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Understanding Factors Affecting the Use of Mobile Health Innovation, Attitude and Synthesis

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Abstract: Advancements in information and communication technologies have positively affected various sectors, and healthcare is no exception. Healthcare industry has been affected by smartphones that caused the use of mobile phones for providing healthcare services, which is known as Mobile health (mHealth). Regardless the benefits of mHealth, the success of this technology ultimately depends on public acceptance. Therefore, the objective of this research is to evaluate the acceptance of mHealth applications. An online survey was employed to collect data related to the variables in the conceptual model. This study utilizes the multivariate PLS-SEM method to evaluate the suggested model. The results indicate that four factors are important for the acceptance of mHealth: perceived usefulness, subjective norms, facilitating conditions and attitude toward behavior. In conclusion, the four factors are important, and decision makers should pay more attention to them to improve the public acceptance of mHealth.

Keywords: Technology acceptance, Technology adoption, Mobile health, mHealth, Healthcare

Introduction

Progress in information and communication technologies has benefitted many disciplines and sectors. By triggering "Mobile Health" (mHealth), smart phones have transformed health, activity (Hoque & Sorwar, 2017; Chen et al.,2018; Binyamin & Zafar, 2021). Due to the general availability of mobile phones and the scarcity of health facilities, mobile health services have increased on a large scale (Cho & Kim, 2020). The authors identified several transferable health benefits, including increased access, which the authors describe in (Alam et al., 2020). In turn, the authors reinforced the authority users have over their own health (Binyamin & Hoque, 2020). The authors suggested the right health strategy to minimize time and geographical constraints (Zhang, et al., 2019). It was recommended an advanced way to reduce healthcare costs (Mansour, 2017).

It was reported that public acceptance of these improvements would determine the expansion and benefits of mobile health and its ultimate success (Keen & Roberts, 2017; Binyamin & Hoque, 2020; Binyamin & Zafar, 2021). The benefits of health services would be lost if people did not use them (Ahmed et al., 2014; Khatun et al., 2015; Hoque & Sorwar, 2017). According to several surveys, the adoption of target consumers and mobile health services is now neglected. This indicates potential barriers to the development of mobile health services. Although only a few researchers have studied this subject, it is crucial to know what motivates people to adopt mobile health care (Binyamin & Zafar, 2021).

Binyamin and Zafar (2021) developed a conceptual approach to measuring portable health adoption based on a comprehensive literature evaluation and multi-phase meta-analysis. Firstly, the researchers reviewed and evaluated 49 scientific papers published between 2010 and 2020 concerning the approval of mobile health technologies. In the second phase, 100 structures, 26 dependent factors, and 170 combinations of pathways were studied in these documents. Then, we determined the most popular correlates in these studies. The authors then suggested a conceptual model based on assessing the significance and strength of recognized associations. Thus, there are five independent factors (perceived usefulness (PU), perceived ease of use (PEOU), subjective criteria (SN), conditions of facilitation (FC), and attitude toward behavior (ATB)) and two dependent factors

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(behavioral intention (BI) and actual use (AU)) as critical factors for acceptance of mobile health services. Figure 1 illustrates the conceptual model and the seven assumptions proposed by Binyamin and Zafar (2021). However, the scientists never experimentally looked at their theoretical framework. This research aims to assess the scale and structural patterns of a theoretical framework using real-world data. This shows that their conceptual model for measuring how well mobile health apps is accepted works and is reliable.

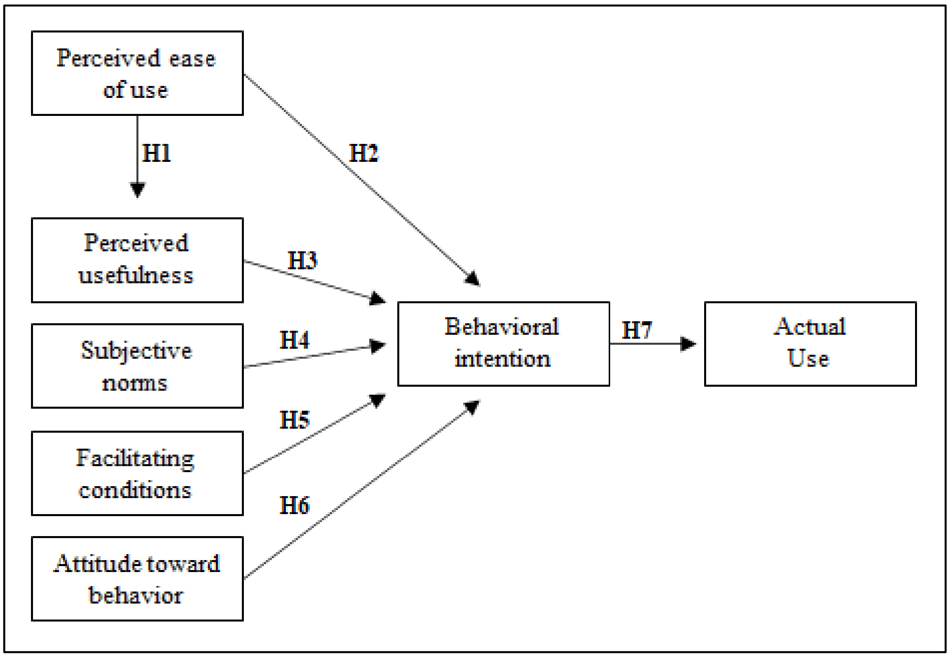

Figure 1. The research, conceptual model

The remaining parts of the paper is arranged as follows: Section 1 introduces the state of art of Mobile Health. The "Methodology" Section 2 discusses the mobile health technology in Saudi Arabia in detail. Section 3 covers the obtained results. These results are discussed in section 4. We conclude the paper in Section 5.

Methodology

Measurement of Constructs

To validate the proposed assumptions, a survey was conducted on Google Forms covering all the variables in the conceptual model of online search. All indications were derived from previously published studies (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012), with only minor modifications to make them applicable to mobile health technology.

Instrument Development

As with most technological acceptance studies, we do quantitative work. In this context, online surveys were used to collect comprehensive information. The study proposed is divided into two sections. Section A includes multiple-choice questions about user demographics, including gender, age, educational level, marital status, and daily use of mobile devices (in hours). Respondents were asked to choose the option most reflective of their condition. In Section B, 21 positive reports express combinations of forms. On a five-point Likert scale, with one point for strong disapproval and five points for strong agreement, the appropriateness of the fixtures was determined. The initial draft of the questionnaire was prepared in English. Since this study was directed at Saudi users of mobile health technologies, Arabic is the mother tongue; the questions had to be translated into Arabic. The online investigation was translated from English to Arabic using the reverse translation method (Brislin, 1986). The exact meaning and originality will be maintained by appointing two Arabic-speaking and fluent English-speaking teachers who have the necessary experience to create surveys. The first faculty member translated the questions from English into Arabic, while the second translated the questions into English. This step was required to ensure survey respondents understood the questions and were not left out because they could not speak English.

Data Collection

Our work aimed to explain user behavior and experience with mobile health technology in Saudi Arabia. Following most technology acceptance studies; a nonprobability convenience sampling technique was used to collect data from the target population. Electronic invitations were sent through social media and WhatsApp mobile app groups for participant recruitment. Respondents were invited to participate in the survey through electronic invitations, and the online link to the questionnaire was attached. The questionnaire was open for two weeks. Concerning ethics, all participants provided their informed consent, online at the beginning of the survey. The ethical approval of the survey was also obtained from King Abdelaziz University's Dean of Scientific Research. In total, participants provided 319 responses. The authors conducted a preliminary review to monitor the data and ensure that the model trials did not include outliers, missing data, or unsolicited responses. This study uses the standard deviation to detect non-binding responses and linear patterns. Answers rated 0 were considered suspicious and were not fully committed to the questionnaire. So, during the preliminary review, 8 replies were thrown out, and 311 responses were used to look at the data. Demographic information for participants is presented in Table 1. Analysis of socio-demographic data shows that most participants are female (61%). Most participants (67%) are under 36 years of age. This is consistent with Saudi Arabia, where most of the population is composed of young people. In terms of academic level, 95% of participants have a licentiate, and more than 36% have a master's degree. Approximately 82% of respondents reported using their mobile devices for more than 3 hours each day.

Table 1. Demographic characteristics of participants

Characteristics	Groups	Frequency	Percentage
Gender	Male	120	38.59%
	Female	191	61.41%
Age	18–25 years old	138	44.37%
	26–35 years old	71	22.83%
	36–45 years old	52	16.72%
	Above 45 years old	50	16.08%
Education	None	17	5.47%
	2-year diploma	52	16.72%
	Bachelor’s degree	127	40.84%
	Graduate degree	115	36.98%
Marital status	Married	170	54.66%
	Divorced	132	42.44%
	Single	4	1.29%
	Widow / widower	5	1.61%
Mobile daily use	Less than 1 hour	7	2.25%
	1-3 hours	49	15.76%
	4-6 hours	135	43.41%
	More than 6 hours	120	38.59%

Data Analysis

Our inquiry utilized the multivariate PLS-SEM method implemented by the Smart-PLS software 3 to assess the suggested model and evaluate the accuracy of the correlations between the input and output variables. This method has been largely used to test and validate assumptions (Hair et al., 2017). SEMS-PLS is also flexible when it comes to sharing data and having a small sample size (Hair et al., 2018).

Results

Measurement Model Evaluation

The validation measurement results of model are presented in Table 2. All external loads above 0.60 show that the reliability of the indicators has been determined (Hair et al., 2017). The author evaluated the reliability of the assemblies using composite reliability (CR) and Cronbach's alpha coefficient (AC), which has a recommended limit value of 0.70 or more (Hair et al.,2018). Based on Table 2, the composite reliability estimates ranged from 0.85 to 0.93, while the Cronbach alpha estimates ranged from 0.74 to 0.89. Consequently, Table 2 indicates that the reliability of the structures is satisfactory. The scaling model is convergent validity because the extracted mean, variance (AV) is greater than 0.5 (Chin, 1998).

Table 2. Measurement model evaluation

Constructs	Indicators	Loadings > 0.6	CR > 0.7	CA > 0.7	AVE > 0.5
Attitude toward behavior (ATB)	ATB01	0.82	0.89	0.81	0.72
	ATB02	0.84			
	ATB03	0.88			
Actual use (AU)	AU01	0.87	0.86	0.77	0.68
	AU02	0.90			
	AU03	0.69			
Behavioral intention (BI)	BI01	0.92	0.93	0.88	0.81
	BI02	0.86			
	BI03	0.92			
Facilitating conditions (FC)	FC01	0.84	0.85	0.74	0.66
	FC02	0.85			
	FC03	0.75			
Perceived ease of use (PEOU)	PEOU1	0.92	0.93	0.89	0.82
	PEOU2	0.85			
	PEOU3	0.93			
Perceived usefulness (PU)	PU1	0.86	0.91	0.85	0.77
	PU2	0.90			
	PU3	0.87			
Subjective norms (SN)	SN1	0.83	0.87	0.78	0.70
	SN2	0.90			
	SN3	0.78			

CR = Composite reliability, CA = Cronbach's alpha coefficient, AVE = Average variance extracted

The author evaluated the discriminant validity of the suggested model using the Heterotrait Monotra Ratio (HTMT) (Henseler, Ringle, & Sarstedt, 2015). This indicator reflects the strength of the relationship between two entities. Table 3: HTMT scores do not exceed the criterion of 0.9, which demonstrates the discriminative validity of the seven components (Henseler, Ringle, & Sarstedt, 2015). The obtained results of the measurement model evaluation show that the reliability and validity of the suggested model are not very important.

Table 3. Heterograft monotrait ratio

	AU	ATB	BI	FC	PEOU	PU
ATB	0.82					
BI	0.76	0.82				
FC	0.63	0.79	0.64			
PEOU	0.41	0.54	0.34	0.60		
PU	0.72	0.85	0.68	0.70	0.55	
SN	0.62	0.62	0.66	0.59	0.24	0.59

Structural Model Assessment

It is essential to evaluate the collinearity of a proposed model to ensure that there are no strong correlation structures. Using the Variance Inflation Factor (VIF), this study examines the collinearity of the suggested model following the recommendations of Hair et al. (2017). Table 4's VIF values are below 3.0, which means that the level of cleanliness is acceptable.

Table 4. Variance inflation factor scores

	AU	BI	PU
ATB		2.40	
BI	1.00		
FC		1.89	
PEOU		1.49	1.00
PU		2.27	
SN		1.46	

Following the advice of PLS-SEM academics (Hair, Hult, Ringle, & Sarstedt, 2017; Hair, Sarstedt, Ringle, & Gudergan, 2018), the correlations between independent and dependent variables were evaluated using three metrics: path coefficients (β), t-value, and p-value. As this study tests hypotheses at a significance level of 0.05, only ideas with a p-value less than the significance level of 0.05 are supported (Hair, Hult, Ringle, & Sarstedt, 2017). The significant and nonsignificant associations are displayed in Table 5. The testing of hypotheses shows six meaningful relationships (PEOU → PU, PU → BI, SN → BI, FC → BI, ATB → BI and BI → AU) and one insignificant and one unimportant relationship.

Table 5. Hypothesis testing

	Path	Coefficients (β)	t-Value	p-Value	Result
H1	PEOU → PU	0.49	9.14	0.00	Supported
H2	PEOU → BI	-0.06	1.35	0.09	Not supported
H3	PU → BI	0.13	1.86	0.03	Supported
H4	SN → BI	0.22	5.00	0.00	Supported
H5	FC → BI	0.10	1.76	0.04	Supported
H6	ATB → BI	0.46	6.49	0.00	Supported
H7	BI → AU	0.65	13.93	0.00	Supported

Significance level = 0.05, one-tailed

Discussion

This paper evaluated a previously presented model to ensure its suitability for assessing mHealth technology adoption in Saudi Arabia (Binyamin & Zafar, 2021). The conceptual model in this study states that behavioral intent is influenced by five distinct factors: PEOU, PU, SN, FC, and ATB. This section discusses the variables influencing mHealth adoption in response to the research questions. The model investigated explains 56% of the variance in BI (adjusted $R^2 = 0.55$) and 43% of the variation in AU of mHealth technology (adjusted $R^2 = 0.43$). Our research shows that the intent to use health technology is strongly influenced by PU, SN, FC, and ATB, confirming that six of the seven association analyses is significant. On the other hand, PEOU does not appear to affect the intention to use mHealth technologies. H1, H3, H4, H5, H6, and H7 are required. Based on the findings, the following proposals to facilitate the use of mobile healthcare technology by the public are discussed.

The author suggested that PU, SN, FC, and ATB positively affect behavioral intent (H3, H4, H5, and H6). The obtained results indicate that PU (β = 0.13, p = 0.03), SN (β = 0.22, p = 0.00), FC (β = 0.10, p = 0.04) and ATB (β = 0.46, p = 0.00), and ATB (β = 0.46, p = 0.00) have a good effect on behavioral intent to use portable health; thus, H3, H4, H5, and H6 are acceptable. Four key factors, thus influence consumers:

1. The performance and utility of mobile health
2. The opinions of key stakeholders
3. The availability of resources and assistance
4. Their favorable attitude towards mobile health.

The obtained results are in line with what other studies (Dwivedi, Shareef, Simintiras, Lal, & Weerakkody, 2016; Alam, Hoque, Hu, & Barua, 2020; Alam & Khanam, 2022), and the UTAUT and UTAUT2 technology acceptance forms (Venkatesh et al., 2003; Venkatesh et al., 2012) have found about how people accept mobile health. Since Saudi Arabia is a collective nation with a high level of force-distance, it is expected that SN will positively affect behavioral intention. The user's attitude towards mobile health is the strongest predictor of behavioral intentions among the parameters considered. So, people who make decisions about whether or not to accept mobile health devices should pay more attention to this factor. Indeed, the obtained results from the literature review prove that PEOU has a positive impact on BI when using mobile health technology. Surprisingly, this survey did not find a significant association between PEOU and BI (β = -0.06, p < 0.09); therefore, H2 is rejected. The literature on TAM, UTAUT, and UTAUT2 is said to contradict the rejection of this theory. However, our results are consistent with several research reports on the adoption of portable health. This research demonstrates that PEOU does not influence intent to use mHealth (Sezgin et al.,2017; Deng et al., 2018; Nunes et al.,2019; Duarte & Pinho, 2019; Alam et al., 2020; Alam & Khanam, 2022). Thus, future research on the acceptance of portable health should focus more on the relationship between PEOU and BI. Furthermore, the findings indicate that PEOU is a significant PU indicator of mobile health technology use (β = 0.49, p < 0.00); hence, H1 is accepted. Indeed, consumers are more likely to utilize mobile health technology if it is simple to learn and employ. If the user-friendliness of mHealth is not recognized, users can reject it and search for an alternative accessible solution. This is due to the fact that mHealth is a fairly new service in Saudi Arabia. In fact, users have little experience with it; hence, the simplicity of the system is vital for this type of user. This conclusion is consistent with previously published studies on technological acceptance models (TAM, UTAUT, and UTAUT2) and acceptance of mobile health (Zhang, et al., 2019; Nezamdoust et al., 2022).

Conclusion

Despite the expansion and benefits of mobile healthcare, the success of this innovation ultimately depends on public acceptance. Previous research indicates that mobile health services are insufficient (Ahmed, et al., 2014; Khatunet al., 2015; Hoque & Sorwar, 2017). Our work focused on empirically analyzing a previously suggested model (Binyamin & Zafar, 2021) and assessing its applicability in mobile health applications' acceptability. The obtained results suggest that PU, SN, FC, and ATB are linked to business intelligence regarding the use of mobile health services. Finally, the four elements are essential, and policymakers should give them greater attention to increase the uptake of mobile health services.

Scientific Ethics Declaration

The author declares that the scientific ethical and legal responsibility of this article published in EPHELS journal belongs to the author.

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