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Factors Affecting the Adoption of M-health Applications in Saudi Arabia: Impact of Healthcare Authority Enforcement

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Completed Research Paper

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Abstract

Mobile health (m-health) applications offer new features to patients to increase the efficiency of healthcare services. However, adopting such technology has not been as expected in some developing countries such as Saudi Arabia. Yet, healthcare providers have recently started to force patients to use some mobile apps during the COVID-19 pandemic. Consequently, it has opened the discussion of whether the enforcement of healthcare providers could influence patients' behavioral intention to adopt m-health apps. This study aims to understand and validate the factors that could influence m-health apps' adoption. Based on the UTAUT model, the proposed model has been extended in this research to include healthcare authority enforcement and tested in Saudi Arabian settings with 343 participants. Findings show the significance of effort expectancy, social influence, and healthcare authority enforcement on behavioral intention. The outcome of this study aims to provide governments, practitioners, and app developers with further understanding.

Keywords: M-health, mobile health, factors, adoption, healthcare, authority, enforcement, Saudi Arabia

Introduction

In recent years, governments and health providers have become profoundly aware of technologies as a valuable resource to improve health services. This advancement in wireless technologies has resulted in the emergence of a modern area of electronic health (e-health) known as m-health (Hoque 2016). E-health is typically used to refer to desktop applications (apps), while m-health is used to refer to mobile apps (Kampmeijer et al. 2016). M-health apps are intended to provide advanced services that improve the quality of healthcare in comparison to e-health (Aljohani and Chandran, 2019). Healthcare initiatives have been updated to address health issues in many developing countries, such as China, Thailand, and India (Hussein et al. 2017). In Saudi Arabia, the use of electronic information systems has increased due to technological development. In 2000, the Saudi government developed strategic IT plan to deliver health care, implementing e-health systems within the country (Aljohani and Chandran 2019). The Saudi government created a national development plan called 'Vision 2030' in 2016. The Ministry of Health (MoH) has established targets to meet Vision 2030 expectations. One of their goals is to enhance the workforce by depending on technology across all sectors (MoH 2017). According to General Authority for Statistics (2019), the current population of Saudi Arabia is approximately 34

million, with a 2.52 growth rate, which means there will be an increase in health services requests. According to the Communication and IT Commission (2017), the number of phone holders in 2011 was only 11.3 million, representing 39.6% of the total population. However, in 2017, the number increased to 29.7 million, representing 93.5% of the current population (Communication and IT Commission 2017). Thus, the majority of Saudi citizens are smartphone holders. Despite possessing a high percentage of smartphone users, some Saudi healthcare providers do not use mobile apps' benefits in the public and private sectors (Aljohani and Chandran 2019). In recent years, some Saudi health-service providers have launched apps, most of which allow users to book appointments, check test reports, and seek online consultations (Chandran and Aljohani 2020).

Nevertheless, based on the 2019 half-yearly report by the National Digital Transformation Unit (2019), around half of the expected number of users have the apps, showing users limited usage. The Saudi Arabia Government is seeking to implement mobile health completely (MoH 2017). For example, MoH published many posts and videos to show the benefits of these recommended apps. These link to the Saudi National Portal "Abshir" to retrieve official citizen details (MoH 2019). Further, the Saudi Red Crescent Authority added a new feature to its "Asefni" or "Save Me" app, to request travel permit during the strict curfew being applied in the country to contain the spread of the coronavirus disease (COVID-19) (MoH 2020). Thus, the Saudi government has started to push its citizens to use these apps. In this context, we carried out this research to understand and validate the factors that could influence m-health apps adoption. Also, this paper discusses the role of healthcare authority enforcement on patients' behavioral intention to adopt m-health apps. This has not previously been examined in other studies. Therefore, the current study seeks to add to this growing field of research by answering the following research questions:

1- What factors influence patients' intention to adopt m-health apps in Saudi Arabia?
2- Does the enforcement by healthcare authority affect patients' behavioral intention to adopt m-health apps in Saudi Arabia?

Findings of this research would help the government, healthcare providers, and app developers with further understanding of their development strategies, which could help raise the adoption rate of m-health apps.

Literature Review

Mobile Health Apps

Over the past few years, mobile and wireless technology have increased substantially, inspiring a technological transformation in health services provision. M-health means leveraging apps on mobile phones, laptops, or other wearable computing devices to improve healthcare, public health, and medical treatment services (Kariuki and Okanda 2017). In developing countries, m-health initiatives have been widely implemented. It can be the most realistic and affordable way to solve many problems within the developing world's healthcare sector. For example, In China, in 2016, the government implemented the "Health China" plan to overcome the problem of finding accessible physicians (Deng et al. 2018). Different nations, such as Malaysia, Thailand, China, and India, have also been implementing technical advancements in healthcare services to enable medical practitioners to use technological developments (Hussein et al. 2017). In India, the government established numerous m-health enterprises worldwide as part of the Digital India Program in 2016 to improve access, make healthcare costs competitive and make the system more robust (Ahamed et al. 2017). Various mobile devices have grown due to recent developments in m-health. For example, "Spring Rain Doctor," China's most successful health application with only 92 million users, makes it the world's most significant mobile physician-patient contact network (Wang et al. 2018).

Mobile Health Apps in Saudi Arabia

Saudi healthcare providers have recently started implementing m-health technologies as part of the Saudi Vision 2030, which the government approved to help achieve its goals. For example, the MoH has implemented two specific applications for patients to conduct two services, remote consultation and appointment booking. The "Seha" app allows patients to hold face-to-face medical consultations remotely with their physicians or relevant specialists regardless of their location (MoH 2017). An interactive application called "Sehaty" has also been created by the King Faisal Specialist Hospital and Research Center that allows patients to access their health care records via their smartphones, which can help them perform different tasks. Patients can also easily view their list of files on symptoms, concerns, treatment, immunization, testing, and radiology. A new application has also been launched for patients' hospital by the National Guard Health Affairs. Patients may use the app to request and cancel appointments, view radiology, laboratory reports, request refills for medicines and other services (Ministry of National Guard Health Affairs 2019). The Saudi Red Crescent Authority has developed a new "Asefni" app, which can enable users to request services in emergencies implemented in most regions of Saudi Arabia (Aljohani and Chandran 2019).

The National Digital Transformation Unit leads in the Kingdom's digital transformation process. Based on its 2019 semi-annual report, the number of appointments to be booked via the "Maud" application in 2019 was expected to be around 20 million appointments. However, there were only nine million appointments booked during this year. It was also estimated that the app would have more than 11 million registered users, while the exact number exceeded 5.5 million users. 23,729 online medical consultations, 18,767 voice calls, and 4,962 video calls were requested for the "Seha" app. The King Faisal Specialist Hospital and Research Center's app has 10,381 registered users and requests for refilling 8,821 medicines. The Saudi Red Crescent Society software received 6,240 queries in Medina, 2565 in Alqasim, and only 1,185 in Hail (National Digital Transformation Unit 2019). These findings raise the question of why the actual outcomes were not as expected or planned.

A research study carried out by Alanzi (2018) shows that m-health has not been fully implemented in Saudi Arabia. In the study, a questionnaire survey was distributed through a WhatsApp group targeting individuals who had diabetes. A diabetes app was used to track the sugar levels of the patients presented for the study. The research showed that there are many barriers to the achievement of m-health services in Saudi Arabia such as skills and human resource shortages, financial and capital investments, legal, privacy, and regulatory barriers. The ministry also uses other platforms such as the Health Electronic Surveillance Network (HESN) for COVID-19 surveillance and the 'Taqasi' Patient Tracing Unit platform, which was created to curb the pandemic's spread (Hassounah et al. 2020). Other m-health apps adopted within Saudi Arabia include; Tetamman, which means 'rest assured' to track the progress of patients and for reporting mild cases and contacts; the Tawakkalna app, which restricts individuals' movements during curfew hours, and Tabaud, meaning 'distancing' which alerts users who crossed paths with confirmed cases of the virus (SDAIA 2020).

Healthcare Authority Enforcement

Healthcare authority enforcement refers to government or healthcare providers' set policies and instructions to use mobile apps. Such policies include privacy and confidentiality laws, distribution regulations, training and development strategies, and financing guidelines from the government. Barkman and Weinehall (2017) argue that governments' political responsibility is to create financing guidelines for m-health apps in a country. As part of their digitalization plans, governments and some healthcare providers have started relying on mobile technologies (Hussain 2017). Lack of legislation and programs may hinder the implementation of e-health strategies at the professional level of organization and health (Hoque and Sorwar 2017). Furusa and Coleman (2018) report as an example of how it is necessary to identify a specific e-health policy that the government of Zimbabwe should set a

strategy to implement e-health systems in public hospitals. They argue that health policy decision-makers should Zimbabwe's government use of e-health systems in public hospitals. In addition, the positive involvement and supportive role of governments have been indicated in different technology adoption studies (Alalwan et al. 2018, Barkman and Weinehall 2017, Hussain 2017, Lin and Ho 2008). Pankomera and Greunen (2018) discuss the implementation of sustainable m-health in strained resource countries – with a focus on Malawi. According to the researchers, poor infrastructure, lack of proper policies and regulations, limitation of financial resources, poor governance, and lack of skilled personnel are factors that hinder the application of mobile applications. In the case of strained resource countries like Malawi, the researchers recommend policy development to bypass the challenges listed. From the researchers' conclusion, it is evident that governments play a critical role in m-health adoption through policy development.

In Saudi Arabia, the government is working hard to revamp the country's healthcare system (Alanezi, 2020). The adoption of m-health is seen as one of the most effective ways of enhancing services to its citizens. Therefore, the government has come up with regulators that will help implement the m-health services. According to Alshahrani et al. (2019), the government's intentions to develop an m-health infrastructure are constrained by the lack of qualified personnel, mostly in remote areas. However, the government has assigned a plan to rely on technology to provide better healthcare to Saudi patients (MoH 2017). As part of this plan, the MoH and some public healthcare providers started to force patients to use m-health for electronic health services such as appointment scheduling.

The Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. in 2003, was the most widely used model in healthcare technology exploration (Ladan et al. 2018) due to its credible and validated solidity in the adoption, acceptance and use of technology in literature. The UTAUT model as shown in figure 1, was developed based on the study of eight previous models in information systems usage behavior. It has four exogenous variables, which are performance expectancy (PE), social influence (SI), effort expectancy (EE), and facilitating conditions (FC), two endogenous variables which are behavioral intention (BI) to use technology and use behavior (UB), and four moderators which are gender, age, voluntariness, and experience (Venkatesh et al. 2003). As these constructs and moderating variables were combined, predictive performance increased by 70% above earlier Technology Acceptance Model (TAM) rates (Venkatesh et al. 2003). A study by Hoque and Sorwar (2017) used UTAUT to understand factors affecting the intention of elderly users to adopt and use m-health services in Bangladesh. The results have showed positive impact on performance expectancy, effort expectancy, social influence, technology anxiety, and resistance to the users' behavioral intention to adopt m-health services. Several studies have used the UTAUT model to adopt healthcare technologies and show the model's credible ability to examine users' behavioral intentions (Hoque and Sorwar 2017, Schomakers et al. 2018, Tavares and Oliveira 2017). Therefore, this research employs behavioral intention as an indicator to characterize patients' motivations for adopting m-health apps.
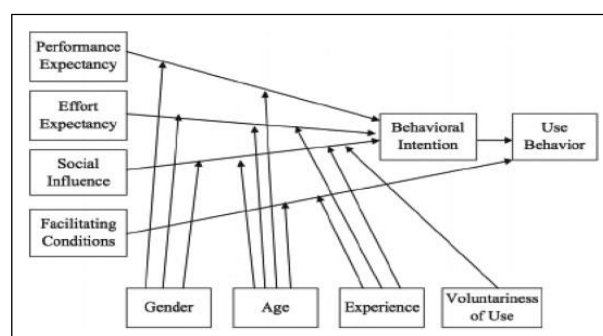
Figure 1. UTAUT Model (Venkatesh et al. 2003)

Current Research

There is little information about m-health adoption in Saudi Arabia due to the absence of studies on its context (Chandran and Aljohani 2020). The research paper attempts to expand on the UTAUT model by adding and examining healthcare authority enforcement's concept to facilitate m-health app adoption rates. Several research studies have looked at new technologies and created various models and frameworks to determine how users can adopt and accept technology. Numerous studies show that intention is critical for m-health service adoption (Hoque and Sorwar 2017, Kariuki and Okanda 2017, Tavares and Oliveira 2017). However, there is a need to add factors that suit the Saudi context. According to Kruse et al. (2016), the decision to adopt technologies may be affected by those who control resources. This enforcement role in adopting m-health apps in Saudi Arabia did not exist before. Therefore, this paper aims to analyze healthcare authority enforcement's influence and the primary constructs of the UTAUT model on behavioral intention to adopt m-health apps in the Saudi context. The facilitating conditions have been excluded because it only affects actual use based on the original study. The "use behaviour" construct has been excluded, as the research model focuses on understanding factors affecting patients' adoption of m-health apps during the early implementation stage. Moreover, the UTAUT model's moderators have been dropped at this stage, as this research has focused on current users of m-health apps in Saudi Arabia, as well as the fact that the m-health concept is new to the Saudi health sector. Understanding these factors will help the government, healthcare organizations, and app developers increase the adoption rate of m-health apps, which could help achieve healthcare digitization plans.

Theoretical Foundation and Hypotheses Development

This study aims to validate the factors that influence m-health apps' adoption. Based on the UTAUT model, the research model has been extended to include healthcare authority enforcement and tested in Saudi Arabian context. Effort expectancy, performance expectance, and social influence have been obtained from the UTAUT model and expanded by adding healthcare authorities' enforcement, the newly added factor.

Performance Expectancy

Performance expectancy is a core construct in the UTAUT model, defined as "the degree to which an individual believes that using the system will help him or her attain gains in job performance" (Venkatesh et al. 2003). In certain studies, performance expectancy has been found to have a significant effect on intention to use (Alam et al. 2020, Hoque and Sorwar 2017, Tavares Oliveira 2017). Performance expectancy was the most influential predictor in their sample where they surveyed 165 German health and diabetes app users (Schomakers et al. 2018). M-health systems are more likely to be accepted where there is a significant performance expectation (Hoque and Sorwar, 2017). Schomakers et al. (2018) define performance expectancy as "the usefulness of a technology," reflecting the value of technology. By reviewing the meaning of different terms of performance expectancy in the Venkatesh et al. study, and the measurement items in various studies (Hoque and Sorwar 2017, Venkatesh et al. 2003), it is possible that performance expectancy would present usefulness and value of the app. When the app can serve users in their requests and they get advantages and priorities, it is more likely to be adopted and accepted. Thus, the following hypothesis is proposed:

H1: Performance expectancy has a positive influence on users' behavior intentions to adopt m-health apps.

Effort Expectancy

Effort expectancy is a core construct of the UTAUT model. It is defined as "the degree of ease associated with the use of the system" (Venkatesh et al. 2003). The strong influence of effort expectancy

has been indicated in several studies (Hoque et al. 2015, Tavares and Oliveira 2017, Veer et al. 2015). Effort expectancy has been identified as a key consideration in regard to mobile health tracking system usage, phone e-health facilities, and medical decision support system use (Hoque and Sorwar 2017). Adopting technology becomes more and more appealing as it is easy to use, which helps users' interest to grow (Njoroge et al. 2017). Ndayizigamiye and Maharaj (2017) argue that end-users of m-health systems must be included in the design phase to avoid developing complex m-health systems. It is fair to assume that effort expectancy provides a clear indicator of its users' satisfaction. Therefore, effort expectancy would greatly influence the intention to adopt m-health apps. Based on the above discussion, the following hypothesis is presented:

H2: Effort expectancy has a positive influence on users' behavior intentions to adopt m-health apps.

Social Influence

Social influence is a core construct of the UTAUT model, which refers to "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al. 2003). Some studies in the literature supported the strong and positive effect of social influence on behavioral intention of adopting or using new technology (Alam et al. 2018, Hoque 2016, Hoque, and Sorwar 2017). Observed social encouragement can be a significant affective variable in supporting behavior shifts. For instance, the empirical findings have reinforced the importance of social impact in determining behavioral intention to adopt mobile health (Alalwan et al. 2018). Social influence has also been studied and its significance shown in different theories and models applied in adopting and accepting health technologies contexts. Tavares and Oliveira (2017) investigated the adoption of Electronic Health Records (EHR) by the individual from two countries, the United States and Portugal. Both countries confirmed the importance of social influence on EHR adoption (Tavares and Oliveira 2017). Based on the literature, social influence has a major impact on patients' intention to adopt m-health apps. Therefore, the following hypothesis is posited:

H3: Social influence has a positive impact on users' behavior intentions to adopt m-health apps.

Healthcare Authority Enforcement

Healthcare providers are regarded as the gatekeepers of health service delivery. The purpose of healthcare providers in implementing m-health is explored by Leigh et al. (2020). According to the researchers, patient safety, quality of clinical outcomes, and recommendations from other providers influence the use of digital health technologies in institutions of care. From the findings, it is possible to conclude that providers are likely to recommend using m-health to their patients if they deem it safe and adhere to the industry's quality standards. Highly knowledgeable and skilled providers are more likely to influence their patients to use specific applications – apps deemed trustworthy (Zhang et al. 2019). For instance, Saudi healthcare providers are starting to incorporate m-health solutions as part of the Saudi Vision 2030. As a result, they developed two apps, "Maud" and "Seha", which help patients to perform health services and remote consultations with doctors. For standard health requests, patients are required to use the "Maud" app (Aljohani and Chandran 2019).

When the COVID-19 issue began, the Ministry of Health in Saudi Arabia had started to push health information and recommendations on its apps about COVID-19 (MoH 2020). These posts include potential symptoms, instruction to avoid causes (MoH 2020). The use of apps such as "Tawakkalna" have become mandatory in Saudi Arabia during the COVID-19 pandemic. Citizens cannot access public places without providing their health status via the app. As a result, millions have downloaded and are using the app directed by the MOH (SADIA 2020). Consequently, the citizens are forced by the circumstances to use the app to carry on with their daily activities. However, there have been technical challenges resulting from high online traffic levels, indicating that many people are already using it. As

the need for more efficient and effective m-health apps increases, the more the public becomes acquainted with them and the more popular they become.

The Saudi Arabia government is positively highlighting the need to install and use COVID-19 related apps to curb the pandemic. This will not only help in fighting the global pandemic but will also change the peoples' attitude towards m-health technology. Despite the various technical hitches associated with the customized apps, the majority population uses them to learn how to use similar m-health apps (Alghamdi et al. 2020). Therefore, this way of forcing the use of m-health apps by healthcare providers would lead to an increase in the number of m-health users. Thus, the following hypothesis is proposed:

H4: Healthcare authority enforcement has a positive influence on users' behavior intentions to adopt m-health apps.

The following research model in figure 2, was developed based on the above hypotheses.
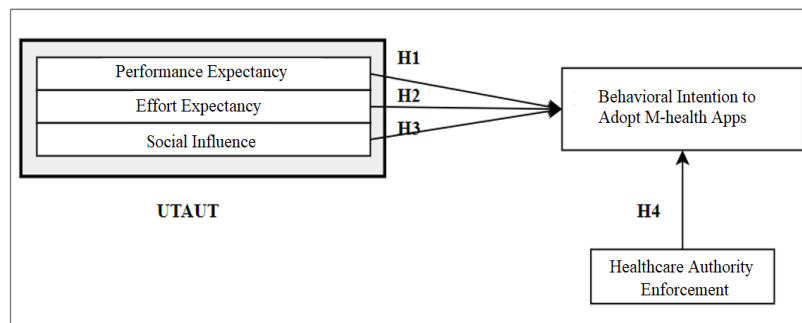
Figure 2. Research Model

Research Methodology

This research employs a quantitative method of collecting numerical data from users of Saudi m-health apps. It embraces and adapts instruments that were earlier validated to certify that the survey items are appropriate (Alanezi 2020, Hoque and Sorwar 2017, Venkatesh et al. 2003). The survey construct, corresponding items, and items sources are present in Table1. The survey has been initially formulated in English and then translated into the Arabic version. To avoid ambiguity in terms, the survey questions were reviewed by a translation professional. Then, a pilot test was conducted to fine-tune the final English/Arabic version, which was sent to some researchers and prospective users. A five-point Likert scale has been used as one of the most frequently employed methods of measuring answers in survey design (1 = strongly disagree to 5 = strongly agree). An online survey was distributed via social media platforms, Twitter and Health WhatsApp groups. Inclusion and exclusion criteria are set to ensure that participants that are fit for the study are received. To be included, participants must only be above 18 and have used m-health apps before. 400 actual users have participated in the survey. The data analysis included a total of 343 responses after the deletion of incomplete responses. This research employed the Partial Least Squares (PLS) approach to test and validate the hypothesis relationships' conceptual model. PLS technique is a statistical analysis based on Structural Equation Modeling (SEM). SmartPLS is one of the popular PLS-SEM software that has been used to analyze the data (Hair et al. 2014). PLS-SEM is relevant for this research because it supports the simultaneous testing of formative and reflective constructs (Hair et al. 2014).This study has used the SmartPLS software version 3.3.3.

Table. 1. Construct with Measurement Items.

Construct	Corresponding Items	Item Sources
Performance Expectancy	PE1. Using m-health apps for booking appointments and request other health services improve my health needs. PE2. Using m-health apps enable me to accomplish tasks more quickly. PE3. If I use m-health apps, I will increase my chances of getting a raise. PE4. Using m-health apps increase health productivity.	(Hoque and Sorwar 2017, Venkatesh et al. 2003). Items were framed to fit the current research context.
Effort Expectancy	EE1. I would find m-health services via apps are easy for me to use. EE2. I would find it easy for me to become skillful at using m-health apps. EE3. I think I would become proficient at m-health app. EE4. My health activities with m-health apps are clear and understandable.	(Hoque and Sorwar 2017, Venkatesh et al. 2003). Items were framed to fit the current research context.
Social Influence	SI1. People who are important to me think that I should use m-health apps. SI2. People who affect my learning behavior think that I should use m-health apps. SI3. My friends and colleagues think that I should use m-health apps. SI4. I think that using m-health apps is fashionable.	(Hoque and Sorwar 2017, Venkatesh et al. 2003). Items were framed to fit the current research context.
Healthcare Authority Enforcement	HAE1.Public healthcare providers and hospitals see m-health apps are important. HAE2. I think we must follow the hospital health plans/instructions. HAE3. I think the hospital management knows better than I do. HAE4. I think I will use the app if the hospital forced me to use it.	Self-developed based on (Alanezi 2020, Ramdani et al. 2020)

Data analysis

Descriptive Analysis

Descriptive analysis shows 56% of participants are male, while 44% of them are female. The majority of participants ages (45%) are between 25-34 years, followed by 32% in the 18-24 years and 16% in the 35-44 years ranges. The participants' educational background includes 51% hold bachelor's degree, followed by 20% who hold high school degrees, and 14% hold master's degrees. A full description of participant demographics is shown below.

Table. 2. Participants Demographics

Variable	Description	Frequency	Percentage
Gender	Male Female	193 150 **Total: 343**	56% 44% **Total: 100%**
Age	18-24 25-34 35-44 45-59 60 and Above	111 154 55 19 4 **Total: 343**	32% 45% 16% 6% 1% **Total: 100%**
Educational level	Less than high school	6	2%

	High school	70	20%		
	Diploma	39	11%		
	Bachelor	173	51%		
	Master	49	14%		
	PhD	6	2%		
		Total: 343	**Total: 100%**		

Measurement Model Assessment

Reliability and Validity Assessment

The first analysis step is performed to test internal consistency, convergent validity and discriminant validity (Hair et al. 2014). Lambert and Durand (1991) have highlighted that to measure a variable, multiple items take part, and each item is essential to measure it; thus, factor loadings show how much each scale item, which is developed to measure a particular variable, contributes to its measurement. Shevlin and Miles (1998) have divided its threshold value into three types. They noted that those factor loadings below 0.3 are termed as low, 0.5 can be regarded as middle factor loadings, while those factor loadings higher than 0.7 are regarded as high factor loadings. In this case, both middle and high factor loadings are acceptable. Table 3 also shows the measurement of reliability. According to Raubenheimer (2004), reliability is a valuable process that proves whether a scale is applicable for measuring a variable. The author further defines it as the process of measuring internal constancy or consistency of the scale. In literature, previous authors have used three important reliability measurement tools, including Cronbach's Alpha Cronbach (1951) and Composite Reliability (CR) McDonald (1970). Moreover, internal consistency is determined using the suggested value of 0.70 for Cronbach's alpha (Hair et al. 2014). The average extracted variance (AVE) and composite reliability (CR) are also used to calculate convergent validity, with appropriate AVE values of 0.50, and the CR should be higher than AVE (Hair et al. 2014). The second type of validity is discriminant validity, which is calculated using each construct's square root AVE, which should have been more than any correlation between the latent variables (Hair et al. 2014). Discriminant validity, which is presented in table 3, shows that the correlation of items under a single variable should be stronger with other items of the same variable compared to their correlation with items of another variable. According to Fornell and Larcker criterion (1981), the bold diagonal values in table 3 should be greater than their correlated values in columns and rows. This table shows that all these values are higher than their respective values in columns and rows, proving discriminant validity.

Table. 3. Reliability and Validity Assessment

	CA	rho_A	CR	AVE	BI	EE	HAE	PE	SI
BI	0.881	0.885	0.918	0.738	**0.859**				
EE	0.840	0.846	0.893	0.677	0.479	**0.823**			
HAI	0.719	0.742	0.825	0.543	0.569	0.406	**0.737**		
PE	0.839	0.843	0.892	0.675	0.435	0.579	0.422	**0.822**	
SI	0.864	0.869	0.917	0.786	0.512	0.405	0.450	0.369	**0.815**

Note:

- BI: Behavioral Intention; EE: Effort Expectancy; HAE: Healthcare Authority Enforcement; PE: Performance Expectancy; SI: Social Influence.

- CA: Cronbach's Alpha; CR: Composite Reliability; AVE: Average Variance Extracted.

Structural Model Assessment

Path Testing

All the developed hypotheses of this study are evaluated through the Structural Equation Modelling (SEM) technique. The following results in table 4 are represented along with coefficient and significance value. By using the bootstrapping procedure, the value of the path coefficient was evaluated. SmartPLS 3.0 can conduct bootstrapping with both the model and experiment to assess the p-value and t-value for relevance and significance (Hair et al. 2014). According to the developed directional hypothesis, a hypothesis is accepted along with a significance p-value less than 0.05 and a t-value greater than 1.96 (Hair et al. 2014). Table 4 and figure 3 show the path test results.

Table. 4. Path Testing

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Decision
EE -> BI	0.186	0.189	0.057	3.259	0.001	Supported**
HAE -> BI	0.344	0.345	0.051	6.676	0.000	Supported**
PE -> BI	0.091	0.093	0.055	1.643	0.101	Not Supported
SI -> BI	0.248	0.250	0.051	4.886	0.000	Supported**
Note:						
- BI: Behavioral Intention; EE: Effort Expectancy; HAE: Healthcare Authority Enforcement; PE: Performance Expectancy; SI: Social Influence.						
- Significant** at P =<0.01, * at P <0.05						
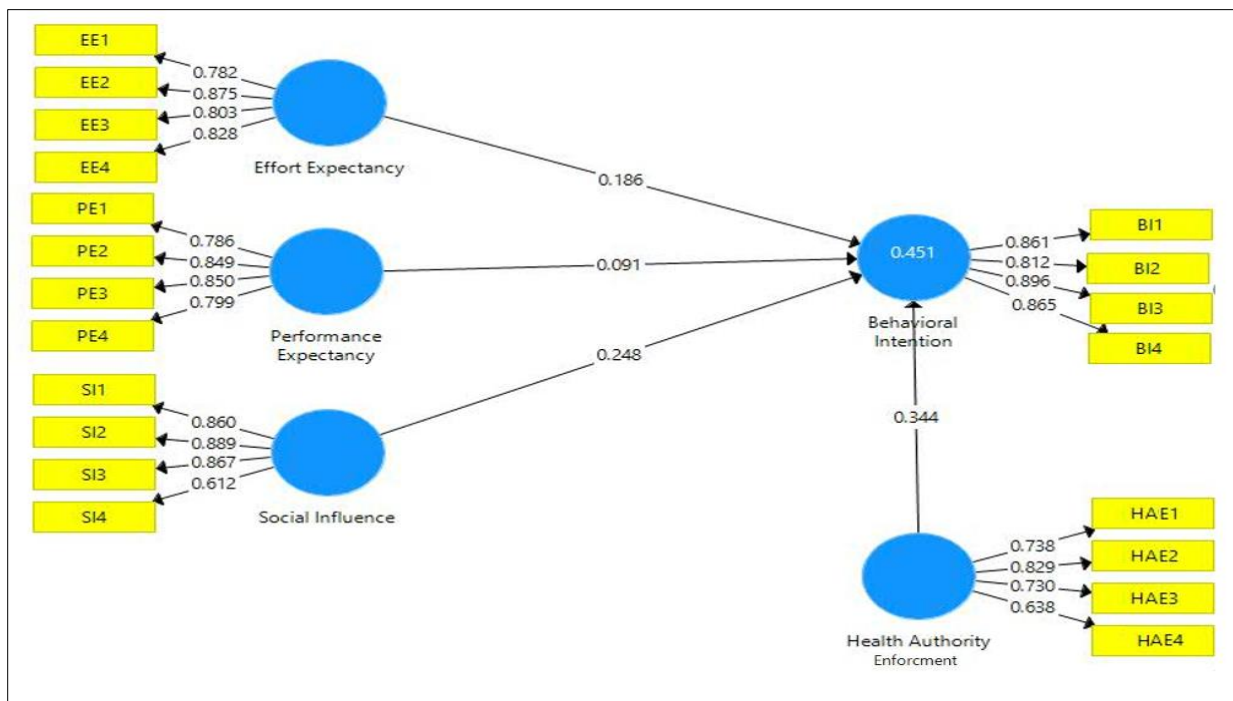
Figure 3. Research Model after Measurement Tests

Coefficient of Determination (R²)

Chin (1998) proposes three R²degrees. R² values greater than 0.67 are considered high, values between 0.33 and 0.67 are considered moderate, and values between 0.19 and 0.33 are considered inadequate or inappropriate. In this research, the R² of behavioral intention is equal to 0.452. Hence, the result is moderate for this research.

Model Fit

It is essential to evaluate the model fitness as being the major part of factor analysis. SmartPLS assures two crucial aspects in model fitness, including Standardized Root Mean Square Residual (SRMR) and Normed Fit Index (NFI). For SRMR, Hu and Bentler (1999) state that SRMR is acceptable if it is lower than 0.08. The second important value for model fitness is NFI. NFI values recommended range is between 0 and 1. Bentler and Bonett (1980) also suggest a threshold value of 0.9 would be highly acceptable. In this study, the value of SRMR is 0.067, and the value of NFI is 0.802. Therefore, these values prove the model fitness of this study. Table 5 shows the model fit results.

Table. 5. Model Fit Test

	Saturated Model	**Estimated Model**
SRMR	0.067	0.067
d_ULS	0.857	0.857
d_G	0.334	0.334
Chi-Square	695.486	695.486
NFI	0.802	0.802

Discussion

In line with the research objectives, this research uses behavioral intention to explain patients' motivations for adopting m-health apps in Saudi Arabia based on the UTAUT model. It aims to examine factors affecting patients' behavioral intention to adopt m-health apps in Saudi Arabia. As shown in table 4 and figure 3, path significance among the factors that significantly affect behavior intention is healthcare authorities' enforcement, followed by social influence and effort expectancy. The findings show no influence of performance expectancy on behavioral intention.

According to table 4, performance expectancy has no significant impact on behavioral intention because the significance value is equal to 0.101, which is higher than 0.05. The t-value is not greater than 1.96; thus, the first hypothesis of this study is rejected. However, effort expectancy significantly impacts behavioral intention as the significance value is 0.001 < 0.05; therefore, this study's second hypothesis is also accepted. Social influence has a 24.8% positive and significant impact on behavioral intention with p<0.05 and t=4.886; thus, the third hypothesis of this study is supported. Finally, healthcare authorities enforcement has a 34.4% positive impact on behavioral intention with a significance value p=0.000<0.05 and t-value=6.676>1.96; thus, this study's fourth hypothesis is accepted.

According to the study results, the order of path significance for factors affecting behavioral intention to adopt m-health apps is healthcare authority enforcement (path coefficient of 0.344), social influence (path coefficient of 0.248), and effort expectancy (path coefficient of 0.186). The results show that effort expectancy, social influence, and healthcare authority enforcement have significant positive influence on the behavioral intention. The results also confirm that the proposed factor, healthcare authority enforcement, has a more significant influence on behavioral intention to adopt m-health apps in Saudi Arabia, even more than technological factors. It means users of Saudi m-health apps could be influenced by others, such as family and friends, and most important the government, to adopt and use

m-health apps. Overall, our analysis supports prior research of technology and apps adoption, with the addition of healthcare authorities' enforcement on patients' behavioral intention.

The current research has some limitations. First, it has employed only a quantitative method. Applying qualitative or mixed approaches on m-health adoption studies can yield more incredible insights and provide more credible data for m-health app studies. Second, the study model did not include all considerations that may affect an individual's behavioral intention to adopt m-health apps. Lastly, the majority of this study's participants were young. Although they are representative of m-health users, they cannot be considered for all age classes. In particular, in an ageing population, older individuals with a high risk of disease are significant potential users. Therefore, it is necessary to verify whether the results are still valid in other age groups. As a result, attempts should be made to use age to predict the factors affecting the adoption of m-health apps in developing countries.

Conclusion

This study makes some important contributions. It adds to the literature of information systems and health technologies by discussing issues and factors regarding adopting m-health apps in the health sector. The results show that effort expectancy, social influence, and healthcare authority enforcement have significant positive influence on the behavioral intention. The results also confirm that the proposed factor, healthcare authority enforcement, has a more significant influence on behavioral intention to adopt m-health apps in Saudi Arabia, even more than technological factors. This research also provides valuable knowledge for future studies in the area. It also gives governments and healthcare decision-makers new knowledge and insights for developing new policies that promote m-health apps. The research did not include all considerations of the technological and external factors that may affect behavior intention to adopt m-health apps. Lastly, this study's results can be similarly applicable to other developing countries with similar contexts as Saudi Arabia, which will help improve the adoption rates of m-health technologies in those countries.

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