eISSN: 2408-1906© 2020 JIR.
https://assumptionjournal.au.edu/index.php/eJIR/index

Evaluating Factors Influencing University Students' Satisfaction and Continued Use of Health Smartwatches in Chengdu

Yang Fan*

Received: March 2, 2025. Revised: April 16, 2025. Accepted: April 23, 2025.

Abstract

Purpose: This study aims to identify the key factors influencing university students' satisfaction and continued use of health smartwatches in Chengdu Factors evaluated in the study include perceived ease of use, perceived usefulness, enjoyment, AI user experience, AI trust, satisfaction, and continuance intention. **Research design, data and methodology:** The researchers employed quantitative techniques (n = 500) to conduct a questionnaire survey among undergraduate students at Chengdu Medical College. The sample was selected using non-probability sampling methods, including judgmental sampling, quota sampling, and convenience sampling. Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) were used to analyze the data and test the proposed research hypotheses. **Results:** The analysis shows that perceived usefulness, enjoyment, AI experience, and AI trust significantly influence student satisfaction in using smartwatches. Additionally, perceived usefulness is statistically proven to be driven by perceived ease of use. Student satisfaction, in turn, influences continued use of health smartwatches. **Conclusions:** The statistics support the six research hypotheses proposed. Thus, it is recommended to optimize the ease of use of smartwatches by enhancing their functionality for greater user-friendliness. Additionally, incorporating more accurate monitoring data and enhancing online protection can promote satisfaction and continued use.

Keywords: Perceived Usefulness, Satisfaction, Continuance Intention, Health Smartwatches, University Students

JEL Classification Code: D91, I20, I23, L67, O30

1. Introduction

Healthcare smartwatches represent a unique category of wearable technology that provides users with real-time feedback, enabling them to monitor their health and take prompt action (Reeder & David, 2016). According to Glowacki et al. (2017), smartwatches effectively integrate smartphone features with continuous health monitoring capabilities, such as energy expenditure tracking, step counting, heart rate monitoring, and physical activity assessment. These features contribute to health promotion. Additionally, smartwatches can continuously track multiple health parameters, store data, and generate reports to assist healthcare practitioners in delivering their services (Uzir et al., 2021). The advent and advancement of healthcare smartwatches have enabled individuals to conveniently monitor their health and fitness at any time and from any location (Lunney et al., 2016). Consequently, smartwatches have gained significant popularity in recent years. Beyond heart rate tracking, step counting, calorie expenditure, and sleep pattern analysis, the latest health and fitness smartwatch models can also measure blood oxygen saturation (SpO2), blood pressure, and stress levels. Lim et al. (2016) suggest that using fitness and health smartwatches as a motivational tool to reduce sedentary behavior and enhance daily physical activity may have positive health effects. Recent studies also highlight the increasing relevance of wearable devices in promoting behavioral

1*Yang Fan, Vincent Mary School of Engineering, Science and Technology Assumption University of Thailand. Email: 13925846@qq.com

change, especially among tech-savvy younger populations such as college students (Alnasser et al., 2019; Nelson et al., 2022).

Since the introduction of the world's first smartwatch in 2013, smartwatch shipments have steadily increased, contributing to rapid market expansion. Compared to foreign markets, China's wearable medical device sector emerged relatively late, offering significant potential for growth and development. In terms of product applications across the industry chain, domestic brands have demonstrated not only innovation but also an accelerating substitution process for foreign products. Furthermore, with the rapid advancement of cloud computing, big data, and 5G technology, there is a growing demand among Chinese consumers for health management solutions that are specialized, standardized, and personalized, presenting promising market opportunities (Zhou et al., 2021). Despite these advancements, limited empirical research has examined how specific demographic groups, particularly college students in China, engage with smartwatch technology for health monitoring and the factors influencing their adoption and sustained use.

This study addresses the following research gap: while previous research has explored the technical features and potential health benefits of smartwatches, there is insufficient understanding of user perceptions, motivations, and behavioral outcomes related to smartwatch adoption among Chinese university students. This gap is especially critical given the rising health awareness and digital literacy among youth.

The problem this study seeks to address is the lack of user-centered research that explores how college students perceive, adopt, and continue to use healthcare smartwatches, particularly in the context of personalized health management. Understanding this is essential to enhancing product relevance and engagement within this high-potential demographic.

The significance of this study lies in its potential to provide practical insights for developers, marketers, and public health advocates aiming to promote healthy behavior through wearable technologies. It also contributes to academic discourse by offering empirical evidence on smartwatch usage behavior in the under-explored Chinese higher education setting.

Accordingly, the main objectives of this research are: (1) to investigate college students' perceptions and usage patterns of healthcare smartwatches; (2) to identify key factors influencing their adoption and continued use of smartwatch technology; and (3) to explore the perceived health benefits and motivational aspects associated with smartwatch usage among this demographic.

By focusing on college students, a younger demographic, this study aims to inform the development of tailored health technologies that align with the lifestyle, expectations, and health priorities of digital-native users. Smartwatches enhance user autonomy by efficiently processing and displaying essential health and fitness information on a compact screen, ensuring transparency and accessibility (Beh et al., 2021).

2. Literature Review

2.1 Theoretical Frameworks Used in the Study

The Technology Acceptance Model (TAM) is a theoretical framework developed by Davis (1986). It is based on the adaptation of the Theory of Reasoned Action (TRA), which posits that technology adoption is primarily determined by cognitive processes. TAM aims to provide a clear, concise, and essential understanding of user behavior and attitudes toward technology. It evaluates the factors influencing an individual's decision to accept or reject a given technology. Oliver (1993) suggested that consumer attitude is influenced by satisfaction, and, in turn, attitude affects behavioral intention.

2.2 Research Hypothesis and Relationship between Variables

2.2.1 Relation between Perceived Ease of Use and Perceived Usefulness

Hidayat-ur-Rehman et al. (2022) explained that Perceived Ease of Use (PEU) refers to the degree of ease perceived by users when operating smart wearable health (SWH) devices (Siepmann & Kowalczuk, 2021). An increasing body of research suggests that individuals interested in health and fitness are more inclined to adopt wearable SWHs (Lee & Lee, 2018). Furthermore, the study’s findings indicate that the ease of use of smartwatches depends on the presence of well-structured and intuitive functionality, making the device straightforward for users to operate. These findings align with those of Ghazali et al. (2020).

Key features such as hardware quality, durability, battery life, large memory capacity, and seamless synchronization with mobile devices are considered important by consumers. Individuals, particularly older adults, tend to feel more comfortable using smartwatches when the design is user-friendly, simple to operate, and requires minimal maintenance. Well-designed layouts, intuitive navigation, and visually appealing interfaces that prioritize simplicity and user-friendliness contribute to reducing stress and enhancing the overall user experience. Based on the literature, the research hypothesis is formulated as follows:

H1: Perceived ease of use has a significant impact on perceived usefulness.

2.2.2 Relation between Perceived Usefulness and Satisfaction

Perceived Usefulness (PU) refers to the extent to which users believe that a smart wearable health (SWH) device can improve their health status. Research on SWH devices has found that PU has significant effects on user satisfaction (Cheung et al., 2019). A growing body of research indicates that individuals interested in health and fitness are more likely to adopt wearable fitness trackers (Lee & Lee, 2018). Furthermore, individuals who engage in regular exercise are more likely to use SWH fitness trackers as a source of motivation (Rupp et al., 2018).

Moreover, Li (2021) demonstrated that since self-tracking is a fundamental aspect of smartwatches, users tend to perceive them as accurate and comprehensive tools for monitoring physiological and biological data. Consequently, they regard smartwatches as highly useful technologies that enhance satisfaction (Chuah et al., 2016). Based on the literature, the research hypothesis is formulated as follows:

H2: Perceived usefulness has a significant impact on satisfaction.

2.2.3 Relation between Enjoyment and Satisfaction

According to Venkatesh (2000), enjoyment is defined as the degree to which the use of a smartwatch is perceived as enjoyable. Enjoyment is an aspect of intrinsic motivation and arises when basic psychological needs are satisfied through the activity performed (Ryan & Deci, 2006). In the context of smartwatch adoption research, Choi and Kim (2016) found that perceived enjoyment has a strong positive effect on satisfaction, which subsequently influences attitudes toward smartwatch usage. Krey et al. (2019) demonstrated that the anticipated sense of enjoyment leads to higher user satisfaction and indirectly increases the intention to adopt smartwatches. Similarly, Nascimento et al. (2018) assessed the impact of enjoyment on satisfaction, concluding that the pleasurable experience associated with using a smartwatch enhances overall user satisfaction. Based on the literature, the research hypothesis is formulated as follows:

H3: Enjoyment has a significant impact on satisfaction.

2.2.4 Relation between AI User Experience and Satisfaction

Individuals who develop a strong attachment to wearable technology may also exhibit a heightened emotional connection and dependency on the device's notifications (Bölen, 2020). Consequently, this attachment can lead to increased user satisfaction. The key attributes of smartwatches, including interactivity, autonomy, wearability, convenience, and the novelty of the experience, significantly enhance the overall user experience. With repeated use, individuals become more familiar with smart wearable health (SWH) devices, thereby increasing their confidence in using them. Based on the literature, the research hypothesis is formulated as follows:

H4: AI user experience has a significant impact on satisfaction.

2.2.5 Relation between AI Trust and Satisfaction

According to Cheung et al. (2019), AI Trust, which refers to health information accuracy (HIA), is the extent to which consumers perceive the health data provided by a smart wearable health (SWH) device as trustworthy and reliable. Shin et al. (2017) examined the relationship between consumers' positive responses to health informatics and the reliability of health data, demonstrating that the adoption of health informatics is significantly influenced by the perceived reliability of health data. Zhang et al. (2017) emphasized that inaccurate health services can lead to significant harm, rendering any associated health information unreliable and ineffective. Furthermore, consumers place great importance on the accuracy of health index monitoring, as it directly impacts health efficacy. Marakhimov and Joo (2017) found that inaccurate data from SWH devices can negatively affect user satisfaction, leading to inadequate health management. Based on the literature, the research hypothesis is formulated as follows:

H5: AI trust has a significant impact on satisfaction.

2.2.6 Relation between Satisfaction and Continuance Intention

The compatibility between user satisfaction and the long-term goal of continued use of wearable technology is crucial. As AI technology continues to evolve and access to essential services such as healthcare expands, self-management of personal health has become increasingly important in ensuring user satisfaction and sustained product use (Najjar et al., 2021). These findings align with those of Windasari and Lin (2021), who posited that consumers are likely to abandon smartwatches if they do not derive sufficient satisfaction from them. Based on the literature, the research hypothesis is formulated as follows:

H6: Satisfaction has a significant impact on continuance intention.

3. Research Methods and Materials

3.1 Research Framework

Based on the works of Uzir et al. (2021), Rehman et al. (2021), and Siepmann and Kowalczuk (2021), the

researcher developed a conceptual framework for this study, as illustrated in Figure 1, to examine the Technology Acceptance Model (TAM) in the context of health smartwatches (HSW). The independent variables included perceived usefulness (PU), perceived ease of use (PEU), enjoyment (EN), AI trust (AIT), and AI experience (AIU). Satisfaction (SA) served as the mediating factor, while the dependent variable was the intention to continue using HSW.

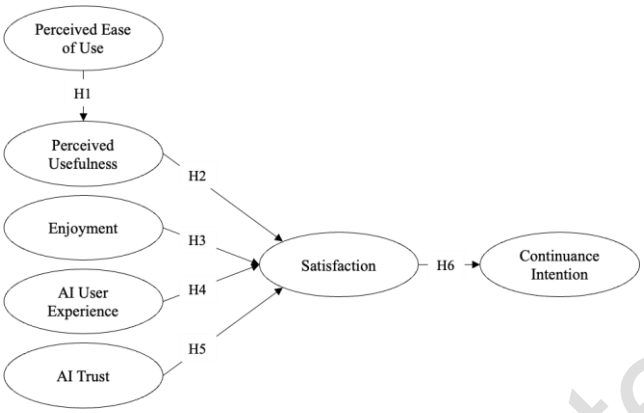

Figure 1: Research Framework

The Expectancy Confirmation Model (ECM), introduced by Bhattacherjee (2001), was also incorporated into the study. ECM assumes that user continuance intention is determined by perceived usefulness and satisfaction, emphasizing post-use expectations rather than pre-use expectations. The TAM and ECM together served as the study's foundational models. To accurately identify the key factors influencing satisfaction, AI experience and AI trust were introduced as external variables within the TAM framework.

For customers to be willing to continue using health smartwatches, the primary factors influencing satisfaction must be strengthened. The study examined six associations between these variables. The primary objective was to investigate the factors influencing the satisfaction and continued use of health smartwatches among university students in Chengdu. Specifically, the study explored the causal relationships between perceived ease of use (PEU), perceived usefulness (PU), enjoyment (EN), AI user experience (AIU), AI trust (AIT), and satisfaction (SA) to gain deeper insights into the factors affecting the continued use of health smartwatches (HSW).

3.2 Research Methodology

The research methodology adopted for this study was quantitative. Undergraduate students from Chengdu Medical College were selected as the target population. To determine an appropriate sample size, Comrey and Lee's (2013) guidelines for factor analysis were followed, which categorize a sample size of 500 as "very good" for ensuring statistical power and stable model estimation. Accordingly, a total of 500 students were selected using a multi-stage sampling technique.

A survey was conducted to collect data from the target demographic. Before performing data analysis, the validity and reliability of the questionnaire instrument were assessed. Content validity was evaluated using the item-objective congruence (IOC) index with three domain experts reviewing the alignment between items and constructs. The IOC values for all items ranged from 0.67 to 1.00, which exceeded the commonly accepted minimum threshold of 0.50 (Rovinelli & Hambleton, 1977), thereby confirming the content validity of the instrument.

Following these revisions, the questionnaire was distributed online via Questionnaire Star, and a pilot test was conducted with 30 respondents who met the screening criteria. Reliability was assessed using Cronbach's alpha for each construct, with all alpha values exceeding 0.70, indicating acceptable internal consistency (Nunnally & Bernstein, 1994). The results confirmed that the instrument was both valid and reliable for full-scale data collection.

The questionnaire consisted of three sections. The first section included screening questions to ensure participants met the eligibility criteria, including having used a health smartwatch (HSW) for more than one year. The second section contained Likert-scale items measuring all study variables, corresponding to the six research hypotheses. Responses were recorded on a five-point Likert scale, ranging from (1) "Strongly Disagree" to (5) "Strongly Agree." The third section gathered demographic information, including gender, age, and profession.

After finalizing the instrument, the main survey was conducted with 500 participants selected through a multi-stage sampling technique. The measurement model was tested using Confirmatory Factor Analysis (CFA), while the structural model and six hypotheses—corresponding to the six variables in the conceptual framework—were examined using Structural Equation Modeling (SEM).

3.3 Target Population and Sample Size

A combination of non-probability sampling, judgment sampling, and quota sampling was employed to select undergraduate students from four distinct majors at Chengdu Medical College. The target respondents for this study are undergraduate students from Chengdu Medical College who have been using a health smartwatch (HSW) for more than one year. The questionnaires were distributed via the online platform Questionnaire Star. Table 1 presented the sample distribution among the four majors of Chengdu Medical College.

Table 1: Quota Sampling of Chengdu Medical College Students

Majors of Chengdu Medical College	Population Size	Proportional Sample Size
Clinical Medicine	2,400	170
Pharmaceutical	1,240	88
Nursing	2,020	143
Medical Laboratory and Medical Imaging	1,400	99
Total	**7,060**	**500**

Source: Chengdu Medical College Academic Affairs Office (2024)

Between February and September 2024, the researcher distributed questionnaires using convenience sampling through online platforms such as WeChat, QQ, and other social media channels. A data screening process was conducted to ensure that participants met the eligibility criteria, confirming the suitability of the target population. All respondents were undergraduate students from four selected majors at Chengdu Medical College in China. To encourage participation, students were invited to voluntarily complete the online questionnaire.

4. Results and Discussion

4.1 Demographic Information

Among the 500 respondents, 54.4 percent were male and 45.6 percent were female. The largest proportion of participants (41 percent) were between the ages of 22 and 24, while 12.2 percent were between 18 and 20 years old, 19.6 percent were between 20 and 22 years old, and 27.2 percent were above 24 years old. On the duration of healthcare smartwatch usage, 32.4 percent of respondents had been using a smartwatch for one to two years, 40.2 percent for two to three years, 18.6 percent for three to four years, and 8.8 percent for more than four years.

Table 2: Respondents' Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	272	54.4
	Female	228	45.6
Age	18-20 years old	61	12.2
	20-22 years old	98	19.6
	22-24 years old	205	41.0
	More than 24 years old	136	27.2
Year of Use	1-2 years	162	32.4
	2-3 years	201	40.2
	3-4 years	93	18.6
	Over 4 years	44	8.8
Function	Heart health	161	32.2
	Sleep	115	23.0
	Sport	193	38.6
	Other	31	6.2

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) was used in this study to examine the underlying factors influencing the use of health smartwatches among university students in Chengdu. CFA was employed to assess the validity and acceptability of each item in the conceptual framework model (Bollen, 1989). The study utilized factor analysis, weight estimation, and goodness-of-fit index testing to evaluate model suitability. The study included seven measurable variables: Perceived Ease of Use (PEU), Perceived Usefulness (PU), AI User Experience (AIU), AI Trust (AIT), Enjoyment (EN), Satisfaction (SA), and Continuance Intention (CI).

Results in Table 3 confirm the internal consistency of the structure, thereby verifying the reliability of the questionnaire. The Cronbach's alpha coefficient was used to measure the level of agreement between questionnaire items, ensuring their consistency.

Table 3: Confirmatory Factor Analysis (CFA), Composite Reliability (CR), and Average Variance Extracted (AVE) Results

Variable	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factor Loading	CR	AVE
Perceived Ease of Use (PEU)	Rehman et al. (2021)	4	0.854	0.737-0.776	0.842	0.571
Perceived Usefulness (PU)	Rehman et al. (2021)	4	0.828	0.695-0.732	0.805	0.509
Enjoyment (EN)	Siepmann and Kowalczuk (2021)	3	0.804	0.762-0.811	0.892	0.617
AI User Experience (AIU)	Uzir et al. (2021)	7	0.902	0.706-0.804	0.903	0.571
AI Trust (AIT)	Uzir et al. (2021)	6	0.902	0.727-0.810	0.902	0.606
Satisfaction (SA)	Siepmann and Kowalczuk (2021)	6	0.899	0.708-0.756	0.874	0.537
Continuance Intention (CI)	Siepmann and Kowalczuk (2021)	3	0.804	0.737-0.764	0.795	0.564

Note: CR = Composite Reliability, AVE = Average Variance Extracted

The researcher examined several key model fit metrics, including root-mean-square residuals (RMR), root-mean-square error of approximation (RMSEA), normed fit index (NFI), incremental fit index (IFI), comparative fit index (CFI), chi-square ratio (χ^2/df), goodness-of-fit index (GFI), and adjusted goodness-of-fit index (AGFI). These indices evaluate how well the proposed model aligns with the observed data. As shown in Table 4, the statistical values of each indicator were compared against established thresholds. The results—CMIN/DF = 1.488, GFI = 0.924, AGFI = 0.910, NFI = 0.922, CFI = 0.973, TLI = 0.970, and RMSEA = 0.031—met the recommended criteria, indicating a good model fit.

Table 4: Goodness of Fit for Measurement Model

Index	Criterion	Statistical Value
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1.488
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.924
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.910
NFI	≥ 0.80 (Wu & Wang, 2006)	0.922
CFI	≥ 0.80 (Bentler, 1990)	0.973
TLI	≥ 0.80 (Sharma et al., 2005)	0.970
RMSEA	< 0.08 (Sica & Ghisi, 2007)	0.031

Note: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

Table 5 displays the results of the discriminant validity analysis, highlighting the correlations among different factors. Since all correlation coefficients remain below the 0.85 threshold, it indicates that each construct is independently defined. This finding verifies that the measurement model maintains strong discriminant validity, ensuring that the variables are well-differentiated. Consequently, the study confirms that the measured constructs are unique and can be analyzed as distinct variables in subsequent research.

Table 5: Discriminant Validity

Variable	Factor Correlations						
	PEU	**PU**	**EN**	**AIU**	**AIT**	**SA**	**CI**
PEU	**0.756**						
PU	0.425	**0.713**					
EN	0.172	0.258	**0.785**				
AIU	0.393	0.433	0.24	**0.756**			
AIT	0.393	0.41	0.196	0.396	**0.778**		
SA	0.414	0.435	0.316	0.435	0.475	**0.732**	
CI	0.368	0.407	0.234	0.377	0.348	0.416	**0.751**

Note: The diagonally listed value is the AVE square roots of the variables

4.3 Structural Equation Model (SEM)

To ensure that the Structural Equation Modeling (SEM) analysis met an acceptable threshold, the model was adjusted. The findings indicate that the degree of freedom, P-value, and chi-square value are all below 0.05, confirming that the results meet the required criteria. Additionally, the goodness-of-fit indices—GFI = 0.854, AGFI = 0.832, NFI = 0.861, CFI = 0.909, TLI = 0.902, and RMSEA = 0.056—demonstrate that the SEM analysis exhibits an overall satisfactory fit. The fact that all fitted parameter values meet the minimum required standards suggests that the data are well-modeled and appropriately represented within the framework.

Table 6: Goodness of Fit for Structural Model

Index	Criterion	Statistical Value
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	2.58
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.854
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.832
NFI	≥ 0.80 (Wu & Wang, 2006)	0.861
CFI	≥ 0.80 (Bentler, 1990)	0.909
TLI	≥ 0.80 (Sharma et al., 2005)	0.902
RMSEA	< 0.08 (Sica & Ghisi, 2007)	0.056

Note: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

Based on path analysis and the results presented in Table 7, this study confirms the significant impact of perceived usefulness, AI user experience, AI trust, and enjoyment on satisfaction, as supported by Hypotheses H2, H3, H4, and H5. Furthermore, Hypothesis H1 establishes that perceived ease of use influences perceived usefulness. Additionally, satisfaction plays a crucial role in shaping continuance intention, as demonstrated in Hypothesis H6, highlighting its importance in the long-term adoption of health smartwatches.

Table 7: Hypothesis Testing Result

Hypothesis	Standardized path coefficients (β)	t-value	Test Result
H1: PEU → PU	0.558	9.533*	Supported
H2: PU → SA	0.483	5.643*	Supported
H3: EN → SA	0.192	4.728*	Supported
H4: AIU → SA	0.227	5.116*	Supported
H5: AIT → SA	0.288	7.000*	Supported
H6: SA → CI	0.504	8.305*	Supported

Note: *=p-value<0.05

The statistical results presented in Table 7 can be summarized as follows:

In H1, the findings indicate that Perceived Ease of Use (PEU) has a significant positive relationship with Perceived Usefulness (PU) ($\beta = 0.588$, $p < 0.05$), confirming Siepmann and Kowalczuk's (2021) study, which suggests that the ease of use enhances users' perception of smartwatches as useful.

In H2, the findings indicate that Perceived Usefulness (PU) is positively associated with Satisfaction (SA) ($\beta = 0.483$, $p < 0.05$), supporting Chuah et al.'s (2016) research, which states that users are more likely to be satisfied with health smartwatches if they perceive them as accurate, comprehensive, and highly useful.

In H3, the findings indicate that Enjoyment (EN) has a significant positive relationship with Satisfaction (SA) ($\beta = 0.192$, $p < 0.05$), validating Krey et al.'s (2019) findings that a sense of enjoyment enhances user satisfaction with smartwatch usage.

In H4, the findings indicate that AI User Experience (AIU) positively influences Satisfaction (SA) ($\beta = 0.227$, $p < 0.05$), confirming Bölen's (2020) research that users tend to be more satisfied with health smartwatches if the product incorporates technology that provides a new or novel user experience.

In H5, the findings indicate that AI Trust (AIT) is positively correlated with Satisfaction (SA) ($\beta = 0.288$, $p < 0.05$), supporting Zhang et al.'s (2017) emphasis on the importance of accurate health devices, which are closely linked to user trust and, consequently, satisfaction.

In H6, the findings indicate that Satisfaction (SA) has a significant positive effect on Continuance Intention (CI) ($\beta = 0.504$, $p < 0.05$), verifying Windasari and Lin's (2021) findings that users' intention to continue using health smartwatches is strongly influenced by their level of satisfaction.

5. Conclusions and Recommendation

5.1 Conclusions

The study population consisted of undergraduate students at Chengdu Medical College. A total of 500 students from four different academic disciplines participated in the study, with data collected through questionnaires. The responses from these completed questionnaires were analyzed to provide empirical support for the conceptual framework presented in this paper. Additionally, this framework aligns with previous research in the field, reinforcing its theoretical foundation. Based on prior literature, it was hypothesized that satisfaction would influence students' continued use of health smartwatches (Bhattacherjee, 2001). The collected data were analyzed using the statistical software packages SPSS and JAMOVI. The conceptual framework demonstrated a satisfactory model fit, as confirmed by the AMOS test, which validated the factor structure of the measurement model. Additionally, the results of the Confirmatory Factor Analysis (CFA) supported the applicability of the factor structure, indicating that the data exhibited a reasonable fit.

The findings indicate that perceived usefulness (PU), AI user experience (AIU), AI trust (AIT), and enjoyment (EN) directly influence students' satisfaction, which in turn significantly impacts their intention to continue using health smartwatches. Satisfaction was found to have a direct effect on continuance intention (CI). Moreover, perceived ease of use (PEU) was shown to directly affect PU, which indirectly influenced satisfaction. While enjoyment had a relatively small effect, it still contributed to satisfaction. The study sample comprised students with a medical background, providing valuable insights into the market for medical smart health watches. The results suggest that a good user experience and perceived usefulness can enhance students' willingness to engage in physical activity. Since smartwatch adoption and initial use require ease-of-use support, it is essential that users receive adequate guidance on how to utilize smartwatch features effectively, including data tracking capabilities.

5.2 Recommendations

In light of the findings presented in this study, several recommendations are proposed. Firstly, the ease of use of smart health watches should be optimized to enhance user experience. This can be achieved by improving the device's functionality, making it more intuitive and user-friendly, particularly for elderly individuals who may face challenges in navigating complex technology.

Secondly, in terms of perceived usefulness, it is recommended that additional portable health monitoring features be incorporated to better align with consumer needs and enhance health protection. Additionally, further evaluation of follow-up support resources is necessary to ensure continuous improvement in smartwatch functionality and effectiveness.

Although satisfaction directly influences the intention to continue using smart health watches, ongoing improvements should focus not only on user satisfaction but also on enhancing the energy efficiency and overall health benefits provided by these devices. Furthermore, there is a need to strengthen the integration of the Internet of Things (IoT) within healthcare systems, fostering stronger connections between doctors, communities, and hospitals. Continuous feedback from users should be collected and analyzed to support the development of features that encourage long-term user engagement.

Lastly, smartwatch manufacturers can leverage the data from this study to further optimize their products. By refining smartwatch design, functionality, and user experience, manufacturers can ensure that their devices meet evolving consumer expectations and promote sustained usage.

5.3 Limitation and Further Study

A limitation of this study is that the variables examined are focused at the individual level, with data collected exclusively from students enrolled in a medical school. This restricts the generalizability of the findings to broader populations. Future research could expand on this study by incorporating similar variables while employing a longitudinal or experimental design to assess changes over time. Additionally, conducting studies at multiple institutions and across diverse academic disciplines would provide a more comprehensive understanding of smartwatch

adoption and continued use. Further research could also explore the influence of external factors such as technological advancements, healthcare policies, and socio-demographic variations on smartwatch adoption. By analyzing user behaviors and usage patterns, brands can develop more adaptable and user-centered products and services, ensuring greater usability and satisfaction.

References

Al-Mamary, Y. H., & Shamsuddin, A. (2015). Testing of the technology acceptance model in context of Yemen. *Mediterranean Journal of Social Sciences, 6*(4). https://doi.org/10.5901/mjss.2015.v6n4s1p268

Alnasser, A., Kyle, J., Aloumi, N., Al-Khalifa, A. S., & Marais, D. (2019). The impact of mobile health interventions on healthy eating knowledge and behaviour: A systematic review with meta-analysis. *Nutrition Reviews, 77*(7), 469-486. https://doi.org/10.1093/nutrit/nuz011

Awang. (2012). *Research methodology and data analysis* (2nd ed.). UiTM Press.

Beh, P. K., Ganesan, Y., Iranmanesh, M., & Foroughi, B. (2021). Using smartwatches for fitness and health monitoring: The UTAUT2 combined with threat appraisal as moderators. *Behaviour & Information Technology, 40*(3), 282-299. https://doi.org/10.1080/0144929X.2019.1685597

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin, 107*(2), 238-246.

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly, 25*(3), 351-370.

Bölen, M. C. (2020). Exploring the determinants of users' continuance intention in smartwatches. *Technology in Society, 60*, 101209. https://doi.org/10.1016/j.techsoc.2019.101209

Bollen, K. A. (1989). *Structural equations with latent variables*. Wiley.

Chengdu Medical College Academic Affairs Office. (2024). *Internal undergraduate student population statistics by major*. Unpublished institutional data.

Cheung, M. L., Chau, K. Y., Lam, M. H. S., Tse, G., Ho, K. Y., Flint, S. W., Broom, D. R., Tso, E. K. H., & Lee, K. Y. (2019). Examining consumers' adoption of wearable healthcare technology: The role of health attributes. *International Journal of Environmental Research and Public Health, 16*(13), 2257. https://doi.org/10.3390/ijerph16132257

Choi, J., & Kim, S. (2016). Is the smartwatch an IT product or a fashion product? A study on factors affecting the intention to use smartwatches. *Computers in Human Behavior, 63*, 777-786. https://doi.org/10.1016/j.chb.2016.06.007

Chuah, S. H. W., Rauschnabel, P. A., Krey, N., Nguyen, B., Ramayah, T., & Lade, S. (2016). Wearable technologies: The role of usefulness and visibility in smartwatch adoption. *Computers in Human Behavior, 65*, 276-284.

Comrey, A. L., & Lee, H. B. (2013). *A first course in factor analysis* (2nd ed.). Psychology Press. https://doi.org/10.4324/9780203775582

Davis, F. D. (1986). *A technology acceptance model for empirically testing new end-user information systems: Theory and results* [Doctoral dissertation]. Massachusetts Institute of Technology. http://hdl.handle.net/1721.1/15192

Ghazali, E., Mutum, D. S., & Woon, M. Y. (2020). Exploring the adoption of wearable payment systems: A conceptual framework. *International Journal of Technology Diffusion, 11*(1), 1-14.

Glowacki, K., Duncan, M. J., Gainforth, H., & Faulkner, G. (2017). Barriers and facilitators to physical activity and exercise among adults with depression: A scoping review. *Mental Health and Physical Activity, 13*, 108-119. https://doi.org/10.1016/j.mhpa.2017.10.001

Hidayat-ur-Rehman, I., Ahmad, A., Akhter, F., & Aljarallah, A. (2022). A dual-stage SEM-ANN analysis to explore consumer adoption of smart wearable healthcare devices. *Journal of Global Information Management, 30*(1), 1-30.

Krey, N., Chuah, S. H. W., Ramayah, T., & Rauschnabel, P. A. (2019). How functional and emotional ads drive smartwatch adoption: The moderating role of consumer innovativeness and extraversion. *Internet Research*, *29*(3), 578-602. https://doi.org/10.1108/IntR-12-2017-0534

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. https://doi.org/10.1016/j.techfore.2018.01.002

Li, H. (2021). An empirical research on the construction of a government website public satisfaction index model in China. *Journal of Global Information Management, 29*(5), 112-137. https://doi.org/10.4018/JGIM.20210901.oa7

Lim, Y. J., Osman, A., Salahuddin, S. N., Romle, A. R., & Abdullah, S. (2016). Factors influencing online shopping behavior: The mediating role of purchase intention. *Procedia Economics and Finance, 35*, 401-410. https://doi.org/10.1016/S2212-5671(16)00050-2

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. https://doi.org/10.1016/j.chb.2016.08.007

Marakhimov, A., & Joo, J. (2017). Consumer adaptation and infusion of wearable devices for healthcare. *Computers in Human Behavior, 76*, 135-148. https://doi.org/10.1016/j.chb.2017.07.016

Najjar, M. S., Dahabiyeh, L., & Algharabat, R. S. (2021). Users' affect and satisfaction in a privacy calculus context. *Online Information Review, 45*(3), 577-598. https://doi.org/10.1108/OIR-05-2020-0188

Nascimento, B., Oliveira, T., & Tam, C. (2018). Wearable technology: What explains continuance intention in smartwatches?. *Journal of Retailing and Consumer Services, 43*, 157-169. https://doi.org/10.1016/j.jretconser.2018.03.017

Nelson, L. A., Mulvaney, S. A., Gebretsadik, T., Johnson, K. B., & Osborn, C. Y. (2022). The MEssaging for Diabetes (MED) intervention improves medication adherence and glycemic control in adults with type 2 diabetes. *Journal of General Internal Medicine, 37*(7), 1758-1766. https://doi.org/10.1007/s11606-021-07160-4

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Oliver, R. L. (1993). Cognitive, affective, and attribute bases of the satisfaction response. *Journal of Consumer Research, 20*(3), 418-430.

Reeder, B., & David, A. (2016). Health at hand: A systematic review of smart watch uses for health and wellness. *Journal of Biomedical Informatics, 63*, 269-276. https://doi.org/10.1016/j.jbi.2016.09.001

Rehman, I. H. U., Ahmad, A., Akhter, F., & Aljarallah, A. (2021). A dual-stage SEM-ANN analysis to explore consumer adoption of smart wearable healthcare devices. *Journal of Global Information Management, 29*(6), 1-30. https://doi.org/10.4018/JGIM.20211101.oa29

Rovinelli, R. J., & Hambleton, R. K. (1977). On the use of content specialists in the assessment of criterion-referenced test item validity. *Educational and Psychological Measurement, 37*(2), 463-468. https://doi.org/10.1177/001316447703700220

Rupp, M. A., Michaelis, J. R., McConnell, D. S., & Smither, J. A. (2018). The role of individual differences on perceptions of wearable fitness device trust, usability, and motivational impact. *Applied Ergonomics, 70*, 77-87. https://doi.org/10.1016/j.apergo.2018.02.005

Ryan, R. M., & Deci, E. L. (2006). Self-regulation and the problem of human autonomy: Does psychology need choice, self-determination, and will? *Journal of Personality, 74*(6), 1557-1586. https://doi.org/10.1111/j.1467-6494.2006.00420.x

Sharma, S., Mukherjee, S., Kumar, A., & Dillon, W. R. (2005). A simulation study to investigate the use of cutoff values for assessing model fit in covariance structure models. *Journal of Business Research, 58*(7), 935-943. https://doi.org/10.1016/j.jbusres.2003.10.007

Shin, D. H., Lee, S., & Hwang, Y. (2017). How do credibility and utility play in the user experience of health informatics services? *Computers in Human Behavior, 67*, 292-302. https://doi.org/10.1016/j.chb.2016.11.009

Sica, C., & Ghisi, M. (2007). The Italian versions of the Beck Anxiety Inventory and the Beck Depression Inventory–II: Psychometric properties and discriminant power. In M. A. Lange (Ed.), *Leading-edge psychological tests and testing research* (pp. 27-50). Nova Science Publishers.

Siepmann, C., & Kowalczuk, P. (2021). Understanding continued smartwatch usage: The role of emotional as well as health and fitness factors. *Electronic Markets, 31*(4), 795-809. https://doi.org/10.1007/s12525-021-00475-6

Uzir, M. U. H., Al Halbusi, H., Lim, R., Jerin, I., Hamid, A. B. A., Ramayah, T., & Haque, A. (2021). Applied Artificial Intelligence and user satisfaction: Smartwatch usage for healthcare in Bangladesh during COVID-19. *Technology in Society, 67*, 101780. https://doi.org/10.1016/j.techsoc.2021.101780

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. https://doi.org/10.1287/isre.11.4.342.11872

Windasari, N. A., & Lin, F. R. (2021). Why do people continue using fitness wearables? The effect of interactivity and gamification. *SAGE Open, 11*(4), 21582440211056606. https://doi.org/10.1177/21582440211056606

Wu, J.-H., & Wang, Y.-M. (2006). Measuring KMS success: A respecification of the DeLone and McLean's model. *Information & Management, 43*(6), 728-739. https://doi.org/10.1016/j.im.2006.05.002

Zhang, M., Luo, M., Nie, R., & Zhang, Y. (2017). Technical attributes, health attributes, consumer attributes, and their roles in adoption intention of healthcare wearable technology. *International Journal of Medical Informatics, 108*, 97-109. https://doi.org/10.1016/j.ijmedinf.2017.09.013

Zhou, Y., Kong, N., Duan, Y., & Chen, J. (2021). Research on innovation path of wearable medical devices based on industry chain perspective. *Journal of Physics: Conference Series, 1971*(1), 012103. https://doi.org/10.1088/1742-6596/1971/1/012103