Factors Affecting the Adoption of Smartwatch for Tracking Health

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Abstracts: Smartwatches are widely used now for a variety of functions, from keeping track of time as they would have in the past to getting general wearer data—including activity data, which is a feature that is particularly well-liked. Wearing a smartwatch can offer additional advantages, such as useful health-related data. By examining exercise, sleep, the accuracy of health information, and pricing value as external factors, this study investigates important aspects influencing the adoption of smartwatch technology and tests hypotheses within the conceptual model of a technological acceptance model (TAM). In order to ascertain the correlations between these characteristics, a comprehensive statistical analysis and structural equation modeling (SEM) were performed on a sample of 200 participants who had undergone screening in Thailand. The findings of this research show that factors such as exercise, sleep patterns, the quality of health information, perceived utility, and pricing value all have a substantial impact on people's intentions to use smartwatches for tracking their health. The goal of the study is to offer a comprehensive knowledge of the variables affecting the uptake of wearable health monitoring equipment. Additionally, this article offers more details about customer preferences for using smartwatches to track health.

Keywords: Smartwatch, Tracking Health, Health Monitoring, Technology Acceptance Model.

1. INTRODUCTION

Wearable technology is currently experiencing a rise in popularity and a lot of attention. According to projections, the wearable technology market would be worth more than US$138 billion by 2025. [1](Hayward, J., 2021). Within this expansive market, the fitness and medical wearables segment is expected to contribute significantly, potentially reaching a market value of US$62 billion [2]. One noteworthy category within this domain is the smartwatch, which is characterized as a wearable device akin to traditional wristwatches, offering multifarious features and serving as an innovative and apt solution for health monitoring and screening. Smartwatches have integrated seamlessly into daily life, enabling users to monitor their activities and behaviors [3]. They are equipped to provide real-time data on a range of health parameters, including but not limited to exercise, sleep patterns, heart rate, reproductive status recognition, drug effects, and more [4]. These devices furnish users with real-time data, which can be processed and analyzed through dedicated applications or tools. The multifaceted nature of smartwatches has spurred a growing body of research aimed at evaluating their performance and assessing the accuracy of the data they provide [5]. Studies have also leveraged the data generated by smartwatches for monitoring and analysis, often employing machine learning models to predict the occurrence of various health conditions [6]. Moreover, research in this field extends to the design and evaluation of technology acceptance models specifically tailored for medical wearable devices [7]. This work is often conducted in conjunction with the examination of psychological factors that influence user acceptance [8]. Furthermore, studies emphasize the importance of privacy considerations [9]. and trustworthiness in technology utilization [10]. Additionally, research addresses the adoption and acceptance of wearable technology among elderly populations [11].

A literature study of wristwatch technology for recording health data finds two significant areas of interest. Firstly, it is evident that there exists a noticeable dearth of research surrounding the utilization of smartwatch technology for health tracking. Additionally, a prevalent theme emerges regarding the importance of consumer acceptance and awareness of novel technology or products in this context [12]. Secondly, the prevailing research on the acceptance of smartwatch technology for health tracking predominantly revolves around the application of the Technology Acceptance Model (TAM) framework [13, 14] While this framework provides valuable insights, it primarily concentrates on the general structure of acceptance. However, there is a notable gap in the literature concerning an in-depth analysis of the technological capabilities of smartwatches, tailored to meet the specific needs of consumers. This gap hinders a comprehensive understanding of the factors that influence consumers' adoption of smartwatch for tracking health.

The research was conducted by constructing elements affecting health tracking on the structure of TAM, with a focus on activity factors, sleep factors, and health information accuracy factors. Including the challenging factor of price value, which may have different results depending on the characteristics of the target group, with reports that it has no influence on behavior intention to use [15]. Consequently, this article focuses on the behavior of using smartwatch technology to tracking health information, which is anticipated to enhance health awareness and improve consumers' well-being. The hypothesis was determined based on factors consisting of Activity, Sleep Activity, Health Information Accuracy, Price Value, Perceived Usefulness, Perceived Ease of Use, Attitude toward using and Behavioral Intention to Use. Then, structural equation modeling (SEM) will be performed to examine the relationship of factors leading to technology adoption.

This research will investigate into the factors that influence the use of smartwatches for health tracking. Notably, it stands out for its incorporation of external factors that pertain to the measurement technology of smartwatches, extending its scope to encompass aspects related to activity tracking and sleep monitoring. Moreover, this study delves into the critical evaluation of health information accuracy while also considering the role of price value propositions. By doing so, it offers valuable insights into consumer expectations regarding future technology and its potential implications. The findings from this research are expected to provide guidance to researchers and stakeholders in the realms of public relations and marketing. Additionally, the industrial sector may benefit from the insights generated in the development of products that align with consumer needs and preferences, ensuring accessibility and appropriateness.

2. LITERATURE REVIEW

2.1. Technology Adoption

2.1.1 TAM

Technology Acceptance Model (TAM) is a basic theory that represented acceptance of technology. There are components of external factors that lead to the main factors consisting of perceived usefulness and perceived ease of use, which are factors that affect attitude toward use, leading to behavioral intention to use, and finally to actual system use [16]. The technology acceptance model presents the main factors including: Perceived usefulness means believing that using a any system will increase work efficiency and can be used beneficially. And perceived ease of use means believing that using a any system must be effortless or easy to use [17]. The perceived usefulness and perceived ease of use will directly affect the intention to using. TAM is the most popular model for understanding the factors affecting technology adoption. Can be adapted and applied in various contexts, including Smartwatches [7, 8, 18]. Understanding the factors and monitoring activities of elderly patients [19, 20]. Exercise factor analysis [21]. These studies recognize the importance of external factors in affecting behavioral intention to use. This research therefore uses the Technology Acceptance Model (TAM) as the main structure of the study to examine external factors and demonstrate the consistency of the results.

2.1.2 UTAUT

Unified Theory of Acceptance and Use of Technology (UTAUT) is one of the theoretical models that has four key constructs that will have a direct impact on technology acceptance and behavior intention, including performance expectancy, effort. expectancy, social influence, and facilitating conditions. Age, gender, experience, and voluntariness moderate all relationships in the model [22]. There are studies that use the UTAUT construct to analyze factors influencing behavioral intention to assess technology adoption in healthcare [10, 23, 24]. and used to examine the technology used by clinicians and hospitals [25]. However, UTAUT theory has been extended to UTAUT2, which introduces consumer acceptance and use of information technology, by adding three new factors: Hedonic Motivation, Price Value, and Habit. from the four main structures and removing voluntariness factor from the structure in order to adapt it to the context of consumer technology use [26]. For example, it is used for consumer decision in adopting wearable technology for health care. and can understand the acceptance of health information technology [27]. Using smartwatches for health and fitness monitoring. using smartwatches for health and fitness monitoring [28]. Including Privacy awareness is a significant contributor to smartwatch adoption [29].

2.2. Structural Equation Modeling (SEM)

Structural Equation Modeling provides researchers with a comprehensive method for evaluating and transform the traditional theoretical models. The structural equation model specifies the relationship with the laid down infrastructure. It can evaluate whether any structural model is appropriate and whether it is acceptable or unacceptable [30]. Structural modeling must include the amount of data and the distribution of the data to determine the statistical estimation process, and a conceptual model will be provided to determine the appropriateness of the statistical model analysis, include statistical results to confirm the explanation of results or conclusions. Additionally, during the analysis process the presence of questionnaire items can provide a more understanding and analysis of the model results. Structural equation models are often represented by graphical path diagrams [31]. [32] presented a model by collecting data and analyzing it with AMOS. The data represents the intelligence test scores of girls. There are hypothesized factors, namely word composition ability and spatial dimensions. There are external latent factors that are assumed to cause changes among the other 6 variables, and the paths of the factors are determined showing that the two factors are related to each other. There are two types of SEM methods: covariance-based structural equation modeling (CB-SEM) and partial least squares structural equation modeling PLS-SEM; also called PLS path modeling [33]. CB-SEM is primarily used to confirm (or reject) theories. It does this by determining how well a proposed theoretical model can estimate the covariance matrix for a sample data. In contrast, PLS-SEM, focuses on explaining the variance in the model's dependent variables [33, 34]. A tested using the partial least squares structural equation modelling (PLS-SEM) approach to examine the significance levels of path coefficients significant relationships with behavioural intention to use smartwatches for fitness and health monitoring [28].

2.3. External Factors Literature Review

Table 1. Content Review of External Factors Hypothesis

Topics	External Factors			
	Activity (ACT)	Sleep Activity (SA)	Health Information Accuracy (HIA)	Price Value (PRV)
Wearable Sleep Technology in Clinical and Research Settings [35]	-	ü	-	-
Detecting sleep outside the clinic using wearable heart rate devices [36]	ü	ü	-	-
Wearable technology for cardiology: An update and framework for the future [37]	ü	-	-	-
A comprehensive accuracy assessment of Samsung smartwatch heart rate and heart rate variability [38]	ü	ü	-	-
A Clinician's Guide to Smartwatch "Interrogation" [39]	ü	ü	-	-
Factors influencing the adoption of mHealth services in a developing country: A patient-centric study [40]	ü	-	-	-
A new acceptance model for artificial intelligence with extensions to UTAUT2: An empirical study in three segments of application [15]	ü	-	-	-
Acceptance of Commercially Available Wearable Activity Trackers Among Adults Aged Over 50 and With Chronic Illness: A Mixed-Methods Evaluation [19]	ü	-	-	-

Topics	External Factors			
	Activity (ACT)	Sleep Activity (SA)	Health Information Accuracy (HIA)	Price Value (PRV)
Reliability and validity of ten consumer activity trackers depend on walking speed [41]	ü	-	-	-
Performance of seven consumer sleep-tracking devices compared with polysomnography [5]	-	ü	-	-
Using smartwatches for fitness and health monitoring: the UTAUT2 combined with threat appraisal as moderators [28]	-	ü	-	ü
Consumer adaptation and infusion of wearable devices for healthcare [42]	-	-	ü	-
Development of a health information technology acceptance model using consumers' health behavior intention [43]	-	-	ü	-
Self-efficacy and trust in consumers' use of health-technologies devices for sports [44]	-	-	ü	-
How do credibility and utility play in the user experience of health informatics services? [45]	-	-	ü	-
Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology [26]	-	-	-	ü
An acceptance model for smart watches Implications for the adoption of future wearable technology [46]	-	-	-	ü
Understanding the Drivers of Wearable Health Monitoring Technology: An Extension of the Unified Theory of Acceptance and Use of Technology [47]	-	-	-	ü
Exploring the adoption of wearable healthcare devices among the Pakistani adults with dual analysis techniques [48]	-	-	-	ü

Notes. ACT: Activity, SA: Sleep activity, HIA: Health information accuracy, PRV: Price value.

3. THE ADOPTED MODEL AND HYPOTHESES DEVELOPMENT

3.1. Sleep Activity (SA)

Currently, the average adult sleep worldwide is 6.8 hours per day. Sleep directly affects the development of various diseases and depression, and the functioning of the immune system. Including decreased labor productivity and increased mortality [49]. Polysomnogram (PSG) is the gold standard for diagnosing sleep disorders [50]. Consumer sleep technology (CST) is an alternative for sleep monitoring, means smartwatches that are easy to use, low-cost, and reduce complexity. Users can understand the health of their sleep. However, there are many studies that have been examined the performance of wearables against gold standard PSG [35]. In a study of the effectiveness of seven consumer sleep tracking devices, It has been found to be highly effective in detecting sleep and is mostly equivalent to (or better than) actigraphy, standard (CST) in detecting sleep and is promising for monitoring sleep when compare to the gold standard (PSG) [5]. A study developed device-agnostic algorithms that can assess sleep in both free living conditions and in the laboratory without the need for a diaries [36]. Studying the parameters obtained from the measurements of the smartwatch device and using the data to analyze sleep [38]. As mentioned above, sleep activity has been analyzed and examined for efficiency using smartwatches that can record sleep data from home throughout the night. However, the sleep results need to be analyzed with caution, understand the benefits and pitfalls of this technology used in sleep diagnosis [35]. This research therefore used sleep activity factors to examine whether they affect the acceptance of technology to tracking health information. Therefore, the following hypothesis is postulated:

H1: Sleep activity (SA) has a positive effect on perceived usefulness (PU)

3.2. Health Information Accuracy (HIA)

Health data analysis that produces quality results requires the accuracy of health data, obtained from the measurements of the smartwatch. A reliable information is more likely to be viewed as providing useful, high-quality information that is in the consumer's best interest, consumers tend to perceive the potential for benefit. Only if health information is reliable and trustworthy [45]. [43] study has a consistent explanation of health behavior intentions of using health information technology (HIT). The accuracy and usefulness of consumers' health status information are key factors in successful health behavior decisions. On the contrary, if consumers doubt the accuracy and reliability of health data received from health wearables They would evaluate it as a threat to their health and well-being than a challenge to the adoption of health wearables [42]. Including, perceived information accuracy had positive correlations with usage experience, they tend to feel positive or satisfied with technologies devices for sport affect motivated to use health-technologies [44]. Health Information Accuracy is an interesting factor due to the fact that many researches have examined its accuracy and influence on the adoption of technology. Therefore, the following hypothesis is postulated:

H2: Health information accuracy (HIA) has a positive effect on perceived usefulness (PU)

3.3. Activity (ACT)

Conducting daily activities, nowadays smartwatches technology can display measurements such as energy expenditure, step count, heart rate, screening for atrial fibrillation, fall detection, O2 Monitoring, Sleep–wake detection [39]. During sleep and during waking hours, the smartwatch can accurately measure heart rate and heart rate variability [38]. For adults over 50 years of age, significant potential has been found in the use of wearable fitness trackers, where health professionals can help older adults become more aware of wearable activity trackers and have the opportunity to be used and through use to create more awareness about physical activity [19]. In addition to daily activities, social influence involves the impact of activities on a person's behavior [40]. A wearable device daily activity information can then be seamlessly integrated into clinical decision support to develop and improve user outcome [37]. Activities in various fields are therefore factors that may influence the use of technology to prove both its usefulness and ease of use. Therefore, the following hypothesis is postulated:

H3: Activity (ACT) has a positive effect on perceived usefulness (PU)

H4: Activity (ACT) has a positive effect on perceived ease of use (PEOU)

3.4. Price Value (PRV)

Price value is part of the structure of UTAUT2 model that has a path to usage intention behavior [26]. A study showed no significant influence of price value on behavioral intentions [15, 47]. In contrast, studies indicate that price has effects on intentions to continue to use smart watches [46, 51]. In emerging economies, price value dictates the adoption of technologies [52]. Therefore, it is important to emphasize to consumers the functionality of the product and the benefits of using it so that they feel that the product is worth the price [48]. The price value factor may depend on the target audience of the participant or the participating countries that will influence the adoption of smartwatch technology. This is because there are various summaries of the results, so we have taken the aforementioned factors to study and consider further to suit the context of the research. Therefore, the following hypothesis is postulated:

H5: Price value (PRV) has a positive effect on perceived ease of use (PEOU)

3.5. Perceived Ease of Use (PEOU)

Conceptually, perceived ease of use reflects aspects of the technology (e.g., low complexity, high level of user friendliness) and directly affects the level of user efficiency, which is a person's self-assessment of his approximate ability to use technology [53]. Several studies on the adoption of perceived ease of use to hypothesize the behavioral intentions to use smart wearable health care devices and digital health wearables [20, 54-56]. Perceived ease of use was found to have related to attitude towards using smartwatches [18, 46]. On the other hand, some studies have found no significant impact on attitude toward using the smartwatch [57]. We expected that Perceived ease of use has a positive effect on perceived usefulness and attitude toward using. Thus the following hypothesis is proposed:

H6: Perceived ease of use (PEOU) has a positive effect on perceived usefulness (PU)

H7: Perceived ease of use (PEOU) has a positive effect on attitude toward using (ATU)

3.6. Perceived Usefulness (PU)

Perceived usefulness is an important structure that leads to usage behavior [16]). Perceived usefulness here means the degree to which an individual believes that using a particular system will improve his or her performance. This follows from the definition of useful: "Can be used in a useful way" [17]. In the context of this study, we define perceived usefulness as the degree to which an individual believes that using a smartwatch for health tracking leads to improvement or good health. Perceived usefulness influences acceptance and has an effect on intention to use. Currently, there are many studies on perceived usefulness to lead to acceptance and intention to use such as Smartwatch [7], Application [58], Privacy Concerns [29], telemedicine service [59], internet Banking [60], shows that perceived usefulness is recognized as one of the most important variables in predicting and explaining user intentions, especially intentions to utilization smart watch [13, 18]. We hypothesize that perceived usefulness is positively associated with the Attitude toward Using to adopt smartwatch for tracking health. Thus, we propose:

H8: Perceived usefulness (PU) has a positive effect on attitude toward using (ATU)

3.7. Attitude Toward Using (ATU)

According to the structure of TAM Important to such behavioral intention to use is attitudes towards use [17]. The study found that if users perceive a smartwatch to be flexible, intuitive, and easy to use, This perception may encourage positive attitudes towards smartwatch use [61]. Attitude toward using such as social support and perceived usefulness are considered to be an important factor towards smartwatch adoption among older adults [62]. Attitude towards use is a positive factor that stimulates behavior and intention to use. Thus, the following hypothesis is proposed:

H9: The positive impact of attitude toward using (ATU) on behavioral intention to use (BIU) of the smartwatch for tracking health

Based on the discussion above, the research model is shown in Figure 1.

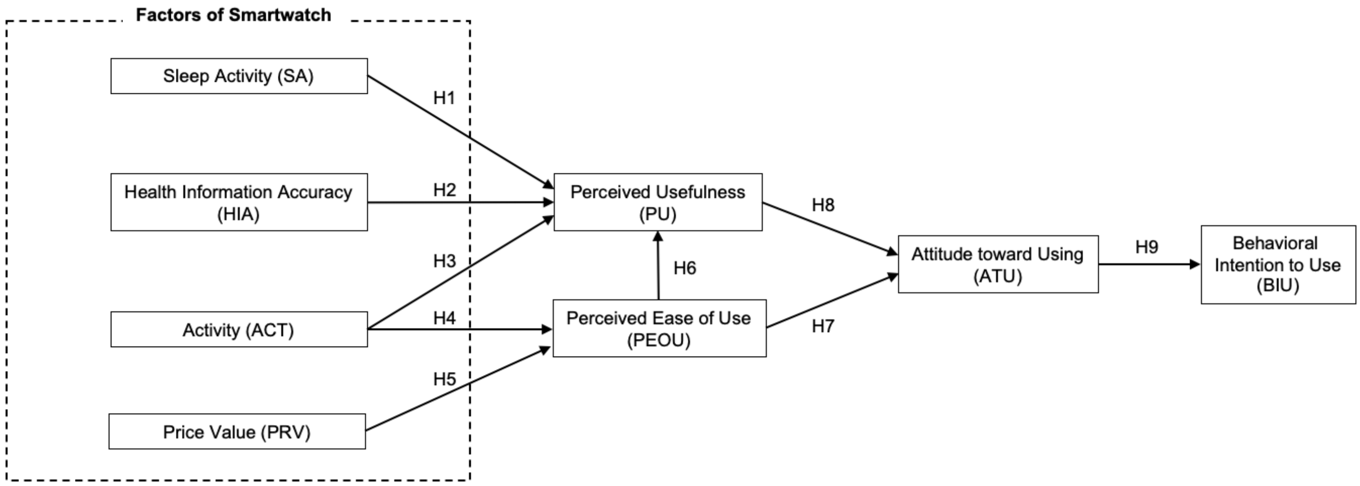

Figure 1. Research model.

4. RESEARCH METHODOLOGY

4.1. Data Collection

The data of this study is from Thailand population. The population in Thailand has an interesting point: Thailand is a developing country and has increased awareness and use of smartwatch technology. Including products from a variety of manufacturers, the smartwatch market is growing rapidly. As a result, there are many research gaps in this population for the adoption intention of smartwatch technology. Moreover, the conclusions from the analysis in this study have important implications for the use of smartwatches for health tracking in emerging markets or consumers. All data were collected by an online survey. Thai was the language used to administer the questions. We used the five-point Likert scale ranging from strongly agree (5) to strongly disagree (1) to measure all constructs in the research model [63]. The survey questionnaire had four sections: demographic, experience in smartwatch, factors affecting to adoption, opinion and suggestion. After analyze the responses, we removed three kinds of invalid surveys, a) incomplete surveys; b) participants with chronic diseases; c) participants who had no experience using a smartwatch. In total, we received 200 valid samples. Detailed for the demographic characteristics of respondents were presented in Table 2. The research method, research equipment and data collection form were considered in the Ethics Review Board of Rangsit University, authorized the questionnaire and certificate of approval number COA. No. RSUERB2023-137.

4.2. Data Analysis

In this paper, a SmartPLS 4.0, is employed for data analysis to test the scale of reliability, validity and availability for the measurement model, and then we used bootstrapping approach to 5,000 samples is to test the hypotheses and assumptions of modeling structural equations (SEM). In order to confirm the proposed factors and the readiness of the model, the measurement model is tested by evaluating its reliability and validity. Reliability can be assessed by Cronbach's alpha and composite reliability (CR), which has a recommended value of greater than 0.7 [64] and validity can be evaluated by average variance extracted (AVE), should be above recommended value of 0.5 [65]. Detailed for the construct Reliability and Validity were presented in Table 3.

5. RESULTS AND DISCUSSIONS

This section explains the analysis of the data obtained from questionnaire participants, including the extraction of respondent details and the examination of the measurement model created from the screened questions. The next part examines the assumptions of structural equation modeling (SEM) through hypothesis testing and data analysis.

5.1 Demographic Data of Respondents

The demographic characteristics of the 200 valid responses, about 45% of the respondents are male, and 53.5% are female, while 1.5% are Non-specific. Respondents were most to be 26–35 years old, accounting for 34.5 percent, followed by respondents aged 36–45 years old, accounting for 23.0 percent, 18–25 years old, accounting for 20.5 percent, 46–55 years old, accounting for 14.5 percent, over 55 years old, accounting for 7.5 percent. In terms of educational level of the respondents, It was found that the majority, 56 percent, had a bachelor's degree. This was followed by a master's degree at 27.5 percent and a doctoral degree at 9 percent. The least amount, 7 percent, had lower than a bachelor's degree, were presented in Table 2.

Table 2. Demographic Data of Respondents

Characteristics	Values	Frequency	Percent (%)
Gender	Male	90	45.0
	Female	107	53.5
	Non-specific	3	1.5
Age (years)	18-25	41	20.5
	26-35	69	34.5
	36-45	46	23.0
	46-55	29	14.5
	> 55	15	7.5
Education	< Bachelor	14	7.0
	Bachelor	112	56.0
	Master	55	27.5
	Doctorate	19	9.5

5.2 Construct Reliability and Validity

In this part of the measurement model testing, confirmatory factors were examined to confirm the reliability and validity. According to [33, 66]. We obtained Cronbach's Alpha, CR values with the highest is 0.913 and the lowest is 0.795, which is acceptable as it is within the recommended value of 0.7. The extracted average variance (AVE) provided values between 0.622 and 0.848 and are higher than the 0.5 threshold. It infers that all factors in measurement model have sufficient reliability, which is shown in Table 3

Table 3. Construct Reliability and Validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
ACT	0.797	0.828	0.867	0.622
ATU	0.883	0.883	0.927	0.810
BIU	0.897	0.899	0.936	0.829
HIA	0.911	0.921	0.944	0.848
PEOU	0.870	0.870	0.920	0.793
PRV	0.795	0.795	0.880	0.710
PU	0.867	0.867	0.919	0.790
SA	0.913	0.918	0.939	0.793

5.3 Individual Item Validity (Cross Loading)

From Table 4. shows the measurement model to examine the conditions for the convergent validity requirements to be supported according to the Fornell-Larker criteria [65], which is set to be higher than the threshold of 0.7. Our research discovered that the AVE values which are factor loading ranged from 0.609 to 0.799.

Table 4. Individual Item Validity (Cross Loading)

	ACT	ATU	BIU	HIA	PEOU	PRV	PU	SA
ACT1	0.747	0.778	0.741	0.718	0.778	0.762	0.759	0.786
ACT2	0.770	0.735	0.707	0.756	0.761	0.790	0.786	0.779
ACT3	0.873	0.726	0.795	0.791	0.768	0.718	0.790	0.743
ACT4	0.848	0.769	0.706	0.775	0.722	0.791	0.742	0.778
ATU1	0.733	0.899	0.704	0.783	0.783	0.718	0.850	0.748
ATU2	0.769	0.903	0.747	0.729	0.758	0.727	0.899	0.790
ATU3	0.759	0.898	0.756	0.731	0.724	0.726	0.834	0.741
BIU1	0.731	0.780	0.917	0.787	0.703	0.700	0.714	0.791
BIU2	0.716	0.721	0.918	0.763	0.745	0.793	0.860	0.711
BIU3	0.796	0.732	0.897	0.720	0.786	0.731	0.865	0.712
HIA1	0.729	0.786	0.742	0.932	0.781	0.768	0.791	0.746
HIA2	0.796	0.717	0.796	0.916	0.745	0.728	0.782	0.779
HIA3	0.727	0.771	0.745	0.914	0.706	0.782	0.718	0.714
PEOU1	0.751	0.728	0.721	0.722	0.895	0.752	0.711	0.785
PEOU2	0.716	0.747	0.777	0.754	0.895	0.796	0.704	0.722
PEOU3	0.755	0.770	0.700	0.727	0.882	0.736	0.729	0.758
PRV1	0.700	0.752	0.790	0.774	0.720	0.811	0.760	0.766
PRV2	0.707	0.737	0.790	0.716	0.704	0.883	0.741	0.765
PRV3	0.788	0.782	0.739	0.783	0.790	0.831	0.782	0.751
PU1	0.723	0.730	0.731	0.796	0.725	0.701	0.879	0.764
PU2	0.740	0.768	0.794	0.709	0.758	0.755	0.880	0.796
PU3	0.734	0.760	0.767	0.740	0.757	0.703	0.908	0.812
SA1	0.741	0.704	0.779	0.720	0.798	0.761	0.722	0.838
SA2	0.798	0.749	0.711	0.737	0.746	0.775	0.835	0.899
SA3	0.793	0.730	0.793	0.750	0.706	0.798	0.801	0.907
SA4	0.752	0.744	0.739	0.789	0.733	0.707	0.802	0.917

5.4 Fornell-Larcker Criterion

For discriminant validity, the square root of the AVE was used to evaluate the criteria [65]. Diagonal values within a construct must be higher than off-diagonal values, which should have a criterion value of at least 0.70. Table 5. shows that all the values meet these criterions for discriminant validity.

Table 5. Fornell-Larcker Criterion

	ACT	ATU	BIU	HIA	PEOU	PRV	PU	SA
ACT	0.789							
ATU	0.616	0.900						
BIU	0.565	0.818	0.911					
HIA	0.527	0.572	0.648	0.921				
PEOU	0.532	0.654	0.561	0.375	0.891			
PRV	0.592	0.582	0.522	0.464	0.481	0.842		
PU	0.636	0.735	0.747	0.580	0.578	0.509	0.889	
SA	0.558	0.622	0.593	0.559	0.473	0.545	0.665	0.891

5.5 Heterotrait-Monotrait Ratio (HTMT)

Heterotrait-Monotrait ratio (HTMT) is part of the measurement of discriminant validity. The value of each factor should be below the threshold of 0.85 as recommended by [67]. The studies found that all condition factors had values within a range capable of confirming discriminant validity, presented in Table 6.

Table 6. Heterotrait-Monotrait Ratio (HTMT)

	ACT	ATU	BIU	HIA	PEOU	PRV	PU	SA
ACT								
ATU	0.720							
BIU	0.656	0.818						
HIA	0.608	0.634	0.714					
PEOU	0.621	0.746	0.635	0.420				
PRV	0.741	0.695	0.618	0.544	0.577			
PU	0.755	0.840	0.846	0.648	0.665	0.613		
SA	0.662	0.696	0.657	0.612	0.531	0.643	0.745	

5.6 Collinearity (VIF)

In the final part of the measurement model, the Variance Inflation Factor (VIF) was examined and scores range 1.442 and 4.164, which is below the threshold of 5. As a result, there is not significant of a collinearity problem between any of the variables. Detailed for the Collinearity (VIF) were presented in Table 7.

Table 7. Collinearity (VIF)

	VIF
ACT1	1.617
ACT2	1.442
ACT3	2.416
ACT4	2.208
ATU1	2.512
ATU2	2.502
ATU3	2.416
BIU1	2.830
BIU2	3.035

	VIF
BIU3	2.496
HIA1	3.143
HIA2	3.159
HIA3	2.924
PEOU1	2.319
PEOU2	2.411
PEOU3	2.172
PRV1	1.508
PRV2	2.134
PRV3	1.814
PU1	2.165
PU2	2.171
PU3	2.569
SA1	2.252
SA2	2.912
SA3	3.884
SA4	4.164

5.7 Results of The Structural Model

The structural model and hypothesis were validated using SmartPLS 4.0, and to evaluate the structural model we used bootstrapping with 5000 iterations at a significance level of 0.05 ($p < 0.05$) [68] to examine the statistical significance of the hypothesis relationship between dependent and independent variables by path coefficient. Table 8. Shown structural model results of the path coefficients, t-values, p-values and decision for all hypotheses related. As a result, the findings indicate that the relationships between sleep activity (SA) and perceived usefulness (PU) ($t = 3.415$, $p < 0.05$), Health information accuracy (HIA) and perceived usefulness (PU) ($t = 2.938$, $p < 0.05$), Activity (ACT) and perceived usefulness (PU) ($t = 3.230$, $p < 0.05$), Activity (ACT) and perceived ease of use (PEOU) ($t = 5.237$, $p < 0.05$), Price value (PRV) and perceived ease of use (PEOU) ($t = 3.235$, $p < 0.05$), perceived ease of use (PEOU) and perceived usefulness (PU) ($t = 3.086$, $p < 0.05$), perceived ease of use (PEOU) and attitude toward using (ATU) ($t = 4.209$, $p < 0.05$), perceived usefulness (PU) and attitude toward using (ATU) ($t = 6.332$, $p < 0.05$) and attitude toward using (ATU) and behavioral intention to use (BIU) ($t = 22.222$, $p < 0.05$). Thus, H1– H9 that all hypotheses are supported and Figure 2. depicts path coefficient of the model from the SmartPLS.

Table 8. Structural Model Results

	Original sample	Sample mean	Standard deviation	T statistics	P values	Decision
ACT -> PEOU	0.380	0.382	0.073	5.237	0.000	Supported
ACT -> PU	0.235	0.236	0.073	3.230	0.001	Supported
ATU -> BIU	0.818	0.817	0.037	22.222	0.000	Supported
HIA -> PU	0.192	0.191	0.065	2.938	0.003	Supported
PEOU -> ATU	0.345	0.352	0.082	4.209	0.000	Supported
PEOU -> PU	0.231	0.231	0.075	3.086	0.002	Supported
PRV -> PEOU	0.256	0.258	0.079	3.235	0.001	Supported
PU -> ATU	0.536	0.530	0.085	6.332	0.000	Supported
SA -> PU	0.317	0.315	0.093	3.415	0.001	Supported

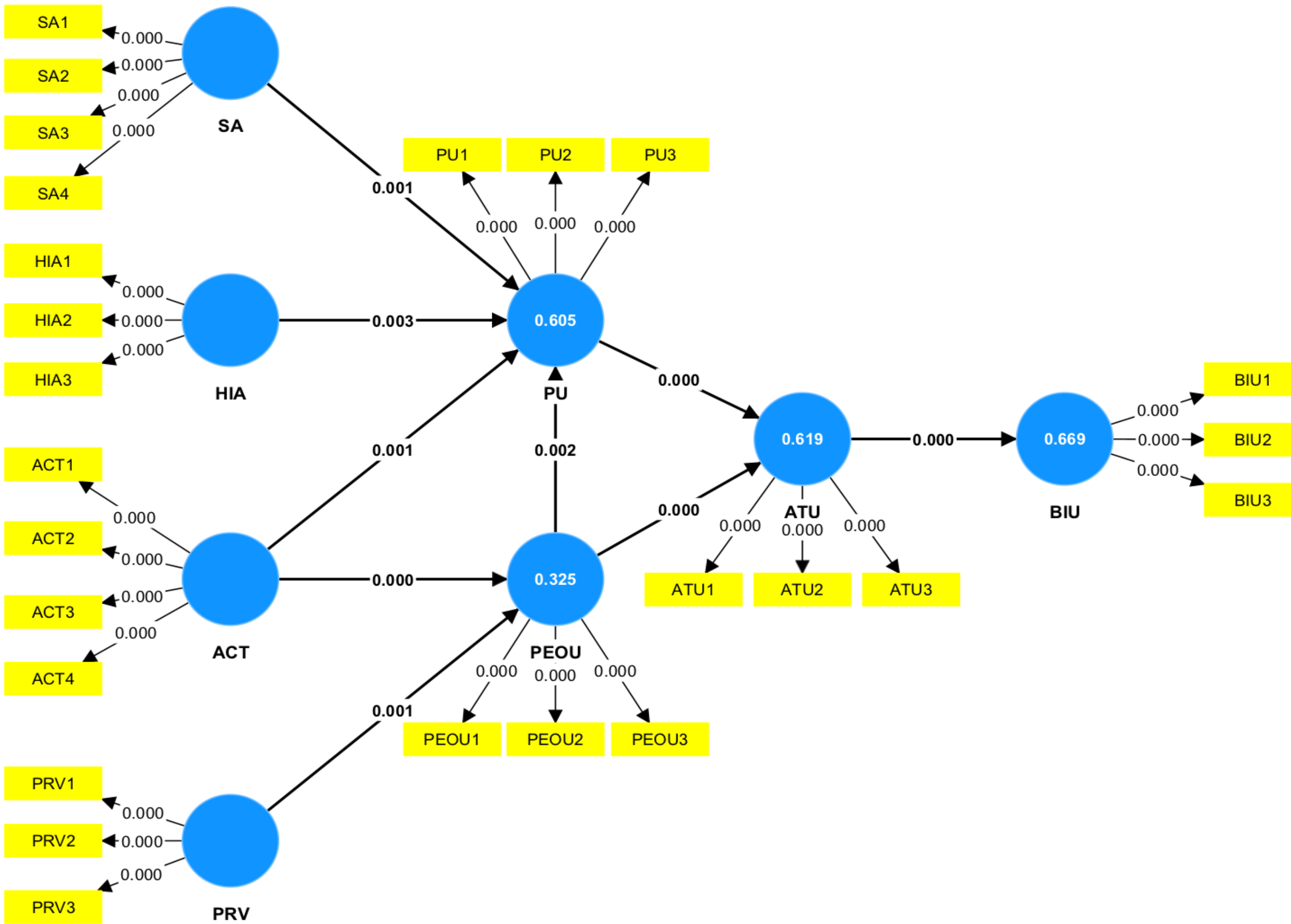

Figure 2. Path coefficient of the model.

From reviewing past literature and establishing the origins of the research model that emphasizes the strengths of smartwatch technology in measuring activity and sleep activity, it is essential to focus on the quality and accuracy of the health data that technology users receive, as well as the price value that may impact developing country, including those with a significant presence of smartwatches in the market. By incorporating these factors into the design of a structural model and the development of surveys on various issues, we gain insight into the significance of both sleep data and activity data in understanding its benefits, just as the accuracy of health-related data is crucial for recognizing its advantages. Furthermore, daily activities have a significant correlation with the perceived usefulness and perceived ease of use. At the same time, price sensitivity has a substantial impact on the perceived ease of use. As a result, external factors these outcomes in the same way. The fundamental structure of the TAM includes both the perceived usefulness and perceived ease of use, which are significantly related to the intention to use, ultimately leading to the adoption of smartwatch for tracking health technology.

CONCLUSION

This study develops a structural model for the acceptance of smartwatches for tracking health, employing the PLS structural equation model to analyze data from 200 research participants who valid to condition of research. The participants' age group was diverse and representative of various sources within Thailand. This research underscores the current benefits of smartwatch usage, offering diverse functionalities that can significantly enhance health monitoring and screening. This may contribute to disease prevention and early detection of physiological irregularities, enabling prompt and detailed diagnosis. The study incorporates various elements related to daily health-related activities, sleep evaluation, the accuracy of health data obtained from smartwatches, and the cost-effectiveness of these devices. These components are examined within the framework of the TAM, a flexible model that can accommodate additional external factors of interest to address the defined objectives. Perceived usefulness and perceived ease of use continue to be pivotal factors in the adoption of technology in contemporary times. This study aims to provide valuable insights into the adoption of smartwatches for tracking health and its potential implications.

The results of the study indicate that all the factors proposed in the research significantly influence the behavior intention to use. This is particularly pronounced in the domains of activity, sleep and price value. However, the health information accuracy also wields a similar and substantial influence. Furthermore, the analysis of these external factors can provide a deeper understanding of the context of smartwatch usage. The study has identified a growing demand for Smart Watch technology and additional insights from study participants. These include the ability to predict or assess the risk of disease occurrence, monitoring blood pressure and blood sugar, nutritional recommendations, emergency hospital connectivity, and the linkage of personal health data with hospital databases. The study findings emphasize the significant impact of these factors on users' behavioral intentions and their adoption of smartwatches for tracking health.

Furthermore, governmental or public sector entities can also play a role in enhancing the credibility of these devices by establishing criteria or standards for the products and providing appropriate health-related usage recommendations. Therefore, product developers can opportunities and directions for development that align with consumer needs. They can also leverage this data to enhance marketing strategies and public relations efforts. In this context, consumers in this target group place significant importance on cost-effective solutions. Finally, in terms of limitations and further directions, this study examined a sample of healthy individuals and did not include factors related to disease occurrences. Additionally, the study different results when analyzed based on gender and age groups.

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