International Journal of E-Business Research
Volume 19 • Issue 1

What Makes Consumers Adopt a Wearable Fitness Device?

The Roles of Cognitive, Affective, and Motivational Factors

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ABSTRACT

Wearable fitness devices are equipped with internet connectivity and capable of tracking, storing, and transmitting health data. A research model is proposed and tested, which shows how cognitive, affective, social, and motivational consumer factors affect the intention to adopt wearables, respectively. The antecedents of these factors are also studied, including perceived usefulness, ease of use, and effectiveness for cognitive factors; positive and negative feelings for affective factors; perceived number of users, number of peers, and social images for social factors. An online survey was conducted among 297 non-wearable-users in the U.S. to collect data. Structural equation modeling was used to test the intention model. The results showed that three factors—cognitive, affective, and motivational—emerged as key determinants of consumers' intention to adopt wearables, with affective factors showing the most explanatory power. The role of the price factor was also revealed. Theoretical and business practical implications are discussed based on the current findings.

KEYWORDS

Affective Attitudes, Health Motivation, Relative Advantages, Technology Acceptance Model, Theory of Reasoned Action, Wearable Fitness Devices

INTRODUCTION

Wearable technology constitutes a touchpoint across technological trends, including mobile, big data, the Internet of Things, and virtual/augmented/mixed reality (Tarabasz & Poddar, 2019). According to Globe Newswire (2022), the value of the wearable technology market reached over $100 billion in 2021 and is predicted to reach about $380 billion by 2028, seeing a three-fold increase. Wearable fitness devices are one of the important digital transformations that will affect business and consumer

DOI: 10.4018/IJEBR.323204

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interactions. During the past decade, different wearable fitness or health gadgets have taken the consumer market. More and more consumers are wearing smart watches, wristbands (e.g., Pebble and Fitbit), and body metric textile (Swan, 2012). Wearables are a particular form of the Internet of Things; they are connected to the Internet by linking to a smartphone or via sensors embedded in the device (Canhoto & Arp, 2017; O'Brien, 2015). These devices provide tracking capabilities and storage of health and fitness indicators and statistics, including body temperature, steps, heart rate, and sleep (Weber, 2015). Largely because of the quantified-self movement (Paluch & Tuzovic, 2019), about 78 million U.S. consumers adopted wearables in 2021, and the number will surpass 90 million by 2024, reaching 25.5% of the U.S. population (Phaneuf, 2023). Such steady growth does not imply that we should take the widespread adoption of wearables for granted (Babič et al., 2021). To capture the remaining consumer segments, this project addresses the following research question: What makes consumers adopt wearables?

There is a growing research interest surrounding wearable fitness devices, including the adoption and use (e.g., Kalantari, 2017; Grosová et al., 2022; Liu & Han, 2020), intermittent discontinuance (Shen et al., 2018), and continued use (Zhang & Mao, 2022). Studies have revealed the influencing factors such as perceived ease of use (e.g., Kim & Chiu, 2019), perceived usefulness (e.g., Cheung et al., 2021; Kim & Chiu, 2019; Felea et al., 2021), visibility - the extent to which a technology is apparent in the sense of sight of observable to others (Chuah, 2019), and social influences - the effect of the social surroundings on individual consumers (e.g., Cheung et al., 2019). Those factors have shown to have positive effects on the acceptance/adoption of wearables. In studies of consumer use intentions, researchers have found the following significant factors: attitude, perceived usefulness, and design aesthetics (Kim & Shin, 2015; Muller & Klerk, 2020; Felea et al., 2021). The meta-analysis has been conducted to reveal that most of the key variables identified in the studies have significant effect sizes in their relations to attitudes and adoption intention (Chiu & Cho 2021; Gopinath et al., 2022) and that the technological characteristic typically had stronger positive effects on adoption than consumer characteristics (Peng et al., 2021).

Some or most of these existing studies take a perspective from the information system. Our project aims to investigate consumers' perception of the adoption of wearable fitness devices. This project expands the current understanding of consumer adoption by building a cognitive-affective-social-motivational model. Specifically, we start with the theory of reasoned action (TRA; Fishbein & Ajzen, 1975) and create a behavioral intention model, detailing four antecedents in predicting the adoption of wearables - cognitive, affective, social, and motivational. The cognitive antecedent studies the concept of relative advantage (Rogers, 2003), which is a critical adoption characteristic in the diffusion of innovation process. The affective antecedent examines the combination of positive and negative feelings related to the perception of wearables. The social antecedent expands subjective norms, and finally, the motivational antecedent studies the health-related motivations and interests.

The significance of this project is three-fold. First, this project contributes to the ongoing effort in studying adoption and use of wearable technology (e.g., Kim & Park, 2019; Krey et al., 2019; Nayak et al., 2022; Sağtaş & Aslan, 2022). It brings new knowledge about wearable technology to scholars and business and healthcare professionals. It hopefully sparks more research interests in this area. Second, through an affective-cognitive-social-motivational framework, the project supports and extends current theoretical frameworks, including the technology acceptance model and the theory of reasoned action, in the technology area of wearables. Third, our findings about perceived usefulness, relative advantage, positive feelings, and health motivation will provide critical insights for both manufacturers and marketers to plan and develop programs that boost consumer adoption of wearables in an era of the quantified-self movement (Paluch & Tuzovic, 2019).

For the rest of the article, we first review pertinent literature on technology acceptance and theory of reasoned action in consumer attitude studies and develop our behavioral intention model, which comprises affective, cognitive, social, and motivational components. Following that, the study methodology, detailing the survey samples and instruments that are used to measure constructs in the model, is presented. We then report the results of the structural equation modeling and hypothesis testing. Finally, the theoretical contributions of our research in the adoption literature and practical implications of the results for wearables manufacturers and marketers are discussed.

CONCEPTUAL FRAMEWORK

In studying how consumers form their high-effort, cognitive attitudes and how these attitudes predict their behavioral intention, Fishbein & Ajzen (1975) proposed the theory of reasoned action (TRA). Since then, TRA has been widely applied to investigate various adoption behaviors (e.g., Cyr et al., 2009; Davis et al., 1989; Venkatesh et al., 2003), setting the foundation for the technology acceptance model (Davis et al., 1989). As posited by TRA, behavioral intention is likely to depend on the combined effects from attitudes toward a behavior and subjective norms (a social factor). The latter concerns if opinions from important others will affect individuals' behavioral intentions. Later, Ajzen (2001, p. 34) proposed a multi-component perspective on attitude, which "assumes that evaluations are influenced by cognition as well as affect.'' Affective attitudes are based on emotions and feelings, whereas cognitive attitudes are based on opinions and thoughts (Hoyer et al., 2018). We decide to study the affective and cognitive antecedents for attitudes in our intention model. We use relative advantage (Rogers, 2003) as the cognitive antecedent, which is influenced by two factors in the technology acceptance model (Davis et al., 1989) and effective quality (Segars & Grover, 1993). Both positive and negative feelings are the affective antecedents. We next explain the affective-cognitive-social-motivational antecedents and hypothesize the impact of each antecedent on the adoption intention, as well as their influencing factors.

Cognitive Antecedents: Relative Advantage and Technology Acceptance Model (TAM)

TAM has been widely applied in studies about the adoption, use, and continuation of the use of information technologies for the past decades. The information technologies range from mobile phones (Lam et al., 2008), to social media usage (Parida et al., 2016), to mobile payments (Constantiou et al., 2006), and to wearable devices (Chiu & Cho 2021). According to TAM (Davis et al., 1989; Mathieson, 1991), consumers' intention to adopt/accept a particular technological innovation is influenced by their attitudes toward using the technology, which subsequently, is affected by two key cognitive factors - perceived ease of use and perceived usefulness. Perceived ease of use is defined as the cognitive effort required to learn about the new technology, and perceived usefulness is studied as the consumers' personal judgment of the utilitarian functions of the technology (Davis et al., 1989). As predicted by TAM, we expect that perceived ease of use and perceived usefulness affect consumers' adoption of wearables.

Next, we also notice that the empirical results about the effects of TAM factors, perceived ease of use and perceived usefulness, have been inconsistent in the literature. For example, adoption of e-commerce studies showed the direct effects of these two factors (de Luna et al., 2017; Park et al., 2017), whereas others did not find such direct effects (e.g., Dastan & Gürler, 2016). We did not connect the perceived usefulness and ease of use factors directly with the attitude or intention; instead, we bring in *relative advantage* as an intermediate variable. Relative advantages are the superior benefits consumers perceive in an innovation compared to current technologies (Karahanna et al., 1999; Rogers, 1995). Perceived usefulness will help consumers understand the performance and functionality of the new technology, whereas perceived ease of use will help them quickly assess the efforts they have to spend learning about the new technology. We predict that both TAM factors will influence individuals' opinions on the relative advantage of using wearables, which influence their adoption intentions. Therefore, we hypothesize that:

H1a: Perceived ease of use of wearables will positively predict perceived relative advantage of wearables.
H1b: Perceived usefulness of wearables will positively predict perceived relative advantage of wearables.
H1: Perceived relative advantage of wearables will positively predict intention to adopt wearables.

In addition, effectiveness, or effective quality (Segars & Grover, 1993) may also influence relative advantage. Different from the perceived usefulness and ease of use, we define effectiveness as how a piece of new technology can help consumers accomplish their target goals. How effectiveness influences consumer adoption has been investigated in information systems (e.g., Grover et al., 1998) and e-learning acceptance (Selim, 2003). Hence, we predict that:

H1c: Perceived effective quality of wearables will positively predict perceived relative advantage of wearables.

After discussing cognitive antecedents in the intention model and how perceived usefulness, ease of use, and effectiveness affect relative advantage, which affects adoption intention, we now turn to affective antecedents in consumer adoption. Kulviwat et al. (2007) included feelings in their consumer acceptance model. We have seen evidence of the role of feelings or affect in consumer adoption in multiple studies, such as the adoption of nanotechnology (Reinares-Lara et al. 2016) and adoption of mobile payments (Zhang & Mao, 2020).

Affective Antecedent: Positive and Negative Emotions

We focus on two types of consumer emotions - pleasure and dominance - in the consumer acceptance model (Kulviwat et al., 2007) in the current project. We believe these two emotions connect to favorable or positive and unfavorable or negative feelings, respectively. Pleasure means having fun and being entertained. This entertainment value arising from using certain consumer technology is likely to affect adoption intention (Childers et al., 2001). For example, Lee et al. (2003) found pleasure feelings to positively influence consumers' attitudes toward shopping on the Internet, while Bruner and Kumar (2005) found it influenced the choice of Internet devices. The second feeling - dominance defined as having power or influence over others or being in control - may be negative in nature, leading to feeling anxious or stressful. To explain, when considering an adoption of a new technology, consumers may forecast feeling dominance and empowered due to the possession of the new technology. Therefore, a lack of dominance or being in control may foster confusion, frustration, or even fear. These negative feelings are shown to affect adoption and use of computer technology (Igbaria & Parasuraman, 1989; Kulviwat et al., 2007).

In this project, we examine both positive and negative feelings and predict that:

H2a: Positive feelings will positively predict affective attitudes.
H2b: Negative feelings will negatively predict affective attitudes.
H2: Affective attitudes will positively predict intention to adopt wearables.

We have discussed how affective and cognitive antecedents influence the adoption intention. The next antecedent we want to focus on is social influences. Slade et al. (2015) found that subjective norms in TRA serve as social influences and predict behavioral intention in adopting mobile payment services. The effect of social influences becomes more salient when consumers have not adopted or used wearables. Because they do not have first-hand experience with a new technology, consumers may largely depend on observing others or taking others' opinions to form their adoption intention. Below, we discuss social influences and bring in network externalities as their antecedents.

Social Antecedent: Subjective Norms and Network Externalities

Social influences highlight how the social environment and social interaction with others influences behavioral intention. We reasoned that non-wearables users may have limited or no experience with the technology, hence, they may be inclined to use social norms to form their opinions and change their behavior. Past research has shown that social influences can create social pressure and make consumers conform to using new payment services (e.g., Arvidsson, 2014). Such influences are found to have a direct effect on the intention to adopt wearable technology devices (e.g., Ghazali et al., 2020; Sergueeva & Lee, 2020). As such we hypothesize that:

H3: Social influences will positively predict consumers' intentions to adopt wearables.

To assess which factors affect social influences in the adoption context, we turn to network externalities, as demonstrated in Wei and Lu (2014) and Gupta and Mela (2008). This variable reveals how a consumer changes their use of a particular technology, because of seeing several other users of the same technology (e.g., Economides, 1996; Zhang & Mao, 2020). Consumers are leaning toward adopting a new technology or service if they realize that other people also use it, and especially when other people are from their social circles (Kraut et al., 1998). Consistent with Wei and Lu (2014), we study network externalities in terms of the perceived number of users and perceived number of peers, and hypothesize that:

H3a: Perceived number of users of wearables will positively predict social influences.
H3b: Perceived number of peers who use wearables will positively predict social influences.

In addition, we examine if social image will have a direct impact on social influences. We define social image as if and how the use of an innovation helps improve an individual's image or status in society (e.g., Moore & Benbasat, 1991; Rogers, 2003). Rogers (2003) first approached social image as a factor related to relative advantage. Recent research, however, has shown that social images are an important factor affecting the adoption of new technologies, aside from relative advantage (e.g., Adapa et al., 2018; Hernandez & Mazzon, 2007). We speculate that perceptions about using wearables to boost consumers' stylish image or group approval in their social networks will influence their adoption intention via social influences. We predict that:

H3c: Perceived social images of using wearables will positively predict social influences.

Motivational Antecedent: Health Motivation

We now turn to the last antecedent in the model: health motivation. Moorman and Matulich (1993) defined health motivation as one's goal-directed arousal to form health intentions start and maintain health-related actions. The relevance of health motivation is obvious, because wearables are primarily used to monitor one's health and fitness factors. Consumers who have stronger health motivations or health beliefs are more likely to participate in the quantified-self movement via using wearables (Grosová et al., 2022; Paluch & Tuzovic, 2019; Zhang & Mao, 2022). Research has demonstrated the effects of health-related psychographic factors on one's exercise maintenance and subjective well-being (e.g., Mowen, 2000; Zhou & Krishnan, 2019). Interestingly, not a lot of studies on adoption and use of wearables investigate health-related factors (e.g., Cheung et al., 2019). Considering the effect of health motivation on one's health intentions and health-related actions, we expect that:

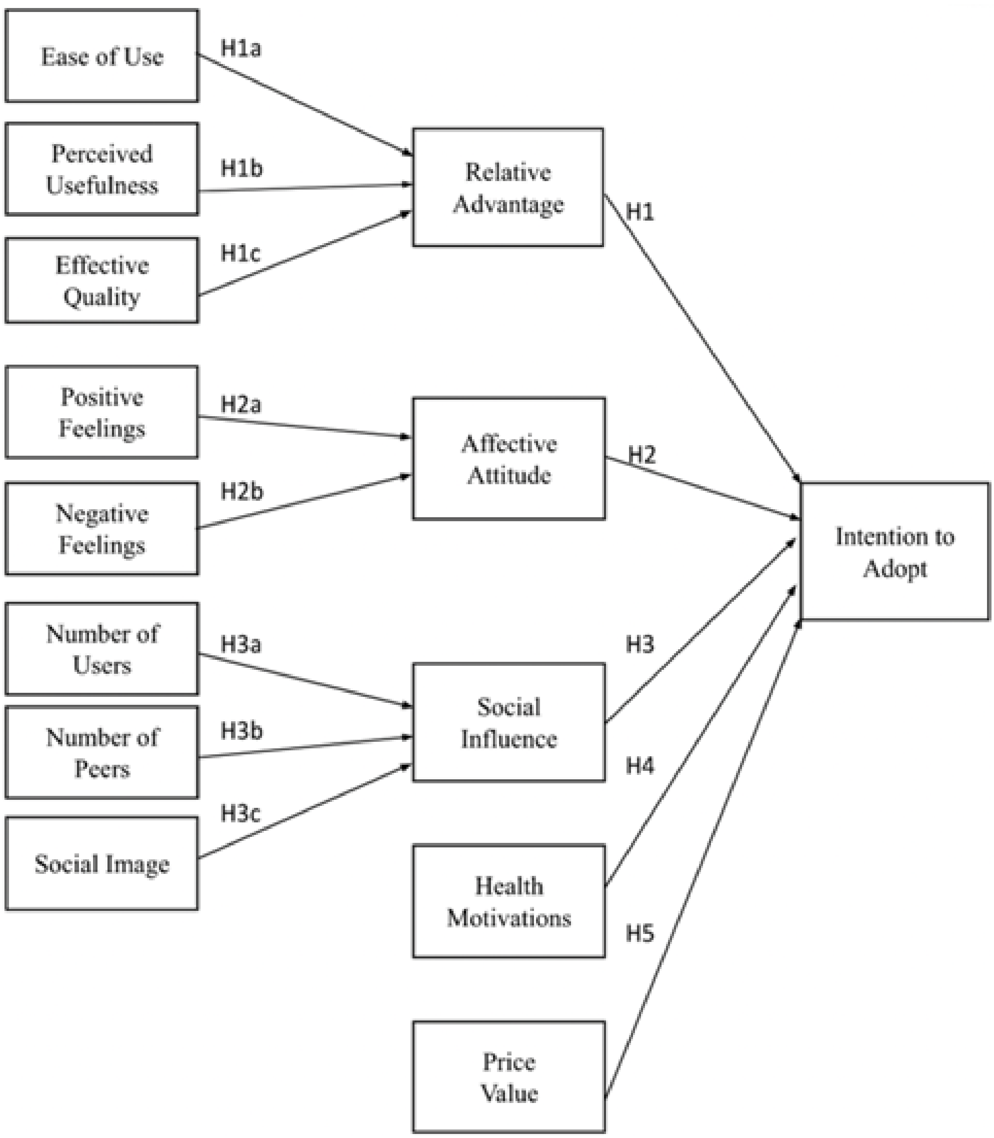
H4: Health motivation will positively predict consumers' intention to adopt wearables.

Our affective-cognitive-social-motivational model suggests relative advantage, affective attitudes, social influences, and health motivation influence adoption intention toward wearables. Perceived usefulness, perceived ease of use, and effective quality influence the relative advantage. Affective attitudes are affected by positive and negative feelings connected to using wearables. Social influences are affected by the perceived number of users, perceived number of peers, and social images. We believe our model reflects the roles of consumers' affective responses, cognitive evaluations, social influences, and motivational involvement in their adoption decisions.

To increase the predictive power of the model, we also add consumers' price perception as the final antecedent. We define price value as the cognitive tradeoff between the perceived benefits of the technology and the monetary cost of using it (Venkatesh et al., 2012). See Figure 1 for our full research model. The effect of price on adoption has produced mixed results. Some studies found the effect to be not significant (Beh et al., 2021; Sergueeva & Lee, 2020; Talukder et al., 2019), whereas others reported significant findings (Kim & Shin, 2015; Park, 2020). In particular, studies of wearable technology showed that perceived cost has a positive impact on users' intention to use wearable devices (Kim & Shin, 2015). Given that wearable devices are available at different price levels, which will create quite a variation in price perception, we predict that:

H5: Price value will positively predict consumers' intention to adopt wearables.

Figure 1. Research Model



METHODOLOGY

The Research Sample

A survey approach was used to collect data for our research. The participants included subjects from Amazon M-Turk and a public university on the West Coast. Our research focuses on potential adopters of wearable devices; therefore, the survey included a screening question to identify whether the participants own a wearable fitness device. We classified 312 respondents who continued with the survey as non-users of wearables. We gathered data from 312 participants, 205 from M-Turk and 107 from the public university. We removed fifteen responses from our study because of substantial missing data, resulting in a sample of 297 to test our research model. Our sample represented a diverse age range from 19 to 71. The average age of our sample is 30. The gender was relatively evenly distributed (female: 154; 51.85%). When asked to choose a reason they would purchase a wearable if they decide to, our respondents mentioned the following reasons: to "keep track of your progress" (38%), to "monitor your health" (23%), and to "help you stay motivated" (15%). See Table 1 for other demographic information.

The Research Instrument

To develop our research instruments, we utilized the constructs and their measurements from existing research. Items are adapted for wearable devices and potential adopters. Each research construct contains a minimum of three 7-point Likert scale items with anchor points of "1" representing "strongly disagree'' and "7" represents "strongly agree." One exception is the measurement of intention to adopt wearables. The responses ranged from "1" (impossible, unlikely, improbable, and definitely

Table 1. Research sample demographics

Characteristic	Number	Percentage
Gender		
Male	143	48.15%
Female	154	51.85%
Ethnicity		
Asian / Pacific Islander	123	41.41%
White or Caucasian	108	36.36%
Hispanic or Latino	35	11.78%
Black or African American	15	5.05%
Multicultural	12	4.04%
Other	4	1.35%
Personal Income (before taxes)		
Less than $10,000	104	35.02%
$10,000 - $19,999	56	18.86%
$20,000 - $29,999	45	15.15%
$30,000 - $39,999	34	11.45%
$40,000 - $49,999	15	5.05%
$50,000 - $74,999	23	7.74%
$75,000 - $99,999	10	3.37%
$100,000 or more	10	3.37%

would not buy) to “7” (possible, likely, probable, and definitely would buy). Affective attitude is a composite measure of positive feeling and negative feeling items. The sources of the construct, descriptive statistics, and the actual measurement items are shown in Table 2.

Table 2. Research constructs, sources, and items

Construct (Source)	Mean	Standard Deviation	Item
Intention to Adopt (Bhattacherjee, 2001; Susanto et al., 2016)	4.52	1.97	1. What is the likelihood of you buying a wearable fitness device? Scale ranges from “Impossible” to “Possible”
	3.89	2.11	2. What is the likelihood of you buying a wearable fitness device? Scale ranges from “Unlikely” to “Likely”
	3.92	2.03	3. What is the likelihood of you buying a wearable fitness device? Scale ranges from “Improbable” to “Probable”
	3.81	1.91	4. What is the likelihood of you buying a wearable fitness device? Scale ranges from “Definitely would not buy” to “Definitely would buy”
Relative Advantage (Karahanna et al., 1999)	4.56	1.49	1. Using a wearable fitness device would improve the quality of my exercise
	4.53	1.45	2. The advantages of using a wearable fitness device outweigh the disadvantages
	4.66	1.34	3. The wearable fitness device has greater advantages and offers more functions than previous gadgets
Perceived Usefulness (Dastan & Gurler, 2016)	5.07	1.21	1. I believe a wearable fitness device would accurately track my performance.
	4.63	1.37	2. I believe I would get the results I want from a wearable fitness device.
	4.93	1.4	3. I believe I would gain valuable insights about myself by using a wearable fitness device.
	4.93	1.47	4. I feel that using a wearable fitness device would hinder my performance.
Perceived Ease of Use (Dastan & Gurler, 2016)	5.17	1.53	1. I believe I would have trouble understanding the functions of wearable fitness devices.
	5.2	1.3	2. I believe using a wearable fitness device would be straightforward.
	5.23	1.2	3. The information on wearable fitness devices would be easy to understand.
Effective Quality (Adapted from Grover and Segar, 2005)	4.7	1.42	1. Having a wearable fitness device would help me reach my fitness goals.
	4.72	1.39	2. I feel that having a wearable fitness device would make a positive impact on my life.
	4.7	1.41	3. I would improve my habits if I have a wearable fitness device.
	3.98	1.54	4. Having a wearable fitness device would not affect my lifestyle.
Positive Feelings (Russell & Pratt, 1980)	4.7	1.43	1. I would feel content if I track my workouts using a wearable fitness device
	4.49	1.5	2. I would feel satisfied if I use a wearable fitness device.
	4.28	1.49	3. I would feel good about myself if I use a wearable fitness device.
Negative Feelings	2.44	0.99	1. I would feel stressed if I use a wearable fitness device.
(Russell & Pratt, 1980)	2.34	1.03	2. I would feel bad about myself if I use a wearable fitness device
	2.37	1.03	3. I would feel anxious if I track my workouts using a wearable fitness device.
Social Influences (Arvidsson, 2014; Wei & Lu, 2014)	2.88	1.75	1. If I use a wearable fitness device, I would like to share my fitness goals and achievements on social media.
	3.27	1.6	2. People who influence my behavior would think I should use a wearable fitness device.
	3.63	1.79	3. If I use a wearable fitness device, I would like to share my fitness goals and achievements in my friend circle.
	3.25	1.61	4. People who are important to me would think I should use a wearable fitness device.

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Table 2. Continued

Construct (Source)	Mean	Standard Deviation	Item
Number of Users (Arvidsson, 2014; Wei & Lu, 2014)	4.34	1.51	1. I perceive that a good number of people use a wearable fitness device.
	3.37	1.49	2. I perceive that most people use a wearable fitness device.
	4.75	1.43	3. I perceive that there will be many more people using a wearable fitness device in the future.
Number of Peers (Arvidsson, 2014; Wei & Lu, 2014)	3.55	1.61	1. I perceive that many friends around me use a wearable fitness device.
	3.17	1.58	2. I perceive that most of my friends use a wearable fitness device.
	4.13	1.55	3. I perceive that many friends will use a wearable fitness device in the future.
Social Images (Zhang & Mao, 2020)	3.09	1.61	1. The use of wearable fitness devices would help me feel acceptable.
	3.14	1.63	2. The use of wearable fitness devices would improve the way I am perceived.
	3.2	1.6	3. If I use a wearable fitness device, I would make a good impression on other people.
	3.01	1.65	4. The use of wearable fitness devices would give me social approval.
	3.16	1.7	5. The use of wearable fitness devices would make me feel cool.
	3.39	1.74	6. The use of wearable fitness devices would make me feel trendy and sophisticated.
Health Motivation (Moorman & Matulich, 1993; Mowen, 2000)	4.87	1.38	1. I try to prevent health problems before I feel symptoms.
	5.01	1.26	2. I am concerned about health hazards and try to take action to prevent them.
	5.05	1.22	3. I try to protect myself against health hazards I hear about
Price Value (Adapted from Beh, Ganesan, Iranmanesh & Foroughi, 2021)	4.95	1.51	1. I don't want to spend money on such a device.
	4.43	1.45	2. The price for wearable fitness devices is not affordable.
	4.54	1.51	3. The price to purchase such a device would not be acceptable to me.

DATA ANALYSIS AND RESULTS

The Measurement Model

To test our research model, we first assessed the measurement model. In the initial step, we evaluated the reliability of our constructs. The results shown in Table 3 confirmed that our constructs are reliable. We also showed the construct abbreviations and variance extracted in Table 3. The average variance extracted (AVE) values are all above 0.68. The construct reliability was further validated by the composite reliability (exceeded 0.86 for all constructs), the Cronbach's Alpha (exceeded 0.76 for all constructs). We then assessed the discriminant validity. In this assessment, we compared the square root of the AVE to the inter-construct correlations. As shown in Table 4, the minimum value of a square root of AVE (shown diagonally in the matrix in bold) is 0.82 between N_USERS and EOU, which was larger than the maximum inter-construct correlation coefficient, which was 0.80 between EQ and PF. The inter-construct correlation coefficient values are the numbers shown in Table 4, excluding the diagonal. The correlation between NF and PF with Affective Attitude (AFFECT), which is modeled as a composite construct of both NF and PF. The construction of the composite AFFECT construct followed the repeated indicators approach advocated by Wetzels et al. (2009).

The Structural Model

We tested our structural model and research hypotheses using SmartPLS 3.3.7 (Ringle et al., 2005), which is commonly used for the Partial Least Squares (PLS) analysis. In our model, indicators for relative advantage, affective attitude, social influences, health motivations, and price value modeled the intention to adopt. The determinants of relative advantage include perceived ease of use, perceived

Table 3. Research construct reliability

Construct	Abbreviation	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)	R2
Intention to Purchase	INT	0.96	0.97	0.89	0.438
Relative Advantage	RA	0.86	0.92	0.78	0.597
Perceived Usefulness	PU	0.85	0.91	0.77	
Perceived Ease of Use	EOU	0.77	0.86	0.68	
Effective Quality	EQ	0.91	0.94	0.84	
Positive Feelings	PF	0.92	0.95	0.87	
Negative Feelings	NF	0.88	0.93	0.81	
Social Influences	SI	0.86	0.90	0.70	0.425
Number of Users	N_USERS	0.76	0.86	0.68	
Number of Peers	N_PEERS	0.85	0.91	0.77	
Social Image	IM	0.95	0.96	0.79	
Health Motivation	HM	0.89	0.93	0.82	
Price Value	PRICE	0.82	0.88	0.71	

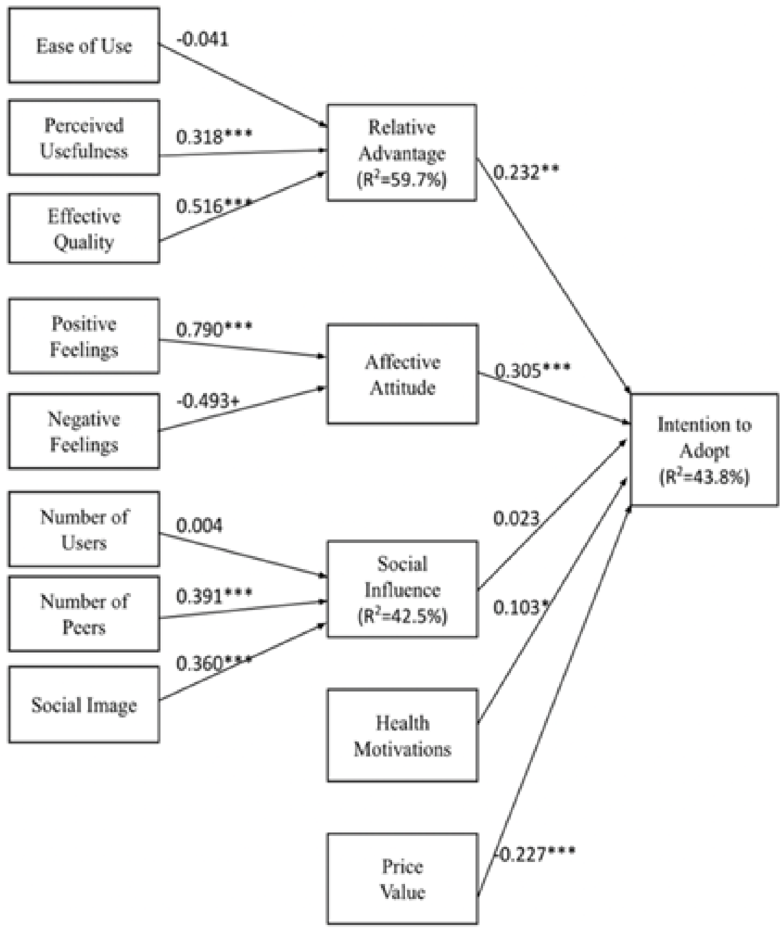
Table 4. Inter-construct correlations and square roots of AVE

	N_PEERS	N_USERS	EOU	EQ	HM	INT	NF	PF	PU	PRICE	RA	IM	SI
N_PEERS	0.88												
N_USERS	0.72	0.82											
EOU	0.16	0.20	0.82										
EQ	0.37	0.41	0.35	0.92									
HM	0.12	0.22	0.31	0.34	0.91								
INT	0.30	0.25	0.21	0.52	0.24	0.94							
NF	0.00	0.02	0.30	0.13	0.15	0.28	0.90						
PF	0.35	0.39	0.30	0.80	0.28	0.53	0.17	0.93					
PU	0.39	0.44	0.47	0.78	0.33	0.46	0.25	0.70	0.88				
PRICE	0.22	0.10	0.05	0.16	0.08	0.41	0.21	0.19	0.16	0.84			
RA	0.49	0.54	0.29	0.75	0.27	0.54	0.15	0.72	0.70	0.25	0.88		
IM	0.49	0.45	0.02	0.37	0.01	0.24	0.04	0.44	0.30	0.16	0.48	0.89	
SI	0.57	0.45	0.11	0.35	0.12	0.28	0.02	0.41	0.34	0.19	0.43	0.55	0.84

*Diagonal elements in bold represent the square root of average variance extracted (AVE)
Item Abbreviations (full name): N_PEERS (Number of Peers); N_USERS (Number of Users); EOU (Perceived Ease of Use); EQ (Effective Quality); HM (Health Motivation); INT (Intention to Purchase); NF (Negative Feelings); PF (Positive Feelings); PU (Perceived Usefulness); PRICE (Price Value); RA (Relative Advantage); IM (Social Image); SI (Social Influences).

usefulness, and effective quality. The number of users, number of peers, and social images were antecedents of social influences. The t-values used for assessing the significance of the path coefficients are based on the bootstrapping method. SRMR (0.073) shows a good model fit, according to Hu and Bentler (1998). Figure 2 presents the key statistics for the structural model testing. We summarize hypothesis testing results in Table 5.

Figure 2. Testing results of the research model



Note: **** p < .001, ** p < .01, * p < .05, + p < .10. Path coefficients are labeled along the path in the diagram. Variance extracted are in the parentheses under construct names.*

The research model explained a substantial amount of variance in the intention to adopt wearables, relative advantage, and social influences: $R_{INT}^2 = 0.438$, $R_{RA}^2 = 0.597$, and $R_{SI}^2 = 0.425$. Our model supported nine of the thirteen research hypotheses and partially supported one hypothesis. Specifically, relative advantage, affective attitude, health motivation, and price perception significantly influenced intention to adopt, lending support to H1, H2, H4, and H5. Affective attitude appeared to play a major role in affecting adoption intention. This may suggest that consumers' behavioral intentions are largely shaped by their affection. The effect of social influences on intention (H3) was not supported. This finding is not congruent with studies such as Ghazali et al. (2020) and Sergueeva and Lee (2020). This may suggest that the adoption decision is largely driven by personal opinions on the functional, emotional, and health benefits of using a wearable. The social influence such as seeing peers have wearables does not have a powerful impact on their adoption decisions.

As hypothesized, perceived usefulness and effective quality significantly affected relative advantage, lending support to H1b and H1c. The effect of ease of use was not significant, failing to support H1a. This differs from Kim & Chiu (2019)'s finding. Our explanation is that without

Table 5. Hypothesis testing results

Hypothesis	Path	Path Coefficient	Supported
H1	RA→ INT	0.232**	S
H1a	EOU→ RA	-0.041	NS
H1b	PU→ RA	0.318***	S
H1c	EQ→ RA	0.516***	S
H2	AFF→ INT	0.305***	S
H2a	PF→ AFF	0.790***	S
H2b	NF→ AFF	-0.493+	PS
H3	SI→ INT	0.023	NS
H3a	N_USERS→ SI	0.004	NS
H3b	N-PEERS→ SI	0.391***	S
H3c	IM→ SI	0.360***	S
H4	HM→ INT	0.103*	S
H5	PRICE→ INT	-0.227***	S

Notes: S = Supported at .05 (*) or .001 (***) level; PS = Partially Supported at .10 (+) level.

Item Abbreviations (full name): N_PEERS (Number of Peers); N_USERS (Number of Users); EOU (Perceived Ease of Use); EQ (Effective Quality); HM (Health Motivation); INT (Intention to Purchase); NF (Negative Feelings); PF (Positive Feelings); PU (Perceived Usefulness); PRICE (Price Value); RA (Relative Advantage); IM (Social Image); SI (Social Influences).

experience of using a wearable device, participants may not be able to assess the ease of use dimension of wearables accurately. Consistent with past studies (Cheung et al., 2021; Kim & Chiu, 2019; Felea et al., 2021), the perceived usefulness was found to be a significant factor. Perceived ease of use did not affect participants' perception of relative advantage of the device as expected. The effect of positive feelings on affective attitude was supported (H2a) while the effect of negative feelings on affective attitude was partially supported (H2b). The results also showed that social influence was significantly impacted by the number of peers and social images, thus supporting H3b and H3c. The effect of perceived number of users on social influence was not supported (H3a). Compared to the effect of perceived number of peers, this insignificant result with perceived number of users suggested that participants' immediate social environments (e.g., peers, family members, co-workers) have direct influence whereas other users (e.g., strangers who have wearables) in social environments do not.

CONCLUSION AND DISCUSSION

This study proposes and tests a cognitive-affective-social-motivational model in studying the adoption of wearable fitness devices. The results show how consumers' cognitive, affect, and motivational factors affect their intentions to adopt wearables. The model explains 43.8% of the variance in the adoption intention. Consistent with the predictions, perceived usefulness and effective quality significantly affect relative advantage, explaining 59.7% of its variance. Perceived number of peers and social images affect social influences, explaining 42.5% of its variance. The valence of the affective factors matters in this model, as positive and negative feelings predict affective attitudes in the expected directions. While we found social influences do not affect adoption intention, our results show that consumers' health motivations positively affect their intention to adopt.

Theoretical and Practical Contributions

There are three key areas of contributions from the current project. First, the project continues and stimulates the research effort in understanding the adoption and use of new technologies. By showing how the combination of the affective, cognitive, and motivational factors affects consumers' intention to adopt wearables, we assist the growing research interest in the topic and the accumulation of consumer insights into the technology acceptance literature.

Second, our project validates and advances existing models and theories, such as the technology acceptance model and the theory of reasoned action (Davis et al., 1989; Fishbein & Ajzen, 1975) in a new technology area – wearables. Congruent with the theory of reasoned action, we found that individuals' personal attitudes affect their intention to adopt wearables, whereas perceived social influences are not. By adding the third and fourth determinants, the affective and motivational factors, we create a broad affective-cognitive-social-motivational approach to understanding consumer adoption of technology. Based on the diffusion of innovation theory, we can determine that the 25.5% of adoption rate in the current U.S. wearable market (Phaneuf, 2023) has captured the innovators and early adopters, which make up about 2.5% and 13.5% respectively of the population (Rogers et al., 2003). We are possibly looking at the adoption behavior of the early and late majority. The early majority are those who adopt products that are proven to work (cognitive factors) while the late majority are very cost conscious (price value).

Third, we share several practical implications of our results for wearables manufacturers and marketers. To begin with, significant findings about perceived usefulness and effective quality suggest that they can improve their devices and software interface on these factors to increase consumers' intention to adopt. Next, professionals should highlight innovation enhancements in their marketing effort. For example, considering the direct effect of relative advantage on adoption intention, it is important to market to the nonusers the superior or incomparable benefits or values that wearables can offer compared to other health devices. Their marketing efforts can highlight the positive feelings of having wearables to increase consumers' affective attitudes toward using wearables, which leads to the intention to adopt. This discussion suggests that understanding the multi-component antecedents in the adoption of wearables will help develop competitive innovation edges and strategize marketing efforts for wearable device providers. In addition, as the market shifts to the late majority, we advise wearable providers to create cheaper models to attract those cost-conscious consumers.

Limitations and Future Research

Given the current study design and findings, at least two areas of limitations are worth mentioning. First, our behavioral intention model proposes the effects of assorted factors on intention to adopt wearables. Our findings supported the positive effects of these factors (except negative feelings). We call for future research to reexamine these factors and study other facilitators, such as technological characteristics (Upadhyay & Jahanyan, 2016). In addition, future studies can investigate consumer concerns or inhibitors that interfere consumer adoption, such as perceived security (Shin & Lee, 2014; Yi, 2016), perceived trust (Dastan & Gurler, 2016), and perceived privacy risk (e.g., Yang et al., 2015; Wurster, 2014). These new findings will increase our knowledge about the adoption and use of wearables. Second, we use convenient sample data from crowdsourcing and a university to test the model. As shown from the demographics, we over-sampled one ethnic group, Asian Americans. We recommend probability sampling for future research. By testing the affective-cognitive-social-motivational model with probability sample data, we can confirm the adoption intention model and yield generalizable results about the wearable adoption. And finally, as extended reality (XR) and metaverse are gaining momentum, attracting more professional and consumer users (Chuah, 2019), future research may consider studying the adoption of wearable technology in these innovative applications in contexts such as gaming, education, healthcare, and entertainment.

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