Available online at www.HighTechJournal.org

HighTech and Innovation Journal

ISSN: 2723-9535

Vol. 4, No. 4, December, 2023

Evaluating the Determinants of Young Runners' Continuance Intentions toward Wearable Devices

Zhaoxia Guo [1*], Guoqing Liu [1], Zhiguo Liu [2], Asif Khan [3, 4]

[1] College of Physical Education, Taiyuan University of Technology, Taiyuan, Shanxi, 030024, China.

[2] College of Physical Education, Yantai University, Yantai, Shandong, 264005, China.

[3] Southern Taiwan University of Science and Technology, Tainan, Taiwan.

[4] ANScientistify INC., Tainan, Taiwan.

Received 31 August 2023; Revised 12 November 2023; Accepted 18 November 2023; Published 01 December 2023

Abstract

Running has gained popularity as a fitness activity in China, with a growing number of young runners utilizing wearable devices to monitor their running routines and engage in quantified self-practices. The continuous evolution of wearable devices in terms of products and services has expanded the choices available to young runners. Therefore, there is a need to analyze the factors influencing the continuance intention of young runners, providing insights into how to promote the sustained growth of these products or services in the market. This study is grounded in the Technology Acceptance Model and the Theory of Planned Behavior, with an extension incorporating the quantified self to explore the impact of users' continuance intentions to use wearable devices. A survey was conducted among 468 young runners who already used wearable devices, and the data collected were analyzed using PLS-SEM. The results indicate that perceived usefulness and attitudes from the Technology Acceptance Model positively influence intentions for continued use. Additionally, subjective norms according to the Theory of Planned Behavior positively influence continuance use intentions. However, perceived behavioral control does not have a significant effect on continuance use intentions. Conversely, the Quantified-Self positively influences continuance use intentions and partially mediates the relationship between perceived usefulness and continuance use intentions. This research has several theoretical implications for the Theory of Planned Behavior, the Technology Acceptance Model, and the Quantified-Self research construct. Moreover, this study has practical implications for practitioners concerning the adoption and acceptance of wearable devices by young people. This approach enables practitioners to target and implement precise strategies to meet the current demands of the young runner market.

Keywords: Partial Least Squares (PLS); Structural Equation Model (SEM); Young Runners; Wearable Devices; Attitude; Quantified-Self; Continuance Intentions to Use.

1. Introduction

Wearable devices, defined as mobile electronic devices worn on the body or integrated into the user's clothing or accessories [1], operate on various systems, akin to smartphones, impacting their market and product shares. Common forms of wearable devices include smart watches, fitness bands, earworm devices, and smart glasses. Notably, according to Statista, the leading suppliers of wearable devices are Apple, Xiaomi, Samsung, and Huawei [2]. As the production technology for wearable devices continues to improve, costs are reduced while enhancing functionality to meet the needs

* Corresponding author: 904136621@qq.com

http://dx.doi.org/10.28991/HIJ-2023-04-04-02

of different consumers. In the sports realm, wearable devices are being increasingly applied, spanning everyday activities to professional sports and contributing to health monitoring during exercise [3], healthcare applications [4, 5], and training monitoring [6]. With the growing popularity of running as a fitness activity, an increasing number of young runners are using wearable devices to track their running routines, utilizing data such as heart rate and stride length to monitor progress. Additionally, these devices motivate young runners to follow and share their fitness data online through platforms such as Fitbit, which enables friendly competition and the exchange of encouragement or advice through leaderboards.

However, previous research on wearable devices has predominantly concentrated on investigating users' initial adoption of such devices [3, 7], with limited studies on the continuance usage intentions (CIs) of active individuals in the sports domain. Research examining the factors influencing users' usage or continued usage intentions has utilized mainly the technology acceptance model [8-11] and the theory of planned behavior [12, 13].

Furthermore, in addition to the CI of users [14], several theories exist for analyzing consumers' attitudes (ATT) toward the current digitalization of products. However, the technology acceptance model (TAM) is considered to be the most relevant and popular theory for measuring 'consumers' ATT toward a product [11, 15]. The original TAM model includes perceived usefulness (PU) and perceived ease of use (PE) as the main antecedents for determining the ATT of users and their CI toward a technology or product [8, 16]. If a certain technology is deemed easy to use, the users will harbor a positive ATT toward that technology [17]. Hence, this research aims to analyze the relationship between the ATT and CI of young runners toward smart wearable devices.

Moreover, the TAM was chosen as a key theoretical framework for its extensive applicability in analyzing user adoption across diverse technologies [17-22]. Previous research on TAM covered a wide range of technologies, including tablets [23], smartphones [24, 25], long-term evolution (LTE), cloud technology [26], and e-books [27]. Hence, this study employed the TAM to measure the impacts of PU and PE on the ATT and CI of young runners.

This research also employed the theory of planned behavior (TPB) to gain further insights into the CI and ATT of young runners. According to the TPB, subjective norms (SNs) and perceived behavioral control (PBC) impact both the ATT and CI of users [28]. The SN reflects the degree to which a user is important for engaging in a certain conduct [29], suggesting that the more users value a certain conduct, the more motivated they are to perform it. Previous research has demonstrated the significant impact of the SN on CI [29, 30]. Furthermore, PBC is related to the difficulty or ease of engaging in a certain conduct [29]. Users will experience greater PBC if there are adequate resources to support that conduct; hence, PBC can be considered to have a significant impact on CI [29-31]. Similarly, users are likely to have a higher degree of PBC for smart wearable devices if they possess the necessary resources to support their conduct. Consequently, this study aimed to explore the impact of SN and PBC on the CI of young runners.

With the rapid advancement of information technology, wearable devices and their associated products or services are undergoing continuous upgrades and transformations, leading to intensified market competition. Manufacturers consistently strive for distinctive designs to augment added value and competitiveness. However, despite this, young runners, as users of wearable devices, possess unique needs that have not been adequately addressed in prior research on these devices. Consequently, this study concentrates on young Chinese runners as research subjects, investigating how they perceive and sustain the use of intelligent wearable devices at an individual level. The aim is to provide insights that foster the sustainable growth of wearable device products or services in the market. Since its inception in 2007, quantified self (QS) has garnered considerable attention globally. QS involves capturing real-life events using mechanical devices and converting them into readable data to meet human needs or assist in decision-making, evaluation, and comparison between humans and computers [32]. With the escalating use of intelligent devices and applications to generate substantial data about personal behaviors, self-tracking has become increasingly popular. Wearable devices, such as smartwatches, have emerged as favorable tools for QS [33, 34]. Gathering information during the QS process enables users to receive more accurate and potentially experiential services, prompting self-reflection. Some studies suggest that users with prominent features of quantified design primarily engage in the information feedback process [35, 36]. Young runners can employ wearable devices in conjunction with mobile smart QS activities to experience the essence of this quantification practice. Hence, this study aimed to explore the relationship between QS and CI in young runners.

This research seeks to analyze the factors influencing young runners' CI. The study encompasses the following research objectives. First, this research aimed to explore the relationship between young 'runners' ATT and CI. Second, this research aims to explain the impacts of PE and PU on the ATT and CI of young runners. Third, this research aims to analyze the impacts of 'TPB's SN and PBC on CI. Finally, this research investigated the relationship between the QS and CI of young runners. This study introduces QS variables and combines them with the Technology Acceptance Model and the Theory of Planned Behavior to understand the factors influencing young runners' intentions to continue using wearable devices, providing insights into the enduring impact of wearable devices in sports activities.

2. Theoretical Background and Hypothesis Development

2.1. Technology Acceptance Model (TAM)

Based on the Theory of Reasoned Action, Davis [8] proposed the Technology Acceptance Model (TAM) to investigate users' understanding of the acceptance of information technology. Lee et al. [32] considered the TAM the most widely used model for explaining consumer behavior in technology adoption. TAMs have been applied in acceptance studies of various information technologies, including wearable devices [4, 9]. Due to its robust theoretical foundation and ease of modification and expansion, this study employs the TAM to identify the variables influencing young runners' continued use of wearable devices.

The TAM posits that perceived usefulness (PU) and perceived ease of use (PE) are fundamental determinants of user technology acceptance. As defined by Davis [33], PU reflects the extent to which users believe a specific system will enhance their job performance, while PE pertains to the ease with which users believe that using a particular system will occur. Behavior intention to use denotes the strength of a user's intention to perform a specific behavior, while attitudes signify positive or negative emotions toward task behavior [34]. When individuals encounter a new information technology, their perception of its usefulness increases with an increase in PE, consequently positively impacting user attitudes toward adoption [33]. User attitudes influence behavioral intention to use, subsequently affecting actual use [35].

2.1.1. Attitude and Continuance Intention

CI use refers to the user's intention to continue using a system after the initial trial; this is also known as consistent usage intention [36]. In the context of wearable devices, it signifies the subjective intention to continue using a particular product or service in the future [7]. CI is a key outcome in consumer research, contributing to the sustained growth of a product or service in the market. Therefore, we consider this parameter the outcome variable for predicting young runners' CIs when wearing wearable devices.

Attitudes refer to an individual's positive or negative evaluation of a specific behavior [12] and are one of the essential factors for predicting behavioral intention. Attitude is a significant influencing variable in the TAM. Previous research has supported the significant relationship between attitudes and CI [33, 37, 38]. In the sports domain, Song et al. [39] found a positive correlation between consumers' attitudes toward smart-connected sports products and their CIs. If young runners hold positive attitudes toward wearable devices after using them, their intention to continue using them may be more decisive. Therefore, we hypothesize the following.

Hypothesis 1 (H1): *Young runners' attitudes are positively related to their continuance intention to use wearable devices.*

2.1.2. Perceived Usefulness and Continuance Intention

PU is one of the most influential variables in the TAM for technology adoption. In the context of wearable devices, previous research has identified PU as a significant predictive factor for user intentions to adopt such wearable devices [5, 40]. For example, the PU of smartwatches has been found to positively impact users' CIs [46, 47]. However, some studies suggest that PUs do not significantly influence users' confidence in smart fitness wearables [41]. Additionally, related research has shown that PUs positively impacts user attitudes [29, 42] and can subsequently influence CI through attitudes [3]. For young runners, a crucial factor influencing their CI is whether wearable devices can enhance their exercise efficiency and effectiveness. If individuals perceive fitness benefits or improved athletic performance from using wearable devices, they may develop favorable attitudes toward the devices, thereby influencing their CI. Therefore, we propose the following hypotheses:

Hypothesis 2 (H2): Young runners' perceived usefulness of wearable devices is positively related to their intention to continue using wearable devices.

Hypothesis 3 (H3): Young runners' perceived usefulness of wearable devices positively influences their attitude toward wearable devices.

Hypothesis 3a (H3a): Perceived usefulness positively influences young runners' intention to use wearable devices through their attitudes.

2.1.3. Perceived Ease of Use and Continuance Intention

PE stands out as a key factor in the TAM and is deemed reliable for predicting user adoption of new technologies. This finding suggests that if a technology is easy to use, users are more likely to continue using it. For instance, Ashfaq et al. [43] identified PE as an important predictive factor for users' continued use of chatbots. Previous research has also demonstrated a significant relationship between PE and attitude. For example, Yu and Huang [38] discovered that PE positively influenced users' attitudes toward using the CMG Mobile App to view the Olympics (β=0.241, P<0.01). This effect could further impact users' intention to reuse technology through the mediating role of attitude [44].

Moreover, in the TAM model, PE positively influences PU, a belief variable [8]. This implies that if users perceive a new technology or system as easy to use, they are more likely to accurately recognize the value of these technologies and systems. Prior research has also revealed that the ease of use of wearable devices positively influences PU [4]. For young runners, if wearable devices are perceived as easy to use, they are more likely to accurately recognize the value of these technologies and services, cultivate positive attitudes toward their continued use, and subsequently influence their intention to use them. Therefore, we hypothesize the following:

***Hypothesis 4 (H4)*:** Young runners' perceived ease of use is positively related to their perceived usefulness of the tool.

Hypothesis 5 (H5): Young runners' perceived ease of use positively influences their attitude toward the continued use of wearable devices.

Hypothesis 6 (H6): Young runners' perceived ease of use positively influences their ability to use wearable devices.

Hypothesis 4a (H4a): Perceived ease of use positively influences continuance intention through attitudes.

Hypothesis 4b (H4b): Perceived ease of use positively influences attitudes toward the continued use of wearable devices through perceived usefulness.

Hypothesis 4c (H4c): Perceived ease of use positively influences continuance intention through perceived usefulness.

Hypothesis 4d (H4d): Perceived ease of use positively influences continuance intention through perceived usefulness and attitudes.

2.2. Theory of Planned Behavior (TPB)

The theory of planned behavior (TPB), akin to the TAM, is rooted in the theory of reasoned action and posits that an individual's attitude, subjective norms (SNs), and perceived behavioral control (PBC) influence behavioral intentions [12]. The TPB has been widely used to explain intentions to use various forms of information technology [29, 45]. This study employs SN and PBC as factors for young runners' confidence in wearing wearable devices.

2.2.1. Subjective Norms and Continuance Intention

A SN pertains to an individual's perception of how significant others, such as family, friends, and peers, want them to engage in a particular behavior [46]. It reflects the social pressures and expectations that a decision maker feels about making or refraining from the behavior in question [12]. Users share their fitness data through wearable devices and receive support or advice from others. In this process, social influence or peer pressure motivates them to engage in sports and competitions [47]. Previous research on wearable devices has shown that SNs positively impact users' intention to use [13] and actual usage behavior [3]. Young runners are influenced in their decisions to engage in physical activity by sharing and receiving relevant information through the use of wearable devices. Therefore, we hypothesize the following:

Hypothesis 7 (H7): Subjective norms positively influence young runners' continuance intention to use wearable devices.

2.2.2. Perceived Behavioral Control and Continuance Intention

PBC refers to the perceived ease or difficulty of performing a behavior [12]. It is assumed to be based on accessible control beliefs that can facilitate or hinder behavioral performance. Ajzen [48] suggested that high levels of PBC can strengthen an individual's intention to perform a behavior and increase their effort and persistence. PBC may be a crucial factor influencing users' CI. Previous research in the context of wearable devices has also shown that PBC positively affects CI [39, 47]. Therefore, we hypothesize the following:

Hypothesis 8 (H8): Perceived behavioral control positively influences young runners' intention to use wearable devices.

2.3. Quantified-Self and Continuance Intention

Wearable devices have the capability to continuously track users' physiological and behavioral data, providing them with the ability to analyze their QS data to gain insights into their health status and establish exercise plans, among other benefits. These devices can precisely quantify metrics such as steps, heart rate, pace, and energy expenditure. In innovative research focusing on wearable device applications, heart rate and pace stand out as frequently used quantified indicators. For example, Sunne et al. developed a mobile application that enables users to compete based on real-time heart rate data gathered at the gym [49]. Mauriello et al. introduced "social fabric fitness", a wearable application that supports group running by displaying heart rate and pace on the back of runners' shirts using dynamic electronic textiles [50]. Other studies have employed caloric intake as a quantified indicator of users' emotional and social responses [51].

In addition to individual support, some wearable device applications incorporate built-in social features. Yang et al. discovered that through the front display screen of SocialBike, cyclists can share competitor data, perceive the presence of rivals, and enhance their intrinsic motivation during cycling [52].

This study posits that young runners use wearable devices to self-track, employing quantified indicators such as heart rate, pace, and caloric intake. By monitoring their activities and decision-making efficiency, young runners can make informed behavioral choices. Hassan identified the significant impact of QS on users' intention to continue using wearable devices [51]. Throughout the quantification process, young runners immerse themselves in tracking activities, which can enhance their ability to use wearable devices.

Moreover, prior research has suggested that the utility and user friendliness of mobile intelligent and wearable device information platforms can stimulate users' engagement in QS experiences [53]. Qualitative studies have also indicated that when users perceive the functionality of the data, accessing it will motivate individuals and further engage them in QS activities [54]. For young runners, the usability and usefulness of wearable devices can stimulate their participation in QS activities, thereby influencing their CI. Therefore, the hypotheses of this study are as follows:

Hypothesis 9 (H9): Perceived usefulness positively influences young runners' engagement in the quantified self.

Hypothesis10 (H10): Perceived ease of use positively influences young runners' engagement in the quantified self.

Hypothesis 11 (H11): The self-quantification positively influences young runners' continuance intention to use wearable devices.

Hypothesis 11a (H11a): Perceived ease of use positively influences users' continuance intention to use wearable devices through the quantified self.

Hypothesis11b (H11b): Perceived usefulness positively influences users' continuance intention to use wearable devices through the quantified self.

Hypothesis 11c (H11c): Perceived ease of use positively influences the quantified self through perceived usefulness.

Hypothesis11d (H11d): Perceived ease of use positively influences users' continuance intention to use wearable devices through perceived usefulness and the quantified self.

Based on the above analysis, this study proposes the following hypothetical model (see Figure 1): PE, PU, SN, and PBC are the independent variables; attitude and QS are the mediating variables; and continuance intention is the dependent variable.

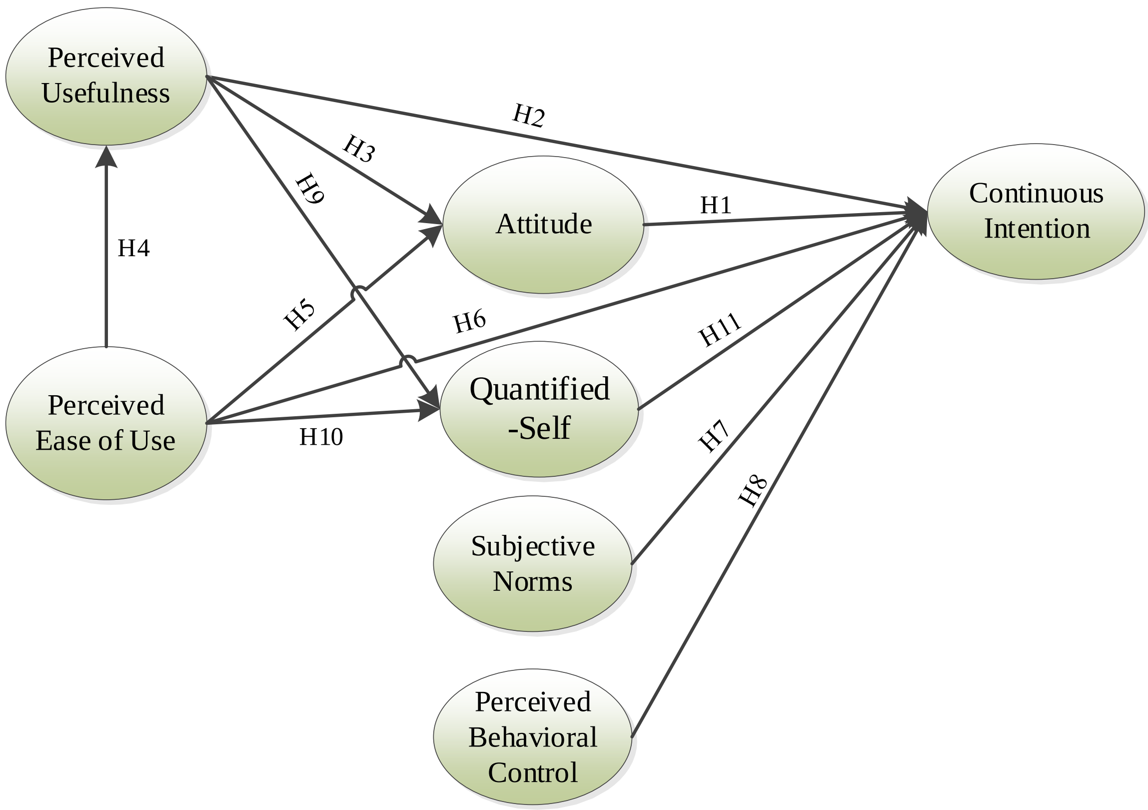


Figure 1. Research framework

3. Research Design and Methodology

3.1. Data Collection

In this study, data were gathered from young runners aged 15 to 34 years who were already utilizing wearable devices. The data collection spanned from April to August 2022. The survey was distributed through online platforms, such as "Marathon Enthusiasts Group" and "Running Enthusiasts Group," using a voluntary and self-administered questionnaire approach. To ensure the anonymity and consent of the users, the questionnaire included the following informed consent statement at its outset. The respondent in the study could withdraw from responding to the questionnaire at any time without providing any reason. Furthermore, the engagement of the respondent in this study was voluntary, and responses to the questionnaire items were not tracked back to the respondent to ensure their anonymity (see Appendix I).

Incentives were offered upon completion of the questionnaire to maintain response quality. By August 20, 2021, 525 questionnaires were collected, 468 of which were considered valid. The characteristics of the valid questionnaire sample are presented in Table 1. Among the young runners already utilizing wearable devices, 265 were males and 203 were females. Regarding education level, 189 participants had a bachelor's or associate's degree, while 256 participants had a master's degree or above. The majority of runners (25.85%) had 1-2 years of running experience. The wearable devices used by the participants included smart wristbands, smartwatches, smart running shoes, and smart glasses, among others.

Table 1. Characteristics of Young Runner-Wearable Devices Survey Participants (N=468)

Variable	Category	Frequency	Percentage
Gender	Male	265	56.63%
	Female	203	43.37%
Age	15～20	42	0.90%
	21～25	255	54.48%
	26～30	121	25.58%
	31～35	50	10.68%
Education	Below Junior High	3	0.64%
	High School/Technical School	20	4.27%
	Bachelor's/Associate Degree	189	40.38%
	Master's Degree or above	256	54.7%
Running Experience	Less than one year	123	26.28%
	1-2 years	121	25.85%
	2-3 years	81	17.30%
	3-4 years	57	12.17%
	4-5 years	21	4.48%
	5-6 years	15	3.20%
	More than six years	50	10.68%
Type of Wearable Devices Used	Smart Wristbands	287	61.32%
	Smartwatches	242	51.7%
	Smart Running Shoes	56	11.96%
	Smart Glasses	41	8.76%
	Others	19	4.05%

3.2. Measurement Instruments

The Technology Acceptance Model (TAM) was used to measure variables, including PU, PE, attitude, and CI, using scales developed by Davis [33] and Lee [29]. Each variable consists of four items. The theory of planned behavior (TPB) variables, including SN and PBC, were measured using scales developed by Ajzen and Driver [46]. Each variable consists of three items. The QS was measured using scales from studies by Hassan [51] and Jin [53], among others, composed of four items. All the items were rated on a 7-point Likert scale ranging from strongly disagree (1) to strongly agree (7). Please refer to Table 2 for further details.

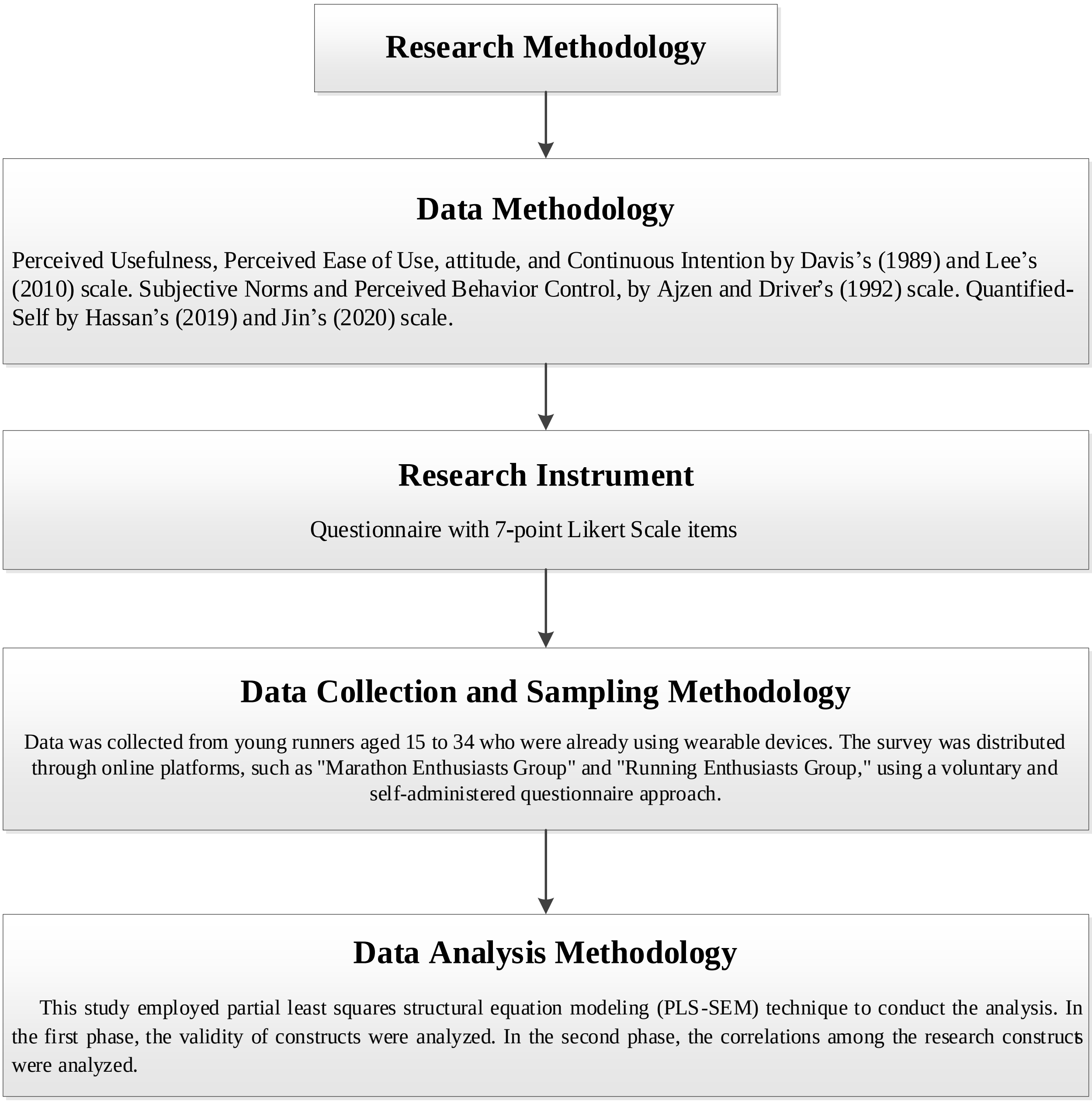


Figure 2. Research Methodology Flowchart

4. Measurement Model and Structural Model

4.1. Measurement Model Analysis

This study employed partial least squares structural equation modeling (PLS-SEM). According to Hair et al. [55], the measurement model should evaluate the factor loadings, reliability, convergent validity, and discriminant validity of the items (see Table 2). The factor loading of each item should be > 0.708 [55]. In this sample, all factor loadings ranged from 0.757 to 0.901, surpassing the threshold of 0.708 and meeting the requirement. The reliability of the measurement model can be assessed by $\alpha > 0.70$ [56]. In this study, the α values ranged from 0.823 to 0.912, all of which exceeded the recommended threshold, indicating high reliability, as shown in Figure 3. Convergent validity was evaluated using composite reliability (CR) and average variance extracted (AVE) [57, 58]. In this sample, both CR (>0.7) and AVE (>0.50) exceeded the recommended thresholds, as indicated in Figures 4 and 5, respectively, indicating good convergent validity. Discriminant validity was assessed using the square root of the AVE [57] and the Heterotrait–Monotrait ratio (HTMT) (<0.85). The square root of the AVE for each construct was greater than the correlation with other constructs (see Table 3 and Figure 6), indicating good discriminant validity.

Table 2. Reliability and Validity Testing of Wearable Devices for Young Runners

Construct	Item	Mean	Factor Loading	VIF	α	CR	AVE
Perceived usefulness (PU)	Using wearable devices helps me monitor my physical health condition	5.532	0.870	2.371	0.878	0.916	0.731
	Using wearable devices helps me improve my physical health condition	5.184	0.831	2.095			
	Using wearable devices enhances the efficiency of monitoring my physical health condition	5.487	0.870	2.517			
	Based on my perception of wearable devices, I believe they have excellent functionality	5.438	0.849	2.067			
Perceived ease of use (PE)	Interacting with wearable devices is clear and understandable	5.423	0.845	2.022	0.845	0.896	0.683
	It is easy for me to use wearable devices proficiently	5.583	0.813	1.774			
	I think it is easy to continue using wearable devices to do what I want	5.308	0.825	1.999			
	I think continuing to use wearable devices requires minimal effort	5.333	0.823	1.827			
Attitude (ATT)	I am interested in continuing to use wearable devices	5.605	0.872	2.700	0.887	0.922	0.747
	I think continuing to use wearable devices is a good idea	5.630	0.899	2.957			
	I believe continuing to use wearable devices is enjoyable	5.509	0.871	2.484			
	I like using wearable devices to monitor my physical health condition	5.526	0.813	1.833			
Continuance intention (CI)	I am willing to frequently use wearable devices	5.524	0.871	2.340	0.912	0.935	0.741
	I plan to continue using wearable devices in the future	5.603	0.882	2.556			
	I would recommend the use of wearable devices to my family and friends	5.316	0.829	2.010			
	I will make an effort to continue using wearable devices in the next six months	5.380	0.875	2.510			
Subjective norms (SN)	Important people to me would think I should continue using wearable devices	4.994	0.880	2.342	0.908	0.936	0.784
	Influential people would think I should continue using wearable devices	4.827	0.901	2.607			
	Many people similar to me think I should continue using wearable devices	5.011	0.850	1.985			
Perceived behavioral control (PBC)	I can use wearable devices effectively to monitor my physical health condition	5.308	0.869	1.984	0.838	0.903	0.756
	I believe continuing to use wearable devices will be entirely within my control	5.404	0.870	2.058			
	I think I have the resources, knowledge, and ability to continue using wearable devices	5.393	0.869	1.884			
Quantified-self (QS)	Recording step count	5.647	0.810	1.847	0.823	0.883	0.653
	Recording exercise details (pace, distance, etc.)	5.829	0.809	1.713			
	Recording calorie expenditure	5.374	0.757	1.549			
	Recording heart rate	5.682	0.854	1.985			

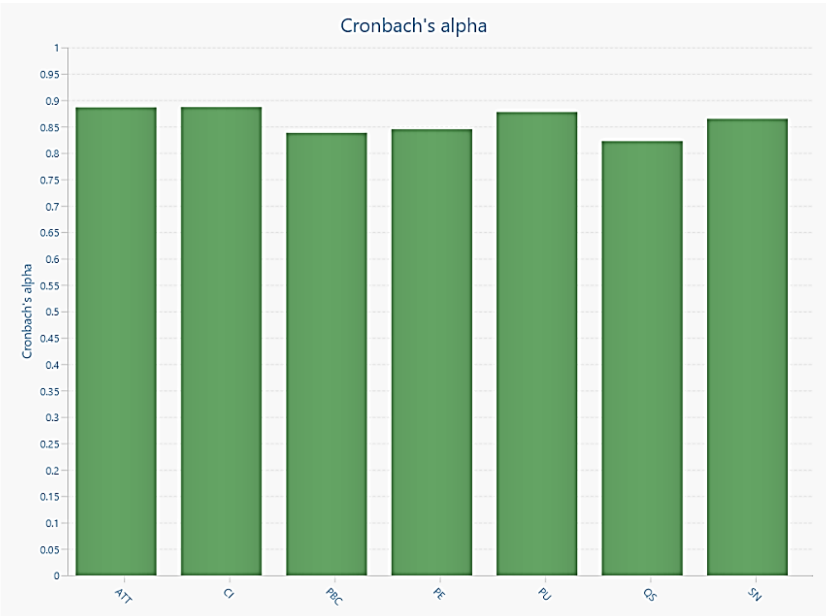


Figure 3. Cronbach's alpha values of the research constructs

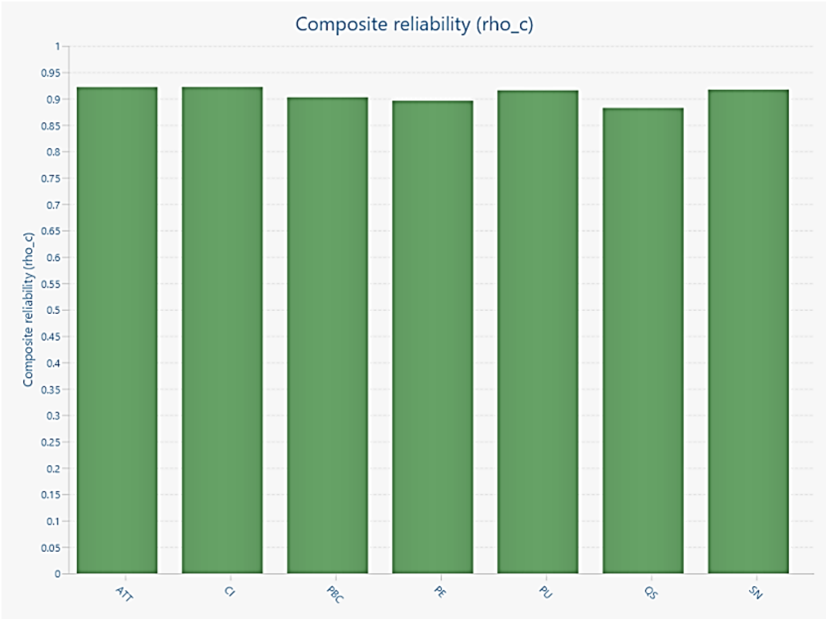


Figure 4. Composite Reliability values of the research constructs

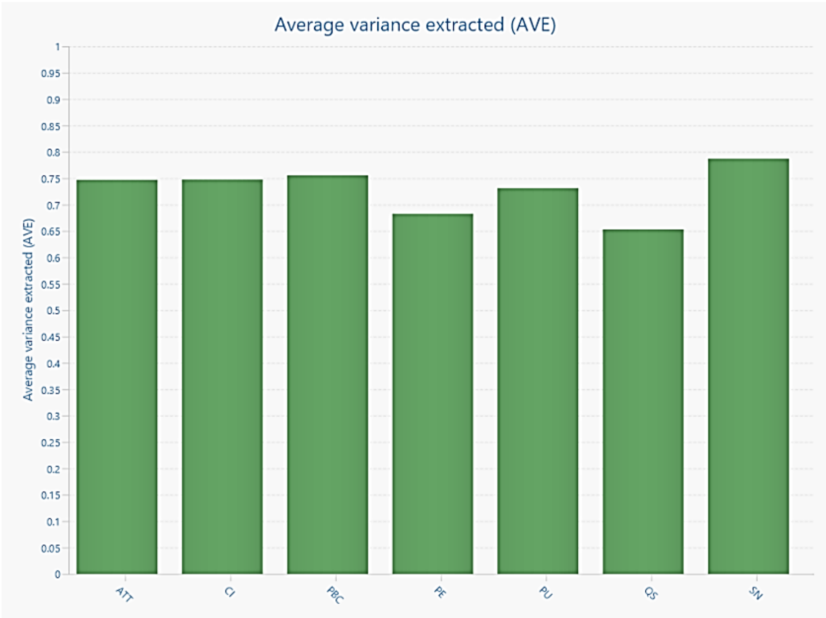


Figure 5. Average variance extracted values of the research constructs

Table 3. Discriminant validity

Construct	Square Root of AVE							HTMT					
	ATT	**CI**	**PBC**	**PE**	**PU**	**QS**	**SN**	**ATT**	**CI**	**PBC**	**PE**	**PU**	**QS**
ATT	**0.864**												
CI	0.695	**0.865**						0.781					
PBC	0.542	0.542	**0.869**					0.626	0.626				
PE	0.613	0.572	0.584	**0.826**				0.705	0.657	0.693			
PU	0.641	0.665	0.657	0.634	**0.855**			0.720	0.749	0.764	0.733		
QS	0.619	0.610	0.503	0.528	0.630	**0.808**		0.721	0.709	0.603	0.627	0.736	
SN	0.458	0.506	0.505	0.507	0.532	0.404	**0.887**	0.520	0.577	0.593	0.591	0.611	0.476

Note: ATT stands for attitude; CI represents continuance intention; PBC stands for perceived behavioral control; PE indicates perceived ease of use; PU represents perceived usefulness; QS stands for quantified self; SN indicates subjective norms; the diagonal represents the square root of AVE values.

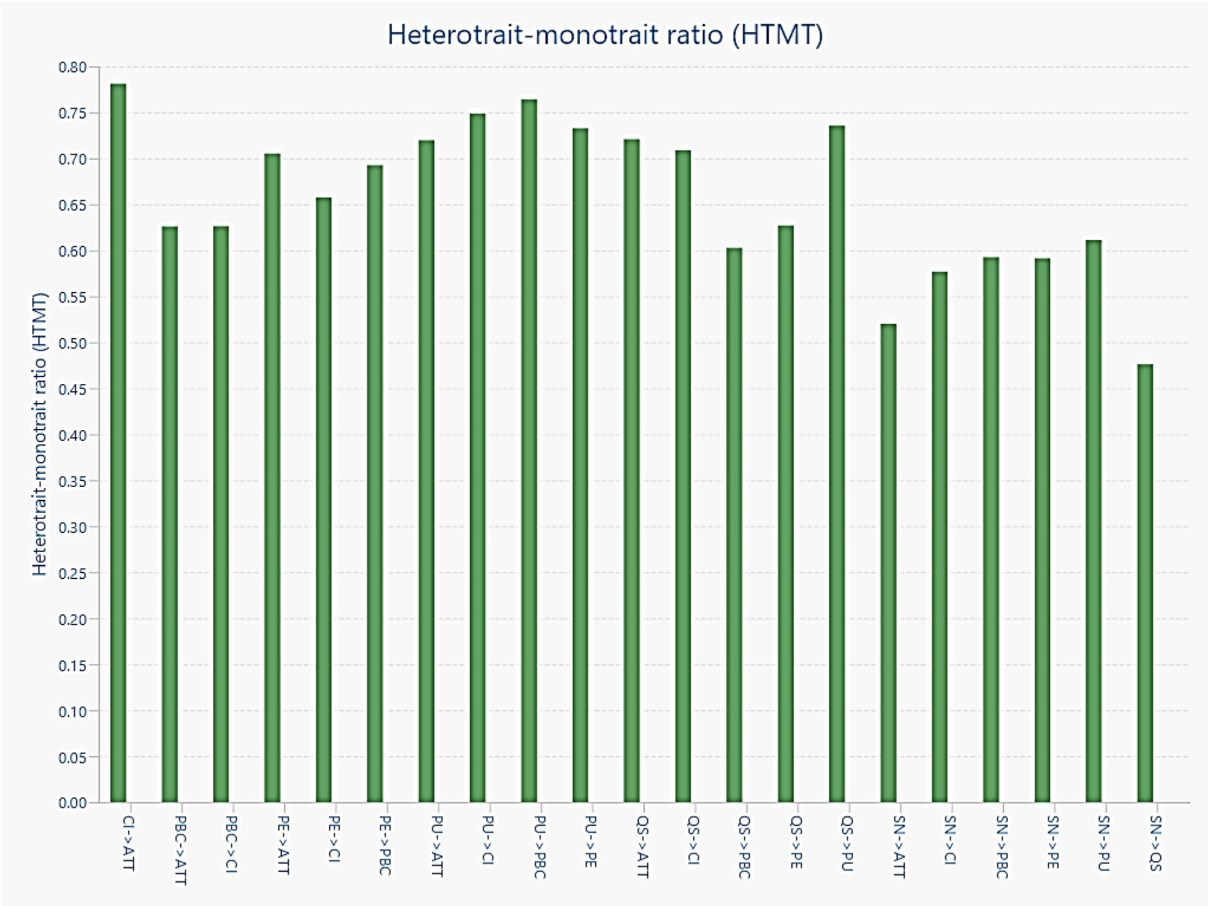


Figure 6. Heterotrait–Monotrait ratio graph of the research constructs

Before examining the structural model, the model's fit was evaluated using the standardized root mean square residual (SRMR), with a recommended threshold of SRMR < 0.08 [59, 60]. The SRMR for this study was 0.053, which is below the suggested maximum value of 0.08, indicating a good fit for the model. According to Hair et al. [61], the variance inflation factor (VIF) was used to test for multicollinearity, with a threshold of VIF < 5. The results showed that all the measurement indicators had VIF values less than 3 (Table 1), indicating a low likelihood of multicollinearity issues in the model.

This study collected data using self-report survey methods, necessitating an assessment of common method bias (CMB). The Harman single-factor test was employed, where if a single factor accounts for more than 50% of the variance, CMB may exist [62]. The results of this study indicated that the variance accounted for by a single factor was 46.025%, which was lower than the 50% total variance, suggesting a low possibility of CMB.

4.2. Structural Model

The validity of the structural equation model was assessed by evaluating the explained variance (R2) [63], predictive relevance (Q2) [64], and goodness-of-fit index (GOF) [65] of the endogenous variables. In this study, the R2 values of the endogenous variables were greater than 0.33, indicating moderate explanatory power (Figure 7). Mainly, the R2 for CI was 0.597. All the endogenous variables in this study had Q2 values greater than 0, indicating strong predictive relevance, with a Q2 value of 0.270 for QS. Additionally, the computed GOF value (as the square root of the product of average communality and average R2) was 0.578, exceeding the maximum threshold of 0.36 for goodness-of-fit. These findings suggest that the structural model has good validity.

4.3. Direct Effects

After confirming the reliability and validity of the measurement and structural models, bootstrapping with 5000 resamples was applied to test the proposed hypotheses and path coefficients. The specific results are shown in Figure 7 and Table 4.

According to the TAM, attitude ($\beta = 0.348$, $t = 4.272$, $p < 0.001$) and PU ($\beta = 0.218$, $t = 2.498$, $p < 0.05$) had significant positive effects on CI in the use of wearable devices. However, PE did not significantly influence CI use of wearable devices ($\beta = 0.052$, $t = 0.610$, $p > 0.05$). PE had a significant positive effect on PU ($\beta = 0.634$, $t = 12.560$, $p < 0.001$), and PE (β = 0.347, t = 4.355, p < 0.001) and PU (β = 0.420, t = 5.100, p < 0.001) had significant positive effects on attitude. Therefore, in the TAM model, H1, H2, H3, H4, and H5 were supported, while H6 was rejected.

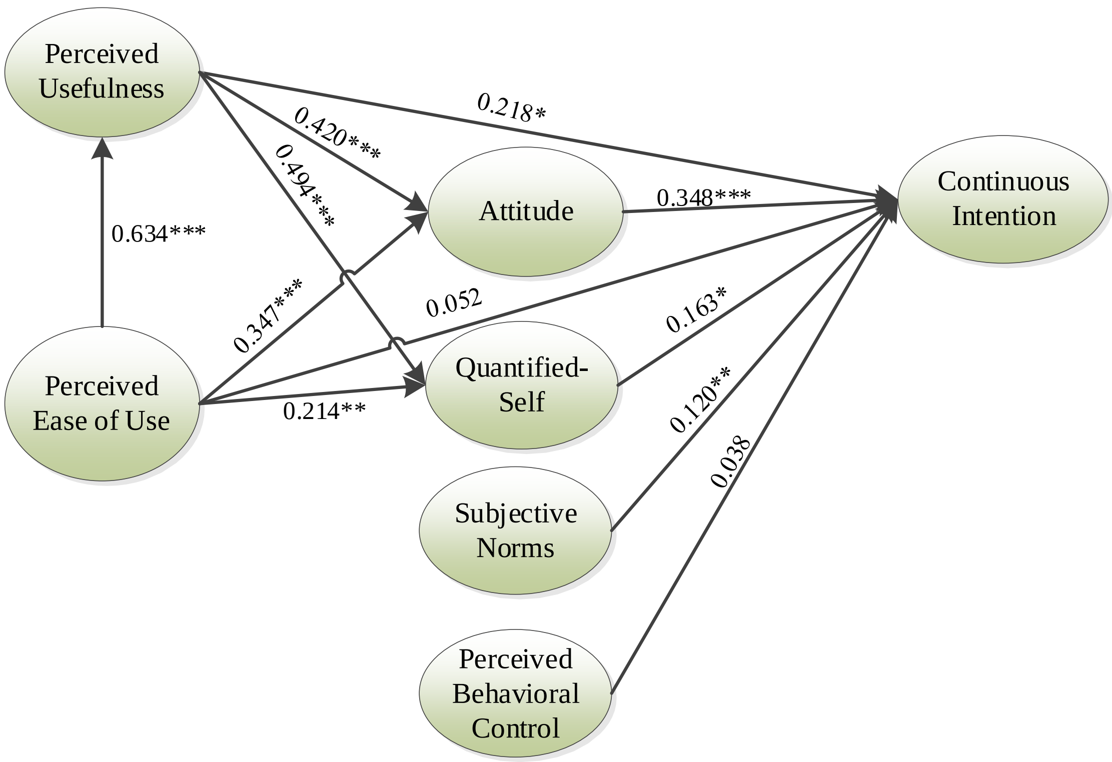
According to the TPB, SN had a significant positive effect on CI (β = 0.120, t = 2.842, p < 0.05), but PBC did not significantly influence CI when wearable devices were used (β = 0.038, t = 0.604, p > 0.05). Thus, H7 was supported, while H8 was rejected.

Finally, PU (β = 0.494, t = 8.221, p < 0.001) and PE (β = 0.214, t = 3.167, p < 0.01) had significant positive effects on QS. QS also significantly positively affected CI in the use of wearable devices (β = 0.163, t = 2.170, p < 0.05). Therefore, H9, H10, and H11 were supported.

Table 4. Results of Direct Effects Testing

Hypothesis	Path	Beta	Standard Deviation (std)	t value	p value	Results
H1	ATT→CI	0.348	0.081	4.272	0.000	Supported
H2	PU→CI	0.218	0.087	2.498	0.013	Supported
H3	PU→ATT	0.420	0.082	5.100	0.000	Supported
H4	PE→PU	0.634	0.050	12.560	0.000	Supported
H5	PE→ATT	0.347	0.080	4.355	0.000	Supported
H6	PE→CI	0.052	0.085	0.610	0.542	Rejected
H7	SN→CI	0.120	0.042	2.842	0.004	Supported
H8	PBC→CI	0.038	0.062	0.604	0.546	Rejected
H9	PU→QS	0.494	0.060	8.221	0.000	Supported
H10	PE→QS	0.214	0.068	3.167	0.002	Supported
H11	QS→CI	0.163	0.075	2.170	0.030	Supported

Note: ATT stands for attitude; CI represents continuance intention; PBC stands for perceived behavioral control; PE indicates perceived ease of use; PU stands for perceived usefulness; QS represents quantified self; SN stands for subjective norms; the diagonal indicates the square root of the AVE values.



Note: * p value < 0.05; ** p value < 0.01; *** *p* value < 0.001.

Figure 7. Framework of the Model Results

4.4. Indirect Effects

The indirect effects between variables were examined using bootstrapping with 5000 iterations (see Table 5). First, in the TAM, PU (β=0.146; t=2.999; p<0.01) and PE (β=0.121; t=3.043; p<0.01) had significant positive effects on attitudes toward and CI use of wearable devices. PE had a significant positive effect on attitude (β=0.266; t=4.483;

p<0.001) and CI toward wearable devices (β=0.139; t=2.488; p<0.01) through PU. Additionally, PE significantly positively affected CI in relation to wearable devices through PU and attitude (β=0.093; t=2.605; p<0.01). Therefore, H3a, H4a, H4b, H4c, and H4d were supported.

Second, QS mediated the relationship between PU and CI when wearable devices were used (β=0.080; t=2.240; p<0.05), but it did not mediate the relationship between PE and CI when wearable devices were used (β=0.035; t=1.637; p>0.05). PU partially mediated the relationship between PE and QS (β=0.313; t=6.214; p<0.001). H11a and H11c were supported, while H11b was rejected. Finally, PU and QS had chain mediating effects on the relationship between PE and CI use of wearable devices (β=0.051; t=2.320; p<0.05). H11d was supported.

Table 5. Results of Indirect Effects

Hypothesis	Path	Beta	Standard Deviation(std)	t value	p value	Results
H3a	PU→ATT→CI	0.146	0.049	2.999	0.003	Supported
H4a	PE→ATT→CI	0.121	0.040	3.043	0.002	Supported
H4b	PE→PU→ATT	0.266	0.059	4.483	0.000	Supported
H4c	PE→PU→CI	0.139	0.056	2.488	0.013	Supported
H4d	PE→PU→ATT→CI	0.093	0.036	2.605	0.009	Supported
H11a	PU→QS→CI	0.080	0.036	2.240	0.025	Supported
H11b	PE→QS→CI	0.035	0.021	1.637	0.102	Rejected
H11c	PE→PU→QS	0.313	0.050	6.214	0.000	Supported
H11d	PE→PU→QS→CI	0.051	0.022	2.320	0.020	Supported

Note: ATT stands for attitude; CI stands for continuance intention; PBC stands for perceived behavioral control; PE stands for perceived ease of use; PU stands for perceived usefulness; QS stands for quantified self; SN stands for subjective norms; the diagonal represents the square root of AVE values.

5. Discussion and Implications

5.1. Main Findings of the Study

This study delved into young runners' CIs to use wearable devices by integrating the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) with the inclusion of the QS variable. The findings demonstrated that the TAM/TPB integrated model had moderate explanatory power for young runners' CIs regarding wearable devices. Additionally, young runners' QS positively influenced their ability to use wearable devices. Therefore, QS in the TAM/TPB integrated model provides a better understanding of young runners' CIs toward wearable devices.

5.2. Comparison with Other Studies

The findings revealed that PU and attitude significantly influenced CI use of wearable devices among young runners, further validating the validity of the TAM theory in the context of sports and wearable devices. Specifically, the study revealed that PU (β=0.218; t=2.498; p<0.05) had a significant positive effect on young runners' CI from using wearable devices, which aligns with the findings of previous research [8, 43, 66]. This finding also corresponds with the results of Ong et al. [67], who observed a positive effect of PU on CI among online game users. However, the study showed that PE did not have a significant impact on young runners' ability to use wearable devices, contradicting the findings of Davis et al. [33]. Nevertheless, these findings align with the results of Chang et al. [66] and Ashfaq [43], who found no significant relationship between PE and the intention to use wearable devices. Interestingly, the study showed that the PU fully mediated the relationship between PE and CI use of wearable devices (β=0.139; t=2.488; p<0.01). This finding suggested that young runners' expectations for the continued use of wearable devices are primarily determined by their perception of usefulness rather than by ease of use, consistent with the view of Davis et al. [33], who argued that usefulness has a stronger relationship with usage than does ease of use. However, it should be noted that PE still positively impacts CI's use of wearable devices through its influence on PU, indicating that it is still a factor worthy of consideration.

This study revealed that attitude had a highly significant positive impact on young runners' CI in using wearable devices (β=0.348; t=4.272; p<0.001), which is consistent with the findings of previous research [68]. The study also established that young runners' PU of wearable devices had a highly significant positive effect on their attitude (β=0.420; t=5.100; p<0.001). Furthermore, attitude partially mediated the relationship between PU and CI when wearing devices were used, aligning with the findings of Lunney et al. [3] in their study on wearable fitness technology. Additionally, PE had a significant positive impact on attitudes toward the continued use of wearable devices (β=0.347; t=4.355; p<0.001), which is consistent with the results of Davis et al. [33] and Venkatesh et al. [69]. Furthermore, the study revealed a significant chain mediating effect of PU and attitude between PE and CI toward wearable devices (β=0.093; t=2.605; p<0.01). These findings underscore the importance of attitude as a significant predictor of young runners' CI when wearing wearable devices. Moreover, PE and PU indirectly influence young runners' CI through their impact on attitude.

This study utilized the theory of planned behavior (TPB) to scrutinize the predictive role of SN and PBC in young runners' CIs when using wearable devices. These findings revealed a significant positive effect of the SN on CI use of wearable devices (β=0.120; t=2.842; p<0.05), aligning with previous findings [3, 70]. SNs reflect individuals' perceptions of how important others, such as family members, friends, and peers, are in their lives and expect them to engage in a particular behavior. It has been suggested that individuals are more likely to be influenced by in-group information than out-group information [71]. Given that young runners often participate in group running events or engage in running and fitness activities with others, they are susceptible to the influence of their peers. Moreover, wearable devices themselves have social functionalities, such as ranking users and their friends based on daily (or weekly) step counts or calories burned and facilitating communication and interaction among users. These social aspects also expose young runners to the influence of others. However, the coefficient for the ability of the SN to predict young runners' CI when wearing devices was used was relatively low, suggesting that its practical impact may be limited. One possible reason for this difference is that running is primarily an individual activity and is less influenced by social or interpersonal factors.

Furthermore, this study revealed that PBC had no significant effect on young runners' CI in using wearable devices (β=0.038; t=0.604; p>0.05). This finding contrasts with those of several previous studies [72, 73] but aligns with research that found no significant impact of PBC on usage intention [74]. One possible explanation for this discrepancy is that PBC's role may vary across user groups and technology products. As wearable devices represent a rapidly evolving technology, young runners may have limited knowledge and weaker control over these new technologies. Additionally, wearable devices may raise privacy concerns, which can influence the decision-making process.

This study demonstrated that QS positively impacted young runners' intention to use wearable devices (β=0.163; t=2.170; p<0.05). Furthermore, PE (β=0.214; t=3.167; p<0.01) and PU (β=0.494; t=8.221; p<0.001) had significant positive effects on QS, aligning with previous research [14]. Previous studies have indicated that linking the quantified self with data helps users contextualize events and that combining quantitative data and qualitative experiences strengthens long-term usage habits [75, 76]. The quantitative results of this study support the qualitative findings mentioned earlier. Additionally, the results revealed that PU, rather than PE, significantly positively influenced young runners' intention to use wearable devices through QS. PE had an impact only through PU, indicating that users highly value the functionality and purpose of wearable devices. Young runners utilize wearable devices to track their relevant data in real time, allowing them to experience their physical and mental states within specific data areas. This feeling contributes to the achievement of their health and performance goals.

5.3. Implication and Explanation of Findings

This study yields various academic and practical implications concerning the use of smart wearable devices. This study aimed to provide a complete theoretical background by integrating the TPB, TAM, and QS to analyze the ATT and CI of young runners. This study revealed a significant and positive association between the ATT and CI of young runners. These findings indicate that practitioners in the health care industry, such as healthcare professionals and sports managers, can plan, design, and implement strategies that will enhance the ATT of young runners toward CI to use smart wearable devices. Furthermore, this study employed the TPB to analyze the impacts of SN and PBC on CI [28]. These findings indicated that SN and PBC were positively related to CI. This implies that healthcare practitioners should develop promotional strategies targeting the young population, emphasizing societal pressures to motivate the young target market to use smart wearables. Thus, the ATT and CI of young runners should be increased to use smart wearables.

Additionally, this study employed the PE and PU of the TAM to further explore the ATT and CI of young runners. The findings of this research revealed that 'TAM's PE and PU significantly impacted the ATT and CI of users. Hence, TAM score was a significant predictor of 'users' CI, which was in accordance with previous research [17, 25, 77]. The major contribution of this study was to theoretically integrate the TAM with QS and the TPB, providing an extended modified TAM framework.

Finally, this research utilized QS to analyze the CI of young runners toward smart wearable technologies [78]. The results indicated a significant relationship between QS and CI. These findings encourage healthcare practitioners to emphasize the use of QS for healthcare tracking by users with the help of smart wearable devices. Furthermore, healthcare practitioners and managers are encouraged to include various interactive activities beyond exercise tracking, such as monitoring food and water consumption, to enhance user engagement. The findings provide further guidelines for practitioners regarding the design and implementation of QS-related strategies, directing them toward more human-centered strategies by ensuring the inclusion of widely used constructs such as autonomy, understanding, choice, and consciousness.

5.4. Strengths and Limitations

First, the participants in this study consisted of young runners from various provinces in China, providing a certain level of representativeness among these demographic variables. However, the sample scope remains limited, and future research could delve into the quantified experiences and usage behavior of wearable devices among middle-aged and elderly individuals. Second, this study did not dynamically track the participants' perceived differences in various stages of wearable device usage. Future research could investigate the behavioral changes in users' continued use of wearable devices over time. Finally, this study did not address the privacy and security issues associated with the use of wearable devices. Subsequent research could focus on exploring these aspects.

6. Conclusion, Recommendations, and Future Directions

For young runners, the most crucial aspect influencing their continued selection of wearable devices is their usefulness. Continuous improvement in product performance should be directed toward improving product performance to meet the specific needs of this user group. This can be achieved by offering accompanying fitness apps that provide personalized health reports and analyze user data trends, among other features. For instance, a device equipped with a six-axis sensor can track the wearer's running posture, accurately identify running posture, and correct any incorrect postures. By providing users with more effective information during usage, their PU can be enhanced. Some wearable devices can offer more in-depth data monitoring metrics to help consumers gain a more comprehensive understanding and offer them more accurate guidance and recommendations.

For young runners, the PE of wearable devices is an important factor. They should be able to understand the user instructions and use the devices easily. This involves accurately identifying errors and understanding the causes of those errors. The devices should prioritize lightweight and user-friendly designs, ensuring smooth system performance and compatibility. The user interface should be simple and intuitive, minimizing elements and operations on the screen. Voice control can facilitate usage while running. Recognizing the social nature of many young individuals by adding interactive features to the device interface, such as social sharing and competition, can encourage communication, challenge each other, and foster the sharing of running experiences.

However, users continue to use wearable devices for data collection and for quantified self-engagement. However, during interviews, some participants raised concerns about discrepancies between the displayed heart rate data and their actual experience. For example, with certain fitness bands, heart rate data for "recovery time" and "training effect" functions may show high values after aerobic exercise but low values after strength training, which contradicts users' actual experiences. Therefore, continuous optimization of product performance is crucial for enhancing users' authentic experience and improving their sense of immersion.

7. Declarations

7.1. Author Contributions

Conceptualization, Z.G., G.L., Z.L., and A.K.; methodology, Z.G., G.L., and Z.L.; formal analysis, Z.G., G.L., Z.L., and A.K.; writing—original draft preparation, Z.G., G.L., Z.L., and A.K.; writing—review and editing, Z.G., G.L., Z.L., and A.K. All authors have read and agreed to the published version of the manuscript.

7.2. Data Availability Statement

The data presented in this study are available in the article.

7.3. Funding

The authors appreciate the support of The Philosophy and Social Sciences Research Project of Colleges and Universities in Shanxi Province (201801015) and the Shanxi Postgraduate Education Innovation Project (2021-27).

7.4. Institutional Review Board Statement

Not applicable.

7.5. Informed Consent Statement

Not applicable.

7.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

8. References

[1] Xie, J., Chen, Q., Shen, H., & Li, G. (2020). Wearable graphene devices for sensing. Journal of the Electrochemical Society, 167(3), 037541. doi:10.1149/1945-7111/ab67a4.

[2] Bhatti, D. S., Saleem, S., Imran, A., Iqbal, Z., Alzahrani, A., Kim, H. J., & Kim, K. I. (2022). A Survey on Wireless Wearable Body Area Networks: A Perspective of Technology and Economy. Sensors, 22(20), 7722. doi:10.3390/s22207722.

[3] Lunney, A., Cunningham, N. R., & Eastin, M. S. (2016). Wearable fitness technology: A structural investigation into acceptance and perceived fitness outcomes. Computers in Human Behavior, 65, 114–120. doi:10.1016/j.chb.2016.08.007.

[4] Kang, M. J., & Hwang, Y. C. (2022). Exploring the Factors Affecting the Continued Usage Intention of IoT-Based Healthcare Wearable Devices Using the TAM Model. Sustainability (Switzerland), 14(19), 12492. doi:10.3390/su141912492.

[5] Chau, K. Y., Lam, M. H. S., Cheung, M. L., Tso, E. K. H., Flint, S. W., Broom, D. R., Tse, G., & Lee, K. Y. (2019). Smart technology for healthcare: Exploring the antecedents of adoption intention of healthcare wearable technology. Health Psychology Research, 7(1). doi:10.4081/hpr.2019.8099.

[6] Cosoli, G., Antognoli, L., Veroli, V., & Scalise, L. (2022). Accuracy and Precision of Wearable Devices for Real-Time Monitoring of Swimming Athletes. Sensors, 22(13), 4726. doi:10.3390/s22134726.

[7] Gopinath, K., Selvam, G., & Narayanamurthy, G. (2022). Determinants of the Adoption of Wearable Devices for Health and Fitness: A Meta-analytical Study. Communications of the Association for Information Systems, 50(1), 445–480. doi:10.17705/1CAIS.05019.

[8] Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. Management Science, 35(8), 982–1003. doi:10.1287/mnsc.35.8.982.

[9] Yang, H., Yu, J., Zo, H., & Choi, M. (2016). User acceptance of wearable devices: An extended perspective of perceived value. Telematics and Informatics, 33(2), 256–269. doi:10.1016/j.tele.2015.08.007.

[10] D'Ambrosi, L. (2017). The global active citizenship network in Italian local contexts: Using social media to promote sustainable behaviours. Javnost-The Public, 24(1), 34-48. doi:10.1080/13183222.2017.1267161.

[11] Zhao, H., & Khan, A. (2022). The Students' Flow Experience with the Continuous Intention of Using Online English Platforms. Frontiers in Psychology, 12, 807084–807084. doi:10.3389/fpsyg.2021.807084.

[12] Ajzen, I. (2012). The theory of planned behavior. Handbook of Theories of Social Psychology: Volume 1, 50(2), 438–459. doi:10.4135/9781446249215.n22.

[13] Jung, T., Claudia Tom Dieck, M., Lee, H., & Chung, N. (2020). Relationships among beliefs, attitudes, time resources, subjective norms, and intentions to use wearable augmented reality in art galleries. Sustainability (Switzerland), 12(20), 1–17. doi:10.3390/su12208628.

[14] Tao, Y. T., Lin, M. Der, & Khan, A. (2022). The impact of CSR on green purchase intention: Empirical evidence from the green building Industries in Taiwan. Frontiers in Psychology, 13. doi:10.3389/fpsyg.2022.1055505.

[15] Xu, Y., Wang, Y., Khan, A., & Zhao, R. (2021). Consumer Flow Experience of Senior Citizens in Using Social Media for Online Shopping. Frontiers in Psychology, 12. doi:10.3389/fpsyg.2021.732104.

[16] Davis, F. D. (1993). User acceptance of information technology: system characteristics, user perceptions and behavioral impacts. International Journal of Man-Machine Studies, 38(3), 475–487. doi:10.1006/imms.1993.1022.

[17] Kim, K. J., & Shin, D. H. (2015). An acceptance model for smart watches: Implications for the adoption of future wearable technology. Internet Research, 25(4), 527–541. doi:10.1108/IntR-05-2014-0126.

[18] Howard, M. C., & Hair, J. F. (2023). Integrating the Expanded Task-technology Fit Theory and the Technology Acceptance Model: A Multi-wave Empirical Analysis. AIS Transactions on Human-Computer Interaction, 15(1), 83–110. doi:10.17705/1thci.00084.

[19] Lu, K., Pang, F., & Shadiev, R. (2023). Understanding college students' continuous usage intention of asynchronous online courses through extended technology acceptance model. Education and Information Technologies, 28(8), 9747–9765. doi:10.1007/s10639-023-11591-1.

[20] An, S., Eck, T., & Yim, H. (2023). Understanding Consumers' Acceptance Intention to Use Mobile Food Delivery Applications through an Extended Technology Acceptance Model. Sustainability (Switzerland), 15(1), 832. doi:10.3390/su15010832.

[21] Jariyapan, P., Mattayaphutron, S., Gillani, S. N., & Shafique, O. (2022). Factors Influencing the Behavioural Intention to Use Cryptocurrency in Emerging Economies During the COVID-19 Pandemic: Based on Technology Acceptance Model 3, Perceived Risk, and Financial Literacy. Frontiers in Psychology, 12, 5935. doi:10.3389/fpsyg.2021.814087.

[22] Mustafa, A. S., Alkawsi, G. A., Ofosu-Ampong, K., Vanduhe, V. Z., Garcia, M. B., & Baashar, Y. (2022). Gamification of E-learning in African universities: Identifying adoption factors through task-technology fit and technology acceptance model. In Next-Generation Applications and Implementations of Gamification Systems, Issue April, 73–96.

[23] Park, E., & Del Pobil, A. P. (2013). Technology acceptance model for the use of tablet PCs. Wireless Personal Communications, 73(4), 1561–1572. doi:10.1007/s11277-013-1266-x.

[24] Joo, J., & Sang, Y. (2013). Exploring Koreans' smartphone usage: An integrated model of the technology acceptance model and uses and gratifications theory. Computers in Human Behavior, 29(6), 2512–2518. doi:10.1016/j.chb.2013.06.002.

[25] Kim, K. J., & Sundar, S. S. (2014). Does screen size matter for smartphones? Utilitarian and hedonic effects of screen size on smartphone adoption. Cyber psychology, Behavior, and Social Networking, 17(7), 466–473. doi:10.1089/cyber.2013.0492.

[26] Park, E., & Kim, K. J. (2014). An integrated adoption model of mobile cloud services: Exploration of key determinants and extension of technology acceptance model. Telematics and Informatics, 31(3), 376–385. doi:10.1016/j.tele.2013.11.008.

[27] Jung, Y. (2011). Understanding the role of sense of presence and perceived autonomy in users' continued use of social virtual worlds. Journal of Computer-Mediated Communication, 16(4), 492–510. doi:10.1111/j.1083-6101.2011.01540.x.

[28] Ku, W. T., Lai, H. M., & Hsieh, P. J. (2020). Understanding continuous wearable technology use behavior for fitness and self–health management among middle-aged and elderly people. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 12207 LNCS, 280–288. doi:10.1007/978-3-030-50252-2_21.

[29] Lee, M. C. (2010). Explaining and predicting users' continuance intention toward e-learning: An extension of the expectation-confirmation model. Computers and Education, 54(2), 506–516. doi:10.1016/j.compedu.2009.09.002.

[30] Lu, Y., Zhou, T., & Wang, B. (2009). Exploring Chinese users' acceptance of instant messaging using the theory of planned behavior, the technology acceptance model, and the flow theory. Computers in Human Behavior, 25(1), 29–39. doi:10.1016/j.chb.2008.06.002.

[31] Hsieh, P. J. (2015). Physicians' acceptance of electronic medical records exchange: An extension of the decomposed TPB model with institutional trust and perceived risk. International Journal of Medical Informatics, 84(1), 1–14. doi:10.1016/j.ijmedinf.2014.08.008.

[32] Lee, Y., Kozar, K. A., & Larsen, K. R. (2003). The technology acceptance model: Past, present, and future. Communications of the Association for information systems, 12(1), 50.

[33] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly: Management Information Systems, 13(3), 319–339. doi:10.2307/249008.

[34] Ajzen, I., & Fishbein, M. (1975). A Bayesian analysis of attribution processes. Psychological Bulletin, 82(2), 261–277. doi:10.1037/h0076477.

[35] Venkatesh, V., & Davis, F. D. (2000). Theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. Management Science, 46(2), 186–204. doi:10.1287/mnsc.46.2.186.11926.

[36] Bhattacherjee, A. (2017). Understanding information systems continuance Understanding information systems continuance : an expectation-confirmation model. MIS Quarterly, 2017148.

[37] Amoroso, D., & Lim, R. (2017). The mediating effects of habit on continuance intention. International Journal of Information Management, 37(6), 693–702. doi:10.1016/j.ijinfomgt.2017.05.003.

[38] Yu, Z., & Huang, Y. (2022). The Influencing Factors of Users' Attitudes and Continuance Intention for Olympic Viewing on Mobile Applications in China. Systems, 10(5), 190. doi:10.3390/systems10050190.

[39] Song, J., Kim, J., & Cho, K. (2018). Understanding users' continuance intentions to use smart-connected sports products. Sport Management Review, 21(5), 477–490. doi:10.1016/j.smr.2017.10.004.

[40] Cheung, M. L., Leung, W. K. S., & Chan, H. (2020). Driving healthcare wearable technology adoption for Generation Z consumers in Hong Kong. Young Consumers, 22(1), 10–27. doi:10.1108/YC-04-2020-1123.

[41] Gupta, A., Dhiman, N., Yousaf, A., & Arora, N. (2021). Social comparison and continuance intention of smart fitness wearables: an extended expectation confirmation theory perspective. Behaviour & Information Technology, 40(13), 1341-1354. doi:10.1080/0144929X.2020.1748715.

[42] Zaremohzzabieh, Z., Samah, B. A., Muhammad, M., Omar, S. Z., Bolong, J., Hassan, M. S., & Shaffril, H. A. M. (2015). A Test of the Technology Acceptance Model for Understanding the ICT Adoption Behavior of Rural Young Entrepreneurs. International Journal of Business and Management, 10(2), 158–169. doi:10.5539/ijbm.v10n2p158.

[43] Ashfaq, M., Yun, J., Yu, S., & Loureiro, S. M. C. (2020). I, Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. Telematics and Informatics, 54, 101473. doi:10.1016/j.tele.2020.101473.

[44] Hung, S. W., Chang, C. W., & Ma, Y. C. (2021). A new reality: Exploring continuance intention to use mobile augmented reality for entertainment purposes. Technology in Society, 67, 101757. doi:10.1016/j.techsoc.2021.101757.

[45] Venkatesh, V. (2000). Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model. Information Systems Research, 11(4), 342–365. doi:10.1287/isre.11.4.342.11872.

[46] Ajzen, I., & Driver, B. L. (1992). Application of the Theory of Planned Behavior to Leisure Choice. Journal of Leisure Research, 24(3), 207–224. doi:10.1080/00222216.1992.11969889.

[47] Zhu, Y., Dailey, S. L., Kreitzberg, D., & Bernhardt, J. (2017). "Social Net Workout": Connecting Social Features of Wearable Fitness Trackers with Physical Exercise. Journal of Health Communication, 22(12), 974–980. doi:10.1080/10810730.2017.1382617.

[48] Ajzen, I. (2002). Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior. Journal of Applied Social Psychology, 32(4), 665–683. doi:10.1111/j.1559-1816.2002.tb00236.x.

[49] Sonne, T., & Jensen, M. M. (2014). Race by hearts: Using technology to facilitate enjoyable and social workouts. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 8770, 125–132. doi:10.1007/978-3-662-45212-7_16.

[50] Mauriello, M. L., Gubbels, M., & Froehlich, J. E. (2014). Social fabric fitness: The design and evaluation of wearable E-textile displays to support group running. Conference on Human Factors in Computing Systems - Proceedings, 2833–2842. doi:10.1145/2556288.2557299.

[51] Hassan, L., Dias, A., & Hamari, J. (2019). How motivational feedback increases user's benefits and continued use: A study on gamification, quantified-self and social networking. International Journal of Information Management, 46, 151–162. doi:10.1016/j.ijinfomgt.2018.12.004.

[52] Yang, N., van Hout, G., Feijs, L., Chen, W., & Hu, J. (2020). Facilitating physical activity through on-site quantified-self data sharing. Sustainability (Switzerland), 12(12), 4904. doi:10.3390/SU12124904.

[53] Jin, H., Yan, J., Zhang, Y., & Zhang, H. (2023). Research on the influence mechanism of users' quantified-self immersive experience: on the convergence of mobile intelligence and wearable computing. Personal and Ubiquitous Computing, 27(3), 1111–1122. doi:10.1007/s00779-020-01484-2.

[54] Jin, H., Peng, Y., Chen, J., & Park, S. T. (2022). Research on the Connotation and Dimension of Consumers' Quantified-Self Consciousness. Sustainability (Switzerland), 14(3), 1504. doi:10.3390/su14031504.

[55] Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24. doi:10.1108/EBR-11-2018-0203.

[56] Hair Jr, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate Data Analysis. Pearson Prentice, New Jersey, United States.

[57] Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Journal of Marketing Research, 18(1), 39. doi:10.2307/3151312.

[58] Chen, C. C., Khan, A., Hongsuchon, T., Ruangkanjanases, A., Chen, Y. T., Sivarak, O., & Chen, S. C. (2021). The role of corporate social responsibility and corporate image in times of crisis: The mediating role of customer trust. International Journal of Environmental Research and Public Health, 18(16), 8275. doi:10.3390/ijerph18168275.

[59] Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling, 6(1), 1–55. doi:10.1080/10705519909540118.

[60] Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. Industrial Management and Data Systems, 116(1), 2–20. doi:10.1108/IMDS-09-2015-0382.

[61] Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., & Thiele, K. O. (2017). Mirror, mirror on the wall: a comparative evaluation of composite-based structural equation modeling methods. Journal of the academy of marketing science, 45, 616-632. doi:10.1007/s11747-017-0517-x.

[62] Harman, H. H. (1976). Modern Factor Analysis. University of Chicago Press, Chicago, United States.

[63] Chin W, M. G. (1998). The Partial Least Squares Approach to Structural Formula Modeling. Advances in Hospitality and Leisure, 8(2), 5.

[64] Hair, J. F., Sarstedt, M., Pieper, T. M., & Ringle, C. M. (2012). The Use of Partial Least Squares Structural Equation Modeling in Strategic Management Research: A Review of Past Practices and Recommendations for Future Applications. Long Range Planning, 45(5–6), 320–340. doi:10.1016/j.lrp.2012.09.008.

[65] Wetzels, M., Odekerken-Schröder, G., & Van Oppen, C. (2009). Using PLS path modeling for assessing hierarchical construct models: Guidelines and empirical illustration. MIS Quarterly: Management Information Systems, 33(1), 177–196. doi:10.2307/20650284.

[66] Chang, H. S., Lee, S. C., & Ji, Y. G. (2016). Wearable device adoption model with TAM and TTF. International Journal of Mobile Communications, 14(5), 518–537. doi:10.1504/IJMC.2016.078726.

[67] Ong, A. K. S., Prasetyo, Y. T., Robas, K. P. E., Persada, S. F., Nadlifatin, R., Matillano, J. S. A., Macababbad, D. C. B., Pabustan, J. R., & Taningco, K. A. C. (2023). Determination of Factors Influencing the Behavioral Intention to Play "Mobile Legends: Bang-Bang" during the COVID-19 Pandemic: Integrating UTAUT2 and System Usability Scale for a Sustainable e-Sport Business. Sustainability (Switzerland), 15(4), 3170. doi:10.3390/su15043170.

[68] Lee, S. Y., & Lee, K. (2018). Factors that influence an individual's intention to adopt a wearable healthcare device: The case of a wearable fitness tracker. Technological Forecasting and Social Change, 129, 154–163. doi:10.1016/j.techfore.2018.01.002.

[69] Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. Decision Sciences, 39(2), 273–315. doi:10.1111/j.1540-5915.2008.00192.x.

[70] Liao, C., Chen, J. L., & Yen, D. C. (2007). Theory of planning behavior (TPB) and customer satisfaction in the continued use of e-service: An integrated model. Computers in Human Behavior, 23(6), 2804–2822. doi:10.1016/j.chb.2006.05.006.

[71] Hogg, M. A., & Smith, J. R. (2007). Attitudes in social context: A social identity perspective. European Review of Social Psychology, 18(1), 89–131. doi:10.1080/10463280701592070.

[72] Jain, K., Sharma, I., & Singh, G. (2018). An empirical study of factors determining wearable fitness tracker continuance among actual users. International Journal of Technology Marketing, 13(1), 83–109. doi:10.1504/IJTMKT.2018.099877.

[73] Ferreira, J. J., Fernandes, C. I., Rammal, H. G., & Veiga, P. M. (2021). Wearable technology and consumer interaction: A systematic review and research agenda. Computers in Human Behavior, 118, 106710. doi:10.1016/j.chb.2021.106710.

[74] Tweneboah-Koduah, E. Y., Adams, M., & Acheampong, G. (2019). The role of theories in social marketing in predicting physical activity behavior among the youth. Journal of Social Marketing, 9(4), 398–417. doi:10.1108/JSOCM-01-2018-0005.

[75] Lee, V. R., Drake, J., Cain, R., & Thayne, J. (2021). Remembering What Produced the Data: Individual and Social Reconstruction in the Context of a Quantified Self Elementary Data and Statistics Unit. Cognition and Instruction, 39(4), 367–408. doi:10.1080/07370008.2021.1936529.

[76] Gilmore, J. N. (2016). Everywear: The quantified self and wearable fitness technologies. New Media and Society, 18(11), 2524–2539. doi:10.1177/1461444815588768.

[77] Chun, H., Lee, H., & Kim, D. (2012). The integrated model of smartphone adoption: Hedonic and utilitarian value perceptions of smartphones among Korean college students. Cyber psychology, Behavior, and Social Networking, 15(9), 473–479. doi:10.1089/cyber.2012.0140.

[78] Shin, D. H., & Biocca, F. (2017). Health experience model of personal informatics: The case of a quantified self. Computers in Human Behavior, 69, 62–74. doi:10.1016/j.chb.2016.12.019.

[79] Al-Adwan, A. S., Li, N., Al-Adwan, A., Abbasi, G. A., Albelbisi, N. A., & Habibi, A. (2023). "Extending the Technology Acceptance Model (TAM) to Predict University Students' Intentions to Use Metaverse-Based Learning Platforms". Education and Information Technologies, 28(11), 15381–15413. doi:10.1007/s10639-023-11816-3.

[80] Almaiah, M. A., Al-Otaibi, S., Lutfi, A., Almomani, O., Awajan, A., Alsaaidah, A., Alrawad, M., & Awad, A. B. (2022). Employing the TAM Model to Investigate the Readiness of M-Learning System Usage Using SEM Technique. Electronics (Switzerland), 11(8), 1259. doi:10.3390/electronics11081259.

[81] Khurana, A., Kumar, V. V. R., & Sidhpuria, M. (2020). A Study on the Adoption of Electric Vehicles in India: The Mediating Role of Attitude. Vision, 24(1), 23–34. doi:10.1177/0972262919875548.

[82] Anser, M. K., Zaigham, G. H. K., Imran Rasheed, M., Pitafi, A. H., Iqbal, J., & Luqman, A. (2020). Social media usage and individuals' intentions toward adopting Bitcoin: The role of the theory of planned behavior and perceived risk. International Journal of Communication Systems, 33(17), 4590. doi:10.1002/dac.4590.

Appendix I: Questionnaire (Research Instrument)

Constructs	Codes	Questions
Perceived usefulness [15, 79]	PU1	Using wearable devices helps me monitor my physical health condition
	PU2	Using wearable devices helps me improve my physical health condition
	PU3	Using wearable devices enhances the efficiency of monitoring my physical health condition
	PU4	Based on my perception of wearable devices, I believe they have excellent functionality
Perceived ease of use [10, 80]	PE1	Interacting with wearable devices is clear and understandable
	PE2	It is easy for me to use wearable devices proficiently
	PE3	I think it is easy to continue using wearable devices to do what I want
Attitude [46, 81, 82]	ATT1	I am interested in continuing to use wearable devices
	ATT2	I think continuing to use wearable devices is a good idea
	ATT3	I believe continuing to use wearable devices is enjoyable
	ATT4	I like using wearable devices to monitor my physical health condition
Continuous intention [4]	CI1	I am willing to frequently use wearable devices
	CI2	I plan to continue using wearable devices in the future
	CI3	I would recommend the use of wearable devices to my family and friends
	CI5	I will make an effort to continue using wearable devices in the next 6 months
Subjective Norms [13, 29]	SN1	Important people to me would think I should continue using wearable devices
	SN2	Influential people would think I should continue using wearable devices
	SN4	Many people similar to me think I should continue using wearable devices
Perceived behavioral control [13, 29]	PBC1	I can use wearable devices effectively to monitor my physical health condition
	PBC2	I believe continuing to use wearable devices will be entirely within my control
	PBC3	I think I have the resources, knowledge, and ability to continue using wearable devices
Quantified-self (QS) [51]	QS1	Recording step count
	QS2	Recording exercise details (pace, distance, etc.)
	QS4	Recording calorie expenditure
	QS5	Recording heart rate