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Understanding the Drivers of Wearable Health Monitoring Technology: An Extension of the Unified Theory of Acceptance and Use of Technology

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Abstract: The market for wearable health monitoring technology is promising globally and in Saudi Arabia particularly. The country has a very high prevalence of chronic diseases that can be managed using wearable health monitoring technology. However, wearable devices are not fully advantageous if people do not accept them. Due to the parsimony of studies on the acceptance of wearable health monitoring technology, understanding the key drivers of using wearable health monitoring technology remains uncertain. This cross-sectional study extends the extended unified theory of acceptance and use of technology (UTAUT2) to explain the variance in the adoption intention of wearable health monitoring technology. A total of 256 responses were analyzed using the partial least squares structural equation modeling technique, in addition to the importance-performance map analysis. The results indicate that performance expectancy (PE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM) and habit (HA) significantly impact users' behavioral intention (BI) to adopt wearable health monitoring technology. The results also demonstrate that effort expectancy (EE), price value (PV), government health policy (GHP) and trust (TR) are not important. Based on the findings, this research presents a set of recommendations for decisions makers, managers and system developers in the healthcare sector to enhance the use and quality of wearable technology.

Keywords: wearable health monitoring technology; UTAUT2; technology acceptance; developing country; Saudi Vision 2030

1. Introduction

With the recent developments in information and communication technology, new healthcare innovations have emerged to fulfill the needs of patients, such as wearable devices. Wearable health monitoring technology, including smartwatches, fitness bands, eyewear and earwear, is being increasingly used for monitoring health conditions by tracking vital signs, medicine actions and even physiological states. These devices are equipped with sensors, actuators, global positioning systems and accelerometers for continuous health monitoring and location tracking and feedback on a real-time basis [1]. While younger people use wearable health monitoring technology mostly for improving their fitness efficiency, the uses of wearables for older people are extended for monitoring neuropathic pain, muscle degeneration, fall identification and prevention, mental status monitoring and other serious conditions, such as chronic obstructive pulmonary disease, hypoglycemia and heart attack [2]. The introduction of wearable health monitoring technology has added more control to patients, and its standards meet clinical requirements. The emergence of wearable health monitoring technology has provided users with anywhere-anytime access to their personal information, which is an important feature for the younger generation [3]. Consequently, the advantages of wearable health monitoring technology are not limited to the expenditure reduction of healthcare; wearable health monitoring technology can also contribute directly to clinical decision-making [4].

The global market for wearable devices has received a great deal of attention [1]. A recent report published by Business Insider underlines that wearable health monitoring technology can improve the efficiency of a workout by up to 20%, and nearly 80% of people who do not use wearable health monitoring technology would like to use it for maintaining their fitness [5]. Furthermore, the use of wearable health monitoring technology grew from 9% to 33% in four years [5]. Global Data, a renowned United Kingdom (UK)-based data-driven company, has projected the wearables industry sector to reach $54 billion by 2023, following compound growth of 19% annually [6].

Saudi Arabia has been identified as one of the most promising markets for wearable devices, such as wristwear, bodywear and footwear [7]. The market size for wearable health monitoring technology in Saudi Arabia is expected to reach $61 million by 2024 [8]. Around 14% of those who use healthcare technology in Saudi Arabia (84%) use wearable health monitoring technology for health management [9]. The country has a very high prevalence of chronic diseases such as diabetes, hypertension, heart disease and obesity [10]. For instance, according to the Ministry of Health in Saudi Arabia, 60% of residents suffer from obesity [11]. Furthermore, Saudi Vision 2030 has launched an electronic health program that supports various digital transformation initiatives in the Saudi healthcare sector, focusing on improving the effectiveness of the healthcare sector through information technology and digital transformation [11]. The Government of Saudi Arabia is keen to reduce the cost of healthcare by adopting digital technologies to curb the prevalence of chronic-disease-related complications across the kingdom. Thus, the scope for growth in the wearable technology market displays significant signs of future success.

Despite the potential advantages and promising global market, wearable health monitoring technology is not fully beneficial if users do not recognize its value and accept it [1]. Obstacles remain regarding the acceptance of wearable health monitoring technology. For example, wearable health monitoring technology manufacturers use sensors and internet-of-things technology to collect and share the device-generated sensitive data, such as users' learning moods, mental condition, food habits, sleeping patterns, workout and mobility. Thus, privacy and trust concerns are a possible challenge regarding the acceptance of wearable health monitoring technology. These concerns can adversely influence user perception toward the value of wearable health monitoring technology and its acceptance. In this respect, only a limited number of academic attempts (see Section 2) have tried to respond to this issue by investigating the acceptance of wearable health monitoring technology [3,12–14]. This parsimony is plausible as wearable technology is a relatively new technology. Nevertheless, the majority of these studies [3,12,13,15] used the technology acceptance model (TAM) as a theoretical framework for their own proposed models. Furthermore, although the influence of both government health policies (GHPs) and trust (TR) regarding users' behavioral intention (BI) has been demonstrated in information systems, none of these studies incorporated the two constructs to measure quantitatively their effect on user BI to use wearable health monitoring technology. Addressing this gap, this present research considers contextual differences and proposes a model based on the extended unified theory of acceptance and use of technology (UTAUT2) to fill the knowledge gap and investigate which factors contribute to the acceptance of wearable health monitoring technology from the perception of Saudi users. The results will facilitate the ubiquitous use and acceptance of wearable health monitoring technology.

This research contributes to the existing literature in multiple ways. First, this study uses the UTAUT2 as a theoretical framework to explain the acceptance of wearable health monitoring technology. This has been disregarded by researchers. Second, the authors propose a novel model by extending the UTAUT2 and adopting two factors related to wearable health monitoring technology: GHP and TR.

Finally, a multi-stage approach was utilized to identify the key determinants of BI to use wearable health monitoring technology, the partial least squares structural equation modeling (PLS-SEM) technique and Importance-performance map analysis (IPMA).

This paper is organized as follows: first, literature related to the adoption of wearable health monitoring technology is presented. The research model is proposed in Section 3, followed by Section 4, which focuses on the research methodology. Sections 5 and 6 contain the research findings and discussion. Finally, the implications, limitations and conclusion are presented in Sections 6–8, respectively.

2. Literature Review

While the demand for wearable health monitoring technology continues to grow, most researchers have responded by mainly focusing on the establishment, design and accuracy of wearable health monitoring technology [13,14]. However, a small number of researchers have employed technology-acceptance models to examine the acceptance of wearable health monitoring technology in the past few years. Table 1 summarizes the research conducted in different contexts, including the technology under investigation, theory used and country/region.

Table 1. Studies on the acceptance of wearable health monitoring technology.

Study	Technology	Theory Base	Country
[1]	Wearable health monitoring technology	UTAUT	USA
[3]	Wearable health monitoring technology	TAM	Korea
[12]	Wearable health monitoring technology	TAM	China
[13]	Wearable fitness technology	TAM	USA
[14]	Wearable fitness technology	UTAUT2 + DOI	China
[15]	Wearable devices	UTAUT	China
[16]	Wearable cardiac warming	TAM	Taiwan
[17]	Wearable health monitoring technology	Undefined	China
[18]	Wearable health monitoring technology	UTAUT	China
[19]	Wearable health monitoring technology	UTAUT2	China

UTAUT: unified theory of acceptance and use of technology; TAM: technology-acceptance model; UTAUT2: extended unified theory of acceptance and use of technology; DOI: diffusion of innovation theory.

Reviewing existing studies revealed that researchers have overlooked the acceptance of wearable health monitoring technology. This lack could be attributed to the recent development of wearable health monitoring technology. Furthermore, although a small number of studies have been conducted to explain the acceptance of wearable health monitoring technology, most investigations were carried out in North America and East Asia. Developing and Arab countries, such as Saudi Arabia, are under-researched. Thus, the acceptance of wearable health monitoring technology remains uncertain; therefore, it is necessary to conduct further research to explain the factors that influence the use of wearable health monitoring technology.

Moreover, several studies listed in Table 1 did not improve the original models regarding adopting technology-related factors. See Table 1, for example, Dai et al., who used the unified theory of acceptance and use of technology (UTAUT) model to examine factors that affect the acceptance of wearable devices by patients with dementia [15]. Extending technology-acceptance models with additional variables is beneficial for understanding constructs that influence the acceptance of wearable health monitoring technology and for explaining greater variance in the output constructs.

On the other hand, some studies have extended technology-acceptance models with external factors, such as compatibility [12,14] social risk [12], privacy risk [1,17], technology anxiety [15,16], innovativeness [3,14,17] and resistance to change [15,16]. However, although the influence of GHP and TR on user behavior has been demonstrated in the literature regarding the acceptance of information systems in the health sector [20], the effects of these factors on the acceptance of wearable health monitoring technology have yet to receive sufficient attention from researchers. Thus, in this research, we bridge the gap and extend the UTAUT2 to adopt two additional factors: GHP and TR.

3. Theoretical Framework

A handful number of technology-acceptance models have been utilized by researchers to investigate the acceptance of information systems, such as the theory of reasoned actions, the diffusion of innovation theory (DOI), the theory of planned behavior, the TAM, the augmented TAM and the UTAUT. Therefore, it is important to select the appropriate theory or model as a theoretical basis to best explain user behavior toward the technology under investigation [21]. To provide answers for the research questions, this study proposes a theoretical framework based on the UTAUT2 due to its higher explanatory power to examine the acceptance of wearable health monitoring technology.

The UTAUT model was developed based on a comprehensive examination of eight technology-acceptance models to propose a unified view for technology acceptance [22]. It was theorized that user BI to use a new technology is influenced by four constructs: performance expectancy (PE), effort expectancy (EE), social influence (SI) and facilitating conditions (FC). Venkatesh et al. extended the UTAUT and adopted three additional determinants: hedonic motivation (HM), price value (PV) and habit (HA) [23]. They conclude that the UTAUT2 can explain as much as 74% of variance in BI and 52% in actual behavior. As stated in previous literature, research on using the UTAUT2 to test the acceptance of wearable health monitoring technology remains incomplete. Moreover, the application of the UTAUT2 in specific information system fields requires further modifications and revisions, as suggested by Venkatesh et al. [23]. Therefore, the constructs of the UTAUT2 are included in this research.

The UTAUT2 was adopted in this study as the main theoretical framework for multiple reasons. First, previous research on information systems has demonstrated that the UTAUT2 achieved profound success, with a high explanatory power, in assessing factors that affect the acceptance of various technologies [14]. Second, the UTAUT2 includes a comprehensive core model that enables researchers to improve the model further by adding external factors related to the technology under investigation (e.g., wearable technology in healthcare) to measure their effect on BI [21]. In addition, the UTAUT2 has yet to receive sufficient attention from researchers regarding the acceptance of wearable health monitoring technology (see Table 1), which necessitates further investigation to bridge this gap. Finally, the UTAUT2 was extended by adopting the constructs of DOI in an empirical study on the acceptance of wearable fitness technology by Talukder et al. [14]. Their research states that previous literature does not adequately explain the antecedents that affect the acceptance of wearable health monitoring technology, and they recommend including more external factors to extend the UTAUT2 and to understand better the acceptance of wearable health monitoring technology. Thus, to extend the UTAUT2, the authors of this present study included two external factors (GHP and TR) in addition to the core constructs of the UTAUT2.

The conceptual research model comprises three parts. The first part consists of the seven independent variables of the UTAUT2: PE, EE, SI, FC, HM, PV and HA. The second part of the model comprises the dependent variables of BI and actual use (AU). The third part comprises the two newly adapted constructs, namely government health policy (GHP) and trust (TR). The following subsections provide more information about the adapted constructs and the proposed hypotheses.

3.1. Performance Expectancy

Performance expectancy is a key construct in both the UTAUT and the UTAUT2. Venkatesh et al. described PE as the degree to which a person believes that using a specific technology will improve their performance [23]. In this study, PE refers to the extent to which users of wearable health monitoring technology think that using wearables enhances their performance to manage their health. In many studies, it has been empirically demonstrated that PE is an important predictor for user BI regarding using various technologies, such as mobile health [21], electronic health records [24] and mobile banking [25]. Compared with other constructs, the description of PE is similar to the perceived usefulness construct in the TAM, the TAM2, the TAM3 and the augmented TAM. Therefore, the following hypothesis is posited to understand how PE impacts user BI to use wearable health monitoring technology:

Hypothesis 1 (H1). *PE has a positive effect on the BI to use wearable health monitoring technology.*

3.2. Effort Expectancy

The factor of perceived ease of use was initially developed by the TAM as a strong predictor for BI, and has since been introduced in later versions of the TAM, such as the TAM2, the TAM3, the augmented TAM and the UTAUT. In the UTAUT2, EE refers to the degree to which a person believes that using a specific technology will not require considerable effort [23]. Venkatesh et al. have provided evidence of how EE impacts user BI to use technology [23]. This finding indicates that users usually prefer a technology that requires little effort. Multiple studies on the acceptance of wearable health monitoring technology have revealed that EE positively influences user BI to use wearable health monitoring technology [14,15,19]. Therefore, it is expected that when users perceive wearables as easy to use, they are more likely to intend to use them. To test the effect of EE on BI, the following hypothesis is proposed:

Hypothesis 2 (H2). *EE has a positive effect on the BI to use wearable health monitoring technology.*

3.3. Social Influence

Social influence refers to the degree to which a person believes that important people think they should use a specific technology [23]. Alternatively, a person might experience pressure from individuals who are important to them, and thus, this pressure may influence the engagement in a specific action [22]. Such individuals can be parents, relatives, friends, co-workers, family and media [25]. The term SI has been used differently among researchers, such as subjective norm and social norm. The significant effect of SI on user BI to use technology has been proven in various technology-acceptance theories, such as the theory of reasoned action, the theory of planned behavior, the TAM2, the augmented TAM, the TAM3 and the UTAUT. Based on the strong influence of SI on user BI as observed in previous literature, the following hypothesis is proposed:

Hypothesis 3 (H3). *SI has a positive effect on the BI to use wearable health monitoring technology.*

3.4. Facilitating Conditions

Facilitating conditions is a key construct in both the UTAUT and the UTAUT2. Venkatesh et al. described FC as the degree to which a person believes that organizational resources are available to facilitate the use of technology [23]. In this study, FC indicates that the resources and knowledge necessary to use wearable health monitoring technology are available for users. Facilitating conditions was found to be a necessary antecedent of user BI to use wearable health monitoring technology [12,15]. For example, Dai et al. investigated factors that affect caregivers' acceptance of wearable health monitoring technology in China, and demonstrated a significant relationship between FC and BI [15]. Compared with other factors, FC might be more important for determining user BI considering that wearable devices might depend on the support of wireless networks and internet service providers to transfer a large number of health-monitoring data [12]. Following the UTAUT and the UTAUT2, the authors propose the following hypothesis:

Hypothesis 4 (H4). *FC has a positive effect on the BI to use wearable health monitoring technology.*

3.5. Hedonic Motivation

Hedonic motivation refers to the degree to which a person believes that using a specific technology would be fun. The term HM has been used differently among researchers, such as for perceived enjoyment. According to Venkatesh et al. [23], HM plays a direct role in user BI to accept information systems. Regarding the acceptance of wearable health monitoring technology, multiple studies have empirically agreed with this theory [18,19]. Hedonic motivation is a fundamental determinant in the acceptance of wearable health monitoring technology because wearable devices are considered to be different from other types of healthcare technologies in terms of usage purpose, methods and functions [18]. These devices are not only developed for health-related advantages, but also to improve social communication and enjoyment [19]. Based on this argument, the following hypothesis is proposed:

Hypothesis 5 (H5). *HM has a positive effect on the BI to use wearable health monitoring technology.*

3.6. Price Value

Price value is defined as a person's trade-off between the benefits of a certain technology and the monetary cost of using that technology [23]. The monetary cost of wearable health monitoring technology is associated with the need for a wearable device and internet connectivity (for some types). Venkatesh et al. asserted that PV is a significant predictor for user BI to use information systems, indicating that users are more likely to use products with good PV [23]. Despite the potential advantages of wearable health monitoring technology, some wearable devices are considered expensive for those with a low income [19]. Hence, we assume that when users think that wearable technology offers greater benefit than its cost, users are more likely to adopt wearable devices. To test the effect of PV on BI, the following hypothesis is proposed:

Hypothesis 6 (H6). *PV has a positive effect on the BI to use wearable health monitoring technology.*

3.7. Habit

Habit refers to the degree to which a person believes that using a specific technology is automatic because of learning or experience [23]. Thus, when an individual performs a certain behavior more frequently, HA is developed. Consistent with the UTAUT2, HA has been endorsed as a significant determinant of technology acceptance in various domains, such as mobile health [21], electronic health records [24] and mobile banking [25]. However, the effect of HA on the acceptance of wearable health monitoring technology is still not well established. For example, Talukder et al. examined the acceptance of fitness wearable technology by Chinese users and empirically disproved this effect [14]. To uncover this ambiguity, the following hypotheses are postulated in this study:

Hypothesis 7 (H7). *HA has a positive effect on the BI to use wearable health monitoring technology.*

Hypothesis 8 (H8). *HA has a positive effect on the AU to use wearable health monitoring technology.*

3.8. Government Health Policy

Although some researchers have addressed GHP as a strong influential factor in the acceptance of healthcare information systems [26–28]. the effect of GHP on the acceptance of wearable health monitoring technology remains uncertain. The construct of GHP refers to the extent to which official authorities have developed policies to support and allocate resources for the acceptance of wearable health monitoring technology [29]. Government health policy has played an important role in the use of technology in the healthcare industry in many countries. For example, Ahmadi et al. found that GHP is the most influential factor for adopting healthcare information systems in Malaysia [28]. Gagnon et al. examined factors that impact the acceptance of electronic health records by physicians in Canada [27]. They recommended future researchers to investigate factors that influence the use of health-related technologies at macro levels, such as GHP. Thus, this research adapts the construct of GHP into the UTAUT2 to explain the acceptance of wearable health monitoring technology and posits the following hypothesis:

Hypothesis 9 (H9). *GHP has a positive effect on the BI to use wearable health monitoring technology.*

3.9. Trust

Trust means the willingness of a person to rely on an exchange partner in which they have confidence to share sensitive information [30]. In this study, TR indicates the general beliefs in the good intention, efficiency and reliability of wearable health monitoring technology [31]. Trust has been identified as a crucial factor that plays an important role in the acceptance of healthcare technology [21]. This aspect is also considered the most significant factor for predicting the adoption of mobile health [32]. Addressing the TR concern becomes even more complicated when data are outsourced in cloud servers for analysis and processing. Users usually hesitate to use web-based services as they do not know the providers and are reluctant to share their information for irresponsible use. Thus, research suggests that the use of healthcare information systems depends on TR, and that a lack of TR is a barrier to its wide adoption [33]. Using the TAM, Asadi et al. proposed a model to examine the acceptance of wearable health monitoring technology in Malaysia and found a positive relationship between TR and BI [34]. The effects of TR might differ greatly because of the contextual difference (e.g., social norms). This indicates that TR may influence the acceptance of wearable health monitoring technology in Saudi Arabia differently compared with other contexts because of differences in social and cultural norms. Consistent with previous studies, the authors of this research expect that, when users trust wearable technology, it is more likely to enhance their intention to use this innovation. Therefore, the following hypotheses are proposed:

Hypothesis 10 (H10). *TR has a positive effect on the BI to use wearable health monitoring technology.*

Hypothesis 11 (H11). *BI has a positive effect on the AU of wearable health monitoring technology.*

4. Materials and Methods

4.1. Measurement of Constructs

To examine the proposed hypotheses, an online survey via Google Forms [35] was conducted that covers all the variables in the conceptual model of the research. All the indicators were adopted from previously published studies and were slightly updated to become appropriate for the context of wearable health monitoring technology. More details about the indicators of each construct and their sources are presented in Appendix A.

4.2. Instrument Development

This study is quantitative in nature, as is the majority of research on technology acceptance (see for example [3,12,13,15]). The data were collected through online surveys. The questionnaire consists of two sections. Section A focuses on user demographic information in a multiple-choice format, including gender, age, education, marital status and health condition. The respondents were asked to select the choice that best represented their health condition: excellent, very good, good, fair and poor. Section B contains 38 positive statements that symbolize the constructs included in the UTAUT2 and the two newly added constructs, namely GHP and TR. The constructs were measured using a five-point

Likert scale, in which 1 stands for strongly disagree and 5 stands for strongly agree. The items in the questionnaire were adopted from various studies about the UTAUT2 and the additional factors mentioned above.

The questions in the survey were initially developed in the English language. As this research targeted users of wearable health monitoring technology in the Kingdom of Saudi Arabia, where Arabic is the first language, it was necessary to translate the questions into Arabic. The back-translation method [36] was utilized to translate the online survey from English into Arabic by hiring two faculty members who are native Arabic speakers, fluent in English and have expertise in questionnaire development to guarantee the same meaning and originality. The first faculty member translated the questions from English into Arabic, and the second faculty member translated the questions back into English. This step was important to ensure that the participants understood the survey questions and were not excluded because of language barriers.

4.3. Data Collection

This study targeted those users who have experience with wearable health monitoring technology in the Kingdom of Saudi Arabia. Following the vast majority of studies on technology acceptance (see for example [3,12,13,16]), a non-probability convenience sampling technique was employed to collect data from the target population. Concerning the recruitment of participants, electronic invitations were sent via social media and WhatsApp mobile application groups. In the electronic invitations, the respondents were asked to contribute to this research, and the online link to the questionnaire was attached. The questionnaire was available for two weeks. In terms of ethical considerations, online informed consent was collected from all participants at the beginning of the questionnaire. Furthermore, ethical approval for the survey was obtained from the Deanship of Scientific Research, King Abdulaziz University (No. J: 57-156-1441). A total of 282 responses were received from participants. The authors conducted a preliminary examination to monitor data and to ensure that model testing did not include outliers, missing data and unengaged responses. This study benefits from utilizing the standard deviation to detect unengaged responses and straight lining patterns. Responses with a score of 0 were considered as suspicious responses and not completely engaged in the questionnaire. Thus, 26 responses were removed during the preliminary examination, and 256 responses were used for data analysis.

The demographic information of participants is listed in Table 2. The analysis of socio-demographic characteristics indicates that the majority of participants are female (59%). Most respondents (29%) are aged between 36 to 45 years. About 83% of participants reported that their health condition is either excellent or very good. In terms of education, 86% of respondents have a university degree.

Table 2. Demographic characteristics for the sample.

Characteristics	Groups	Frequency	Percentage
Gender	Male	105	41
	Female	151	59
Age	18 to 25	68	27
	26 to 35	79	31
	36 to 45	74	29
	46 and above	35	14
Education	Diploma	24	9
	Bachelor's	109	43
	Master's	58	23
	Doctoral	51	20
	Other	14	5

Table 2. *Cont.*

Characteristics	Groups	Frequency	Percentage
Marital status	Single	105	41
	Married	130	51
	Widowed	6	2
	Divorced or separated	15	6
Health condition	Excellent	110	43
	Very good	103	40
	Good	36	14
	Fair	6	2
	Poor	1	1

4.4. Data Analysis

Our investigation utilized the multivariate PLS-SEM technique via SmartPLS software 3 [37] to examine the proposed model and test the accuracy of the relationships between the input and output variables. This technique has been widely used for hypothesis testing and theory validation [38]. Furthermore, PLS-SEM is characterized by its flexibility regarding data distribution and the requirement of a small sample size [39].

Data were analyzed in several stages. First, the collected data were exported from Google Forms [35] into Microsoft Office Excel [40] to assign an identification number to each case and to encode the data. To ensure the validity of multivariate analysis [41], a preliminary examination of the data via Statistical Package for the Social Sciences (SPSS) [42] was conducted, including outliers, missing data and unengaged responses. In the third stage, the PLS algorithm was used to assess the reliability and validity of the measures. Then, the bootstrapping algorithm was run for hypothesis testing. Finally, an IPMA was executed to identify the key determinants that highly impact user BI to use wearable health monitoring technology.

5. Results

5.1. Measurement Model Assessment

The measurement model was examined by evaluating indicator reliability, construct reliability, convergent validity and discriminant validity [39]. This assessment is crucial, as the path analysis conducted in the next phase has no value if the measurement model assessment does not meet the cut-off values of reliability and validity [43]. Table 3 summarizes the results of the measurement model assessment. The authors assessed the reliability of indicators through their loadings, and all indicators achieved the recommended value of 0.6 [38]. The construct reliability was measured in terms of composite reliability and Cronbach's alpha coefficient, in which a value of 0.7 or higher is acceptable [39]. The values of composite reliability range from 0.870 to 0.953, whereas the Cronbach's alpha coefficient values range from 0.802 to 0.925. Thus, the results in Table 3 indicate that the construct reliability is established for the proposed model. The convergent validity is supported as the scores of the average variance extracted (AVE) are above the threshold of 0.5 [44]. One way to evaluate the discriminant validity in SmartPLS [37] is the heterotrait-monotrait ratio (HTMT) [45], representing the scores for the construct's correlation with the other constructs. The values of the HTMT presented in Table 4 do not exceed the recommended value of 0.9, which assures the discriminant validity among the 11 constructs [45]. Thereby, the results of this assessment provide evidence of the reliability and validity of the measurement model.

Table 3. Measurement model assessment.

Constructs	Indicators	Loadings	CR	Cronbach's Alpha	AVE
Actual use (AU)	AU1 AU2 AU3	0.864 0.891 0.851	0.902	0.837	0.754
Behavioral intention (BI)	BI1 BI2 BI3	0.939 0.842 0.934	0.932	0.892	0.821
Effort expectancy (EE)	EE1 EE2 EE3 EE4	0.876 0.892 0.894 0.822	0.927	0.895	0.760
Facilitating conditions (FC)	FC1 FC2 FC3 FC4	0.821 0.885 0.903 0.690	0.897	0.845	0.688
Government health policy (GHP)	GHP1 GHP2 GHP3	0.820 0.879 0.870	0.892	0.822	0.734
Habit (HA)	HA1 HA2 HA3	0.949 0.870 0.939	0.943	0.909	0.846
Hedonic motivation (HM)	HM1 HM2 HM3	0.916 0.950 0.933	0.953	0.925	0.870
Performance expectancy (PE)	PE1 PE2 PE3 PE4	0.854 0.774 0.895 0.912	0.919	0.882	0.741
Price value (PV)	PV1 PV2 PV3	0.805 0.914 0.919	0.912	0.857	0.776
Social influence (SI)	SI1 SI2 SI3 SI4	0.806 0.800 0.822 0.737	0.870	0.802	0.627
Trust (TR)	TR1 TR2 TR3 TR4	0.746 0.697 0.885 0.868	0.878	0.819	0.645

CR: Composite reliability, AVE: average variance extracted.

Table 4. Heterotrait-monotrait ratio.

	AU	BI	EE	FC	GHP	HA	HM	PE	PV	SI
BI	0.746									
EE	0.414	0.430								
FC	0.588	0.644	0.713							
GHP	0.318	0.428	0.226	0.358						
HA	0.878	0.667	0.308	0.475	0.384					
HM	0.646	0.612	0.410	0.522	0.392	0.513				
PE	0.628	0.650	0.469	0.514	0.340	0.631	0.616			
PV	0.628	0.501	0.251	0.516	0.289	0.610	0.486	0.394		
SI	0.595	0.681	0.313	0.503	0.453	0.684	0.497	0.639	0.447	
TR	0.215	0.300	0.274	0.292	0.499	0.285	0.233	0.344	0.360	0.326

5.2. Structural Model Assessment

The authors examined collinearity to ensure that there are no high correlations between constructs. Collinearity may cause interpretation issues and can be measured through the variance inflation factor (VIF) [39]. Table 5 presents the values of VIF below the threshold of 3.0, demonstrating that collinearity is not critical in the proposed model.

Table 5. Variance inflation factor.

Constructs	Actual Use	Behavioral Intention
Behavioral intention (BI)	1.606	
Effort expectancy (EE)		1.757
Facilitating conditions (FC)		2.079
Government health policy (GHP)		1.419
Habit (HA)	1.606	2.107
Hedonic motivation (HM)		1.759
Performance expectancy (PE)		2.021
Price value (PV)		1.678
Social influence (SI)		1.817
Trust (TR)		1.347

This research examines the relationships between the independent and dependent constructs by using path coefficients (β), t-value and p-value. This study benefits from utilizing the one-tailed option and a significance level of 0.05. As a result, hypotheses with a p-value above the value of 0.05 are considered insignificant [39]. In Table 6, the authors list the proposed hypotheses and the results of the path analysis. Seven relationships are significant.

Table 6. Hypothesis testing.

Hypotheses	β	t-Value	p-Value	Result
H1: PE—BI	0.137	2.270	0.024	Supported
H2: EE—BI	0.004	0.030	0.976	Not supported
H3: SI—BI	0.189	2.627	0.009	Supported
H4: FC—BI	0.231	2.508	0.012	Supported
H5: HM—BI	0.176	2.362	0.019	Supported
H6: PV—BI	0.026	0.516	0.606	Not supported
H7: HA—BI	0.212	3.262	0.001	Supported
H8: HA—AU	0.578	10.132	0.000	Supported
H9: GHP—BI	0.045	0.879	0.380	Not supported
H10: TR—BI	−0.001	0.050	0.960	Not supported
H11: BI—AU	0.308	4.399	0.000	Supported

β: path coefficient.

5.3. Importance-Performance Map Analysis

Importance-performance map analysis, also known as importance-performance matrix or priority map analysis, contrasts the independent constructs' importance (total effects) when predicting the target construct with the independent constructs' performance (average latent variable scores) [38]. The main objective of conducting IPMA is to address constructs that have a relatively low performance but a relatively high importance for improvement priorities [39]. This analysis is a useful approach for providing a simultaneous representation of both importance and performance in a two-dimensional matrix, in which importance is presented on the x-axis and performance is presented on the y-axis [46].

In this research, the authors ran IPMA to contrast the total effects (importance) of the independent constructs in determining the target construct (BI) with the performance of the independent constructs. Our objective is to draw useful conclusions about the examined factors in the proposed model by identifying constructs that have a relatively low performance but a relatively high importance in predicting the acceptance of wearable health monitoring technology. The results of this analysis indicate that PE, FC, HM and HA are important variables for predicting the acceptance of wearable health monitoring technology, as these achieved high total effects (importance) in comparison with the other constructs. Nevertheless, the performance of SI, PV and HA were lower than the other constructs.

6. Discussion

This current research proposed and empirically investigated a model that might be beneficial for predicting the acceptance of wearable health monitoring technology by users in Saudi Arabia. This research extends the UTAUT2 with two external constructs, namely GHP and TR. This section provides answers to the research question, which is concerned with the factors that influence the acceptance of wearable health monitoring technology. Our proposed model explains 57% variance (adjusted R2 = 0.57) in BI and 64% variance (adjusted R2 = 0.64) in the AU of wearable health monitoring technology. In our investigation, the acceptance of wearable health monitoring technology is significantly prejudiced by PE, SI, FC, HM and HA, indicating that 7 out of 11 path relationships in the proposed model are important. In contrast, EE, PV, GHP and TR do not appear to influence significantly the adoption of wearable health monitoring technology. Accordingly, H1, H3, H4, H5, H7, H8 and H11 are supported. The following insights are described, based on the results, to enhance the acceptance of wearable health monitoring technology.

In our research, it was assumed that PE has a positive effect on BI to use wearable health monitoring technology (H1). The results reveal that PE positively influences BI ($\beta = 0.137$, $p < 0.05$), and thus, H1 is supported. Therefore, users are driven by the usefulness provided by the technology, which is in accordance with technology-acceptance models, such as the TAM, the augmented TAM, the TAM2, the TAM3, the UTAUT and the UTAUT2. This result means that when wearable technologies help users to accomplish their healthcare activities more quickly, improve their access to their health information and improve their ability to manage their health, they are more likely to use wearables. Compared to other models in the healthcare field, the finding regarding PE conforms with other studies on the acceptance of wearable health monitoring technology [1,3,12,14]. If the usefulness of wearable health monitoring technology is not recognized, users may reject the technology and search for another, more useful technology. This effect can be attributed to wearable health monitoring technology being a relatively new technology and most users having little experience with it, and the effect of PE on BI is usually stronger for this type of user. This argument is aligned with technology-acceptance researches [47,48].

It was hypothesized that BI is positively influenced by the EE of wearable health monitoring technology (H2). This research provides evidence that EE does not impact BI ($\beta = 0.004$, $p = 0.976$); thus, H2 is not supported. Although this result might appear surprising, given that the UTAUT2 endorses a positive relationship between EE and BI, it is in accordance with past studies on the acceptance of wearable health monitoring technology [1,12,19]. For example, the acceptance of wearable technology for health monitoring was examined in China, and it was revealed that the ease of using wearables is not significant [12]. Similarly, the effect of EE on BI was not important in the acceptance of wearable technology for fitness monitoring [19]. One reasonable justification for this finding is that some wearable devices require no more effort than wearing them and observing the alerts, which is considered an easy task. Users can learn how to use wearable devices from social media and video tutorials with little effort. Talukder et al. conclude that when HM is significant, which is the case in this study, the importance of EE in the acceptance of wearable health monitoring technology is reduced [18]. Furthermore, Venkatesh et al. assert that when both PE and EE are significant, the importance of FC in predicting BI is reduced. In our case, when both PE and FC were significant, the importance of EE in predicting BI to use wearable health monitoring technology was diminished [22]. This effect might be attributed to the challenges related to the context of Saudi Arabia, such as awareness, availability and infrastructure [15].

The findings in this research demonstrate that SI is an important predictor for BI to use wearable health monitoring technology (β = 0.189, $p < 0.01$); thus, H3 is supported. This result means that users are motivated to use wearable health monitoring technology when people who are important to them or influence their behavior think that they should wearable technologies. This finding was expected as Saudi Arabia is considered a typical representative of those nations that have a high level of power distance and collectivism, which respect social hierarchy and group goals [49]. Therefore, SI has been considered as an important factor in the context of Saudi Arabia when measuring the acceptance of various technologies, such as e-learning [50]. The result indicates that without an obvious SI of wearables, BI to use wearable health monitoring technology is minimized, which, in turn, affects the AU of wearable technology. Following previous literature on the acceptance of wearable health monitoring technology [1,14,15,18,19], this finding implies that people who have a great influence on users can motivate the acceptance of wearable health monitoring technology. For instance, the acceptance of wearable devices by patients with dementia was examined using the UTAUT, and it was revealed that SI is one of the significant factors [15]. In the same line, the effect of SI on BI was important in the acceptance of wearable technology for fitness and medical monitoring [19].

The authors hypothesized that FC has a positive influence on BI (H4). It was found that FC has a significant effect on BI (β = 0.231, $p < 0.05$); thus, H4 is supported. More accurately, FC is the strongest predictor for BI to use wearable health monitoring technology among the other constructs. The result implies that the availability of resources, help, support and knowledge is necessary to motivate people to use wearable health monitoring technology. This confirms that the adoption of wearable health monitoring technology cannot be increased by only enhancing wearable technology itself, but requires the availability of resources and knowledge necessary to use wearable health monitoring technology. This result is supported by a number of studies on the acceptance of wearable health monitoring technology [12,16]. For example, the acceptance of wearable technology for health monitoring was examined using the TAM, and it was found that FC is important to motivate users [12]. Another study investigated the acceptance of wearable devices by patients with dementia using the UTAUT, and it was revealed that FC is one of the significant factors [15].

Another inference highlighted by the findings is the importance of HM in predicting the acceptance of wearable health monitoring technology. More specifically, HM is the second strongest predictor for BI to use wearable health monitoring technology among the other constructs (β = 0.176, $p < 0.05$). This finding suggests that the users of wearable health monitoring technology pay more attention to the fun and enjoyment element when deciding whether to use wearable health monitoring technology. Compared to other models in the healthcare field, this result is consistent with other studies on the acceptance of wearable health monitoring technology [18,19]. Using the UTAUT2, researchers examined the antecedents of wearable technology acceptance by Chinese users and empirically approved this relationship [18].

The results provide evidence of a positive effect of HA on the acceptance of wearable health monitoring technology. It was demonstrated that HA is a significant predictor for both BI (β = 0. 212, $p < 0.01$) and AU (β = 0.578, $p < 0.001$). When the use of wearable health monitoring technology becomes natural to users, they are more likely to use wearables. That is to say, the continuous use of wearable health monitoring technology turns into HA, as users feel the need to wear wearable health monitoring technology all the time to observe their health and fitness activities [14]. Thus, the acceptance of wearable health monitoring technology relies not only on functionality, but also on continuous use.

However, this research found no noteworthy relationships between three factors (PV, GHP and TR) and BI to use wearable health monitoring technology; thus, H6, H9 and H10 are not supported. Although Venkatesh et al. found a significant relationship between PV and BI in the acceptance of information technology by consumers [23], our result is unsurprising in the domain of wearable devices. Using the UTAUT2, Talukder et al. examined the acceptance of fitness wearable technology by Chinese users and empirically disproved this hypothesis [14]. This result can be explained by Saudi

Arabia being the largest oil exporter [51]; thus, most Saudi citizens can easily afford wearable health monitoring technology. Consequently, the importance of price is reduced in the case of Saudi Arabia.

Regarding GHP, health policies legalized by the Government do not play an important role in supporting the widespread adoption of wearable health monitoring technology. Perhaps the participants were unaware of the relevant health policies, and thus, the significance of health policies in the acceptance of wearable health monitoring technology was limited [26]. Furthermore, most Saudi citizens can easily afford wearable health monitoring technology, and thus, the prominence of resources allocated by the GHP might be reduced. This result also conforms with previous literature on the acceptance of health technology [26,29].

Finally, the findings reveal that TR is not a significant predictor for BI to use wearable health monitoring technology. This finding can be attributed to multiple reasons. First, the authors found that both HM and PE are important determinants of BI; therefore, the enjoyment and benefits from using the functionalities of wearable health monitoring technology might be the real reason that the users displayed fewer TR concerns. When users perceive wearable health monitoring technology as entertaining and useful, they are more willing to share sensitive data. Second, 27% of the participants in this study belonged to Generation Z (see Table 2), which is generally very knowledgeable about technology and less concerned about sharing information than older generations [52]. Considering the increasing trend of adopting wearable technologies among the youth segment in Saudi Arabia [53], the finding in this study might be a true reflection of the dwindling TR concerns in the kingdom when adopting new technologies such as wearable health monitoring technology. Finally, this study had around 59% female participants. Today, women in Saudi Arabia are more empowered than previously and are heavily involved in economic activities [11]. As the female participation in different outdoor activities increases, the perception and willingness to share personal information are changing in the society in general.

6.1. Theoretical Implications

This research is beneficial for researchers and academic objectives in the area of technology acceptance and diffusion. Based on the findings, this research provides both theoretical and practical implications. Theoretically, this research extensively investigated factors that affect BI to use wearable health monitoring technology. The research advances the theory of technology acceptance by extending the UTAUT2 and further explaining the effect of multiple factors adopted from existing literature in the application of information systems in the health sector (GHP and TR) on the acceptance of wearable health monitoring technology. The proposed model explains around 57% of variance in BI to use wearable health monitoring technology. In addition to the use of the UTAUT2, the extension of that theory in this study is theoretically significant because, rather than simply considering how the UTAUT2 constructs offset each other's influence in using wearable health monitoring technology, it also considers how other significant factors (e.g., GHP and TR) might interplay with the ratio of those constructs when affecting BI to use wearable health monitoring technology. This approach has not received sufficient attention from researchers, as most previous studies used the TAM or the UTAUT as a theoretical basis for their examination (see Table 1). Using this new approach means this study helps researchers use a new perspective for examining how external factors might govern the decision-making process regarding the AU of wearable health monitoring technology.

In addition, our investigation opens up possibilities for and removes uncertainty about the acceptance of wearable health monitoring technology in developing countries and Arab territories. The acceptance of wearable health monitoring technology in those geographical areas remains obscure due to the limited number of research initiatives. Furthermore, our study statistically validates the effectiveness of using the UTAUT2 to measure wearable health monitoring technology usage in developing countries. Therefore, the findings imply that the UTAUT2 and the proposed model in this study could be beneficial for producing effective results in other countries in the Middle East.

Moreover, in addition to examining the direct relationships, this study contributes to the literature by conducting priority analysis to provide better insights into the importance and performance of the key drivers of accepting wearable health monitoring technology. Thus, the puzzle of post-adoption behavioral intention to use wearable health monitoring technology can be resolved with useful justification. Furthermore, the diagram of priority analysis classifies the input variables into four quadrants based on their importance and performance. The four quadrants are useful for policymakers to understand the 'big picture' regarding which input variables have better priority to enhance strategies. Few studies have conducted such analysis in the domain of wearable health monitoring technology [18]; hence, the current research can be utilized by future researchers as a forerunner for using IPMA in studies on the acceptance of wearable health monitoring technology.

6.2. Practical Implications

This study provides guidelines for managers, manufacturers and decision-makers in the healthcare sector to improve the use and acceptance of wearable health monitoring technology. According to Saudi Vision 2030, the Government of Saudi Arabia is keen to reduce the cost of healthcare by adopting digital technologies [11]. This study contributes to this subject by increasing the adoption of wearable health monitoring technology to curb the prevalence of chronic disease-related complications across Saudi Arabia.

Empirically, this research provides evidence that BI to use wearable health monitoring technology is significantly affected by PE, SI, FC, HM and HA. Developers can enhance the quality of wearable devices in the healthcare sector by ensuring that wearables accomplish healthcare services more quickly and improve the ability of users to manage their health. As SI is an important predictor of BI, managers should consider different ways to exploit this factor among users. For example, managers can deliver speeches, share best practices and encourage influencers and champions who are familiar with wearable health monitoring technology to promote wearables [18]. Furthermore, FC is the strongest determinant of BI in the proposed model, implying that executives should ensure top management support, allocate resources and provide knowledge necessary to use wearables to realize the relative advantage of wearable health monitoring technology. Additionally, the fun element should not be neglected when designing these devices. Finally, decision-makers are advised to urge users to wear wearable health monitoring technology all the time to become part of their daily routine. Based on IPMA, both HA and FC require more managerial attention to improve the acceptance of wearable health monitoring technology. These results provide useful information for the practitioners of wearable health monitoring technology to develop policies to enhance the acceptance of wearable devices.

However, EE, PV, GHP and TR do not appear to play important roles in the intention to use wearable health monitoring technology. This study concludes, with a strong theoretical basis (e.g., the UTAUT2), that users of healthcare technology today are highly goal-orientated, thereby emphasizing the relative advantages of using a specific technology more than the associated ease of use, price, GHP and TR. To improve the acceptance of wearable health monitoring technology, managerial activities should concentrate on functional congruence, social presence, allocated resources, fun and continuous use.

7. Limitations and Future Work

Although this research extends our knowledge of factors that affect the acceptance of wearable health monitoring technology, some limitations should be addressed. First, this study integrates two external factors, namely GHP and TR, in addition to the original constructs of the UTAUT2 to measure their effect on the use of wearable health monitoring technology. As previous literature on the acceptance of wearable health monitoring technology is deemed to be limited, a potential avenue for future researchers could be to investigate the effect of other health-related factors, such as privacy concerns. Second, this study examined the influence of direct relationships between constructs without considering socio-economic differences between participants (e.g., gender, age and experience). Hence, future studies should consider socio-economic factors as moderators to either confirm or reject the hypotheses proposed in this study. In addition, the sample frame of this research was based on a non-probability convenience sampling technique to target participants who use wearable health monitoring technology in Saudi Arabia; thus, the generalizability of findings on the entire population or a global scale should be treated with caution. Future investigators could replicate the proposed concept using different sampling techniques in other countries and cultures to provide better understandings of the examined factors. Finally, a future study could classify wearable health monitoring technology into medical and fitness types and examine the influences of the factors used in this study separately.

8. Conclusions

Despite the relative advantages of wearable technology, little research has been conducted to understand the acceptance of wearable health monitoring technology. Consequently, a small amount of variance in user BI to use wearable health monitoring technology has been explained by external variables. Explaining what determines BI to use wearable health monitoring technology is practically useful during decision-making by executives and developers. In this regard, this paper proposed a theoretical framework based on the UTAUT2 and examined the effects of GHP and TR on user BI to use wearable health monitoring technology. The findings reveal that PE, SI, FC, HM and HA are associated with BI to use wearable health monitoring technology. Overall, those devices that are supported by management and consider entertainment are more likely to be adopted by users.

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Appendix A

Table A1. Constructs and indicators.

Constructs	Indicators	Source
Actual use (AU)	AU1. Wearable health monitoring technology is a pleasant experience. AU2. I use wearable health monitoring technology currently. AU3. I spend a lot of time using wearable health monitoring technology.	[23]
Behavioral intention (BI)	BI1. I have high intention to use wearable health monitoring technology. BI2. I intend to learn about using wearable health monitoring technology. BI3. I plan to use wearable health monitoring technology to manage my health.	[23]
Effort expectancy (EE)	EE1. Learning how to use wearable health monitoring technology is easy for me. EE2. My interaction with wearable health monitoring technology is clear and understandable. EE3. I find wearable health monitoring technology easy to use. EE4. It is easy for me to become skillful at using wearable health monitoring technology.	[23]
Facilitating conditions (FC)	FC1. I have the resources necessary to use wearable health monitoring technology. FC2. I have the knowledge necessary to use wearable health monitoring technology. FC3. Wearable health monitoring technology is compatible with other technologies I use. FC4. I can get help from others when I have difficulties using wearable health monitoring technology.	[23]

Table A1. *Cont.*

Constructs	Indicators	Source
Government health policy (GHP)	GHP1. Government policy consistently supporting wearable health monitoring technology is important. GHP2. Government policy must ensure appropriate resource allocation for accessing wearable health monitoring technology. GHP3. Government policy supporting wearable health monitoring technology would result in widespread adoption.	[54,55]
Habit (HA)	HA1. The use of wearable health monitoring technology has become a habit for me. HA2. I must use a wearable health monitoring technology service. HA3. Using a wearable health monitoring technology service has become natural to me.	[23]
Hedonic motivation (HM)	HM1. Using a wearable health monitoring technology service is fun. HM2. Using a wearable health monitoring technology service is enjoyable. HM3. Using a wearable health monitoring technology service is very entertaining.	[23]
Performance expectancy (PE)	PE1. Using a wearable health monitoring technology service helps me accomplish my healthcare activities more quickly. PE2. Using a wearable device would improve my access to my health information. PE3. A wearable health monitoring technology would improve the quality of my healthcare. PE4. Using a wearable health monitoring technology would improve my ability to manage my health.	[23]
Price value (PV)	PV1. Wearable health monitoring technology service is reasonably priced. PV2. Wearable health monitoring technology service offers greater benefit than its cost. PV3. At the current price, wearable health monitoring technology service provides good value.	[23]
Social influence (SI)	SI1. People who are important to me think that I should use wearable health monitoring technology. SI2. People who influence my behavior think that I should use wearable health monitoring technology. SI3. People whose opinions I value prefer that I use wearable health monitoring technology. SI4: If I see people I know are using wearable health monitoring technology, this would motivate me to use them.	[23]
Trust (TR)	TR1: Using wearable health monitoring technology depends on trust. TR2: Lack of trust is a barrier regarding using wearable health monitoring technology. TR3: Trust in the authenticity of information is important in wearable health monitoring technology adoption. TR4: Trust in the reliability of service is important in wearable health monitoring technology adoption.	[56]

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