Digitization for Fun or Reward? A Study of Acceptance of Wearable Devices for Personal Healthcare

Full paper

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ABSTRACT

We examine the factors predicting behavioral intention to use wearable devices for personal healthcare with the aim to understand the role of personality characteristics in adopting digital life technology. A web survey was conducted among consumers in China. Mobile affinity and compatibility, two facets of technological personality, have positive influences on acceptance of smart bands; individuals who value mobile phones to a high degree will adopt smart bands for health monitoring and improvement, and individuals will use digital life technology which performs similar functions as the technology already adopted. Behavioral-disposition traits, namely fun seeking and reward responsiveness, moderate the relationships of use intention with perceived ease of use and perceived usefulness, respectively. Fun seeking personalities will use smart bands when their perceived ease of use is low, while reward responsiveness personalities will use smart bands when their perceived usefulness is high. Implications to research and development of digital life technology are discussed.

KEYWORDS

Wearable devices, smart bands, technology acceptance, personality traits, behavioral motivation, digital life technology

1 INTRODUCTION

Individuals' attention to healthy living and healthy lifestyle is increasing, as well as individuals' interest in technology supporting this end. Health-supporting technologies such as wearable devices and dedicated healthcare applications help people record, monitor, and communicate fitness activities and other health-related data. The concept of wearable technology is not new. The first conceptualizations and practical applications were developed in early 1980s. However, the first developments were cumbersome to use and were initiated in research and development projects [1]. Nowadays, the advances in electronic and mobile technology created the premises for wearable devices to be used as consumer devices in everyday tasks as well as by various professions to increase productivity (see e.g., [2,3]). The possibilities of wearables to enhance people lives contribute to the so-called digitization of the individual [4]. Digitization of the individual or digital life refers to the integration of technology into the everyday life of a person by the means of sensors to capture information about the individual and its context, analysis and interpretation of the generated data, and continuous processing and communication of information [4].

Wearable technology is defined as a small computer incorporated into clothes and accessories which can be worn on the body [5]. The wearable computer has storage and communication capabilities allowing the user to access the information in real time, as well as sending the information to a mobile device through a web service where more advanced analytics can be produced and displayed. One advantage over a laptop and mobile device is that wearables can embed sensors that can measure and track physiological signals [5]. This feature makes the wearable devices particularly suitable for healthcare and fitness applications (see e.g., [6]).

Healthcare is a target application for wearables because of its role in our lives, but also in the economy and business; the industry of wearable technology for fitness tracking growing fast [7-9]. Three potential benefits of wearable devices in healthcare are highlighted (see [1]): health monitoring (e.g., glucose monitoring by people with diabetes), health data access (e.g., elderly data can be accessed by authorized close family and friends by notifying them when certain thresholds are exceeded), and medical education (e.g., wearables as tools for medical students to learn during practice). Another benefit is a better accountability of diet and exercise [10]. Hess et al. [4] also point out that in healthcare domain, digitization of the individual is strongly centered on the citizen (as opposed to institution-centered view) and advocates an electronic record for the entire life of the individual comprising "any data referring to health, like sports activities, traveling, environmental influences, or situation-specific vital parameters, which can be used to provide adequate care." (p. 248). To date, the most popular wearable devices among individual consumers are smart bands, watches, and glasses [10,11]. Wearable devices for personal healthcare combine with web and mobile apps to achieve functionalities such as sports tracking, sleep monitoring, event notifications, and heart rate recording [11].

Nevertheless, the adoption of wearable technology is not yet widespread, but it is limited to early adopters [1], as defined in Rogers' [12] diffusion of innovations trajectory which means about 13.5 percent of potential consumers (p. 262). Among the challenges to large-scale adoption are: privacy and security issues, battery life, price, the range of available applications, design, aesthetics, user acceptance, convenience, accessibility, and social acceptability [1,13,14]. Regarding users' acceptance, a study in 2014 in China showed that 40.5% of respondents considered that the functionality of wearable devices and dedicated healthcare applications are incomplete [15]. Furthermore, the same study showed that 45.7% of users abandoned using smart bands within a month.

In this study, we focus on smart bands because of their increased popularity; one in ten U.S. adults possessing a fitness tracker [16]. Smart bands or fitness bands are intelligent bracelets that record real-time data such as for monitoring physical activity and sleeping patterns [17]. These data synchronize with mobile phone or tablet apps with the purpose to guide a healthy life through data.

We examine the factors that predict consumers' behavioral intention to use smart bands for personal healthcare, with a focus on personality influences. Bariff and Lusk showed already long time ago that personality dispositions are important to be taken into account when developing successful information systems [18]. Several studies since then address issues of personality characteristics influencing technology adoption (see e.g., [19,20]), however, the literature lacks studies on how personality affects wearables adoption despite the specificity of this technology. Moreover, if individual characteristics are addressed these are operationalized as demographics and experience, rather than personality traits.

Our study is predictive in nature and aims to understand the role of personality characteristics in adopting digital life technology. We designed the empirical study within the tradition of theory-testing, deriving the constructs and relationships from established models that explain intention to use technology, such as, the technology acceptance model (TAM; [21]) and the unified theory of acceptance and use of technology (UTAUT and UTAUT2; [22,23]), as well as from emerged models of technology acceptance in relevant contexts such as online and mobile shopping (i.e., [24-26]). In the study, personality characteristics are viewed as two-fold; 1) technological personality as a concept reflecting personal relationships with the technology such as experience, habits (see [24]); and 2) behavioral motivation as a concept reflecting personality traits determining approach and withdrawal behavior (see [27]). This is the first study to introduce behavioral motivation constructs into a predictive model of technology acceptance and to show the significant role of behavioral motivation dispositions in the acceptance of personal healthcare wearables.

2 THEORETICAL FRAMEWORK AND RESEARCH HYPOTHESES

2.1 Beliefs and Evaluations of the Qualities of a System

Technology acceptance theories explain the individual behavior of technology use. The most prominent model in this area is the technology acceptance model (TAM) developed by Davis (1989) [21], based on the theory of reasoned action (TRA; [28]). TAM conceptualizes the acceptance of technology as behavioral intention (BI) to use a technology, while adoption is referred to as the actual use of technology. In the model, behavioral intention leads to actual use (i.e., acceptance leads to adoption).

TAM explains the acceptance of technology by perceived ease of use, perceived usefulness, and attitude towards technology [21]. In terms of TRA, these constructs are reflecting the individuals' beliefs in the consequences of adopting a certain behavior and the subjective evaluation of these consequences [29]. Perceived ease of use (PEOU) is defined as "the degree to which a person believes that using a particular system would be free of effort" ([21], p. 320). PEOU influences the behavioral intention indirectly, through the mediation of attitude towards technology.

In the context of smart bands for personal healthcare, perceived usefulness can be defined as the degree to which a person believes that using wearable devices would be beneficial to his or her health. According to TAM, behavioral intention to use a technology is influenced by PU and attitude towards technology. PU influences directly the behavioral intention to use technology and also a person's attitude towards technology. In the model, PEOU is also shown to influence PU (see also [25,30-33]).

In newer models of acceptance, attitude towards technology was omitted because of poor empirical evidence (i.e., TAM2, UTAUT, and UTAUT2; [22,23,34] and [25,30,31,33,35]). Thus, we hypothesize:

H1. PU positively influences the behavioral intention to use smart bands.

H2. PEOU positively influences the behavioral intention to use smart bands.

H3. PEOU positively influences PU of smart bands.

2.2 Trust

In many models of technology acceptance, trust is included as a direct antecedent of behavioral intention to use technology (e.g., [25,36]). Trust is conceptualized as being related to cognitive and affective perceptions regarding positive consequences of a desired outcome [25]. It has been also shown that trust, privacy concerns, as well as compatibility with users' needs or usefulness influence attitude toward e-health technology (e.g., [35,37-39]). Trust is an antecedent of perceived risk, and both trust and perceived risk influence intention to use technology [40]; however, empirical data show a stronger effect of trust on the use intention than the effect of perceived risk [40].

Smart bands and health-related applications rely on physiological data recording and on processing the data over the internet, while the generated information has an impact on the lives of individuals. Security, privacy, and reliability of the data and information should be essential for customers (see e.g., [41]). Moreover, consumers, regardless of their demographics, are concerned with the privacy and security of the personal information handled by wearable devices, as well as with the usefulness of the information provided [10]. In our model, we omit perceived risk, and focus only on trust because the two are related [40]. For the sake of simplicity, as we chose to omit the attitude from the model, we omit the effect of trust on attitude, and predict only the direct effect of trust on behavioral intention similarly with the models and empirical findings of online shopping and mobile banking acceptance (see [25,42-44]). Thus, we hypothesize the following:

H4. Trust positively influences the behavioral intention to use smart bands.

As exposed above, trust represents the belief in the positive consequences of an outcome and, in the case of smart bands, the major aspects that are evaluated are the quality of the output in terms of usability or ease of use, reliability, and accuracy, as well as the privacy and security issues (see e.g., [10]). PEOU is an antecedent of trust; ease of use increases the confidence of using the technology and the confidence in the quality of the output, e.g., with respect to its capability to provide understandable and actionable information (see [25,36,45]). Moreover, trust was shown to influence PU (see [25,36,45]). Our hypotheses are:

H5. PEOU positively influences Trust on using smart bands; perceived ease of use of smart bands determines a higher trust in smart bands.

H6. Trust has positive effect on PU to use smart bands; higher trust in the characteristics of smart bands influences positively the perceived usefulness.

2.3 Social Influence

According to TRA, behavior is also determined by normative beliefs and motivations such as social norm [28,46]. Social influence or social norm is a construct that captures an individual's perceived expectations of specific referent individuals or groups, and his or her motivation to comply with these expectations [28,46]. Subsequent models of technology acceptance such as TAM2, UTAUT, and UTAUT2 [22,23,34] incorporate social influence as a direct antecedent of the behavioral intention to use technology. In these models, social influence refers to the individual's perception that important social actors expect that he or she should use a technology.

It is believed that social influence affects BI through three mechanisms: compliance, internalization, and identification [22,34]. Compliance appears significant in mandatory use of technology; users agree to use a technology that is recommended by peers or superiors in order to gain a reward or avoid punishment [22,34]. The smart bands for personal healthcare are typically used in voluntary situations, thus, compliance is not a relevant mechanism for their acceptance. Internalization refers to the process of recognizing the merits of a technology based on the recommendations of the peers or other social actors [22,34]. In the context of smart bands for personal healthcare the internalization can manifest as a result of others' recommendations. The third mechanism, identification, refers to perceived social status gains associated with the use of technology [22,34]. This mechanism can also be triggered by others' recommendations, but in this situation the determining motivation does not consist of the belief in system qualities, but the desire of the potential consumer to identify himself or herself with people and people's experiences he or she values and find significant. Brand communities play an important role in brand identification and feelings of affiliation to a relevant community [47]. Identification theory describes that media and customers are two ways of communicating company or brand identity [44]. In addition, the ads and presentation media induce feelings of personal participation, connectivity with social actors, personal experiences and social presence [48]. Nowadays, social media became fundamental to the way people acquire and share information, as well as to how people interact with and relate to others [10] and consumers use social platforms as well as product review forums to make purchases decisions [49]. Thus, in our model, we extend the meaning of social influence to include perceived influence of both close others as well as other social actors such as media and other users. Therefore, we hypothesize:

H7. Social influence positively influences behavioral intention to use smart bands; higher score of social influence is associated with increased behavioral intention to use smart bands.

2.4 Technological Personality

Research on task-technology-fit indicates that users' individual characteristics play an essential role in the choice of technology and decision to utilize technology (see e.g., [50]). Generally, computer self-efficacy, defined as the perception of own capability to use a computer, has a significant effect on computer usage [51]. In online shopping [26], web skills influence enjoyment and attention, which in turn affect shopping behavior. Personal traits (including computer skills) were shown to influence also healthcare technology acceptance [52,53]. As smart bands are used in tandem with smart phones, we define mobile technologies skills as the individual perception of own capability to use mobile technology (adapted from [51]) and predict that:

H8: Mobile technology skills positively influence acceptance of smart bands.

Mobile shopping behavior is influenced by certain technology personality variables such as affinity to the mobile medium, compatibility, and innovativeness [24]. Affinity is defined as being the importance attached to the medium in the life of an individual [54] and influences mobile-shopping intention and adoption [24,55]. Mobile affinity is conceptualized as the individual inclination to use mobile technology in everyday life. The measurement and conceptualization of medium affinity is strongly related to medium dependency, and it was found that internet dependency predicts purchase intention, and that internet affinity predicts internet dependency [56]. Moreover, internet dependency predicts acceptance of e-health among patients [57]. Medium affinity has been linked with television viewing levels (see [58]), which suggests that affinity correlates with technology (or media) usage. These results lead us to hypothesize:

H9: Mobile affinity positively influences acceptance of smart bands; the more inclined the individual is to use mobile technology in everyday life, the more likely is that he/she has a stronger intention to use smart bands.

Rogers defines compatibility as being "the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters." ([12], p. 224). The concept of technology cluster ([12], pp. 15-16) has been used to identify technologies that perform similar functions (see also [24]). Accordingly, consumers are likely to adopt a new technology if it provides similar functions with the ones already adopted; i.e., they belong to a technology cluster with which the consumer is already familiar. It has been shown that the technology cluster is related to the adoption and positive perception of new technology in different contexts such as videotext messaging, mobile commerce, online banking [24]. In a work context, it has been shown that compatibility has a significant effect on nurses' behavioral intention to use an information system [36]. We predict that:

H10: Compatibility positively influences acceptance of smart bands; that is, previous experiences with searching health information on the internet as well as using mobile apps for health predict consumers' behavioral intention to use smart bands for personal healthcare.

Innovativeness is conceptualized as "the degree to which an individual […] is relatively early in adopting new ideas" compared to others" ([12], p. 22), emphasizing the early-timing of adoption. Two types of innovativeness have been identified [24]: 1) open-processing innovativeness that reflects a cognitive style [59]; and 2) domain-specific innovativeness reflecting "the tendency to learn about and adopt innovations within a specific domain of interest" ([60], p. 211). In shopping contexts, domain-specific measures are more predictive of the purchase of new items than global innovativeness (see [61]). Moreover, Agarwal and Prasad [62] conceptualized and operationalized the construct of personal innovativeness in the IT domain and showed that it has a moderating effect on intention to use technology. Smart bands are relatively new instruments for health monitoring and fitness tracking, thus the degree of innovativeness as a personality trait may play an important role in the decision to use wearable devices. We adapt Agarwal and Prasad's definition to reflect the inclination of consumers towards digitally innovative products. We hypothesize the following:

H11: Innovativeness positively influences acceptance of smart bands; a higher degree of individual innovativeness is linked with higher behavioral intention to use smart bands.

2.5 Moderator variables

2.5.1 Gender and age. Age and gender have an impact on the acceptance of technology [22,52,63]. According to UTAUT, the effects of performance expectancy (e.g., perceived usefulness), effort expectancy (perceived ease of use), and social influence on behavioral intention are moderated by gender and age [22]. Thus, we included in the model these variables as control variables, but also as moderators. Thus, we hypothesize:

H12: Age moderates the relationships PU – BI, PEOU – BI, and social influence – BI such that the effect on BI is stronger for younger people.

H13: Gender moderates the relationships PU – BI, PEOU – BI, and social influence – BI such that the effect of PU on BI is stronger for men, and the effects of PEOU and social influence on BI are stronger for women.

2.5.2 Behavioral motivation. Gray (1990) conceptualized behavioral motivation as being the inclination of people towards withdrawing from or acting upon novel situations (see [27]). Behavioral motivation has two distinctive physiological mechanisms that determine individual behavior: behavioral inhibition system (BIS) and behavioral activation system (BAS), which determine also distinct personality traits; some people are more inclined towards withdrawal or inhibition behavior in certain circumstances, while other people are inclined towards approach behavior [27]. BAS is believed to regulate appetitive impulses and it motivates individuals to move toward something desired. BIS regulates aversive impulses and influences the withdrawal from something unpleasant. Carver and White [64] developed an instrument to measure these traits, namely the BIS/BAS scales, and identified three types of activation behavior: reward responsiveness, drive, and fun seeking. The BIS/BAS scales and the underlying constructs have been used as moderating variables in studying approach motivation of users in different contexts, such as reading from digital media [65], and communication [66,67]. The results in these studies indicated that people with higher BAS drive and BAS fun seeking experienced higher approach motivation and positive emotions. These, in turn, are believed to engage people in actions and influence their behavior; e.g., behavioral disposition influences purchase decisions [68]. Therefore, we hypothesize:

H14. Behavioral motivation moderates the relationships PU – BI, PEOU – BI, and social influence – BI such that the effects of PU, PEOU, and social influence are differentiated based on the type of motivational dispositions as measured by BIS/BAS scales.

3 RESEARCH MODEL

To summarize, the proposed research model for predicting acceptance of smart bands for personal healthcare (Figure 1) consists of three categories of factors: 1) product intrinsic features and the way individuals perceive them (PU, PEOU, and trust), 2) social influence, and 3) user's technological personality. In addition, three moderators are analyzed: age, gender, and behavioral motivation. The definitions of the factors in the research model follow previous conceptualizations of the constructs, adapted to the smart bands technology (see Table 1).

The model was tested in a survey, by using a questionnaire developed for this purpose (see §4.1).

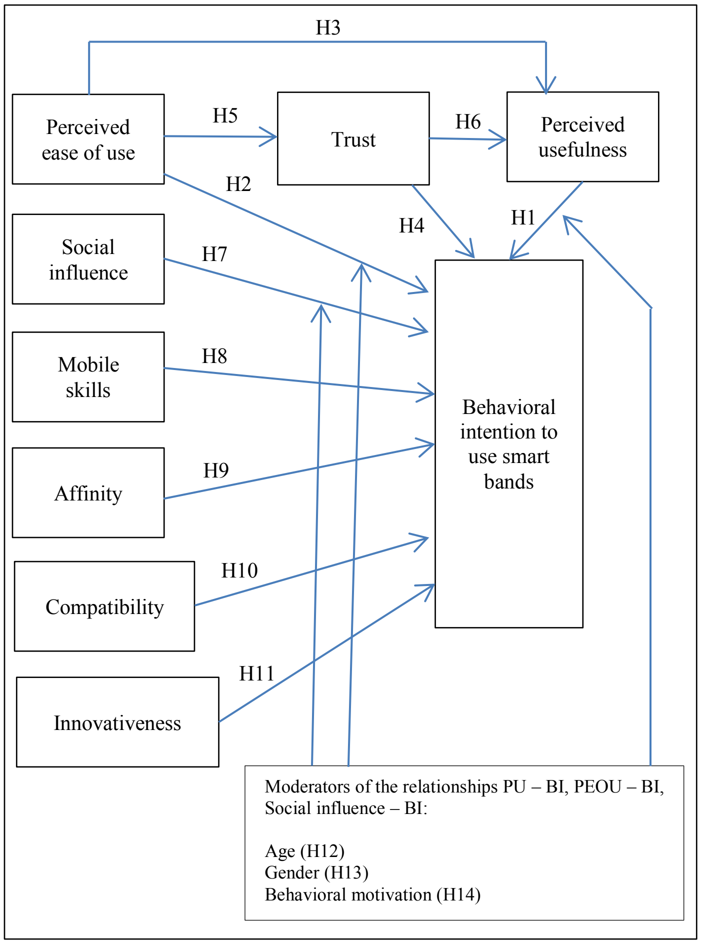

Figure 1: Research model for the acceptance of smart bands for personal healthcare

4 METHODS

4.1 Questionnaire

The survey questionnaire measured the following aspects: 1) technological personality, 2) perception of smart bands for personal healthcare, and 3) background information. In addition, usage patterns were collected from the respondents who reported current or past use of smart bands to reflect the extent of adoption and actual use. The questionnaire was developed in English and then translated into Chinese. For the translation of the BIS/BAS scales, we used the Chinese version of the BIS/BAS scales [70]. Before administering the questionnaire to the target population (Chinese people living in China), a pilot study was conducted to refine the questionnaire. Four Chinese were interviewed to test the Chinese version. The result of pilot study helped to rephrase the sentences and refine the questions.

4.2 Measures

Table 2 shows the questionnaire items of technological personality constructs and perception of smart bands. Items were measured on 7-point Likert-type scale and showed acceptable reliability and consistency.

4.2.1 Technological personality scales were developed based on previous instruments as follows. *Mobile affinity* was measured using four items from [24]. *Innovativeness* was measured with two items adapted from [24] by referring to perception towards innovative digital products. *Compatibility* was adapted from [24,33] so to reflect the match with previous similar behaviors such as searching health-related information on the internet. Finally, *mobile technology skills* were measured by adapting the web skills scale [26,51].

4.2.2 The measures for behavioral intention were adapted from [33,34]. *Perceived usefulness* and *perceived ease of use* items were adapted from [34].

4.2.3 Trust scale was derived from several scales [25,69], but employed specific wording and focused on specific qualities such as reliability, information accuracy, and safety.

4.3.4 Social influence scale was adapted from UTAUT model [22] as well as included two items to reflect also the external social influence exercised by other users and by product ads (see also social image and identification with others, e.g., [44,47-49]).

4.2.5 Background information consisted of gender, age group, education level, income level, as well as behavioral motivation as measured by BIS/BAS scale [64]. To keep the questionnaire short, we have selected only one item per construct from the full list of 20 BIS/BAS items. Thus, BAS reward responsiveness was operationalized as "When I get something I want, I feel excited and energized."; BAS drive: "When I want something I usually go all-out to get it."; BAS fun seeking: "I'm always willing to try something new if I think it will be fun."; and BIS: "If I think something unpleasant is going to happen I usually get pretty "worked up.""

Table 1: Definitions of key factors in the proposed model

	Factor	Definition
	Perceived usefulness	User believes that using smart bands technology would be beneficial to his or her health. (adapted from [21])
	Perceived ease of use	User believes that using smart bands technology would be free of effort. (adapted from [21])
	Trust	User has confidence in quality and reliability of using smart bands technology. (adapted from [69])
	Social influence	Individual perceives that others believe he or she should use smart bands technology. (adapted from [22])
Technological personality	Mobile technology skills	An individual judgment of own capability to use mobile technology. (adapted from [51])
Technological personality	Innovativeness	Willingness to adopt technology that is totally new or have new functionality in the context of own individual experience. (adapted from [12,62])
Technological personality	Mobile affinity	The perceived importance of the mobile technology in the life of the individual. (adapted from [54])
Technological personality	Compatibility	The perceived match between using smart bands technology and existing values, past experiences, and needs of potential adopters (e.g., internet searches for healthcare information). (adapted from [12])

4.3 Sampling Procedure and Sample Characteristics

We conducted the survey online on Weibo and Wechat, which are popular social media in China, similar to Twitter and Line. The questionnaire was administered using the free online tool Sojump. We used a convenience and snowball sampling to invite participants to the study. The data were collected for one week in September 2015. A number of 158 respondents answered the survey. We retained for analysis only the subjects living in China, namely 156 (88 female, 68 male). The age of participants ranged from 18 to 54 (82.7% were between 18 to 29 yrs. old). They were highly educated with 92.3% of them having graduated from college or higher education.

5 RESULTS

5.1 Measurement model

The measurement model was evaluated in terms of reliability and consistency of questionnaire items, discriminant validity, and convergent validity using the PLS procedure in SmartPLS [71]. Table 2 shows the reliability indices of corresponding constructs; Cronbach's alpha coefficients and composite reliability (CR) indices are above the acceptable level 0.7, demonstrating the internal consistency and reliability of the scales (see e.g., [72]). Other assessment criteria were also fulfilled (see [73]). Namely, the factors loadings are higher than 0.7, showing good items reliability and good convergent validity of the latent constructs. The cross-loadings are lower than the factor loadings, denoting acceptable discriminant validity of the scales. The AVE values are higher than 0.5 and the corresponding cross-loadings, indicating that the model is adequate in terms of convergent validity.

5.2 Hypothesis testing

To test the research model and derive the significance of factors, we employed bootstrapping PLS procedure with 5000 samples (see [72,73]). Some factors and interactions had very low predictive effect on BI (e.g., age, gender, mobile skills, the direct effect of trust on BI, and some of the interactions between behavioral motivation and PU, PEOU, and social influence); these were gradually eliminated to obtain a simplified model that it is easier to interpret (see Figure 2). In this model, the coefficient of determination of BI was moderate to strong ($R^2_{BI} = .58$), showing a good model fit in terms of the variance in BI explained by the model. The effect of PEOU on trust was $R^2_{Trust} = .40$, indicating a moderate influence of PEOU on trust. The coefficient of determination of PU was $R^2_{PU} = .54$, showing a moderate to strong effect of PEOU and trust on PU. All coefficients of determination attained significance at $p < 0.001$.

Table 2: Measurement items and reliability indices of latent constructs

Construct	Cronbach's alpha	CR	Items	Measurement items
Perceived usefulness	0.89	0.93	PU1	Using the smart bands would help me monitor my physical health.
			PU2	I think using smart bands would help me improve my physical health.
			PU3	Using the smart bands would enhance my effectiveness in monitoring my physical health.
			PU4	Based on my perception of smart bands, I believe they provide good features.
Perceived ease of use	0.87	0.91	PEOU1	I think the interaction with the smart bands is clear and understandable.
			PEOU2	It would be easy for me to become skillful at using smart bands.
			PEOU3	I think it is easy to get the smart bands to do what I want it to do.
			PEOU4	I think that it takes low mental effort to use smart bands.
Trust	0.78	0.87	TST1	I believe that the smart bands are reliable for the data recording.
			TST2	I believe that the personal information is safe.
			TST3	I believe that the smart bands and their applications provide accurate information.
Social influence	0.72	0.84	SI1	My relatives and friends think that I should use smart bands.
			SI2	Product ads influence me to use smart bands.
			SI3	Former users' comments influence me to use smart bands.
Mobile technology skills	0.90	0.94	MTS1	I am very skilled at using mobile technology.
			MTS2	I know how to find what I want through mobile technology.
			MTS3	I know more about using mobile technology than other users.
Innovativeness	0.83	0.92	INO1	I think I know more about innovative digital products than my circle of friends.
			INO2	I think I would use an innovative digital product even if nobody else I know had used it before.
Affinity	0.89	0.92	AFF1	Using a mobile phone is one of my main daily activities.
			AFF2	If my mobile phone is down, I really miss it.
			AFF3	My mobile phone is important in my life.
			AFF4	I would be lost without my mobile phone.
Compatibility	0.88	0.94	COM1	How often do you search for health related information on the Internet?
			COM2	How often do you use health applications on your mobile phone?
Behavioral intention	0.75	0.89	BI1	I intend to use smart bands in the future.
			BI2	I predict I would use smart bands in the future.

Table 3: Path coefficients and significance levels in the simplified model

Model path	*Sample mean*	*t-test value*	*p*
PU -> BI (H1 ***)	.25	2.71	*.01*
PEOU -> BI (H2)	.06	.56	*.57*
PEOU -> PU (H3 ***)	.37	4.02	*.00*
Trust -> PU (H5 ***)	.44	5.46	*.00*
PEOU -> Trust (H6 ***)	.63	11.05	*.00*
Social influence -> BI (H7 ***)	.33	3.42	*.00*
Affinity -> BI (H10 ***)	.18	3.33	*.00*
Compatibility -> BI (H11 *)	.13	1.85	*.06*
BAS FS -> BI	.02	.14	.89
BAS FS × PEOU -> BI (H14 **)	-.19	2.20	*.03*
BAS RR -> BI	-.08	.77	.44
BAS RR × PU -> BI (H14 **)	.19	2.27	*.02*

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

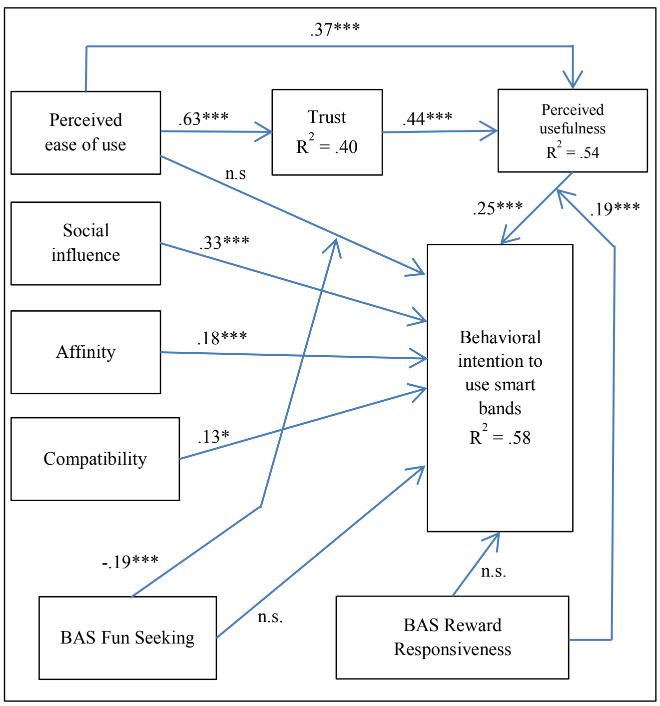

Figure 2: Results in the simplified model including the moderating effects (* p < 0.01; ** p < 0.05; * p < 0.1)**

Table 3 and Figure 2 above show the significant factors and interactions in the model.

5.2.1 Perceived usefulness, perceived ease of use and trust (H1 - H6). Perceived usefulness had a significant effect on behavioral intention to use smart bands (path coefficient = .25; p = .007), thus H1 was confirmed. On the other hand, H2 predicting the effect of PEOU on BI was not confirmed. However, PEOU had an indirect effect on BI, mediated by PU, and thus H3 was confirmed (path coefficient = .37; p < .001). The main effect of trust on BI was not significant; H4 was not confirmed. PEOU was found to be positively associated with trust confirming H5 (path coefficient = .63; p < .001). H6 was also confirmed, the effect of trust on PU being significant (path coefficient = .44; p < .001).

5.2.2 Social influence (H7). Social influence showed a significant predictive effect on BI (path coefficient = .33; p < .001), confirming H7.

5.2.3 Technological personality (H8 - H11). Among technological personality factors, only affinity and compatibility were found significant, thus confirming hypotheses H9 (path coefficient = .18; p < .001) and H10 (path coefficient = .13; p = .064), respectively. The effect of compatibility is rather weak. H8 (effect of mobile skills on BI) and H11 (effect of innovativeness on BI) were not confirmed.

5.2.4 Moderating effect of age, gender, and behavioral motivation (H12 - H14). The moderating effects of age and gender on social influence, PU, and PEOU were not statistically significant, thus H12 and H13 were not confirmed. Among behavioral motivation measures, only BAS fun seeking (FS) and BAS reward responsiveness (RR) had significant effects, thus H14 was partially confirmed. BAS FS had a negative effect on the relationship between PEOU and BI (path coefficient = -.19; p = .03), while BAS RR had a positive influence on the relationship between PU and BI (path coefficient = .19; p = .02).

Figure 3 shows the moderating effects of BAS FS and BAS RR on BI when interacting with PEOU and PU, respectively using the simple slope analysis. Fun seeking type of personality interacts with perceived ease of use in such a way that people with higher scores on fun seeking scale exhibit a higher behavioral intention to use smart bands if perceived ease of use is lower. On the other hand, people with low or very low fun seeking personality disposition elicit higher BI when perceived ease of use is higher. Reward responsiveness motivational disposition interacts significantly with PU in such a way that people with higher RR behavioral motivation exhibit high intention to use smart bands if they perceive them as useful. For this category of people, a perceived low usefulness of smart bands leads to very low acceptance of smart bands. On the other hand, the lower RR motivation, the lower effect of PU on BI is observed.

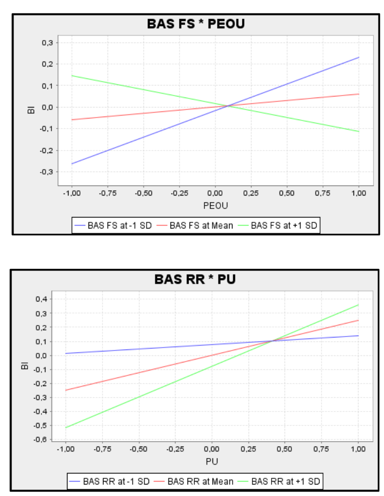

Figure 3: Moderating effects of BAS FS and BAS RR

6 DISCUSSION

This study examined the determinants of smart bands acceptance with the aim to understand the role of personality characteristics in adopting digital life technology. A web survey was conducted among consumers in China. The survey participants were predominantly young and highly educated; with a large proportion of them working in IT industry (33%), but otherwise rather heterogeneous.

6.1 Adoption of smart bands

Our data show that smart bands adoption and abandon rates of 22% and 53%, respectively, are similar with prior reports on other populations (e.g., [10,15,16]) indicating that the smart bands are not yet adopted at large scale; in our sample, only 10.3% of respondents were current users. Moreover, 28% of the past users reported they did not intend to use smart bands in the future. These statistics show that understanding better the usage drivers and users' perceptions on smart bands and digital life technology, in general is important in order to advance the development of these devices towards a better customer satisfaction. Comparing past and current users with respect to their demographic and personality profile, we found that only compatibility scores were significantly different in the two groups; the users who abandoned the smart bands reporting generally a lower compatibility score. This means that people who do not regularly use mobile or web technology for health-related searches or applications are more likely to abandon the smart bands for personal healthcare.

6.2 Determinants of smart bands acceptance

Our results show that perceived usefulness, social influence, affinity, and compatibility have a significant direct positive effect on the acceptance of smart bands. Mobile affinity and compatibility are two facets of the technological personality construct. Affinity reflects the importance that consumers attach to mobile technology in their daily life. This study shows that for people who value mobile phones to a high degree in their daily life, smart bands are a natural choice to make for health monitoring and improvement. On the other hand, compatibility reflects people's previous experiences with mobile health and/or online health information search or applications. The positive effect of compatibility on smart bands acceptance demonstrates the importance of the technological cluster concept [12] which posits that people are likely to use technology which performs similar functions as the technology already adopted.

Trust and perceived ease of use indirectly affect acceptance through the mediated effect of perceived usefulness. This result means that higher trust and higher perceived ease of use are predicting higher perceived usefulness, which in turn positively affects the smart bands acceptance. Trust is also a mediator of the effect of ease of use on usefulness; a higher perceived ease of use is associated with higher trust, which in turn determines a higher perceived usefulness. Thus, trust and perceived ease of use are crucial for consumers in evaluating the perceived usefulness of smart bands.

The data show also that two personality disposition traits significantly moderate the influence of perceived ease of use and perceived usefulness on acceptance. Fun seeking behavioral motivation moderates inversely the effect of ease of use on behavioral intention to use smart bands; people with stronger fun seeking personality report higher intention to use smart bands if they do not perceive smart bands as easy to use, conversely, people with low fun seeking dispositions, are likely to use smart bands only if they perceive them to be easy to use. Reward responsiveness moderates positively the effect of perceived usefulness on acceptance; people with stronger reward responsiveness personality are likely to use smart bands if they perceive them to be useful.

6.3 Contributions and implications

The study has four main contributions. The first and most important contribution is that it shows that behavioral-disposition traits have significant effects in the structural model as moderators. This is the first study to introduce behavioral motivation factors in a technology acceptance model, and to show that fun seeking and reward responsiveness personality traits moderate the relationships between perceived ease of use, usefulness, and behavioral intention to use technology. These findings mean that the qualities of ease of use and usefulness have to be considered together with the users' motivational personalities when developing and marketing digital technology such as smart bands. Thus, the digitization of the individual and the extent of adopting digital life technology are strongly dependent on how the technology fits the personality of the individual (e.g., .fun- or reward-centered).

Second, the study extends the conceptual meaning of the social influence construct so to include external influence from other social actors than family and friends that are typically formalized in social influence measurement scales. Being inspired by literature on brand communities, social image and identity theories [44,47,48] we operationalized the social influence construct so to represent influences from other users and advertisements. The new scale was found reliable and significant in the structural model. The implications for practitioners are to understand the importance of advertising and communicating in social or other media. These are in line with the new research directions on quantifying the effects of online reviews on purchase decisions and/or consumer behavior and making sense of online reviews [74,75], as well as on providing digital solutions to facilitate communication among consumers [76], and understanding consumer social interactions and their impact on business [77]. Moreover, this opens new research directions on conceptualizing, operationalizing, and facilitating social influence for marketing and development purposes.

Third, the study contributes to the modeling and understanding of smart bands acceptance by highlighting new relationships in the structural model for predicting smart bands acceptance compared to a recent study [7]. In this respect, we showed that trust, affinity, and compatibility have significant effects on smart bands acceptance. This has implications on the development and marketing of the smart bands, and digital life technology in general: developers must ensure the accuracy and reliability of the wearable technology for healthcare so to improve the trust in technology, and also to communicate this effectively to target consumers. Individual user characteristics such as mobile affinity and compatibility should be also considered when developing and marketing these devices.

Fourth, the study pointed out that trust and perceived ease of use do not have direct effects on smart bands acceptance, but their effects are mediated by usefulness. This pattern differs from previous findings (e.g., [7]). The differences can be explained by the difference in sample characteristics, especially related to age (i.e., for relatively young people perceived ease of use may not be a crucial factor for the adoption compared with older people, see also [33]; and similarly, trust in technology may be differently perceived and conceptualized by different age groups, see e.g., [38]). This implies that further research should investigate these relationships on different segments of populations. A clustering approach based on individual characteristics such as the one proposed by Schneider et al. [78] could also be employed when defining relevant segments of population.

Owing to the sampling procedure, the sample in this study was slightly biased towards highly educated and young people, and had an imbalanced gender structure (more females than males, and males were predominantly slightly younger). Thus, age and gender were not found to be significant moderators influencing behavioral intention to use smart bands.

7 CONCLUSIONS

Wearable devices for personal healthcare became popular tools for monitoring and improving personal health, and represent a promising technology towards digitization of the individual to enhance his/her everyday life. However, the relatively low adoption rates signal a need to understand the factors and motivations determining adoption and acceptance of these devices to provide developers and marketers with knowledge towards improving digital life technology and customer satisfaction. Our study reveals that personality characteristics and traits play an important role among the more traditional factors such as usefulness, ease of use, trust and social influence. Mobile affinity and compatibility, two facets of technological personality, have positive influences on acceptance of smart bands; thus, individuals who value mobile phones to a high degree are more likely to adopt smart bands for health monitoring and improvement, and individuals will use digital life technology which performs similar functions as the technology already adopted. Behavioral-disposition traits, namely fun seeking and reward responsiveness, moderate the relationships between perceived ease of use and use intention, and between perceived usefulness and use intention, respectively. Stronger fun seeking personalities will use smart bands when perceived ease of use is low, while stronger reward responsiveness personalities will use smart bands when perceived usefulness is high. The results have implications to research and development of the wearables for personal healthcare, and of digitization of the individual, in general, as it points to taking into account the personality factors as well as the conceptualization, operationalization, design, and implementation of social influence and interaction aspect.

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