Original Research

Exploring the mass adoption potential of wearable fitness devices in Malaysia

Naeem Hayat[1], Anas A Salameh[2], Abdullah Al Mamun[3] (ORCID), **Syed Shah Alam[4] and Noor Raihani Zainol[5]**

Abstract

Objective: The current study explores the formation of an intention to use wearable fitness devices (WFDs) with wearable fitness attributes and health consciousness (HCS). Moreover, the research examines the use of WFDs with the health motivation (HMT) and intention to use WFDs. The study also exposes the moderating effect of HMT between the intention to use WFDs and the use of WFDs.

Methods: Five hundred and twenty-five adults participated in the current study, and data were collected from January 2021 to March 2021 through the online survey of Malaysian respondents. The cross-sectional data was analyzed using the second-generation statistical method of partial least square structural equation modeling.

Results: HCS is insignificantly associated with the intention to use WFDs. Perceived compatibility, perceived product value, perceived usefulness, and perceived technology accuracy significantly influence the intention to use WFDs. HMT significantly impacts the adoption of WFDs; however, the intention to use WFDs negatively but significantly influences the use of WFDs. Lastly, the association between the intention to use WFDs and the adoption of WFDs is significantly moderated by HMT.

Conclusions: Our study findings illuminate the significant impact of technology-level attributes of WFDs on the intention to use WFDs. However, an insignificant impact of HCS on the intention to use WFDs was reported. Our result confirms that HMT plays a significant role in the use of WFDs. Such as the moderating role of HMT is vital to transform the intention to use WFDs into the adoption of WFDs.

Keywords

Wearable electronic devices, motivation, health communication

Introduction

The aging population and obesity rates are rising in most developed and emerging countries.[1] Wearable healthcare technologies can substantially empower users and enhance the preventive healthcare system.[2] Additionally, due to advancements in healthcare technology and growing health consciousness (HCS), healthcare devices for fitness are principally employed to track users' health conditions besides exercise habits.[3] Fitness trackers are becoming increasingly popular, which is projected to continue in the years to come.[4] Healthcare monitoring is an emerging market; future market demand epitomizes significant business potential.[5]

[1]Global Entrepreneurship Research and Innovation Centre, Universiti Malaysia Kelantan, Kelantan, Malaysia
[2]College of Business Administration, Prince Sattam Bin Abdulaziz University, Al-Kharj, Saudi Arabia
[3]UKM - Graduate School of Business, Universiti Kebangsaan Malaysia, UKM Bangi, Selangor Darul Ehsan, Malaysia
[4]UKM - Graduate School of Business, Universiti Kebangsaan Malaysia, UKM Bangi, Selangor Darul Ehsan, Malaysia
[5]Faculty of Entrepreneurship and Business, Universiti Malaysia Kelantan, Kota Bharu, Kelantan, Malaysia

Corresponding author:
UKM - Graduate School of Business, Universiti Kebangsaan Malaysia, 43600, UKM Bangi, Selangor Darul Ehsan, Malaysia.
Email: almamun@ukm.edu.my; mamun7793@gmail.com

Currently, many people's lifestyle depends on their health, and personal fitness and health monitoring have become part of their lifestyle.[6,7] Users can now track, save, and send information about their fitness activities due to the widespread use of wearable devices.[8] Wearable fitness devices (WFDs) have arisen as an innovative technology that tracks one's health in real-time.[9] WFDs can be employed to track physiological characteristics, including heartbeat rate, blood pressure, temperature, burned calories, personal mobility, and regular actions.[10,11] Furthermore, WFDs can display a visual dashboard of users' actions and can be combined with other health routine apps like nutrition tracking and health monitoring.[11] The benefits of wearable healthcare technology are not restricted to cost savings in healthcare; WFDs can also help manage healthcare instantly.[10] Fitness trackers, electronic movement monitors, smart wristbands, Fitbit, Jawbone, and smartwatches are some WFDs.[2,12] WFDs are becoming more robust and offering suitable medical services platforms.[13] This is especially valuable with the growing attention on health, well-being, preventing illness, and fitness, in addition to the massive change towards individual-controlled healthcare.[14]

Fitness devices track physiological indicators and everyday activities in real-time, motivating people to adopt a better lifestyle and save money on health care.[15] Individual and societal factors influence the adoption of WFDs.[15] WFDs have received much interest due to their ability to collect and analyze ambient data, raising enthusiasm among users.[13] Fitness trackers provide a solution for individuals seeking to enhance their health by offering them more efficient motivation through personal data-driven information.[16]

The COVID-19 plague emergency worldwide has instigated a surge of attention on healthcare wearables,[14] and healthcare apps have become a primary priority during this pandemic.[2] Given these difficulties and uncertainties during COVID-19, it is probable that interest in healthcare devices and apps will continue to grow in the future.[17] More individuals have become interested in their health and physical and psychological well-being due to the COVID-19 pandemic; they desire to deliver exercises and fitness content to their homes via WFDs.[5]

Although adopting wearable fitness trackers has benefited society,[18] limited scholars have examined the factors influencing users' consciousness and their acceptance and adoption of fitness devices.[19] Health habits, consciousness, and motivation, are a few factors not utilized in literature to examine the instigation of intention and behavior towards using technological healthcare devices.[13,15] Most studies inspect the formation of an intention to use wearable healthcare devices with technological attributes.[14] Identifying the fundamental determinants that affect consumers' or users' behavioral intention to adopt WHDs is crucial because it will help wearable device suppliers to develop a marketing strategy that will result in a greater level of adoption of fitness devices.[20] Besides, understanding customer intent and adoption of WFDs is critical for the wearable health technology industry's future success. Numerous investigations on WFDs have concentrated on "technology-driven" rather than "consumer-driven" over the last few years.[15] The global market for wearable healthcare devices will reach USD 16.2 billion in 2021 and reach USD 30.1 billion by the end of 2026.[21] Malaysian are more inclined towards wearable technologies than other South East Asian residents, and among Malaysian consumers, 65% are using wearable technologies for fitness and healthcare purposes.[22]

Malaysia is regarded as a low HCS nation facing high obesity among adults.[23] The 12th Malaysia Plan intends to change the countrywide healthcare scene digitally.[24] The mounting healthcare charges reduce people's capacity to pay for healthcare expenses and take personal actions to manage their health issues.[5] Besides affordability, healthcare technologies must build on quality and convenience.[25] Malaysian users are suffering a 13.5% increase in the cost of medicinal facilities since the quantity of qualified doctors and nurses for 1000 individuals is 1.5 and 3.5, correspondingly.[23] Therefore, WFDs help users to attain well-being and offer personal convenience to accomplish a healthy life.[25] The number of wearable healthcare users in Malaysia touched 1.6 million at the end of 2022, and USD 29.5 million in market volume.[26]

Wearable devices are still in their beginning stage of market dissemination. There is a nuanced understanding of current consumer demands, particularly in Malaysia; consequently, it is necessary to categorize the features that move Malaysian users' behavioral intention and adoption of WFDs. Additionally, while consumers view wearable technologies as novel, their social acceptance and health-related issues must be examined. Only a few studies have attempted to inspect the role of health motivation (HMT) in the connection among consumer intention and the use of WFDs. As such, the present study introduces HMT as a moderator in the relationship between the use intention and WFDs adoption.

Literature assessment

Theoretical underpinning

Health behaviors develop from multiple social, technological, and psychological factors.[2,14] Technology Acceptance Model (TAM) is a renowned model used to assess the acceptance of new technology among users based on technology factors like ease of use and usefulness.[27] Besides technological attributes, personal inclination is vital in evolving the technology use intention. Another aspect is perceived value, a significant predictor of technology use, in which the product or technology is

viable.[20] The usefulness of technology also positively explains the intention to use novel technology.[16] Meanwhile, technology accuracy helps form a positive attitude toward using technology.[28]

Personal health inclination also influences the intention to use health-linked technologies.[19] HCS, or awareness of any health concerns, promotes an individual's efforts to achieve good health and well-being. As a personal trait, HCS instigates a healthy lifestyle and the use of healthcare technology. On the other hand, HMT plays a substantial part in transforming intention into a healthcare behavior. The current work theoretically adds to the literature that HMT is vital to activating healthcare behavior. The study model is provided in Figure 1.

Hypotheses development

Health consciousness. HCS is the level to which medical issues are merged into a person's normal doings.[2] Health-conscious people are aware of potential health risks, responsible for their health, worried about their physical fitness, and interested in stress and nutritional management.[29] Additionally, health-conscious individuals are concerned about their well-being and attempt to improve and preserve it by establishing healthy behaviors such as eating healthy foods and intending to acquire health-related products, for example, fitness trackers.[30] If an individual is health-conscious, he or she is more inclined to use fitness equipment.[9] According to Chang,[2] health-conscious people are cognizant of and worried about their well-being, which leads to increased enthusiasm to improve or preserve their health. Users or individuals with a healthy lifestyle and who are health-conscious are highly expected to practice preventive health behaviors, for instance, regularly monitoring their health indicators and using healthcare services in fitness devices.[31] Individuals with a higher level of HCS are more attentive and responsive to a healthy diet and lifestyle. Therefore, they are more inclined to adopt and use WFDs.[30] The study proposes the following hypothesis:

H₁ₐ: HCS influences the WFDs' use intention.

Perceived compatibility. Perceived compatibility (PCM) discusses the personal perception of which innovative technology is compatible with prevailing ideals and habits, needs, and experiences of potential adopters.[12] Customers are more inclined to accept a fitness device that is deemed compatible. In contrast, those considered incompatible require extensive adjustments and significant learning about how to use the product.[4] Apart from that, if fitness devices are more compatible with the user's experience and lifestyle, it will be easier to comprehend how to use them.[14,32] Users may deem fitness devices more compatible if they

see the advantages of utilizing them for specific activities. Higher compatibility signifies a connection between the fitness devices and users' behavioral-cognitive skills, reinforcing the longing to benefit from fitness gadgets.[6,11] Hence, the subsequent hypothesis is projected:

H₁ᵦ: PCM influences the WFDs' use intention.

Perceived product value. Perceived value is a vital element in envisioned behavior and is regarded as a critical marketing approach.[33] It is a user's overall valuation of a product's efficacy grounded on insights into what is received and what is given.[34] In healthcare, the overall perception of fitness equipment based on its benefits and costs is described as the perceived value.[33] Furthermore, perceived product value (PPV) refers to the difference between what is received in terms of advantage, worth, and efficacy and what is paid in terms of costs and price.[1,34] Consumers are expected to possess information before they can understand the benefits and values acquired from using a product or service, which might then influence their behavioral intention.[17] Users are enticed to buy fitness equipment because of the health information and benefits they can attain from the equipment.[1,19] A user will be satisfied if the wearable technology device, which includes a fitness tracker, surpasses the desirable health improvement. However, he or she will be dissatisfied if the outcomes are unexpected.[14] Consumers' attitudes, comfort, and usage intention are all influenced by perceived value.[35] Hence, the study puts forth the succeeding hypothesis:

H₁ᵧ: PPV impacts the intention to use WFDs.

Perceived technology accuracy. In the digital and healthcare industries, the accuracy of the technological product is a crucial factor in the intention to adopt.[36] The perceived accuracy of wearable healthcare technologies is critical in determining their perceived credibility and adoption.[31] Furthermore, the accuracy of technology-based information helps assess users' health management.[34] Health information accuracy refers to how accurate and adequate the evidence provided by wearable healthcare technology regarding users' health conditions.[31] Raising the legitimacy and accuracy of a product's quality is crucial for customers, who can be influenced to become potential technological healthcare consumers.[14] The evidence's authenticity, precision, and reliability are termed accuracy.[33] The exactness of health information influences users' willingness to involve in health-related knowledgeable choices.[36] Perceived technology accuracy (PTA) is expected to influence WFDs, per se, the subsequent is proposed:

H₁d: PTA effects the WFDs use intention.
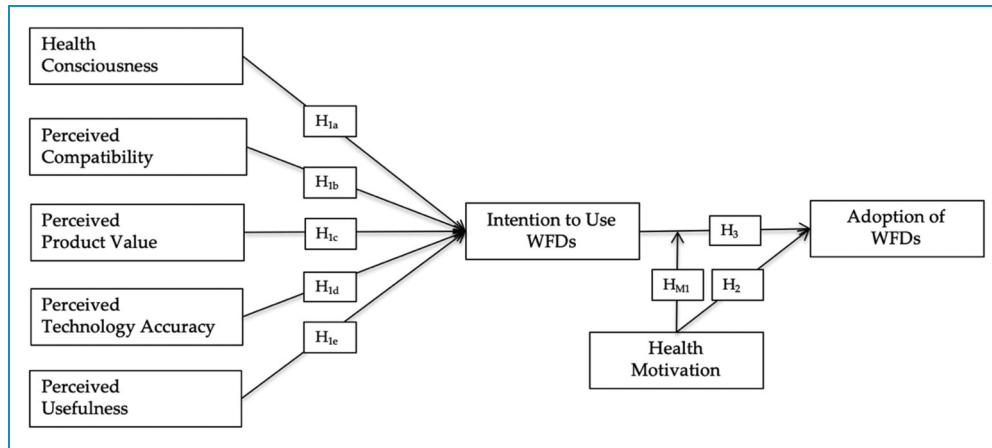
Figure 1. Research framework.

Perceived usefulness. Perceived usefulness (PUS) states users' belief that utilizing innovative technology would improve their performance.[34] PUS influences users' intention to adopt digital technology in the TAM model.[10] In healthcare, PUS is an individual's belief that using a fitness device would enhance his or her health condition.[32] Wearable fitness trackers can make the users' activities more comfortable, simple, and practical, thereby meeting the users' needs more quickly and consequently playing a substantial part in improving their health.[18] Users tend to adopt fitness devices to continually monitor their body conditions if they believe this innovative device can help them better monitor their health and enhance their health and quality of life.[37] The easier people perceive the fitness tracker is to use, the more likely they are to utilize it.[6] Users' behavioral intentions are influenced by the awareness of how easy to use and valuable fitness tracking equipment.[4] Accordingly, the succeeding hypothesis is expressed:

H₁ₑ: PUS influences the WFDs use intention.

Health motivation. HMT is defined as an individual internal attribute of a person, whereas HCS relates to the outward aspects of how a person's health is taken good care.[25] Dehghani[12] describes HMT as the intersection of medical problems, health information acquisition behavior, and technology to deliver novel techniques to meet unique healthcare demands. Individuals interested in their health condition are more prospective to employ and embrace fitness devices.[20] Fitness trackers provide safer and better preventive treatment and more patient-centered practice and enable the transition from a traditional hub-based healthcare system to more individualized solutions.[12] Users with a developed HTM who are actively driven to investigate habits to augment their health condition are expected to learn about the advantages of fitness devices,

increasing their intention to use and adopt fitness devices.[36] Consequently, the current study suggests the next hypothesis:

H₂: HMT influences the use of WFDs.

Intention to use WFDs. Behavioral intention, the strongest indicator of use,[38] is distinct as an individual's mental plan to undertake a specific behavior.[12] "Usage behavior" is crucial for building predictive approaches to understanding why individuals adopt or utilize a specific technology.[18] A widespread consensus is that a positive association exists between behavioral intention and the adoption of healthcare-based technology.[38] Higher intention to use WFDs is significantly related to higher levels of adoption of fitness devices.[8] Users more willing to adopt a fitness wearable technology are inclined to convert adopters and recommend it to others.[31] Hence, the resulting proposition is put forth:

H₃: Intention to use WFDs influences the use of WFDs.

Moderation effect of HMT. HMT reflects a person's involvement in preventative health behaviors such as health information acquisition activities and comprehensive health behaviors.[25] Motivation to utilize WFDs relates to a motivating force that can encourage users to take action to satisfy their essential health conditions.[29] Users who might be more inspired and involved in healthcare are more persuaded to utilize wearable healthcare technology.[14] Besides, users interested in improving health conditions are more likely to use and adopt WFDs to monitor their health conditions instantly and often a day.[20] Based on the study aim, we suggest that the HMT moderates the use intention and adoption of WFDs. The subsequent hypothesis is therefore projected:

HM1: The association amid intention to use WFDs and use of WFDs is moderated by HMT.

All of the abovementioned associations are depicted in Figure 1.

Research methodology

Sample size calculation and data gathering

The present work assumed a confirmatory research design taking the quantitative method. The survey-based data was collected through the cross-sectional procedure using social media. The Google forms were prepared and circulated on social media to collect data from January 2021 to March 2021. The sample size calculation was accomplished using the G-Power 3.1, with a power of 0.95, an effect size of 0.15 with seven input variables, and a total of 153 samples necessary to realize the current study.[39] Hair et al.[40] endorse performing the partial least square structural equation modeling (PLS-SEM) analysis with a minimum of 200 samples. Data analysis was executed with 525 valid replies.

The local ethics team ruled that no prescribed ethics consent was mandatory in the particular study because (a) the data is entirely unidentified as no individual information is being collected; (b) the data is not considered to be sensitive or confidential in nature; (c) the issues being researched are not likely to upset or disturb participants; (d) vulnerable or dependent groups are not included; and (e) there is no risk of conceivable exposes or reporting

Table 1. Reliability and validity.

Construct	No. of items	CA	rho_A	CR	AVE	VIF
HCS	4	0.656	0.700	0.798	0.507	2.087
HMT	3	0.904	0.940	0.932	0.821	1.094
PCM	5	0.932	0.941	0.949	0.789	2.285
PPV	5	0.878	0.902	0.912	0.678	2.059
PTA	5	0.905	0.942	0.931	0.733	2.779
PUF	4	0.909	0.912	0.936	0.786	2.939
IWFD	5	0.927	0.929	0.945	0.775	1.066
UWFD	1	1.000	1.000	1.000	1.000	-

HCS: health consciousness; HMT: health motivation; PCM: perceived compatibility; PPV: perceived product value; PUF: perceived usefulness; PTA: perceived technology accuracy; IWFD: intention to use WFDs; UWFD: use of WFDs. CA: Cronbach's alpha; rho_A: Dijkstra–Henseler's rho; CR: composite reliability; AVE: average variance extracted; VIFs: variance inflation factors.

responsibilities. The current study has been performed in accordance with the Declaration of Helsinki. Informed written consent for partaking was attained from the study participants, and the participation is voluntary. All the study participants were above 18 years old. The inclusion criteria were that the samples were aware of the wearable fitness healthcare devices resident of Malaysia and above 18 years of age. The exclusion criteria were people under the age of 18, not aware of the wearable fitness healthcare devices, not accepting the written consent form, and residing outside of Malaysia.

Measurement scales

The study's measurement scales were derived from known and effective scales. First, HCS was judged using four items taken from Dutta-Bergman[29]; the reported Cronbach's alpha for the scale was 0.72. Second, HMT was assessed with four items taken from Li et al.[25] with the reported Cronbach's Alpha of 0.91. Next, PCM was evaluated using the four items from Yang et al.,[32] having Cronbach's alpha for the scale was 0.96. PUF was assessed with four items taken from Kim et al.,[5] with Cronbach's alpha of 0.93. In the meantime, the perception of technology accuracy was judged using four statements from Alam et al.[31] with Cronbach's alpha of 0.88.

The perception of product value was appraised using four statements taken from Kim et al.[5] and with a Cronbach's alpha of 0.91. On the other hand, the intention to use WFDs was evaluated using four items from Alam et al.[31] and Gao et al.[38] having Cronbach's alpha 0.85 and 0.82, respectively. Lastly, the use of WFDs was gauged with a single-question item. All the questionnaire items relating to exogenous variables were marked using a 5-point Likert scale, whereas endogenous variables were graded based on a 7-point Likert scale. In the research design stage, employing discrete Likert gauges for input and outcome variables can solve the matter of common method variance (CMV).[41]

Common method variance

Using single-source data collection techniques is popular among social science researchers, and it builds the CMV.[41] Harman's one-factor assessment is anticipated as an approach to evaluate the CMV issue in the current research.[41] The outcome of single-factor Harman's assessment supports the idea that the CMV was not a grave issue in the current work; the one-factor account for 31.5% change and less than the recommended 40% edge.[41] Additionally, the study evaluated CMV by testing the complete collinearity, as suggested by Kock.[42] The variance inflation factor (VIF) values were determined: 2.618 (HCS), 2.695 (HMT), 2.488 (PCM), 2.169 (PPV), 2.670 (PUF), 2.188 (PTA), 2.950 (intention to use WFDs), and

2.520 (adoption of WFDs). Since all the VIF values were below 3.3, it indicated the nonappearance of bias from the data collected in unisourced.[41]

Table 2. Demographic features.

	N	%		N	%
Gender			*Education*		
Male	188	35.8	Secondary school certificate	1	0.2
Female	337	64.2	Higher secondary school certificate	21	4.0
Total	525	100	Bachelor's degree or comparable	474	90.3
			Master's degree	29	5.5
Age			Total	525	100
18–20 years	105	20.0			
21–25 years	53	10.0			
26–30 years	145	27.6	*Average Monthly Income*		
31–35 years	190	36.1	Below RM 1500	85	16.4
Above 35 years	32	6.3	RM 1001–RM 2000	120	22.8
Total	525	100	RM 2001–RM 3000	105	20.0
			RM 3001–RM 4000	94	17.9
Province			RM 4001–RM 5000	68	12.9
Kuala Lumpur	45	8.5	More than RM 5000	53	10.0
Pahang	37	7.0	Total	525	100
Penang	40	7.6			
Sarawak	54	10.2			
Terengganu	71	13.5			
Johor Bahru	66	12.5			
Kelantan	61	11.6			
Kedah	55	10.4			
Others	96	18.2			
Total	525	100			

Multivariate normality

PLS-SEM is a nonparametric analysis device, and nonnormal data can be evaluated in the SmartPLS.[43] Consequently, multivariate data normality examination is accomplished with the online tool of web power (https://webpower.psychstat.org/wiki/tools/index).[32] The outcome settles that the present data were nonnormal, as Mardia's multivariate coefficient p-values were below .05.[44]

Analysis of reliability and validity

Relied on Hair et al.,[43] the reliability scores for the study's variables were evaluated using three measurements, i.e. CA, rho, and CR. The CA score must be above 0.650 to depict the reliability of the variables. The outcomes in Table 1 confirmed that all the CA scores were above 0.650, and HCS attained the lowest score with a CA score of 0.656. Meanwhile, the rho scores for all the variables were above 0.70; the lowest score was achieved by PUF, with 0.70. Likewise, the CR values for all the constructs were above 0.70, suggesting that the constructs accomplished reliability. HCS attained the lowest score, and the score was 0.798. Succeeding, the AVE for all the study variables surpassed 0.50, henceforward, suggesting suitable convergent validity.[43] Furthermore, the VIF must be less than 3.3 to represent no subject of multicollinearity.[43] All the study's constructs showed no multicollinearity issue, as the VIF scores were less than 3.3.[42]

The discriminant validity was evaluated using the Fornell–Larcker criterion, HTMT, and cross-loading scores. The Fornell–Larcker criterion was appraised using the square root of the AVE score of particular constructs and compared with the correlation score. The square root of AVE must be higher than the correlation between the other constructs. The outcomes revealed that the study's model achieved discriminant validity. Next, the HTMT ratio was utilized to assess the discriminant validity, and it needs to be below 0.900 to depict the discriminant validity accomplished by the study's constructs. All the HTMT ratio scores were below 0.900; thus, discriminant validity was attained. Lastly, the cross-loading table was employed and evaluated to establish the discriminant validity of the current study's model. Appendix 1 lists the discriminant validity score.

Data analysis method

PLS-SEM is a multivariate analysis technique that empowers the assessment of study models having latent variables. Smart-PLS software 3.3 was utilized to assess the study model and hypotheses.[43] PLS-SEM works well with small data sets, nonnormal data, and intricate-based models.[40] Additionally, the evaluation of goodness-of-fit for a model is not a condition.[43] The first phase of analysis

evaluates the variables' reliability, convergent, and discriminant validity.[43] The second-stage analysis appraises the model and path association.

Results

Respondent profile

As indicated in Table 2, 64.2% of the respondents were females. The respondents' age ranges were: 18–20 years (20.0%), 21–25 years (10.0%), 26–30 years (27.6%), 31–35 years (36.1%), and 35 years old and above (6.3%). On the other hand, the respondent's level of education varied, i.e. secondary school certificate (0.2%), diploma (higher secondary school certificate) (4.0%), bachelor's degree (90.3%), and master's degree (5.5%). Concerning their average monthly income, 16.4% earned below RM 1,500, 22.8% between RM 1001 and RM 2,000, 20.0% between RM 2001 and RM 3,000, 17.9% between RM 3001 and RM 4,000, 12.9% between RM 4001 and RM 5,000, and 10% earned more than RM 5000. The respondents' lived in Kuala Lumpur (8.5%), Pahang (7%), Pulau Pinang (7.6%), Sarawak (10.2%), Terengganu (13.5%), Johor Bahru (12.5%), Kelantan (11.6%), Kedah (10.4%), and others (18.2%).

PLS-SEM analysis

Results of path analysis. The adjusted R^2 score for intention to use WFDs (IWFD) with the five input variables (i.e., HCS, PCM, PPV, PTA, and PUS) indicated that these five variables explained 68.5% of the change in the IWFD. Meanwhile, the Q^2 score for the portion of the study model was 0.526%, displaying high predictive relevance.[45]

The path among HCS and IWFD exposed that HCS had a positive but insignificant impact on the intention to use WFDs, thus, subsisting no provision to accept H_{1a}. The effect size ($f^2 = 0.004$) for the path depicted the small effect of HCS on IWFD. Next, the path value between PCM and IWFD displayed that PCM had a positive and significant effect on the intention to use WFDs. This result offered evidence to accept H_{1b}; the effect size for the path was medium ($f^2 = 0.004$). The path coefficients between PPV and IWFD suggested a positive and significant effect, while the effect size ($f^2 = 0.016$) for the path showed a medium effect size, supporting the acceptance of H_{1c}. On the other hand, the path score for PTA and IWFD demonstrated that PTA had a positive and significant effect on the intention to use WFDs. The outcome offered support to accept H_{1d}; the effect size for the path was medium ($f^2 = 0.050$). Lastly, the path value between PUF and IWFD showed that PUS positively and significantly impacted the intention to use WFDs. This finding meant that H_{1e} was accepted; the effect size for the path was medium ($f^2 = 0.205$). All the consequences are accessible in Table 3.

The adjusted R^2 value for the use of WFDs with the two input concepts (i.e. HMT and intention to use the WFD) proved that HMT and IWFD clarified 10.7% of the disparity in UWFD. The Q^2 score of the model was 0.093, displaying a low predictive relevance.[45] Next, the path between HMT and UWFD revealed the significant positive effect of HMT on the adoption of WFDs. This result offered empirical support for accepting H_2. On the other hand, the path between IWFD and UWFD demonstrated a negative but significant effect of the intention to use on the adoption of WFDs, consequently indicating no sustenance to admit H_3. Table 3 offered the path analysis.

Moderation investigation. The moderation analysis revealed that HMT significantly moderated the association between IWFD and UWFD, offering sustenance to admit HM1. The outcomes are offered in Table 4.

Discussion

The current study intended to discover the development of the intention to use WFDs with HCS and four WFDs attributes (i.e. compatibility, product value, usefulness, and technology accuracy) and whether HMT and intention to use WFDs influenced the adoption of WFDs. The analysis showed that HCS exhibited a positive but insignificant outcome on the intention to use WFDs. The outcome does not concur with the outcome in Chang[2] that health concern builds a healthy attitude and uses healthcare instruments to achieve a healthy lifestyle. Furthermore, the Malaysian respondents showed a low HCS, which did not enable the use of healthcare devices to gain better health. The result accords with the results of Abdullah et al.[46] that 50% of Malaysians are experiencing obesity, and people are practising unhealthy lifestyles in ASEAN countries. A low level of awareness and the lack of a healthy lifestyle promotes a low HCS and quality of life.

Next, the perception of WFDs' compatibility significantly promoted the intention to use WFDs. The outcome approves the verdict reported by Talukder et al.[11] that fitness devices' compatibility positively impacts the intention to use the fitness devices. Technology compatibility facilitates the users by offering the advantage of the ease of using healthcare technology. Besides, compatibility activates the perceived appropriateness to gain the advantage of using healthcare technology.[4] This study also evaluated the association between PPV and the intention to use WFDs. The finding revealed the significant positive effect of PPV on the intention to use WFDs. This outcome matches the result in Sripoothon et al.[17] that the perception of value drives the attention of the prospective users and instigates the intention to use the WFDs. Consumers estimate the expected gains and costs related to technology use, and

Table 3. Path coefficients.

No.	Path	Beta	CI−Min	CI−Max	T	P	r²	Q2	f²	Result
Factors affecting Intention to Use WFDs										
H$_{1a}$	HCS → IWFD	0.054	−0.024	0.139	1.099	0.136	0.004			Rejected
H$_{1b}$	PCM → IWFD	0.145	0.071	0.224	3.089	0.001	0.029			Accepted
H$_{1c}$	PPV → IWFD	0.101	0.041	0.159	2.862	0.002	0.016			Accepted
H$_{1d}$	PTA → IWFD	0.208	0.114	0.305	3.604	0.000	0.050			Accepted
H$_{1e}$	PUF → IWFD	0.436	0.344	0.521	8.030	0.000	0.685	0.526	0.205	Accepted
Adoption of WFDs										
H$_2$	HMT → UWFD	0.137	0.086	0.205	3.057	0.001	0.107	0.093	0.019	Accepted
H$_3$	IWFD → UWFD	−0.244	−0.315	−0.167	5.458	0.000	0.063			Rejected

HCS: health consciousness; HMT: health motivation; PCM: perceived compatibility; PPV: perceived product value; PUF: perceived usefulness; PTA: perceived technology accuracy; IWFD: intention to use WFDs; UWFD: use of WFDs.

Table 4. Moderating effects.

Hyp.	Path	Beta	CI−Min	CI−Max	T	P	Result
H$_{M1}$	IWFD × HMT → UWFD	0.136	0.073	0.202	3.268	0.001	Moderation

HCS: health consciousness; HMT: health motivation; PCM: perceived compatibility; PPV: perceived product value; PUF: perceived usefulness; PTA: perceived technology accuracy; IWFD: intention to use WFDs; UWFD: use of WFDs.

the expected higher gains promote the likelihood of using healthcare technology.[34]

The perception of WFDs' technology accuracy significantly impacted the intention to use the WFDs. This finding concurs with the outcome of Alam et al.[31] that technical accuracy is related to the intention to use healthcare devices. A technology's accuracy builds user confidence, and adequate, accurate information empowers users to manage their health reliably. Moreover, accurate technology empowers users to maintain a healthy lifestyle.[19] The study also inspected the link among PUS and the intention to use WFDs. The result exposed the significant positive consequence of WFDs' usefulness on the intention to use WFDs. This outcome agrees with that reported by Yang et al.,[6] whereby a technology's usefulness affects the intention of WFDs, empowering the users to accomplish their health and achieve a good value of life. Technology usefulness offers users an effective way to monitor and manage their health via WFDs frequently.

On the other hand, personal HMT effect the adoption of WFDs. The study's conclusion agrees with the verdict of Dehghani[12] that users utilize smart technologies with the

right motivation. The fitness technologies facilitate the users and satisfy their health enthusiasm. Only people with precise HMT can use healthcare technologies. Besides, the influence of the intention to use WFDs on the use of WFDs was evaluated, and the outcome showed a significant negative effect of the intention to use on the use of WFDs. The verdict disagrees with the result of Alam et al.[31] that the intention to use healthcare technology promotes the use behavior of the healthcare technology. However, the HMT significantly moderates the relationship between the intention to use and the use of WFDs. Our study outcome achieves acceptance from Lee and Lee[14] that HMT facilitates the use of technological healthcare devices. Our study confirms that individual HMT instigates the use of WFDs.

Theoretical inferences

The existing research augments the theoretical posture towards adopting healthcare technology with HCS and technology attributes. Wearable healthcare devices are unique as these significantly facilitate and empower users

to shape the intention for WFDs use. Second, healthcare technology adoption requires users to have HMT, and HMT moderates the connection between the intention to use and adoption of WFDs. Theoretically, the present effort is among the limited studies that have explained the part of HMT in promoting healthcare technology. The WFDs are practical tools for personal healthcare management and promoting healthy lifestyles among Malaysian adults.

Practical and managerial inferences

The present study's verdicts bid practical suggestions for the healthcare business to promote HCS and HMT. The healthcare industry management can improve the consumer product mix and work closely with them to achieve sustainable health management. Marketing and advertisement campaigns can help promote the healthcare culture and influence attitudes toward wearable healthcare gadgets.[11] The development of personal healthcare concerns facilitates an individual to manage his or her health and the global healthcare system.

Furthermore, public awareness is crucial for promoting personal health concerns. Public spending promotes HMT and attaining a healthy lifestyle, and promoting a healthy lifestyle nurtures a healthy nation and reduces public spending in the healthcare system. Additionally, promoting HCS and HMT can transform the Malaysian national health landscape and promote the individual level of health care besides reducing the obesity rate and unhealthy lifestyles in Malaysia.

Conclusion and future directions

The present work revealed that the WFDs features meaningfully influence the formation of an intention to use the WFDs, and HMT suggestively influences the use of WFDs. The HMT for the study sample significantly moderated the relationship between the intention to use and the use of WFDs. However, the current study has empirically contributed to the existing literature and practice. Nevertheless, three pertinent limitations in the current work pave the way for future research directions. First, only a limited number of variables that affected the adoption of wearable healthcare devices were employed. Hence, future studies must incorporate other technological attributes such as sustenance arrangement, social norms, mass adoption, and facilitating conditions that influence the adoption of WFDs. Next, the study assumed the quantitative design associated with restricted generalization. Future studies need to integrate mixed methods with a qualitative research design to determine the adoption of WFDs. Lastly, technology adoption is complex, and consumers' personal and social factors play a significant role in technology adoption. Furthermore, technology adoption

may undergo different stages and might not be simple. Thus, future studies must explore the continuous intention to adopt, partial adoption, or rejection of products after adoption. Consumers' perception of product value varies, and future studies must explore the personal health conditions in adopting healthcare technologies such as WFDs.

References

1. Jiang X, Deng N, Fan X, et al. Examining the role of perceived value and consumer innovativeness on consumers' intention to watch intellectual property films. *Entertain Comput* 2022; 40: 100453.
2. Chang C-C. Exploring the usage intentions of wearable medical devices: A demonstration study. *Interact J Med Res* 2020; 9: 1–10.
3. Ahmad A, Rasul T, Yousaf A, et al. Understanding factors influencing elderly diabetic patients' continuance intention to use digital health wearables: extending the technology

acceptance model (TAM). *Journal of Open Innovation: Technology, Market, and Complexity* 2020; 6: 81.

4. Naglis M and Bhatiasevi V. Why do people use fitness tracking devices in Thailand? An integrated model approach. *Technol Soc* 2019; 58: 101146.

5. Kim S, Bae J and Jeon H. Continuous intention on accommodation apps: integrated value-based adoption and expectation–confirmation model analysis. *Sustainability* 2019; 11: 1578.

6. Yang Q, Al Mamun A, Hayat N, et al. Predicting the mass adoption of eDoctor apps during COVID-19 in China using hybrid SEM-neural network analysis. *Front Public Health* 2022; 10: 1–17.

7. Xinyan Z, Mamun AA, Ali MH, et al. Modeling the adoption of medical wearable devices among the senior adults: Using hybrid SEM-neural network approach. *Front Public Health* 2022; 10: 1–14.

8. Reyes-Mercado P. Adoption of fitness wearables. *Journal of Systems and Information Technology* 2018; 20: 103–127.

9. Hoque M, Alam M and Nahid K. Health consciousness and its effect on perceived knowledge, and belief in the purchase intent of liquid milk: consumer insights from an emerging market. *Foods* 2018; 7: 150.

10. Binyamin SS and Hoque MR. Understanding the drivers of wearable health monitoring technology: an extension of the unified theory of acceptance and use of technology. *Sustainability* 2020; 12: 9605.

11. Talukder MS, Chiong R, Bao Y, et al. Acceptance and use predictors of fitness wearable technology and intention to recommend. *Industrial Management & Data Systems* 2019; 119: 170–188.

12. Dehghani M. Exploring the motivational factors on continuous usage intention of smartwatches among actual users. *Behav Inf Technol* 2018; 37: 145–158.

13. Asimakopoulos S, Asimakopoulos G and Spillers F. Motivation and user engagement in fitness tracking: heuristics for mobile healthcare wearables. *Informatics* 2017; 4: 5.

14. Lee SM and Lee DH. Healthcare wearable devices: an analysis of key factors for continuous use intention. *Service Business* 2020; 14: 503–531.

15. Siepmann C and Kowalczuk P. Understanding continued smartwatch usage: the role of emotional as well as health and fitness factors. *Electron Mark* 2021; 31: 795–809.

16. Sergueeva K, Shaw N and Lee SH. Understanding the barriers and factors associated with consumer adoption of wearable technology devices in managing personal health. *Canadian Journal of Administrative Sciences / Revue Canadienne des Sciences de L'Administration* 2020; 37: 45–60.

17. Hayat N, Zainol NR, Salameh AA, et al. How health motivation moderates the effect of intention and usage of wearable medical devices? An empirical study in Malaysia. *Front Public Health* 2022; 10: 1–13.

18. Kao Y-S, Nawata K and Huang C-Y. An exploration and confirmation of the factors influencing adoption of IOT-based wearable fitness trackers. *Int J Environ Res Public Health* 2019; 16: 3227.

19. Wang H, Tao D, Yu N, et al. Understanding consumer acceptance of healthcare wearable devices: an integrated model of UTAUT and TTF. *Int J Med Inf* 2020; 139: 104156.

20. Asadi S, Abdullah R, Safaei M, et al. An integrated SEM-neural network approach for predicting determinants of adoption of wearable healthcare devices. *Mobile Information Systems* 2019; 2019: 1–9.

21. *Wearable Healthcare Devices Market by Product (Trackers, Smartwatch)*. Type (Diagnostic (BP, Glucose, ECG), Therapeutic (Pain, Insulin)), Grade (Consumer, Clinical), Channel (Pharmacies, E-commerce), Application (Fitness, RPM), & Region - Global Forecast to 2026. Market and Markets, https://www.marketsandmarkets.com/Market-Reports/wearable-medical-device-market-81753973.html#:~:text=The%20global%20wearable%20healthcare%20devices,13.2%25%20from%202021%20to%202026. (2021, accessed 19 March 2023).

22. *Most common uses for wearable tech in Malaysia in 2022*. Statista, https://www.statista.com/statistics/1053213/malaysia-most-common-uses-for-wearable-tech/ (2023, accessed 19 March 2023).

23. *Health care Statistics*. Organization for Economic Co-operation and Development (OECD), https://www.oecd.org/countries/malaysia/fostering-competition-in-asean.htm (2020, accessed 19 March 2023).

24. *Healthcare in a Digital Economy*. Reimagining the future of health tech in Malaysia. PWC Malaysia. Healthcare in a Digital Economy, https://www.pwc.com/my/en/publications/2021/healthcare-in-a-digital-economy.html (2021, accessed 19 March 2023).

25. Li J, Ma Q, Chan AHS, et al. Health monitoring through wearable technologies for older adults: smart wearables acceptance model. *Appl Ergon* 2019; 75: 162–169.

26. Niknejad N, Hussin AR, Ghani I, et al. A confirmatory factor analysis of the behavioral intention to use smart wellness wearables in Malaysia. *Univers Access Inf Soc* 2020; 19: 633–653.

27. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Q* 1989; 13: 319.

28. Yang Q, Al Mamun A, Hayat N, et al. Modeling the intention and adoption of wearable fitness devices: a study using SEM-PLS analysis. *Front Public Health* 2022; 10: 1–12.

29. Dutta-Bergman MJ. Primary sources of health information: comparisons in the domain of health attitudes, health cognitions, and health behaviors. *Health Commun* 2004; 16: 273–288.

30. Huang Z, Zhu Y-D, Deng J, et al. Marketing healthy diets: the impact of health consciousness on Chinese consumers' food choices. *Sustainability* 2022; 14: 2059.

31. Alam MZ, Hoque MR, Hu W, et al. Factors influencing the adoption of mHealth services in a developing country: a patient-centric study. *Int J Inf Manage* 2020; 50: 128–143.

32. Yang Q, Mamun A, Hayat A, et al. Modelling the mass adoption potential of wearable medical devices. *PLOS ONE* 2022; 17: 1–18.

33. Yu S and Lee J. The effects of consumers' perceived values on intention to purchase upcycled products. *Sustainability* 2019; 11: 1034.

34. Arifah ID and Juniarti RP. Interface aesthetic, perceived value, perceived ease of use, and perceived usefulness on purchase intention of smartwatch consumers. *Proceedings of the*

International Conference on Business and Engineering Management (ICONBEM 2021) 2021; 177: 25–33.

35. Cavdar Aksoy N, Kocak Alan A, Tumer Kabadayi E, et al. Individuals' intention to use sports wearables: the moderating role of technophobia. *International Journal of Sports Marketing and Sponsorship* 2020; 21: 225–245.

36. Cheung ML, Chau KY, Lam MH, et al. Examining consumers' adoption of wearable healthcare technology: the role of health attributes. *Int J Environ Res Public Health* 2019; 16: 2257.

37. Beh PK, Ganesan Y, Iranmanesh M, et al. Using smartwatches for fitness and health monitoring: the UTAUT2 combined with threat appraisal as moderators. *Behav Inf Technol* 2021; 40: 282–299.

38. Gao Y, Li H and Luo Y. An empirical study of wearable technology acceptance in healthcare. *Industrial Management & Data Systems* 2015; 115: 1704–1723.

39. Faul F, Erdfelder E, Lang A-G, et al. G*power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behav Res Methods* 2007; 39: 175–191.

40. Hair JF, Matthews LM, Matthews RL, et al. PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis* 2017; 1: 107–123.

41. Podsakoff PM, MacKenzie SB and Podsakoff NP. Sources of method bias in social science research and recommendations on how to control it. *Annu Rev Psychol* 2012; 63: 539–569.

42. Kock N. Common method bias in PLS-SEM. *Int J e-Coll* 2015; 11: 1–10.

43. Hair JF, Hult GT, Ringle CM, et al. Partial least squares structural equation modeling (PLS-SEM) using R. *Classroom Companion: Business* 2021.

44. Cain MK, Zhang Z and Yuan K-H. Univariate and multivariate skewness and kurtosis for measuring nonnormality: prevalence, influence and estimation. *Behav Res Methods* 2017; 49: 1716–1735.

45. Chin WW. How to write up and report PLS analyses. *Handbook of Partial Least Squares* 2009; 1: 655–690.

46. Abdullah Z, Putri KY, Raza SH, et al. Contrariwise obesity through organic food consumption in Malaysia: a signaling theory perspective. *BMC Public Health* 2022; 22: 1–18.

Appendix 1. Discriminant validity

	HCS	1PCM	PPV	PTA	PUF	HMT	IWFD	UWFD
Fornell–Larcker criterion								
HCS	0.712							
PCM	0.648	0.888						
PPV	0.526	0.580	0.823					
PTA	0.560	0.644	0.676	0.856				
PUF	0.662	0.662	0.630	0.741	0.886			
HMT	0.346	0.246	0.468	0.187	0.242	0.906		
IWFD	0.606	0.661	0.629	0.723	0.785	0.162	0.880	
UWFD	−0.176	−0.177	0.032	−0.081	−0.208	0.128	−0.243	1.000
HTMT ratio								
HCS	-							
PCM	0.865							
PPV	0.704	0.633						
PTA	0.721	0.671	0.775					
PUF	0.853	0.713	0.696	0.803	-			
HMT	0.485	0.278	0.542	0.259	0.261	-		
IWFD	0.776	0.707	0.688	0.769	0.853	0.187	-	
UWFD	0.217	0.178	0.052	0.130	0.219	0.112	0.252	-
Cross loading table								
HCS1	*0.724*	0.414	0.399	0.478	0.542	0.133	0.436	−0.093
HCS2	*0.830*	0.518	0.362	0.427	0.572	0.229	0.501	−0.139
HCS3	*0.785*	0.412	0.388	0.349	0.427	0.249	0.465	−0.168
HCS4	*0.448*	0.558	0.372	0.350	0.312	0.463	0.297	−0.093
PCM1	0.561	*0.884*	0.478	0.571	0.552	0.239	0.538	−0.104
PCM2	0.567	*0.924*	0.522	0.573	0.589	0.218	0.592	−0.165
PCM3	0.614	*0.903*	0.531	0.623	0.644	0.221	0.647	−0.239
PCM4	0.495	*0.799*	0.508	0.477	0.465	0.178	0.491	−0.080
PCM5	0.627	*0.925*	0.535	0.602	0.664	0.233	0.646	−0.174

PPV1	0.262	0.306	*0.631*	0.412	0.360	0.269	0.353	0.080
PPV2	0.426	0.484	*0.810*	0.571	0.488	0.430	0.480	0.050
PPV3	0.493	0.577	*0.900*	0.640	0.626	0.430	0.586	−0.021
PPV4	0.486	0.487	*0.885*	0.595	0.520	0.379	0.523	0.020
PPV5	0.458	0.493	*0.862*	0.546	0.557	0.401	0.600	0.028
PTA1	0.228	0.223	0.579	*0.853*	0.374	0.521	0.309	0.145
PTA2	0.517	0.562	0.550	*0.933*	0.662	0.126	0.629	−0.078
PTA3	0.578	0.661	0.675	*0.899*	0.742	0.128	0.736	−0.112
PTA4	0.496	0.614	0.566	*0.922*	0.684	0.113	0.644	−0.081
PTA5	0.488	0.572	0.576	*0.893*	0.632	0.124	0.668	−0.110
PUF1	0.591	0.532	0.527	0.658	*0.890*	0.231	0.712	−0.147
PUF2	0.592	0.682	0.599	0.687	*0.859*	0.246	0.666	−0.181
PUF3	0.629	0.612	0.582	0.631	*0.896*	0.193	0.750	−0.206
PUF4	0.528	0.522	0.523	0.655	*0.901*	0.188	0.648	−0.205
HMT1	0.257	0.238	0.454	0.138	0.187	*0.866*	0.166	0.040
HMT2	0.311	0.178	0.350	0.130	0.210	*0.935*	0.109	0.147
HMT3	0.351	0.288	0.531	0.242	0.251	*0.916*	*0.198*	0.107
IWFD1	0.504	0.517	0.520	0.545	0.660	0.136	*0.841*	−0.283
IWFD2	0.588	0.578	0.560	0.619	0.750	0.184	*0.923*	−0.220
IWFD3	0.548	0.553	0.528	0.637	0.720	0.151	*0.920*	−0.238
IWFD4	0.453	0.580	0.533	0.724	0.620	0.095	*0.805*	−0.115
IWFD5	0.568	0.679	0.623	0.663	0.701	0.144	*0.907*	−0.211
UWFD	−0.176	−0.177	0.032	−0.081	−0.208	0.128	−0.243	*1.000*

HCS: health consciousness; HMT: health motivation; PCM: perceived compatibility; PPV: perceived product value; PUF: perceived usefulness; PTA: perceived technology accuracy; IWFD: intention to use WFDs; UWFD: use of WFDs.
Source: Author's data analysis.