International Journal of E-Business Research
Volume 18 • Issue 1

Can You Help Me Stay Fit? A Study of Continuance Intention of Wearable Fitness Devices

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ABSTRACT

The main purpose of this study is to reveal the impact of consumer satisfaction on continuance intention to use wearable fitness devices. Building upon the IS Continuance Intention Model, the authors explored the effects of confirmation of ease of use, confirmation of perceived usefulness, positive and negative feelings, and perceived control on consumer satisfaction. The effects of health motivation and social influence on continuance intention were examined alongside satisfaction. Our model consists of twelve constructs and eleven hypotheses. An online survey was conducted among 216 Amazon M-Turk workers to collect data. The measurement model was first tested and validated. Next, structural equation modeling was used to test the hypotheses in the research model. Nine out of eleven hypotheses were supported. The model explains 50.1% of variances in continuance intention, and 63.9% of variance in consumer satisfaction is explained by the aforementioned factors. Both theoretical contributions and practical implications are discussed in the context of wearable technology.

KEYWORDS

Consumer Satisfaction, Continuance Intention, Health Motivation, IS Continuance Intention Model, Perceived Control, Social Influence, Wearable Fitness Devices

INTRODUCTION

In recent years, the growing popularity of wearable fitness or health devices has inundated the consumer market, including wristbands (e.g., Fitbit and Jawbone), smart watches, and wearable body metric textile (Swan, 2012). As a particular form of Internet of Things, wearables are often equipped with internet connectivity, either via sensors embedded in the device (O'Brien, 2015) or by connecting with a smartphone (Canhoto & Arp, 2017). They can track, store, and transmit health and wellness data such as heart rate, sleep, steps, blood pressure, and body temperature (Weber, 2015). According to Business Insider (Phaneuf, 2021), about 62.2 million US consumers are estimated to adopt wearables by 2020, and the number will increase to 72.6 million by 2024, accounting for 27.1% of the US population. It is uncertain, however, whether these wearables will survive and gain their own market position alongside smartphones or tablet personal computers, because they are often viewed as optional accessories and not a necessity (Cho et al., 2019; Matte, 2015). Adding to this uncertainty,

DOI: 10.4018/IJEBR.309392
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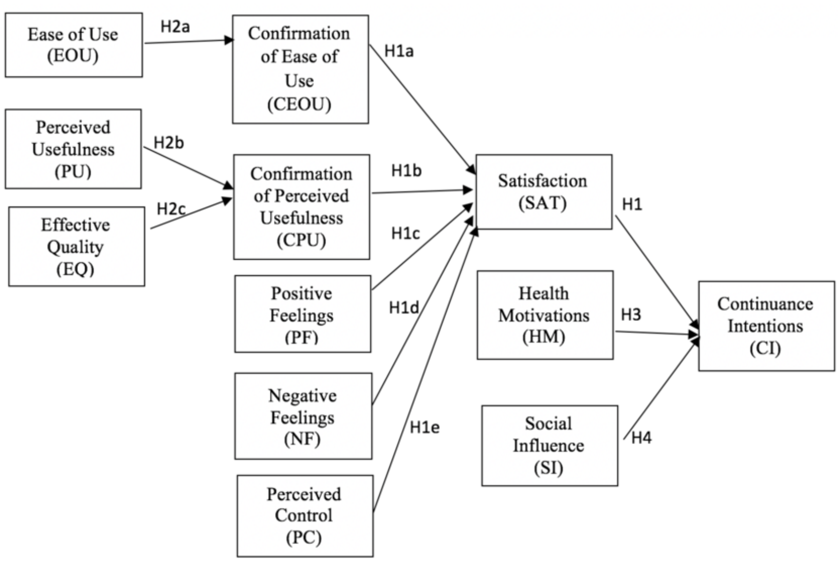
studies on the post-adoption behavior began to show that the user attraction was decreasing, showing a significant drop in the usage after a short period of time (Lazar et al., 2015). According to Canhoto and Arp (2017), nearly half the consumers stopped using their wearables within the first six months. This discussion has shaped the research focus of the current project: What influences consumers to continue to use their wearables?

A growing number of studies have focused on the adoption and use of wearable fitness devices (e.g., Kalantari, 2017; Liu & Han, 2020). Multiple factors including perceived ease of use (e.g., Kim & Chiu, 2019), perceived usefulness (e.g., Cheung et al., 2019; Kim & Chiu, 2019), visibility (Chuah et al., 2016), and social influences (e.g., Cheung et al., 2019) have shown to positively affect consumer acceptance or adoption of wearables. In addition, attitude, perceived usefulness (Kim & Shin, 2015) and design aesthetics (Muller & Klerk, 2020) are found to affect consumer use intention. Research questions remain such as what factors influence wearables users' post-adoption behavior. A handful studies have started to examine intermittent discontinuance (Shen et al., 2018), which is "temporarily discontinuing the use of information technology and readopting it later (p. 508)," and dissatisfaction and attrition (Coorevits & Coenen, 2016; Lazar et al., 2015).

Our study extends the current understanding on the post-adoption usage behavior by focusing on the continuance intention. It fills the research gap in understanding the post-adoption usage as opposed to initial adoption or acceptance. Continuance intention is defined as the user's decision to continue to use a specific technology that they have already been using. The information technology research has shown the importance of such continuance because the ultimate success of the technology largely depends on users' continued use (Bhattacherjee, 2001; Karahanna et al., 1999). Specifically, we developed an extended IS Continuance Intention Model to capture our understanding of continuance intention to use wearables (see Figure 1). The contribution of our project lies in three areas. First, while the existing IS Continuance Intention model treats satisfaction as an affective factor that influences continuance intention, we examine it as a both affective and cognitive factor. Second, the existing model posits that satisfaction is a main factor in affecting intention, we add two more factors - social

Figure 1. Research model



Note: The abbreviations of the constructs are in parentheses below the full construct names.

influence and health motivation - to capture the influences of social and motivational factors on the continuance intention. Third and lastly, this project unpacks the antecedents of consumer satisfaction by considering both affective and cognitive factors, which are propelled by the quantified self-movement, a unique motive for using wearables.

In the next section, we discuss the effect of satisfaction on continuance intention as well as various antecedents for satisfaction, including two confirmation factors, feelings, and perceived control. Then, we explain how additional factors such as health motivation and social influence affect the continuance intention alongside satisfaction.

CONCEPTUAL FRAMEWORK

Satisfaction and IS Continuance Intention Model

In the field of information technologies, continuance intention has been studied using the post-acceptance model of IS Continuance Intention (CI) model and its extended versions. The CI Model assumes that consumers' continuance intention is determined by their satisfaction with the use of technology and the perceived usefulness of using such technology (Bhattacherjee, 2001). The CI model and its extended versions have been validated in different contexts including mobile advertising (Hsiao & Chang, 2014), advanced or disruptive technology (e.g., Fan & Suh, 2014), smartphone banking services (Susanto et al., 2016), and knowledge sharing platforms (Pang et al., 2020). In addition, the importance of satisfaction in the product development and success of wearables is evidenced in a study of consumers' decision making on wearables (Liu & Han, 2020). We therefore state that:

H1: Consumers' satisfaction with wearables will positively predict their continuance intention to use wearables.

Antecedents of Satisfaction: Confirmation

Satisfaction is often viewed as an important indicator for any business to grow and remain competitive in the market. Hence, it has been studied in different types of businesses, ranging from e-health care services (Burr et al., 2007) to internet service providers (Cheng et al., 2008). According to consumer behavior researchers (Hoyer et al., 2018), satisfaction is the feeling that a purchase or adoption decision and consumption experience meets or exceeds one's expectation. This is in line with how Oliver (1981, p. 29) initially defined the concept, stating "[t]he summary psychological state resulting when the emotion surrounding disconfirmed expectations is coupled with the consumer's prior feelings about the consumption experiences." This suggests that both affective factors and cognitive factors (due to the evaluation process regarding if a decision or experience meets one's expectation) contribute to accurately understanding satisfaction. As such, we focus on confirmation of ease of use, confirmation of usefulness, and perceived control as the cognitive factors and positive and negative feelings as the affective factors.

While we build our model based on the Continuance Intention model, we also draw insights about satisfaction from a relevant model, the expectation-confirmation model (Bhattacherjee, 2001; Hsu et al., 2016). According to the expectation-confirmation model, satisfaction is influenced by three constructs, namely, expectation, performance, and confirmation. To explain, if the actual performance of a product or technology is superior to users' original expectation, it will lead to users' confirmation of their prior expectations and bring satisfaction toward the product. Simply put, positive confirmation will enhance users' positive perceptions, leading to satisfaction with the product or technology use.

Perceived ease of use (PEOU) and perceived usefulness (PU) are the two main factors in studying the acceptance or adoption of technology (Davis, 1989; Kim & Shin, 2015). PU addresses the usefulness of the IS and it can help enhance the effectiveness of the user, whereas EOU addresses the easiness of the person-technology interactions (Davis, 1989). The roles of both factors have also been studied with respect to the confirmation and continuance intention. For example, Zhou et al. (2018) found that both PEOU and PU positively affected confirmation, which influenced satisfaction in a study of e-finance continuance intention. In addition, studies showed that PEOU did not affect continuance intention to use smart devices (Cho & Lee, 2020), whereas it affected continuance intention to use m-commerce (Chong, 2013). Given the mixed results presented, we branch out confirmation as two factors - confirmation of PEOU and confirmation of PU. Consistent with the Continuance Intention model, each confirmation factor will have a direct effect on satisfaction. Also, the confirmation factor will be predicted by PEOU and PU, respectively. Hence:

H1a: Confirmation of perceived ease of use will positively predict consumer satisfaction.
H1b: Confirmation of perceived usefulness will positively predict consumer satisfaction.
H2a: Perceived ease of use will positively predict confirmation of perceived ease of use.
H2b: Perceived usefulness will positively predict confirmation of perceived usefulness.

Another possible antecedent that affects the confirmation of PU is effectiveness or effective quality. Segars and Grover (1993) reexamined the studies on the two-factor technology acceptance model and found a potential third factor, which they termed effectiveness. It concerns the extent to which the new technology fulfills users' target goals, which is likely to affect their perception of the usefulness of the technology (Grover & Segars, 2005). We therefore explore the impact of effective quality in the following hypothesis:

H2c: Perceived effective quality will positively predict confirmation of perceived usefulness.

Antecedents of Satisfaction: Feelings

Researchers have recently turned their attention to the effects of affective factors in the adoption and use of technologies (e.g., Lee & Kwo, 2011) or wearables in particular (e.g., Cho et al., 2018; Fritz et al., 2014). Different types of affective factors have been studied and the results have shown that they either have a direct effect on adoption and use or indirectly via perceived usefulness (Zhang & Li, 2005). For example, pleasure, defined as the degree of a wearable user's emotional and hedonic feelings such as interest, joy and happiness when they use their device, was found to affect consumer satisfaction (Cho et al., 2018) and continued use (Fritz et al., 2014). Lee and Kwon (2011) focused on long-term emotional factors, such as familiarity and intimacy, and revealed their impacts on consumer satisfaction and continuance intention to use web-based services. Additionally, studies on the abandonment and continued use also provided support for the role of affective factors, such as entertainment (e.g., Lazar et al., 2015), in keeping users satisfied.

Consistent with Hoyer et al. (2018) work on satisfaction, we study positive and negative feelings as affective factors. Wearables lead users to believe that they will be able to avoid disease and stay healthy by monitoring and collecting data about their health patterns and behavior. Some users find that using this technology has improved their health, as they are more active, and even helped them kick bad habits such as smoking or drinking. In turn, this makes them feel happier and more content with themselves and their lives. Other users may feel failure and stress after fixating on their fitness device because they are not making their goals or cannot see an improvement in the data (Lupton, 2013). Similar negative feelings were also reported in a study of Fitbit use in the workplace (Everett, 2015). Hence, we hypothesize that:

H1c: Positive feelings will positively predict satisfaction.
H1d: Negative feelings will negatively predict satisfaction.

Antecedents of Satisfaction: Perceived Control

The rising popularity of wearables may have been largely influenced by the growing trend of the quantified-self movement and persuaded self-tracking (PST) practice. Quantified-self describes individuals who self-track their bodies by food intake, physical performance, sleep patterns, and heart rate to gain self-knowledge and better themselves health wise (Daly, 2015). The involvement of commercial entities (e.g., health and life insurance, airlines and supermarkets) has speeded up such movement and PST practice. These commercial entities have begun to introduce wearable technology as part of the consumer journey and as a means of enhancing the business value chain. By encouraging PST practice via personalized incentives and rewards, they can collect more users' personal biometric data through wearable technologies (Paluch & Tuzovic, 2019).

Research has shown that PST can help wearable users feel more in control of their lives (Princi & Krämer, 2020; Lupton, 2014; Zhang et al., 2019). Despite having a degree of ambivalence about PST, wearable users indicated a more definitive desire for greater empowerment as PST participants, because they are concerned about a lack of control. PST practice is believed to be more acceptable if wearable users are in control regarding their participation. These users further expect to have control of authorizing the use of and access to their personal data. This is in line with previous consumer research on wearables (Paluch & Tuzovic, 2019; Tuzovic et al., 2015). In observing the effects of perceived control, we hypothesize that:

H1e: Perceived control will positively predict satisfaction.

We have established the relationship between satisfaction and continuance intention in studying wearables as well as the five antecedents for satisfaction. As discussed, three of the five antecedents are cognitive factors, including confirmation of PU, confirmation of EOU, and perceived control and the other two antecedents are positive and negative feelings, which are affective factors. Past studies have shown that satisfaction has limited predictive power for continuance intention. For example, Bhattacherjee (2001) found that about 41% of variance in continuance intention was explained by satisfaction and PU. We propose to add two new factors - health motivation and social influence - to explain the continuance intention alongside the satisfaction factor.

Health Motivation and Social Influence

New factors have been incorporated in the Continuance Intention model to enhance our understanding of consumers' continuance intention. In the existing studies on continuance, factors that influence users' continuance intention have been suggested from two typical perspectives: cognitive and affective (Lin et al., 2005). Relevant to the usage of wearables, we examine the roles of health motivation and social influence in affecting users' continuance intention. These two factors touch upon motivational and social perspectives, respectively.

Health motivation is defined as "consumers' goal-directed arousal to engage in preventive health behaviors" (Moorman & Matulich, 1993, p. 210). As discussed, wearables are mainly used to track users' health and fitness conditions, such as diet, activity levels, and physiological measures like heart rate and weight. The quantified-self movement and persuaded self-tracking practice are more popular among people with stronger health motivations or health beliefs (Paluch & Tuzovic, 2019). Studies have shown that health-related psychographic factors were found to have significant effects on exercise maintenance as well as well-being (Mowen, 2000; Zhou & Krishnan, 2019). However, only a handful of studies have examined these health-related factors in adopting or using wearables. For example, Chueng et al. (2019) showed that health belief was found to positively affect perceived usefulness, which in turn affected adoption intention of wearables. The direct effect of motivation on intention has been established in adoption of news apps (Mittal et al., 2020) and electronic patient record (Henkenjohann, 2021). Given the impact of health motivation on individuals' health maintenance behaviors, we hypothesize a direct relationship that:

H3: Health motivation will positively predict the continuance intention to use wearables.

Next, social influence is the extent to which members of a social network influence one another's behavior (Rice et al., 1990). A number of studies have shown that social influences affected adoption or acceptance of wearables (Buenaflor & Kim, 2013; Canhoto & Arp, 2017; Coorevits & Coenen, 2016; Yang et al., 2016). Without any prior usage experience with wearables, it makes sense that consumers' adoption decision is affected by the opinions or behavior of social others. We argue that social influences also play an important role in the continued use of wearable devices. The observability of wearables worn by social others and/or physical activities those social others carry out will affect users' decisions and behaviors. The role of social influences on the continuance intention has been evidenced in a slightly different context, mobile commerce (Lu, 2014). Hence, we hypothesize that in the context of the wearable technology:

H4: Social influence will positively predict the continuance intention to use wearables.

A research model on consumers' continuance intention to use wearables was therefore developed, consisting of the eleven hypotheses discussed above. See Figure 1.

METHODOLOGY

The Research Sample

An online survey was conducted to collect data via Amazon M-Turk. The first part of the questionnaire screened the participants to see whether they own a wearable fitness device and if they use it. Based on their responses, 228 participants were labeled as current wearables users. Twelve responses were removed from further analysis due to a considerable amount of missing values. Hence, responses from 216 users were used in the final data analysis. The age of our sample ranged from 18 to 68 years old with an average of 35. The gender was skewed toward female respondents (136; 63.0%). We asked respondents to check all the possible reasons why they use wearables. The results showed that the top reason was "keep track of your progress" (191 responses; 57.2%), followed by "helps you stay motivated" (49 responses; 14.7%) and "monitor your health" (27 responses; 8.1%). See Table 1 for other demographics information.

The Research Instrument

The measurements for research constructs were based on prior research and modified for our research purpose. Each construct in the model consisted of multiple items measured using 7-point Likert-scales, ranging from "1" (strongly disagree) to "7" (strongly agree). Two exceptions are measurement of confirmation of ease of use and confirmation of perceived usefulness. The responses ranged from "1" (much worse than expected) to "7" (much better than expected). See Table 2 for the constructs, their sources, means and standard deviations, and corresponding items.

DATA ANALYSIS AND RESULTS

The Measurement Model

The measurement model was tested first. The reliability of the constructs was demonstrated in Table 3. All the average variance extracted exceeded .64, all the composite reliabilities were

Table 1. Demographics of the Research Sample

Characteristics	Number	Percentage
Gender		
Male	80	37.04%
Female	136	62.96%
Ethnicity		
White or Caucasian	157	72.69%
Hispanice or Latino	13	6.02%
Black or African American	23	10.65%
Native American or American Indian	1	0.46%
Asian/Pacific Islander	19	8.80%
Multicultural	3	1.39%
Occupation		
Employed full time	177	78.07%
Employed part time	12	5.77%
Unemployed looking for work	4	2.09%
Unemployed not looking for work	9	5.05%
Retired	3	1.80%
Student	7	4.49%
Disable	4	2.73%
Personal Income (before taxes)		
Less than $10,000	11	5.09%
$10,000-$19,999	12	5.56%
$20,000-$29,999	22	10.19%
$30,000-$39,999	25	11.57%
$40,000-$49,999	32	14.81%
$50,000-$59,999	60	27.78%
$75,000-$99,999	29	13.43%
$100,000 or more	25	11.57%

above .84, and all the Cronbach's Alphas were above .72. The variance extracted for each construct was also shown in Table 3. The discriminant validity of the lower order constructs was further demonstrated by the inter-construct correlation matrix in Table 4, where the square root of the average variance extracted (AVE) for each construct was greater than the inter-construct correlations. The lowest square root of AVE of a construct in our data is .802 (SI) and the highest correlation between any two constructs is .745 (between EQ and PF). The above established the construct validity.

The Structural Model

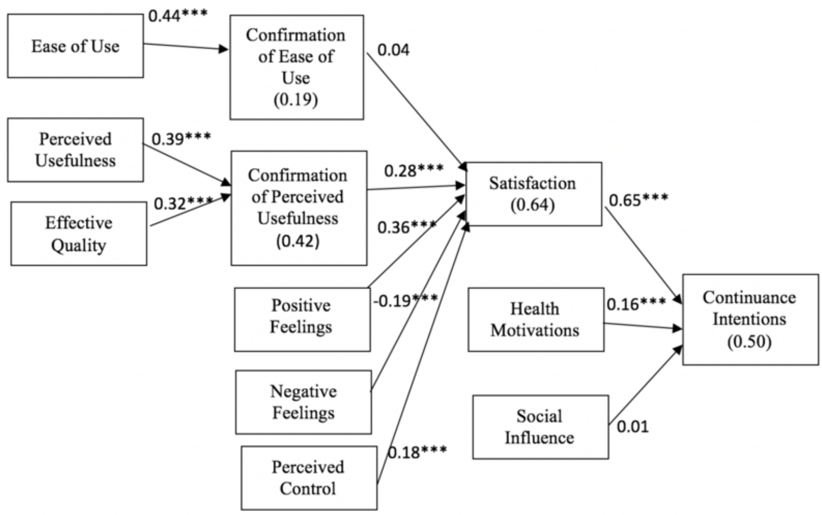
We used SmartPLS 3.3.3 (Ringle et al., 2005), a software using the Partial Least Square (PLS) analysis technique, to test the structural model and research hypotheses. The continuance

Table 2. Research constructs, sources, and items

Construct (Source)	Mean	Standard Deviation	Item
Continuance Intention (Bhattacherjee, 2001; Susanto et al., 2016)	6.32 6.27 6.25	0.947 1.036 1.072	I intend to continue using wearable fitness devices. I intend to continue using wearable fitness devices when I work out. I plan to continue using wearable fitness devices on a daily basis.
Satisfaction (Pang et al., 2020; Susanto et al., 2016)	6.01 6.07 5.81 6.15	1.095 1.002 1.155 0.920	I am pleased with my use of the wearable fitness device. I am content with my use of the wearable fitness device. I am delighted with my use of the wearable fitness device. I am satisfied with my use of the wearable fitness device.
Confirmation of Ease of Use (Pang et al., 2020; Susanto et al., 2016)	5.63 5.46 5.56 6.01	1.26 1.37 1.34 1.24	Compared to my initial expectations, the ability of wearable fitness devices: to be easy to get it to do what I want it to do was to be easy for me to learn to use was... to be easy for me to become skillful at was... to be easy to use was… (“1”) Much worse than expected… (“7”) Much better than expected
Confirmation of Usefulness (Pang et al., 2020; Susanto et al., 2016)	5.56 5.72 5.74 5.85	1.38 1.45 1.47 1.49	Compared to my initial expectations, the ability of wearable fitness devices: to increase my productivity was… to improve my performance was… to enhance my effectiveness was … to be useful was… (“1”) Much worse than expected (“7”) Much better than expected
Perceived Ease of Use (Dastan & Gurler, 2016)	5.84 5.91	0.990 0.933	I believe using a wearable fitness device is straightforward. The information on wearable fitness devices is easy to understand.
Perceived Usefulness (Dastan & Gurler, 2016)	5.75 5.80 5.75 5.20	0.955 0.926 1.093 1.987	I believe a wearable fitness device accurately tracks my performance. I believe I get the results I want from a wearable fitness device. I believe I gain valuable insights about myself by using a wearable fitness device
Effective Quality (adapted from Grover and Segar, 2005.)	5.59 5.79 5.48	1.048 1.113 1.294	Having a wearable fitness device has helped me reach my fitness goals. I feel that having a wearable fitness device has made a positive impact on my life. I have changed my habit by using a wearable fitness device.
Positive Feelings (Russell & Pratt, 1980)	5.91 6.06	1.463 1.405	I feel content if I track my workouts using a wearable fitness device. I feel satisfied if I use a wearable fitness device.
Negative Feelings (Russell & Pratt, 1980)	5.67 5.86 5.89	1.083 1.052 1.077	I feel stressed if I use a wearable fitness device. I feel bad (about myself) if I use a wearable fitness device. I feel anxious if I track my workouts using a wearable fitness device.
Perceived Control (Adapted from Zhang & Mao, 2008; Zhang et al., 2019)	5.50 5.76	1.250 1.094	I feel calm while using a wearable fitness device. I feel I am in control while using a wearable fitness device.
Health Motivation (Moorman & Matulich, 1993; Mowen, 2000)	5.42 5.45 5.52 4.74 4.78	1.280 1.307 1.261 1.689 1.509	I try to prevent health problems before I feel symptoms. I am concerned about health hazards and try to take action to prevent them. I try to protect myself against health hazards I hear about. I do not worry about health hazards until they become a problem for me or someone close to me. I do not take action against health hazards I hear about until I know I have a problem.
Social Influences (Arvidsson, 2014; Wei & Lu, 2014)	5.40 4.46 5.56	1.185 1.584 1.055	I perceive that a good number of people use a wearable fitness device. I perceive that most people use a wearable fitness device. I perceive that there will be many more people using a wearable fitness device in the future.

intention was modeled with indicators from satisfaction, health motivation, and social influence. Satisfaction was modeled with indicators from confirmation of ease of use, confirmation of perceived usefulness, positive and negative feelings, and perceived control. Bootstrapping was conducted to obtain t-values. The results of the structural model testing are presented in Figure 2. Hypothesis testing results are summarized in Table 5. The model fit statistic was also assessed using SRMR which was 0.073, below the acceptable threshold of 0.08 (Hu & Bentler, 1999).

Figure 2. Testing results of research model



Note: *** *p < .001. Path coefficients are labeled along the path in the diagram. Variance extracted are in the parentheses under construct names.*

Table 3. Research construct's reliability

Construct	Abbreviation	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)	R^2
Continuance Intention	CI	0.94	0.96	0.89	0.501
Satisfaction	SAT	0.90	0.93	0.78	0.639
Confirmation of EOU	CEOU	0.85	0.91	0.77	0.193
Confirmation of PU	CPU	0.86	0.90	0.70	0.423
Perceived Ease of Use	EOU	0.77	0.90	0.81	
Effective Quality	EQ	0.81	0.89	0.73	
Health Motivation	HM	0.90	0.94	0.84	
Negative Feelings	NF	0.84	0.90	0.75	
Positive Feelings	PF	0.86	0.91	0.78	
Perceived Usefulness	PU	0.84	0.91	0.76	
Social Influences	SI	0.72	0.84	0.64	
Perceived Control	PC	0.82	0.92	0.85	

RESULTS

A substantial amount of variance was explained by the model. The variance explained by the model for continuance intention to use wearables and consumer satisfaction are $R_{CI}^2 = 0.50$ and R_{SAT}^2=.64, respectively. Nine out of eleven hypotheses were supported. Specifically, consumer satisfaction and health motivations significantly influenced continuance intention. Thus, H1 and H3 were supported. As hypothesized, confirmation of usefulness, positive feelings, negative feelings, and perceived

Table 4. Inter-construct correlations and square roots of AVE

	CI	EOU	EQ	HM	NF	PF	PU	SAT	SI	CEOU	CPU	PC
CI	**0.942***											
EOU	0.488	**0.902**										
EQ	0.488	0.452	**0.852**									
HM	0.353	0.283	0.300	**0.915**								
NF	0.504	0.444	0.320	0.351	**0.869**							
PF	0.613	0.476	0.745	0.295	0.370	**0.881**						
PU	0.598	0.578	0.708	0.338	0.437	0.716	**0.873**					
SAT	0.696	0.505	0.667	0.295	0.457	0.701	0.696	**0.881**				
SI	0.125	0.064	0.164	-0.038	-0.061	0.311	0.220	0.191	**0.802**			
CEOU	0.400	0.444	0.444	0.154	0.194	0.420	0.374	0.431	0.197	**0.878**		
CPU	0.486	0.493	0.596	0.288	0.285	0.535	0.614	0.646	0.273	0.501	**0.835**	
PC	0.445	0.380	0.510	0.331	0.266	0.562	0.541	0.597	0.230	0.329	0.522	**0.921**

*Diagonal elements in bold represent square root of average variance extracted (AVE)

Table 5. Hypothesis testing results

Hypothesis	Path	Path Coefficient	Supported
H1	SAT→ CI	.65***	S
H1a	CEOU→ SAT	.04	NS
H1b	CPU→ SAT	.28***	S
H2a	EOU→ CEOU	.44***	S
H2b	PU→ CPU	.39***	S
H2c	EQ→ CPU	.32***	S
H1c	PF→ SAT	.36***	S
H1d	NF→ SAT	-.19***	S
H1e	PC→ SAT	.18***	S
H3	HM→ CI	.16***	S
H4	SI→ CI	.01	NS

Notes: S = Supported at .001 (***) level.

control significantly affected consumer satisfaction, lending support to H1b, H1c, H1d, and H1e. The results also showed that perceived ease of use positively predicted confirmation of ease of use, and both perceived usefulness and effective quality predicted confirmation of usefulness, supporting H2a, H2b and H2c, respectively. Different from our expectations, H1a (CEOU → SAT) and H4 (SI → CI) were not supported.

CONCLUSION AND DISCUSSION

This study proposed and tested an extended IS Continuance Intention model in studying wearables. We demonstrated the effects of consumers' satisfaction and health motivation on their continuance intentions to use wearables. About 50% of the variance in continuance intention was explained by the model. Also as expected, confirmation of perceived usefulness, positive and negative feelings, and perceived control significantly affect satisfaction, explaining 64% of its variance. We also revealed perceived usefulness and effective quality as the antecedents for confirmation of perceived usefulness and perceived ease of use as the antecedent for confirmation of ease of use.

Theoretical Contributions

First, our study demonstrated the importance of the extended continuance intention model in predicting consumers' continuance intention to use wearables. The model explained about 50% of the variance in continuance intention. This implies that satisfaction as well as health motivation are important in explaining the continuance intention. Satisfaction has been a mainstay factor in the continuance intention model. Consistent with past studies (e.g., Bhattacherjee, 2001; Hsu et al., 2016), satisfaction is found to play the largest role in predicting users' continuance intention. Indeed, it is not surprising that an overall positive confirmation that wearables meet users' expectations will make them feel peace of mind and propel them to continue to use the devices. Our contribution lies in proposing and validating one additional factor, which captures the motivational perspective of using wearables. As expected from studies of health maintenance behaviors (e.g., Moorman & Matulich, 1993; Mowen, 2000), health motivation was found to predict continuance intention to use wearables. The inclusion of the health motivation helped expand the continuance intention model, which better predicted the continuance intention in the current project.

Second, we unpack the satisfaction further by considering both affective and cognitive factors. To begin, we found that both positive and negative feelings associated with using wearables affect the satisfaction. Affective factors are not initially proposed in Bhattacherjee's (2001) Continuance Intention Model model. In line with the definitions by Hoyer et al. (2018) and Oliver (1982), we proposed and validated the role of feelings in the Continuance Intention Model. In addition, we branched out confirmation from one single concept to confirmation of ease of use and confirmation of usefulness. Our results revealed that it is confirmation of usefulness that leads to satisfaction. And finally, due to the growing trend of quantified self-movement and persuaded self-tracking (PST) practice, we include and validate perceived control as another cognitive factor in the current project. This factor captures users' efforts to be in control of using their wearables as part of daily life and experience empowerment in self tracking.

Practical Implications

Based on our current findings, we would like to make two recommendations for marketers to maintain continued use of wearable devices. First, in light of our findings about the significant effects of perceived usefulness and ease of use, we recommend that wearable vendors continue to refine product usefulness in their product development and innovation in hardware and software. It can be achieved through the use of sensors in the wearables as well as linking to other internet of things (IoT). For example, Apple Watch can now open hotel doors. So, users can go for a run on a vacation without carrying a hotel key. It will keep users loyal if we continue to transform and enhance day-to-day tasks with wearables. Wearable vendors need to be mindful of usefulness and effective quality of the device and vigorously test for these factors. The bottom line is that the user experience must be preserved.

Second, the marketing effort should not stop after consumers adopt the wearables. Continued effort needs to be in place to keep users satisfied. According to our findings that positive feelings contribute to satisfaction, marketing programs can portray positive images on how using wearables can help users feel confident and content with their daily exercise and activities. Programs that are designed to address negative feelings such as anxiety or frustration should also be implemented, in an effort to keep users satisfied. Biochemical sensors that can detect signals for anxiety such as increased heart rate and hormones can be incorporated into the wearables and actions can be suggested to change mood, such as get up and dance. Moreover, these actions can be pre-configured to cater to the user.

In addition, given that health motivation affects continuance intention to use wearables, a proper effort on creating external health motivations will help users be engaged. For example, health-related encouraging words such as "way to keep yourself healthy and strong," "you did it," "a fantastic run," or "it is never too late to start jogging," will make users feel the positive vibe of using the wearables. This will help them continue using wearables to fulfill their various needs for such a device.

Limitations and Future Research

Our research demonstrated the effects of consumers' satisfaction and health motivation on their continuance intention to use wearables. We also revealed how confirmation of usefulness, positive and negative feelings, and perceived control affected satisfaction. In light of the current findings, we suggest future research in two different directions. First, we studied continuance intention and measured the concept with self-reported data, not continued use, which is an actual behavior. Future studies may investigate if the effects hold true for continued use. Findings based on the actual user data from secondary data sources may produce more robust results compared to self-report data. Second, the two factors - satisfaction and health motivation have explained a good portion of the variance in continuance intention. We call future research to add other factors to enhance the explanatory power of the current research model. For example, future studies may examine how privacy concerns (Paluch & Tuzovic, 2019), security concerns (Zhang et al., 2019), and trust factors (Hsiao & Chang, 2014) affect continuance intention. Similarly, we also call for research to help understand the antecedents of satisfaction. We believe that studies on antecedents that increase consumers' satisfaction will advance our understanding of the continuance intention to use wearables.

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