questionnaire responses, the surveys were conducted and transcribed by the same well-trained researcher.

3.2. Measurement

The questionnaire used in the survey included two parts: 1) acceptance of smart wearable systems and 2) demographic characteristics of the respondents. Table 2 presents the items used in the current study except the demographic variables. All the variables and indicators in the questionnaire were measured by a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

3.3. Participants

Table 3 displays the detailed characteristics of the participants. A total of 146 Chinese adults aged 60 years or above were selected as participants through convenience sampling primarily from dwelling communities and parks in Shenzhen, China. The largest percentage of participants in each demographic profile category were aged 60–64 (39.0%), living with family members (91.8%), with high school education level (29.5%), married (84.9%), retired (58.9%), with source of income from pension (56.2%), with average economic level (34.9%), and with frequent usage of new technology such as smartphones, tablets, and PCs (33.6%). All the participants are non-users of smart wearable systems.

4. Data analysis

4.1. Effects of demographic variables on IU

The distribution differences in IU across all demographic variables in the survey were examined using Kruskal–Wallis test. The results showed that IU varied significantly with education level ($\chi^2 = 17.533$, df = 4, $p < 0.01$), work status ($\chi^2 = 12.328$, df = 3, $p < 0.01$), source of income ($\chi^2 = 10.552$, df = 3, $p < 0.05$), economic level ($\chi^2 = 22.144$, df = 4, $p < 0.001$), and NTUF ($\chi^2 = 24.979$, df = 4, $p < 0.001$). However, no significant distribution differences in IU were identified in terms of age, gender, living arrangement, and marital status. Therefore, NTUF and economic level were considered as stronger predictors of the propensity to accept smart wearable systems than the other demographic factors. As shown in Table 3, older adults with higher education and economic levels, and who frequently use new technology would have greater means of IU with regard to smart wearable systems. Furthermore, an ANOVA test was performed to examine the equality of means of three NTUF subgroups, and the result showed statistically significant differences in the means of PU ($p < 0.01$) and IU ($p < 0.001$) between frequent users and non-users.

4.2. Measurement model assessment

The measurement model was assessed by confirmatory factor analysis using AMOS 21.0 software to determine whether it provided an understanding of the nature of the constructs. Model fit and parameter

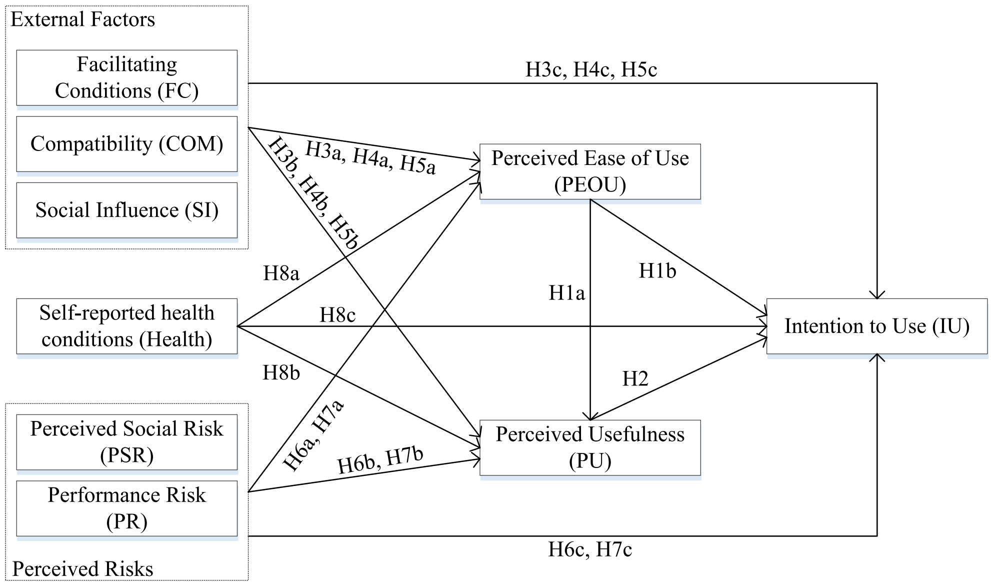

Fig. 1. Proposed SWAM in present study.

Table 2
Measurement constructs, items in this study.

Constructs	Items	Contents	Sources
Intention to Use (IU)	IU1	Using smart wearable system (it) is worthwhile.	Pan and Maryalice (2010)
	IU2	I would be interested in it.	
	IU3	Using a smart wearable system is a good idea.	
	IU4	I intend to use wearable systems in the future.[a]	
Perceived Ease of Use (PEOU)	PEOU1	I think wearable systems are easy to use.	Davis et al. (1989)
	PEOU2	My interaction with smart wearable systems is clear.	
	PEOU3	I can easily learn how to operate such systems.	
Perceived Usefulness (PU)	PU1	Using the system will make one's life more effective.	Davis et al. (1989) and Moore and Izak (1991)
	PU2	My life will become more convenient when I use such systems.	
	PU3	It is very useful to use wearable systems in life.	
Facilitating Conditions (FC)	FC1	Getting help from a person or group is important when I use wearable systems.	Venkatesh et al. (2003) and Ryu et al. (2009)
	FC2	I have the necessary knowledge to use it.	
	FC3	My financial status can support my adoption.[a]	
Compatibility (COM)	COM1	Wearable systems are compatible with my existing electronics (smartphone and others).	Bradford and Florin (2003)
	COM2	Using wearable systems fits into all aspects of my work.	
	COM3	Using it would not affect my daily life (because of its weight, volume, and others).[a]	
Social Influence (SI)	SI1	People who affect my behavior think that I should use wearable systems.	Taylor and Todd (1995) and Pan and Maryalice (2010)
	SI2	My family members and friends support my decision to use it.	
	SI3	If the product has become a trend among people around me, I would consider using it.	
Perceived Social Risk (PSR)	PSR1	People will look at me strangely if they see me using it.	Verdegem and Marez (2011)
	PSR2	I am embarrassed to wear health monitoring devices.[a]	
	PSR3	People around me would laugh at my wearable system adoption.[a]	
Performance Risk (PR)	PR1	I worry about whether it will provide expected benefits (functionalities and others).	Stone & Gronhaug (1993) and Yang et al. (2016)
	PR2	Smart wearable systems may not work satisfactorily (measuring accuracy and quality concerns, and others).	
	PR3	Such systems may lead to privacy violation.[a]	
Self-reported Health Conditions (Health)	Health1	My health status is very good.	McDowell (2006)
	Health2	My health status is very good compared with that of my peers.	
	Health3	My auditory ability, visual ability, and mobility are very good.	

[a] Items that were newly developed for measurement in the present study.

estimation were calculated on the basis of the maximum likelihood method. Five commonly used model fit indices were used to evaluate overall fitness of the measurement model. The results showed that the ratio of χ^2 to degree of freedom was 1.433 (χ^2/df < 2); the comparative fit index (CFI) and Tucker–Lewis index (TLI) were 0.970 and 0.964, respectively (CFI > 0.95; TLI > 0.90); the root mean square error of approximation (RMSEA) was 0.055 (RMSEA < 0.06); and the standardized root mean squared residual (SRMR) was 0.0515 (SRMR < 0.08) (Brown, 2015; Kline, 2015; Steiger, 2007; Hu and Bentler, 1999). All the parameters met corresponding criteria, thereby indicating that the measurement model fit was satisfactory.

Reliability refers to the extent of reliability of the measurement model in reflecting the intended latent variable. In this study, internal reliability was achieved as the value of Cronbach's alpha exceeded the threshold value 0.7 (Nunnally, 1978). Composite reliability (CR), which estimates the proportion of a set of indicators that can explain the

Table 3
Characteristics of participants (N = 146).

Characteristics	Frequency	Percentage (%)	Means (S.D.) of IU
Age			
60-64	57	39.0	4.25 (1.78)
65-69	40	27.4	3.98 (1.43)
70-74	29	19.9	4.00 (2.06)
> =75	20	13.7	4.60 (1.96)
Gender			
Male	82	56.2	4.19 (1.74)
Female	64	43.8	4.16 (1.82)
Living Arrangement			
With family member(s)	134	91.8	4.20 (1.78)
Living alone	6	4.1	3.75 (1.33)
In nursing home	6	4.1	3.96 (2.11)
Education Level			
Informal	30	20.5	3.27 (1.79)
Elementary	31	21.2	4.53 (1.78)
Junior high school	21	14.4	4.05 (1.83)
High school	43	29.5	4.09 (1.43)
Post-high school	21	14.4	5.24 (1.73)
Marital Status			
Married	124	84.9	4.21 (1.78)
Divorced/separated	3	2.1	4.25 (2.18)
Widowed	18	12.3	3.78 (1.68)
Never married	1	.7	6.25 (-)
Work Status			
Full-time work	7	4.8	3.25 (1.27)
Part-time work	4	2.7	4.63 (2.01)
Retired	84	57.5	4.58 (1.67)
Not applicable/never worked	51	34.9	3.60 (1.81)
Source of Income			
Salary	12	8.2	3.94 (1.69)
Pension	80	54.8	4.53 (1.67)
Property income	1	.7	6.00 (-)
Family/relative(s) support	51	34.9	3.60 (1.81)
Government support	2	1.4	5.13 (2.65)
Economic Level			
Very rich	23	15.8	5.32 (1.81)
Rich	48	32.9	4.52 (1.72)
Average	51	34.9	3.84 (1.64)
Poor	17	11.6	3.07 (1.30)
Very poor	7	4.8	3.18 (1.37)
New Technology Usage Frequency (NTUF)			
Frequent user	49	33.6	4.79 (1.61)
Occasional user	60	41.1	4.13 (1.44)
Non-user	37	25.3	3.58 (1.81)

Note: NTUF was measured by the self-reported usage frequency of smartphones, tablets, PCs, or wearable technologies by participants.

construct, was satisfied because all of the CR values were above 0.6 (Hair, 2010). Convergent validity, which refers to the intercorrelations between similar measures, was achieved as all the factor loadings and average variance extracted (AVE) values of every construct were above the threshold value of 0.5 (Huang et al., 2013; Fornell and Larcker, 1981). As shown in Table 4, the standardized factor loadings, CRs, and AVEs together with Cronbach's α were higher than the corresponding minimum acceptable values, indicating fairly good reliability and convergent validity of the measurement model.

Discriminant validity could be achieved when the square root of the AVE value for every construct is greater than the absolute values of correlation coefficients between any two latent constructs (Zait and Bertea, 2011; Farrell and Rudd, 2009). Table 5 indicates that the square root of AVE for every construct met the criteria, thereby indicating satisfactory discriminant validity. In conclusion, the aforementioned entire model fit indices, internal and composite reliability, and convergent and discriminant validity indicated a satisfying measurement model that was suitable for structural model testing.

Table 4
Standardized factor loadings, CRs and AVEs and Cronbach's alphas.

Constructs	Items	Factor Loading	CR	AVE	Cronbach's α
FC	FC1	0.951	0.951	0.867	0.945
	FC2	0.891			
	FC3	0.951			
COM	COM1	0.778	0.891	0.732	0.886
	COM2	0.924			
	COM3	0.859			
SI	SI1	0.947	0.946	0.855	0.944
	SI2	0.946			
	SI3	0.879			
Health	Health1	0.958	0.911	0.775	0.906
	Health2	0.931			
	Health3	0.734			
PSR	PSR1	0.871	0.952	0.870	0.946
	PSR2	0.974			
	PSR3	0.950			
PR	PR1	0.931	0.899	0.748	0.897
	PR2	0.872			
	PR3	0.786			
PEOU	PEOU1	0.951	0.957	0.880	0.956
	PEOU2	0.946			
	PEOU3	0.917			
PU	PU1	0.916	0.965	0.903	0.964
	PU2	0.972			
	PU3	0.962			
IU	IU1	0.958	0.973	0.901	0.973
	IU2	0.952			
	IU3	0.952			
	IU4	0.934			

FC: Facilitating Conditions; COM: Compatibility; SI: Social Influence; Health: Self-reported Health Conditions; PSR: Perceived Social Risk; PEOU: Perceived Ease of Use; PU: Perceived Usefulness; PR: Performance Risk; IU: Intention to Use.

4.3. Structural model testing

The proposed research model was then analyzed with structural equation modeling using AMOS 21.0. The results for five goodness-of-fit indices were $\chi^2/df = 1.493$, CFI = 0.966, TLI = 0.959, RMSEA = 0.058, and SRMR = 0.0519, which indicated that the proposed SWAM could properly represent the hypothesized relationships. The results showed that SWAM could explain 68.7% of the variance in IU, 52.5% of the variance in PU, and 36.4% of the variance in PEOU, which indicated that SWAM could effectively predict the intention to use smart wearables among the older adults.

Table 6 and Fig. 2 present the hypothesis testing results and structural model, respectively. According to the path analysis, 11 out of 21 hypotheses were supported in the model. The effects of FC, COM, PU, and Health on IU were verified, while that of SI, PSR, PR, and PEOU on IU were not in the context of smart wearable systems. Furthermore, the effect of PEOU on IU was tested to be fully mediated by PU ($p < 0.001$).

In terms of exogenous variables, FC was significantly related to PEOU and IU, thereby validating the hypotheses H3a and H3c; COM was significantly related to PEOU, PU, and IU, thereby validating the hypotheses H4a, H4b, and H4c; and Health was significantly related to PU and IU, thereby validating the hypotheses H8b and H8c. Furthermore, SI and PR were significantly related to PU, thereby validating the hypotheses H5b and H7b. However, PSR was examined to have no significant effects on all the three dependent variables.

5. Discussions and conclusions

5.1. Key findings

The advancement of health information technologies would enable users to acquire immediate feedback on their physical conditions

Table 5
Correlation matrix among constructs and square root of AVEs.

	FC	COM	SI	Health	PSR	PR	PEOU	PU	IU
FC	**0.93**								
COM	0.37***	**0.86**							
SI	0.44***	0.37***	**0.92**						
Health	0.08	- 0.01	- 0.06	**0.88**					
PSR	- 0.18*	- 0.16*	- 0.20*	- 0.08	**0.93**				
PR	- 0.19*	- 0.21*	- 0.27**	- 0.03	0.01	**0.86**			
PEOU	0.56***	0.36***	0.36***	0.13	- 0.13	- 0.09	**0.94**		
PU	0.36***	0.48***	0.58***	- 0.10	- 0.02	- 0.30**	0.42***	**0.95**	
IU	0.40***	0.51***	0.53***	- 0.18*	- 0.08	- 0.31**	- 0.34***	0.78***	**0.95**

Note: Diagonal values in boldface are the square roots of the AVEs.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

Table 6
Results of path analysis and hypotheses testing.

Hypotheses	Path coefficient	*p*-value	Result
H1a: FC→PEOU	0.491	0.000***	Supported
H1b: FC→PU	−0.052	0.611	Not supported
H1c: FC→IU	0.183	0.038*	Supported
H2a: COM→PEOU	0.183	0.034*	Supported
H2b: COM→PU	0.334	0.000***	Supported
H2c: COM→IU	0.188	0.021*	Supported
H3a: SI→PEOU	0.110	0.226	Not supported
H3b: SI→PU	0.464	0.000***	Supported
H3c: SI→IU	0.015	0.867	Not supported
H4a: Health→PEOU	0.100	0.185	Not supported
H4b: Health→PU	−0.169	0.029*	Supported
H4c: Health→IU	−0.134	0.047*	Supported
H5a: PSR→PEOU	−0.022	0.856	Not supported
H5b: PSR→PU	0.213	0.078	Not supported
H5c: PSR→IU	−0.068	0.512	Not supported
H6a: PR→PEOU	0.102	0.331	Not supported
H6b: PR→PU	−0.226	0.035*	Supported
H6c: PR→IU	−0.091	0.330	Not supported
H7a: PEOU→PU	0.305	0.000***	Supported
H7b: PEOU→IU	−0.101	0.219	Not supported
H8: PU→IU	0.690	0.000***	Supported

* significant at $p < 0.05$, *** significant at $p < 0.001$.

anywhere and anytime (Bouma et al., 2007). In such a technological context, this study explored elderly-specific factors that affect the acceptance of smart wearable systems, and then developed SWAM with good model fit and predictive ability.

5.1.1. Demographic and attitudinal variables

Education and economic levels were significantly related to intention to use, which was consistent with the results of previous studies (Werner et al., 2011). More importantly, people who frequently use new technology would be more likely to use the smart wearable systems. As hypothesized, perceived usefulness significantly influenced intention to use. However, perceived ease of use did not directly affect intention to use, which is consistent with the findings of Chen and Chan (2014) and Ma et al. (2016), because majority of the participants regarded smart wearable systems as easy to use.

5.1.2. External factors

The supported hypotheses indicated that facilitating conditions might be helpful to increase perceived ease of use and intention to use of smart wearable systems, but not helpful to increase perceived usefulness significantly. Lin et al. (2010) pointed out that middle-aged female adults could become technology literate through social support. In terms of social influence, the present study implied that affirmative

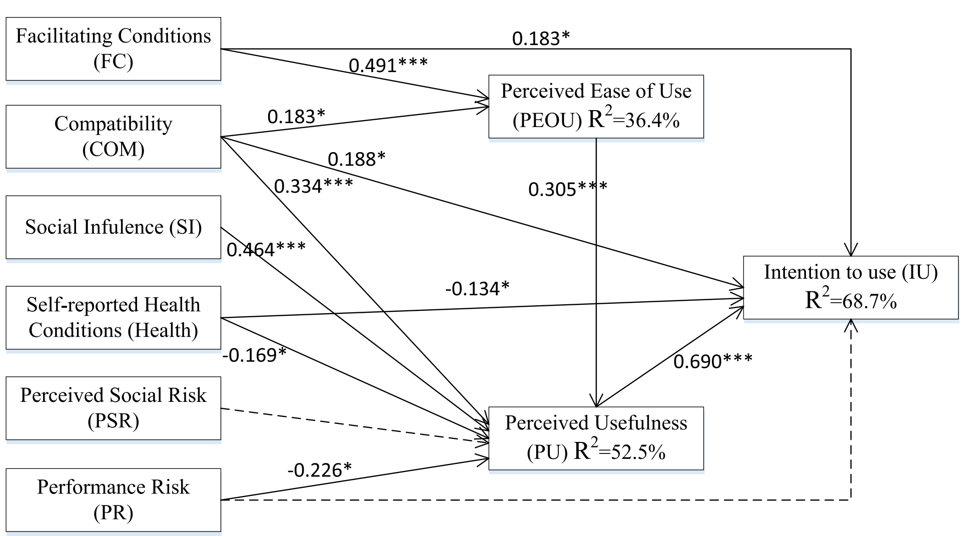

Fig. 2. Results of the smart wearables acceptance model.
*$p < 0.05$, ***$p < 0.001$; Two dotted lines indicating non-significant paths were added in making all proposed factors shown in an integral model.

attitudes or usage of smart wearable systems from others would significantly enhance perceived usefulness among older adults. As previously reported, mobile phone usage decisions of older adults were significantly affected by the opinions of their children and grandchildren (Mallenius et al., 2007). As expected, compatibility had significant positive effects on perceived ease of use, perceived usefulness, and intention to use. Such results indicated that hardware compatibility with current communication equipment, weight and volume of smart wearable systems, and lifestyle of older adults would significantly affect their intention to use smart wearable systems.

5.1.3. Perceived risks

In terms of risk factors, the results showed that perceived social risk was not significantly related to perceived ease of use, perceived usefulness, and intention to use. Such results were attributed to the fact that 95.9% of the participants perceived minimal or no social risk when they would use smart wearable systems. Consistent with previous findings (Featherman and Pavlou, 2003), the results of the present study showed that performance risks, including features like low measuring accuracy, quality issues, and privacy concerns of the smart wearable systems would significantly decrease the perceived usefulness of the systems.

5.1.4. Self-reported health status

Poorer health conditions had significantly positive effects on perceived usefulness and intention to use, but not on perceived ease of use. Similar negative influence has been reported in a previous study on Internet usage (Nayak et al., 2010). Not surprisingly, older adults with worse age-related health status were more inclined to adopt smart wearable systems to ensure continuing surveillance of their physical signs.

5.2. Contributions and implications

The present study confirms the significant roles of perceived usefulness, compatibility, facilitating conditions, and self-reported health status in directly predicting the intention to use of older adults toward smart wearable systems. On the one hand, the findings fill the research gap of older adults' acceptance of smart wearable systems. On the other hand, the study helps practitioners carry out feasible plans to facilitate the adoption of such technologies.

Considering the limited awareness of smart wearable systems for older adults, practitioners need to promote wearable systems in various ways. In the current study, majority of the participants expressed their willingness to accept smart wearable systems at present or in the future. The results showed that perceived usefulness is the major antecedent of intention to use wearable systems. Therefore, practitioners should emphasize the pragmatic functions and benefits of such systems, aimed at improving usability of wearables (Rupp et al., 2018), and the quality of old adults' lives at home or in their community. The significant effects of compatibility on attitudinal variables imply that smart wearable systems should be compatible with current communication technologies (e.g., smartphones, tablets, and PCs) and age-friendly for older adults (e.g., with proper interface design and large font size). Based on participant's interview feedback, such systems are expected to be lighter and smaller, elegantly designed, waterproof, and easy to put on and take off to improve lifestyle suitability for older adults. As pointed out by McCann et al. (2005), wearables design must be compatible with aesthetic and cultural demands of end-users for optimizing the function and appearance of the products. Aesthetics, in terms of individual preferences of color, style and fashion appeal, was implicitly studied under the construct of compatibility in this article. Although aesthetics was not fully studied as a separate construct, designers should take into account the aesthetic preference of end-users because of compatibility's significantly positive effects on attitudinal factors. In addition, facilitating conditions directly contribute to intention to use. Training programs, technical support, and financial aid provided by the practitioners or family members would be crucial in facilitating the use of smart wearables. In accordance with prior studies (Lee and Coughlin, 2014; Mitzner et al., 2010; Demiris et al., 2001), external support such as providing well-designed technology training for older adults is a promising way to help them overcome concerns in using innovation technologies, which in turn will enhance older adults' technology acceptance.

Self-reported health status is a negative predictor, which is reasonable as older adults with better health status are not likely to use such technologies. Therefore, identifying target users of smart wearable systems and highlighting the common functions for healthy people are important. Another negative predictor is performance risk. The survey results indicate that 34.9% of the participants are concerned about the reliability and measuring accuracy of the smart wearable systems. Therefore, the study would suggest that manufacturers show measuring accuracy of the physical signs to older adults and develop a stringent wearable technology certificate to ensure that their products meet industry standards and specific regulatory requirements of target markets. Furthermore, a customized setting of smart wearable systems for transmitting physical signs to caregivers and clinical centers would effectively mitigate the privacy violation concerns of older adults.

5.3. Limitations

This study has certain limitations. First, sample size of 146 is small though Iacobucci (2010) claimed that minimum acceptable sample size is 50. Some previous studies similar to ours had sample size of 101 (Ma et al., 2016), 101 (Or et al., 2010), 163 (Wilson and Lankton, 2004), making our sample not unusually small. Second, participants were selected from a single region of Shenzhen. Additional economic and cultural effects on acceptance of smart wearables should be explored to achieve possible higher predicting ability, and to generalize the results to other regions or countries. Third, intention to use might not be sufficient to predict the actual smart wearables usage of older adults. Prior to formal interview, the researcher presented a simple wristband with function of activity and sleep tracking to participants, rather than using more real wearables. The main reason for not showing more real wearables is that these products are not mature and available in Shenzhen. Another reason is that we assumed image displaying method can reflect their attitudes in general, for example when shopping online, customers select products based on images and descriptions only. Even so, such method might affect participants' real understanding of smart wearables to some extent. Possibly in the future, actual usage experiences should be examined to achieve more accurate research outcomes. Also, in terms of self-reported health conditions, overall empirical data were collected based on the self-assessment of the participants. Therefore, inaccurate and biased health evaluation outcomes may be incurred. Future research should employ objective health status measurement methods for participants. Finally, self-reported new technology usage frequency of the participants is not accurate enough; thus, experimental manipulation of electronic products on the spot can be implemented to determine unbiased usage experience of a target technology for older adults. All the limitations of this study may reveal opportunities for future academic research on the acceptance of smart wearable systems among older adults.

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