South East European Journal of Economics and Business
Volume 17 (2) 2022, 18-33
DOI: 10.2478/jeb-2022-0012

THE USERS' BEHAVIORAL INTENTION TO USE MOBILE HEALTH-TECH APPLICATION TO PREVENT THE SPREADING OF CORONAVIRUS

Ammar Almasri

Abstract

The emergence of mobile health applications (MH-Apps) has enhanced the healthcare field's services, particularly in the treatment, diagnosis, and follow-up. AMAN Mobile Health Application (AMAN MH-App) is one of the health-tech solutions used to fight the Coronavirus pandemic. It has a built-in feature to track users' activities to protect users from contacting an infected person. However, the acceptance of AMAN MH-App in Jordan is still in an early stage, and the number of users has reached 15% of the country's population. Therefore, this study aims to assess the use of AMAN MH-App among young people using the quantitative method. A total of (450) valid samples participated in the study after removing 33 invalid samples. SmartPLS 3.2.7 was used for data analysis. The findings showed that all independent variables (Perceived usefulness, Perceived ease of use value, Subjective norms, Perceived behavioral control, Information Credibility, and Optimism) positively impact on the dependent variable (Behavioural Intention to use AMAN MH-App). We believe that AMAN MH-App's information's credibility (i.e. providing up-to-date, authoritative, accurate, and trustworthy information) will increase the number of the App's users. The results of this research can be applied to similar context and applications in different countries.

Keywords: *Behavioral Intention, Mobile Health Application, AMAN MH-App, Covid-19*

JEL Classification *: M15, M19, I11, I12, I18*

1. Introduction

After incorporating technologies into the health sector, people's motivation to use technology has been central for developing the health care system. It is of great importance to health informatics to consider the way people adapt to the introduction of new technology, such as using smartphones in healthcare. According to the World Health Organization (WHO), Mobile Health Technology (MHT) consistently uses mobile devices in the medical field (World Health Organization Writing Group et al. 2006). Many studies found that younger people are more ready to adopt new technology smartphones than older adults (Almasri 2015a).

The speedy evolutions of mobile devices (Pilav-Velić et al. 2021) contribute the integration of mobile services into the healthcare field as a broad part of daily life (Babic-Hodovic et al. 2017). Mobile

Ammar Almasri, PhD
Lecturer
Department of Management Information Systems
Al-Balqa Applied University
Salt 19117. Jordan, P.O.Box 206
E-mail: Ammar.almasri@bau.edu.jo
ORCID: https://orcid.org/0000-0003-3289-3328

devices help people control and manage diseases by utilizing Mobile Health Applications (MH-Apps) in prevention and health. The MH-Apps are essential in our daily lives to assist health services in disease detection, risk assessment, case recognition, touch tracking, and monitoring circumstances. The MH-Apps, as one of the most important and widely used sub-sectors of e-Health, seeks to increase the quality and access to health services (Erfannia et al. 2020). The MH-Apps are essential in disease management during a pandemic and can support the health system through surveillance of disease (Kodali et al. 2020), risk assessment (Ren et al. 2020), patients and suspected cases identification, contact tracing of positive cases, and status monitoring (Kodali et al. 2020). This process includes collecting anonymous data to track people's movements and tracking confirmed cases to track suspicious cases and their connections (Bassi et al. 2020). These strategies were individual and compulsive in some cases, while in some areas, data was collected public and anonymously (Ekong et al. 2020).

Many countries have used mobile data to respond quickly to Covid19. The Indian Ministry of Family Health and Welfare has developed remote counseling guidelines as the number of cases increases (Bassi et al. 2020). Also, they found that there is a serious need to include remote counseling options in mobile apps. In China (Ye et al. 2020), platforms such as Cloud computing was used to store and analyze disease-related big data. The IoT was used to collect real-time data, and artificial intelligence capabilities were used to intelligently diagnose disease, measure temperature, and provide robots for patients. Also, the 5G platform was used as the infrastructure for video conferencing and remote detection. In the United States (Ekong et al. 2020), $500 million of the $2 trillion economic stimulus budget has been assigned to the Centers for Disease Control and Prevention to build a novel collection and surveillance system to monitor Covid19. Germany, Austria, and Italy collect call detail records (CDRs) to enforce quarantine and stay at home strategies (World Health Organization 2020). In Korea, Hospitals, in addition to collecting vital real-time data from suspected and confirmed patients and displaying it through dashboards to health personnel and data storage in the hospital information system database, provided a rich and up-to-date data source (Ekong et al. 2020).

Through cooperation with telecommunications companies, the governments have started monitoring people with travel history to in the pandemic's early days (Ekong et al. 2020). Also, it is worth noting that the number of countries in the world that have started using virus exposure detection applications as part of the emerging Coronavirus containment strategy is increasing continuously to include India (Bassi et al. 2020), Africa (Umezuruike et al. 2020) South Korea (Bae et al. 2020), Zurich (Vokinger et al. 2020), China (Ye et al. 2020), Switzerland (Zamberg et al. 2020), South Korea (Bae et al. 2020), Nigeria (Ekong et al. 2020), and others. In Jordan, the government has made a series of processes to reduce the physical contact among people, preventing the spreading of Covid-19. One of the innovative steps is developing a mobile health application named "AMAN MH-App" to track infected persons and send alerts to individuals who have been in contact with those infected people.

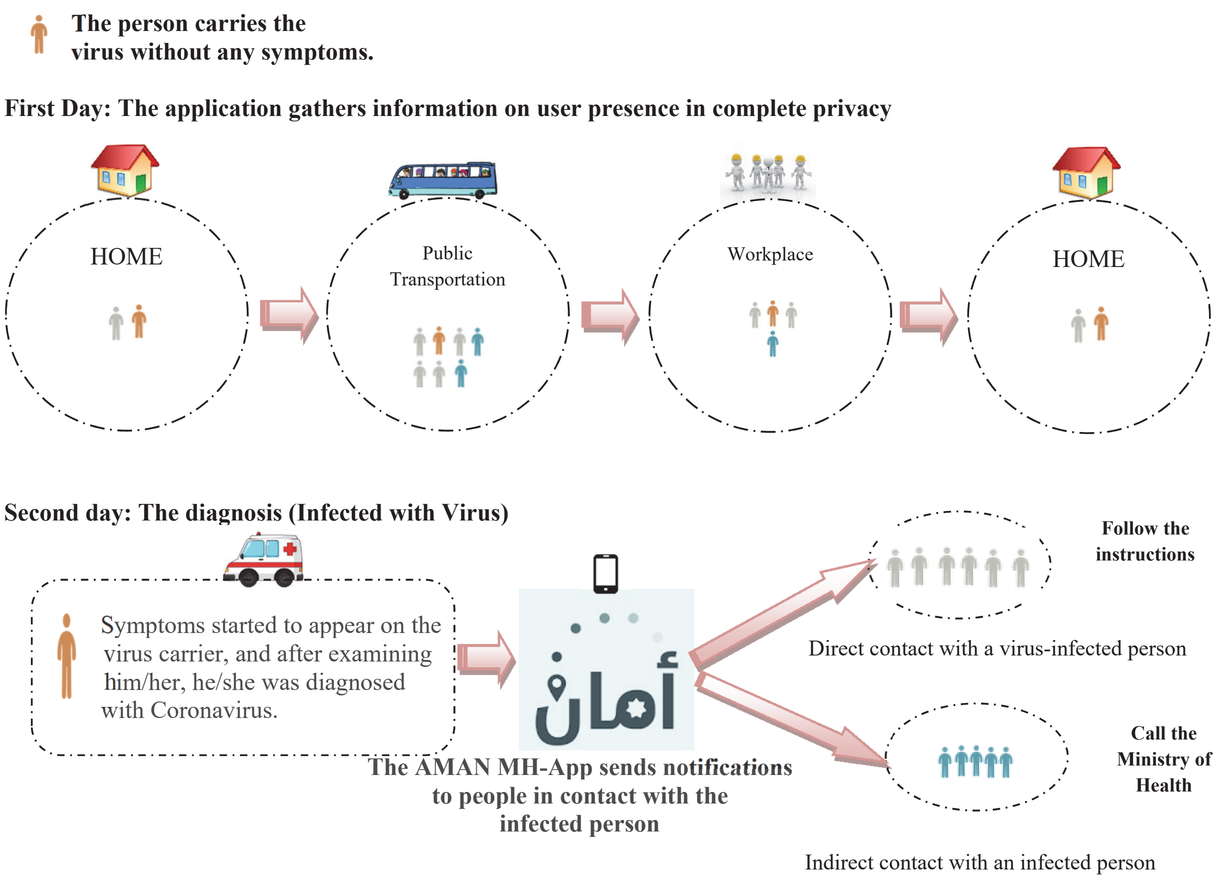
The AMAN MH-App is a tracking app that is part of the Hashemite Kingdom of Jordan's response plan to contain the emerging Coronavirus. That is a privacy-protected mobile program that warns users if they are suspected of being exposed to the virus or in contact with an infected person, using geolocation technology (GPS), and soon Bluetooth. The AMAN MH-App was created as a community project for the Ministry of Health (MOH) by the Covid-19 JOTECH COMMUNITY group. This group of experts volunteer their knowledge and skills to assist Jordan with efforts to contain the spread of Coronavirus and beat this pandemic. The group aim to benefit from Jordanian technological talents in Jordan and the world by providing the Jordanian government with the necessary support. For example, they provide research, offer consultation, share with the government the world's leading countries' experiences in the optimal use of technology to contain the spread of the virus, as well as provide human resources from expert volunteers to support the government in implementing technological initiatives. Day after day, the AMAN MH-App demonstrates its efficacy in controlling interactions and identifying the source of infection, emphasizing that the number of users has reached one million and 650 thousand which represents 15 % of the country's population. However, the number of cases of coronavirus infection is continually growing, owing to the lack of AMAN MH-App use among people.

However, people use MH-Apps unregularly, likely because these apps are realized as an erratic and not secure (Wu et al. 2022). It is believed that high rejection of using MHT will result in delays in the successful implementation of mobile health applications (MH-Apps), or even failure, and will hinder the achievement of related organizational objectives, such as efficient patient records monitoring and analysis (Ghose et al. 2021). The continuous using and development of MH-Apps depends on users' behavioral and intention to use these Apps. Therefore, the success of MH-Apps usage relies on understanding users' behavioral and intention. In addition, resistance to MH-Apps would entail clear policy steps to improve acceptance and perhaps to familiarize future users with the advantages of the IT applications being discussed. So far, research has identified a range of key independent factors that predict user intentions in adopting AMAN MH-App. This study developed and tested our model based on the original Technology Acceptance Model (TAM) and Theory of Planned Behavior (TPB) to determine the best predictors of users' behavioral intentions to use AMAN MH-App. This study aims to determine the relationships between independent variables, namely Perceived Usefulness (PU), Optimism (OP), Subjective Norms (SN), Perceived Behavioral Control (PBC), Information Credibility (IC) and Perceived Ease of Use (PEU) and dependent variables, namely Behavioral Intention (BI) to use AMAN MH-App, and also to find out how the independent variables influence the dependent variable. Also, the results of this research is not limited to one country but it can be applied to similar context and applications in different countries.

2. How does AMAN MH-App work?

The AMAN MH-App application aims to detect virus exposure using GPS and later Bluetooth technology. It allows more straightforward and more effective processes to monitor and isolate new cases of Coronavirus, which leads to the virus being contained and to protect the app users, their families, and their societies (MoH 2020). Applications for the detection of virus exposure show their ability to help control the spread of infectious diseases by warning users as soon as possible of their interaction with infected cases to take the necessary steps promptly (MoH 2020). As far as the evolving Coronavirus is concerned, current studies suggest that many cases of infection with this virus are transmitted by airborne droplets captured at an average distance of about two meters. Consequently, it becomes extremely necessary to warn people who were in contact or were in close proximity to any infected person to speed up the diagnostic process and allow the virus to be managed (see figure 1 for more details).

Figure 1. Flowchart of a Covid-19 detection AMAN MH-App (MoH 2020)



AMAN MH-App operates in two interrelated ways. First, to equate the user's movement with the movement of users who are later diagnosed with the latest Coronavirus by the Ministry of Health, the application saves location data exclusively on the user's computer. Let us suppose that contact happens between a user and another who later tests positive. In this case, the program sends warnings with the location and time to users who have been present in the infected person's vicinity. On the other end, when receiving a warning, the application also displays guidance and measures to be taken by the warned individuals. Moreover, the second method by which the user diagnosed with the new Coronavirus, the application will be able to conveniently recover his/her whereabouts and movements over the last 14 days, including dates, times, and locations. This stage's primary objective is to warn other users who happen to be in the vicinity of the diagnosed user, which eventually speeds up infection detection and virus spread control.

3. Related works on Mobile Health Technology (MHT)

Table 1 provides various research that deployed MHT tools to diagnose, treat, and monitor the Covid-19 pandemic. It also identifies the main objectives of the studies that have implemented MHT in the health sector.

Table 1. Related work on MHT

Authors	MHT opportunities	MHT effect	Study objective
(Pan 2020)	Managing travel and contact with patients	Diagnosis Follow up	This study aims to use the mobile phone to prevent the spreading of Covid-19.
(Pulia et al. 2020)	Active surveillance of disease	Diagnosis Follow up	Using EHR base data to active monitoring of Covid-19patients.
(Ren et al. 2020)	Integration of health data	Diagnosis Follow up	Using MTS (mobile telehealth system) to enable the following patients remotely and discuss the cases.
(Timmers et al. 2020)	Self-assessment, Self-education	Diagnosis Follow up	This paper evaluates mobile health apps' use by people to assist them for 7 days with Covid-19.
(Umezuruike et al. 2020)	Patient tracking	Follow-up	In this study, a tracking and alert system for Covid-19 is proposed.
(Vokinger et al. 2020)	Tracing and geolocation tracking	Diagnosis	This research aims to develop a framework to guide a specific app's alignment with an epidemiological principle.
(Wang, Ding, and Xiong 2020)	Early diagnosis of infection	Diagnosis	Developing a mini program within the app WeChat to early diagnosis of infection is proposed.
(Ye et al. 2020)	Tracking of close contacts Identify of epidemic trends Diagnosis remotely	Diagnosis	Establish a technical system for reacting to the outbreak of Covid-19 using MH-Apps.
(Zamberg et al. 2020)	Providing evidence-based treatment, timesaving	Diagnosis	The use of a dedicated mobile health application (MH-Apps) to keep SARS-CoV-22's patients' data up to date.
(Bassi et al. 2020)	1-A mobile app can self-testing, quarantine monitoring, and contact tracing of Covid-19 patients. 2-Mobile App can increase information dissemination regarding preventative measures.	Diagnosis Treatment Follow-up	Explore mobile apps in India relevant to Covid-19 and discover the apps' roles and emphasize issues in informing the establishment of potential mHealth plan.
(Ekong et al. 2020)	1-Find confirmed cases of mobility and travel patterns. Patients' mobility data is very effective in mapping intervention strategies. 2-Improving the timely outbreak response.	Follow-up	To survey remote contact tracing techniques for the Covid-19 disease and present how the use of mobile location data complies with Nigeria's data protection and regulations.
(Kodali et al. 2020)	High user score acceptance and usefulness. The users also noted expectations to include the app's additional features.	Diagnosis Follow up	Analyzing Arogya Setu app user's experiences and expectations in India

4. Theoretical background and research hypotheses

In the reviewed literature, two approaches were adopted: the first approach is driven by the features of technology in embracing assessments, while the other emphasizes the technical and psychological factors that affect the adoption decision. Accordingly, the Technology Acceptance Model (TAM) represents the first approach to adopt new technology, while the Theory of Planned Behavior (TPB) focuses on psychological factors that affect our decision to adopt new technology.

4.1. TAM model

The Technology Acceptance Model (TAM) is one of the most influential models used to describe the behavior of information technology (IT) usage due to its practicality and appropriateness(Davis, 1989). Specifically, the best predictors of user intentions have been found to be perceived usefulness (PU) and Perceived Ease of Use (PEOU) to the IT applications. In TAM, created by Davis to test the acceptance of new technologies by IBM employees, the tripartite of PU, PEOU, and attitudes have been well summarized. TAM research has grown considerably over the last 20 years, and TAM prominently features among the leading theoretical methods used to evaluate people's intent to use different information technology types. In addition, the novel TAM is extended with different variables by developing alternative models. Thus, the adoption of technology can be witnessed in a number of environments, online banking systems(Munoz-Leiva, Climent-Climent, and Liébana-Cabanillas 2017), e-commerce(Chi 2018), smartphone use(Xia, Zhang, and Zhang 2018), online travel communities (Agag and El-Masry 2016), mobile learning (Almasri 2015b) and health informatics(Ammenwerth 2019). Previous related works on TAM model have proven its stability and reliability, and it can consistently explain a significant amount of variation in technology use behavior. Also, it has found that Perceived Ease of Use (PEU) and Perceived Usefulness (PU) are the main factors of the users' acceptance of an information system or any technology. Nonetheless, few studies have used TAM to model user behaviors intention, especially for mobile health apps. In our study, users' behaviors intention to use AMAN MH-App to control and manage Covid-19 diseases is explained.

4.1.1. Perceived Ease of Use (PEOU)

According to (Davis 1989), PEOU refers to "the extent to which an individual believes that using a particular system is free of effort". Perceived ease of use refers to the degree to which a person feels that a given device is effortless. Related works have agreed that the overall adoption of technologies has been directly impacted by PEOU. Based on our study, the perceived ease of use is to the degree that the individual feels that it is effortless to use the AMAN MH-App and has no trouble coping with it. Therefore, the following hypotheses were suggested:

H1: PEOU will have a positive effect on BI to use AMAN MH-App

4.1.2. Perceived Usefulness (PU)

Perceived usefulness refers to "the extent to which an individual believes that using a particular system would improve work performance"(Davis 1989). PU is also defined as the degree to which an individual assumes that using a particular system will increase the job's efficiency. Previous related works have clearly stated that the overall adoption of technologies has been directly impacted by PU. In this study, PU refers to how users believe that AMAN MH-App provides up-to-date information, which will boost the efficacy in controlling interactions and identifying the source of infection. Therefore, the following hypotheses were suggested:

H2: PU will have a positive effect on BI to use AMAN MH-App.

4.2. The Theory of Planned Behavior (TPB)

To describe actions in various domains, the Theory of Planned Behavior (TPB) was developed by Ajzen and Fishbein (2005). It has been successfully used over the past few decades to describe actions in different contexts, such as consumer behavior, ecological behavior, sexual behavior, and sports participation. In several of these studies, the theory has provided a reasoned explanation of the behavior under consideration. Based on the theory, three kinds of thoughts play a crucial role in human guidance: behavioral beliefs, normative beliefs, and control beliefs. (Guo et al. 2019) suggest that TPB is a useful theory for healthcare administrators' behavioral intention to use a particular technology.

4.2.1. Subjective Norms (SN)

The Subjective Norms (SN) refer to a person's response to social preferences in undertaking a specific behavior (Ajzen 1991; Cheon et al. 2012). It refers to the response of a person to social preferences to a given activity. Many researchers have investigated SN and their impact on users' intention to use innovative technology. Most of them found that SN have a positive effect on the intention and adoption behaviors. Therefore, the following hypotheses were suggested:

H3. SN will have a positive effect on BI to use AMAN MH-App.

4.2.2. Perceived Behavioral Control (PBC)

Perceived Behavioral Control (PBC) refers to "an individual's perception of the degree to which they are capable of, or have control over, performing a given behavior" (Ajzen 1991). It refers to an individual's understanding of whether a given action is straightforward or difficult to execute. PBC is a combination of perceived control and self-efficacy, and there has been a consensus in the literature that PBC has a direct impact on behavior intention (Ajzen 2002). Therefore, the following hypotheses were suggested:

H4. PBC will have a positive effect on BI to use AMAN MH-App.

4.2.3. Information Credibility (IC)

Information credibility (IC) refers to "the degree to which an individual perceives information provided by the mobile applications to be believable"(McKnight and Kacmar 2007). Previous related studies have indicated that users' IC perceptions are linked to the accessibility of application interfaces (Wathen & Burkell 2002), such as the presentation and organizing of information. Ease of use (EOU) interfaces will help create trust, particularly in using online applications that rely on internet aconnection (Gefen, Karahanna, and Straub 2003). EOU apps would be less doubtful (Moon and Kim 2001; Shen, Cheung, and Lee 2013), meaning that PEOU is expected to endorse the users' credibility perceptions by using those apps. Also, evidence has demonstrated that users of EOU interface apps can achieve greater perceived credibility. A user is expected to develop a higher sense of credibility for the applications that greater EOU interfaces. However, few studies have used IC of users' perception regarding their intention to use new technology, especially mobile health apps. In our research, AMAN MH-App's success depends on how reliable people consider the app's data. They will not act on the advice and will not build loyalty to the AMAN MH-App unless people think the app's data is reliable. Therefore, the following hypotheses were suggested:

H5: IC of AMAN MH-App will have a positive effect on BI to useAMAN MH-App.

4.3. Other Factors

4.3.1. Optimism (OP)

It refers to the positive perspective on technology that increases productivity, flexibility, and influence in people's lives (Parasuraman and Colby 2015). It will also be less likely for positive people to emphasize the negative implications and, therefore, tend to implement revolutionary technologies (Walczuch, Lemmink, and Streukens 2007). Thus, the following hypotheses were suggested:

H6: OP will have a positive effect on BI to use AMAN MH-App.

4.3.2. Behavioral intention to use AMAN MH-App (BI)

According to (Ajzen and Fishbein 2005), Behavioral Intentions (BI) refer to the perception that a person will carry out any action. Any behavior or actions can be assumed to be practised using technology. Previous related works within and outside HIT have repeatedly demonstrated that BI is a widely validated true behavior indicator and the most commonly used acceptance determine (Almasri 2014). In our study, users' behavioral intention to use AMAN MH-App to control and manage Covid-19 diseases is introduced as a dependent variable.

4.2. Measures

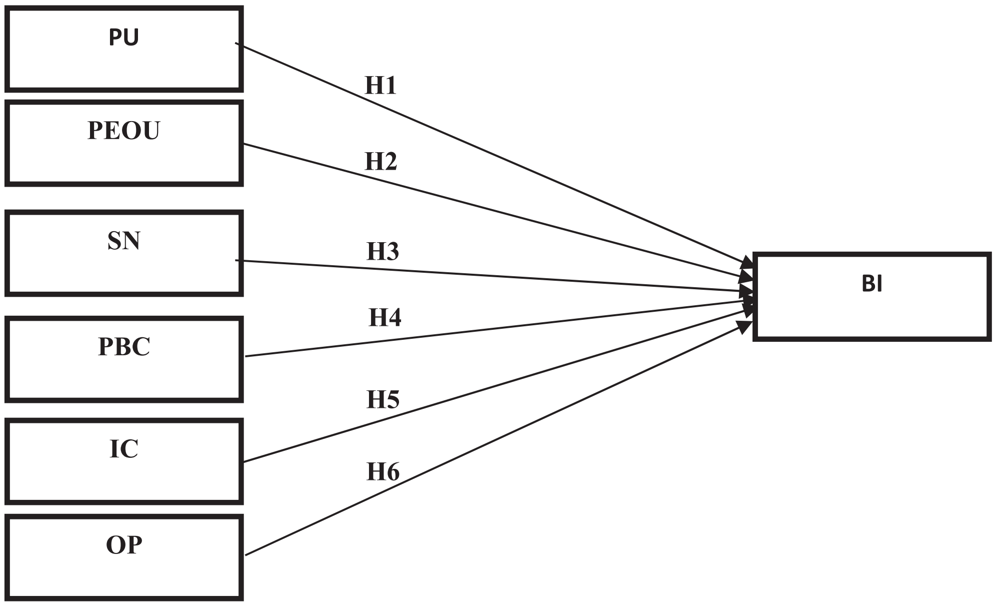
All measurement items for the chosen variables were adapted from previously related works that have already validated them. The data collection instrument was a survey questionnaire that was established based on previous studies. Using a 7-point Likert scale that ranges from (1) extremely disagree to (7) extremely agree, all measurement items were gauged. Table 2 lists the questionnaire elements and their sources.

Table 2. Measurement items

Constructs	Measurement Item	Sources
Perceived Usefulness (PU)	MU1: I find AMAN MH-App offers information that I finduseful.	(Davis 1989)
	MU2: Using AMAN MH-App improve my effectiveness in controlling interactions and identifying the source of infection.	
	MU3: Using AMAN MH-App would save time in virus tracking.	
	MU4: Using AMAN MH-App enables me to detect who is infected quicker.	
Perceived Ease of Use (PEOU)	MEOU1: Wording in the AMAN MH-App is clear and easy tounderstand.	(Davis 1989)
	MEOU2: The information interfaces in the AMAN MH-App are readable.	
	MEOU3: The AMAN MH-App uses easy structures to read.	
	MEOU4: Inside most components of an interface, I can understand AMAN MH-App in seconds.	
Subjective Norms (SN)	SN1: People who can influence my behavior think I should use AMAN MH-App.	(Ajzen 1991)
	SN2: People important to me think I should use AMAN MH-App.	
	SN3: I most certainly prefer to benefit from the knowledge of others and their advice.	
	SN4: People around me encourage me to use AMAN MH-App.	
Perceived Behavioral Control (PBC)	PBC1: I am confident that I could to use AMAN MH-App.	(Ajzen 1991)
	PBC2: For me to use AMAN MH-App is easy.	
	PBC3: The decision to use AMAN MH-App is beyond my control	
	PBC4: Whether I to use AMAN MH-App or not is entirely up to me	
Information Credibility (IC)	IC1: AMAN MH-App providing me up-to-date information.	(McKnight and Kacmar 2007)
	IC2: AMAN MH-App providing me accurate information.	
	IC3: AMAN MH-App providing me trustworthy information.	
	IC4: AMAN MH-App providing me authoritative information.	
Optimism (OP)	OP1: AMAN MH-App gives me more control over my daily life.	(Lu et al. 2011)
	OP2: AMAN MH-App is much more convenient to use.	
	OP3: I like the conception of technologies to tackle illness, and I am not limited by traditional means.	
Behavioral Intention (BI)	BI1: In the near future, I am likely to use AMAN MH-App	(Davis 1989)
	BI2: I would use the AMAN MH-App, granted the opportunity.	
	BI3: In the coming future, I will be able to use AMAN MH-App.	
	BI4: When the chance arises, I aspire to use AMAN MH-App.	
	BI5: I'm going to start thinking AMAN MH-App usage	

Figure 2 shows the conceptual structure of this research paper, demonstrating that the users' behaviors intention to use AMAN MH-App (BI) will be influenced based on the following latent variables: (1) The dimension of the technology characteristics represented by the TAM model with its two main elements, the PU and PEOU, (2) The psychological dimension represented by the SN, PBC, and OP, (3) Information dimension represented by IC. The model aims to explore the relationships between all independent variables (Perceived Usefulness, Perceived Ease of Use value, Subjective Norms, Perceived behavioral Control, Information Credibility, and Optimism) and the dependent variable (Behavioural Intention to use AMAN MH-App). Accordingly, six hypothesized models for this study were proposed.

Figure 2. The Proposed research model



5. Methodology and Results

5.1. Participants

The study proposes a theoretical model to explain citizens' intention to use AMAN MH-App in the emerging Coronavirus (Covid-19). A field survey was conducted in Jordan to collect data from citizens, specifically young people. Thus, Participants were selected from universities in Jordan by random student sampling. As these students formed the largest user community of smartphones in Jordan, we confined our participants to university students, and that a relatively homogeneous sample helps control confounding variables that may confuse the variables under discussion. All respondents possessed a smartphone and had access to the internet and smartphone apps.

Before collecting data through an online questionnaire, we sent short video explains the AMAN MH-App that was downloaded from Ministry of Health (MOH) website to ensure that all students understood AMAN MH-App. Then, the e-questionnaire was created through Microsoft Forms and the link has sent through Microsoft Teams and Moodle platforms in Arabic language. We obtained 450 valid samples for data analysis after removing 33 invalid samples that either did not complete it (missing values) or given too many unreliable answers (e.g. select 1 or 7 for all answers). There were 39.3 % of male and 60.7% of female respondents in the sample.

5.2. Analysis and Results

5.2.1. Measurement Model Analysis

- **Convergent and Discriminate Validity**

The measurement model analysis aims to find "a confirmatory assessment of reliability", "convergent validity", and "discriminant validity" (Anderson & Gerbing 1988). According to (Lowry & Gaskin 2014), reliability is "the degree to which a scale yields consistent and stable measures over time". The first step to measure the model was investigating the values of each item's reliability (factor loading) for each variable using smart PLS (PLS algorithm). The results showed that factor loading for all items exceeded the recommended value of 0.7, and the results were ranged from 0.715 (for IC2) to 0.942 (for PBC1). By evaluating all variables' factor loadings with their corresponding constructs, we evaluated individual items' reliability. At that point, the reliability is usually assessed using two essential methods Cronbach's Alpha and Composite Reliability (Hew, Lee, Ooi, & Lin, 2016). In terms of Composite Reliability (CR), the results showed that all CR of variables ranged from 0.830 (for IC) to 0.961 (for PBC) which means values were greater than 0.7 (Hair Jr, Hult, Ringle, & Sarstedt, 2016). Also, we could see that the Cronbach's Alpha values range from 0.801 (for IC) to 0.913 (for BI). All values have met the lowest value of 0.7 as indicated by(Hair Jr et al. 2016). The results in Table 3 highlight that the model's final reliability measurement (Wynne 1998) and (Fornell and Larcker 1981) were met for all constructs. We thus concluded that our research model's reliability was satisfactory.

The convergent validity refers to "the extent to which a measure correlates positively with alternative measures of the same construct" (Hair Jr et al. 2016). The convergent validity could be tested in this analysis by analyzing the Average Variance Extracted (AVE) values. The AVE for all constructs exceeded 0.5, which fulfilled the requirement (Fornell and Larcker 1981), as shown in Table 3. This also implies that the scales have fair and sufficient convergent validity.

In addition, discriminant validity refers to "the extent to which a construct is truly distinct from other constructs by empirical standards" (Hair Jr et al. 2016). According to (Hair Jr et al., 2016), the Fornell-Larcker and cross-loading requirements should be tested to determine the discriminant validity. The Fornell-Larcker criteria allow each variable's AVE to be greater than its highest association with other variables in the square root. The Fornell-Larcker criteria is fulfilled, according to Table 4. As far as cross-loading is concerned, the outer loading on the relevant construct must be greater than all the cross-loading of the related construct on the other constructs. Based on the readings in Table 5, it can be noticed that the cross-load criterion is satisfied.

Table 3. Indicators measurement in the questionnaire

Latent Variable	Indicator	Standardized Factor Loading	Cronbach's Alpha	Composite Reliability	AVE
		<0.70	<0.70	<0.70	<0.50
Perceived Usefulness (PU)	PU1	0.798	0.835	0.876	0.640
	PU2	0.820			
	PU3	0.810			
	PU4	0.770			
Perceived Ease of Use (PEOU)	PEOU1	0.810	0.842	0.878	0.644
	PEOU2	0.808			
	PEOU3	0.788			
	PEOU4	0.803			
Subjective Norms (SN)	SN1	0.760	0.813	0.837	0.562
	SN2	0.781			
	SN3	0.721			
	SN4	0.735			
Perceived Behavioral Control (PBC)	PBC1	0.942	0.838	0.961	0.862
	PBC2	0.938			
	PBC3	0.924			
	PBC4	0.909			
Information Credibility (IC)	IC1	0.762	0.801	0.830	0.550
	IC2	0.715			
	IC3	0.762			
	IC4	0.726			
Optimism (OP)	OP1	0.881	0.887	0.921	0.795
	OP2	0.895			
	OP3	0.898			
Behavioral Intention (BI)	BI1	0.886	0.913	0.951	0.794
	BI2	0.878			
	BI3	0.893			
	BI4	0.898			
	BI5	0.901			

Table 4. Fornell-Larcker criterion

	BI	OP	IC	PBC	SN	PEOU	PU
BI	**0.891**						
OP	0.508	**0.892**					
IC	0.452	0.552	**0.742**				
PBC	0.528	0.563	0.649	**0.928**			
SN	0.463	0.642	0.575	0.603	**0.750**		
PEOU	0.527	0.643	0.568	0.518	0.627	**0.802**	
PU	0.514	0.625	0.536	0.568	0.537	0.643	**0.800**

Table 5. Cross-loadings results

	BI	OP	IC	PBC	SN	PEOU	PU
BI1	**0.932**	0.632	0.501	0.503	0.403	0.462	0.468
BI2	**0.922**	0.654	0.507	0.409	0.452	0.492	0.503
BI3	**0.931**	0.623	0.524	0.526	0.436	0.466	0.576
BI4	**0.901**	0.623	0.525	0.533	0.401	0.486	0.523
BI5	**0.912**	0.601	0.521	0.536	0.487	0.482	0.501
OP1	0.502	**0.885**	0.475	0.498	0.485	0.572	0.589
OP2	0.532	**0.883**	0.523	0.488	0.515	0.554	0.545
OP3	0.544	**0.887**	0.502	0.504	0.478	0.523	0.561
IC1	0.384	0.456	**0.752**	0.502	0.501	0.456	0.452
IC2	0.301	0.401	**0.726**	0.522	0.499	0.413	0.402
IC3	0.298	0.421	**0.798**	0.489	0.485	0.431	0.421
IC4	0.323	0.389	**0.736**	0.439	0.487	0.436	0.433
PBC1	0.315	0.402	0.452	**0.902**	0.472	0.522	0.388
PBC2	0.382	0.389	0.511	**0.884**	0.418	0.478	0.372
PBC3	0.336	0.410	0.523	**0.889**	0.451	0.465	0.396
PBC4	0.335	0.411	0.505	**0.876**	0.458	0.455	0.412
SN1	0.401	0.502	0.440	0.566	**0.766**	0.519	0.477
SN2	0.398	0.487	0.432	0.521	**0.778**	0.495	0.489
SN3	0.378	0.498	0.485	0.532	**0.736**	0.508	0.478
SN4	0.410	0.521	0.481	0.528	**0.753**	0.509	0.563
PEOU1	0.525	0.535	0.501	0.425	0.521	**0.810**	0.478
PEOU2	0.510	0.542	0.454	0.444	0.542	**0.813**	0.525
PEOU3	0.587	0.521	0.521	0.521	0.487	**0.798**	0.539
PEOU4	0.542	0.487	0.438	0.487	0.475	**0.782**	0.463
PU1	0.413	0.475	0.448	0.378	0.425	0.454	**0.788**
PU2	0.425	0.511	0.492	0.425	0.429	0.475	**0.810**
PU3	0.457	0.517	0.436	0.410	0.431	0.501	**0.822**
PU4	0.425	0.523	0.413	0.372	0.433	0.498	**0.765**

- **Model Testing**

To evaluate the explanatory power of the model, the divergence for the dependent variables should be measured. Thus, R square and path coefficients have been used to assess the structure of our proposed model. As shown in Figure 3, the model has an R Square value of 56% for the independent variable. In other words, the total variance in Behavioural Intention to use AMAN MH-App by users accounted for by six latent variables, namely PU, PEOU, SN, PBC, IC, and OP, was 77%. The structural analysis results expose that the proposed model explains 77% of the variance in using AMAN MH-App.

In terms of path analysis, Table 6 and Figure 3 demonstrate the path coefficients and P-values for each hypothesis. In the model, path coefficients and P-value values for all independent variables were less than 0.2 and greater or equal to 0.05, respectively. Accordingly, all independent variables were directly and significantly predicted BI which indicated that all hypotheses were confirmed, and this points out that all the paths are significant between the independent (PU, PEOU, SN, PBC, IC, and OP) and dependent variables (BI).

Figure 3. Path Analysis Results

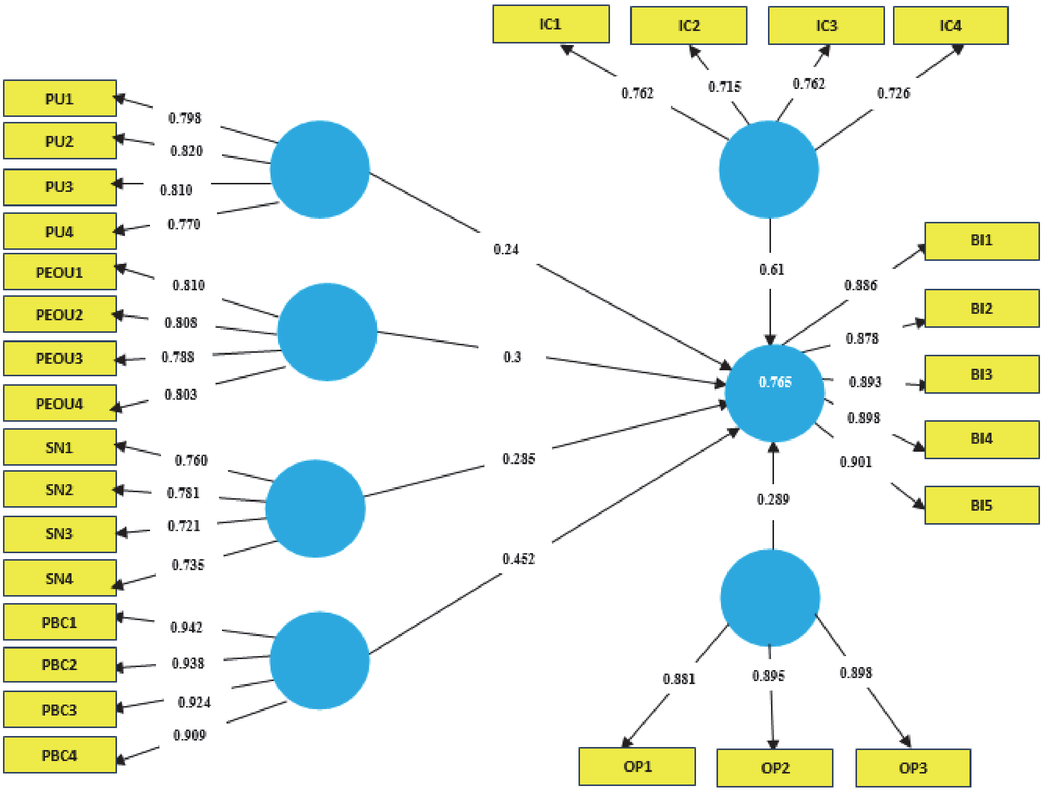


Table 6. Hypothesis testing

Hypothesis: Structural paths	t-value	Path Coefficient	Suppoted
H1: PU →BI	4.185	0.24**	yes
H2: PEOU→ BI	6.184	0.30**	yes
H3: SN→ BI	2.88	0.285**	yes
H4: PBC→ BI	5.21	0.452**	yes
H5: IC→ BI	13.215	0.61**	yes
H6: OP→ BI	2.958	0.289**	yes

Note: **$p < 0.05$

6. Discussion

This study explores the contributing variables of the intention to use AMAN MH-App among young Jordanian citizens. Numerous noteworthy aspects of the results will be discussed in this part as follows. Firstly, this study explains that all independent variables (Perceived Usefulness, Perceived Ease of Use value, Subjective Norms, Perceived Behavioral Control, Information Credibility, and Optimism) significantly impact on the dependent variable (Behavioural Intention to use AMAN MH-App).

The results show that all independent variables were directly and significantly predicted users' behaviors intention to use AMAN MH-App, which is explained by the following. The H1 hypothesis results showed that PU ($\beta = 0.24$, $p < 0.05$) has a positive impact. This indicates users' awareness and understanding that using the AMAN MH-App to reduce physical contact among people will be beneficial for them and protect their health, taking into consideration the fact that this virus is dangerous and deadly, and that was a justified reason for them to use the app in order to prevent Covid-19 from spreading. These results are consistent with previous related works (Wu, Wang, and Lin 2007) which found that perceived usefulness positively impacts on behavioral intentions to use the mobile application. The H2 hypothesis's results found that PEOU ($\beta = 0.3$, $p < 0.05$) has a positive impact. This points to users' recognition that using the AMAN MH-App during spreading Coronavirus will be effortless and easy to use. The majority of respondents asserted that mobile technology is easy to use. The direct reasons may be referred to as their previous knowledge of how to use smartphones, experience, and knowledge of mobile phone technology, especially in distance learning which was a result of the spread of the Coronavirus worldwide. These results are consistent with previous related works (Sun et al. 2013; Wu et al. 2007) which found that perceived ease of use has a significant impact on behavioral intentions to use the mobile application.

In terms of the H3 hypothesis, the results indicated that SN ($\beta = 0.285$, $p < 0.05$) positively impacts on using the app. The person's feelings, opinions, or behavior are influenced by who is important to him/her as a family member or because of other people's encouragement and advice (e.g. friends or relatives) who have already downloaded and used it before. Accordingly, the parents might only be affected by young people's behavior to encourage them to use AMAN MH-App due to their perceived friends' and families' recommendations as highly trustworthy. These results on SN are consistent with previous related works (Ketikidis et al. 2012; Ku and Hsieh 2018; Sun et al. 2013; Zhang, Geng, and Sun, 2017) that found Subjective Norms positively and directly influence the MHIT usage intentions. The H4 hypothesis results showed that PBC ($\beta = 0.452$, $p< 0.05$) has a positive impact. Based on the users' responses, the decision to use the AMAN MH-App stems from their desire and their full confidence in using it. This is due to that fact that young people have a high ability to deal with smartphone applications owing to their skills and experience. These results are consistent with previous related works (Zhang et al. 2017) which found perceived behavioral control positively and directly influences mobile health IT usage intentions. However, (AlBar and Hoque 2019; Ku and Hsieh 2018) found that perceived behavioral control has no significant influence on BI's use of e-health services.

The results of H5 and H6 have showed IC ($\beta = 0.61$, $p < 0.05$) and OP ($\beta = 0.289$, $p < 0.05$) have positive impacts. As far as IC is concerned, the AMAN MH-App provides users with information that is up-to-date, accurate, trustworthy, and reliable, which will encourage them to use it in the Covid-19 pandemic. Thus, young people normally perceive families' recommendations as highly trustworthy, encouraging them to use AMAN MH-App. Accordingly, when they receive useful, up-to-date and accurate information, that would increase their intention to use the app, particularly if they are suspected of being exposed to the virus, or have had contact with an infected person. The study results on Information Credibility effect is consistent with previous related works (Chen, Tao, and Zhou 2019) that found Information Credibility positively and directly influence the mobile health IT usage intentions. In terms of OP impact, this AMAN MH-App is perfect for use in the Corona pandemic and provides advantages that help people control and protect their daily life from infection as they feel positive about the AMAN MH-App usage. These results are consistent with previous related works (Zhang et al. 2017) that found Perceived Optimism positively and directly influences mobile health IT usage intentions.

7. Implications

Since MH-Apps are an emerging technology in Jordan, understanding users' behaviour and intentions of MH-Apps are required. Our purpose is to explore the effects of users' behavioural and intention with MH-Apps from the perspective of the Technology Acceptance Model (TAM) and Theory of Planned Behavior (TPB). There are some theoretical and practical implications in the study need to discuss.

7.1. Theoretical Implications

First, this study pays attention to users' behavioral intention of emerging technologies of MH-Apps. Previous related studies mainly examined the users' initial behavioral intention and continuous usage behaviors of MH-Apps while ignoring the psychological factors that affect our decision to use a new technology. However, users' behaviour and intentions of MH-Apps along with psychological factors are significantly essential for the success of any emerging technologies. This study combines TAM model and TPB theory into one model in the field of MH-Apps usage.

Second, it contributes by incorporating Subjective Norms, Perceived Behavioral Control, and Information Credibility into TAM model to validate the effects of these variable on users' behaviour and intentions with MH-Apps. In the context of healthcare service sector, as a result of the pandemic, Information Credibility is the most vital and direct determinant for their selection. In the context of mobile apps, they believe that mobile apps are valuable sources of information when people consider the app's data as reliable source. They will not be active on the mobile devices or Apps data if not think the app's data and content is reliable. Thus, this study integrates Subjective Norms, Perceived Behavioral Control, and Information Credibility into the TAM model, which enriches the theoretical context.

7.2. Practical Implications

This research has many practical outcomes for encouraging citizen involvement in the MH-Apps. First, The behavioral intent to use the MH-App is mainly due to the app's characteristics (e.g. PU and PEOU), which help produce a more optimistic and credible perception (Moon and Kim 2001; Shen et al. 2013). Thus, the government of Jordan should understand what people use mobile health apps for, outline the advantages of using MH-App and then design the apps to facilitate their intended uses in order to improve the adaptive behavior of MH-App. The friendly and Ease of Use (EOU) interfaces, in particular, facilitate the perception of the functionality and layout of MH-App and create a more relaxed user experience. PEOU can change the mindset of using MH-App. Thus, the plans to increase the usability degree of MH-App are also highly effective because of these applications' increasing difficulty. For example, providing different types of alerts (text message, voice message, auto call ..etc.) if valuable information is sent to infected people, or to people who have had contact with them in order to reduce the transmission of Covid-19. Therefore, in the product life cycle of the application, evaluating and maintaining the design standards of the AMAN MH-App could be a key feature of the government policy. Second implication, Information credibility (IC) is a significant precursor of BI to use AMAN MH-App. Thus, the government should also develop an information monitoring mechanism to guarantee the accuracy of the information provided via AMAN MH-App in order to create a reliable material and atmosphere. Third, family and friends' role in supporting youth decisions regarding the benefits of using such mobile health apps and developing strategies to improve citizens' intention to use health IT should be emphasised. Also, the government has to utalise their role in providing the citizens with a variety of resources and information on Covid-19 through TV, Social Media, Radio, and official websites. However, the path coefficient for the variable PBC is higher than SN. This indicates that the people whose decision to use the AMAN MH-App stems from their complete desire are more willing to use the app than those whose feelings, opinions, or behavior are influenced by others.

In summary, Information credibility is the most vital and direct determinant of intention, followed by perceived ease of use and perceived behavioral control. In determining citizens' intention to use AMAN MH-App, the research demonstrates the comprehensiveness, applicability and efficacy of the integrative model. The analytical outcomes also form the basis on which policies may be formulated to support the intention to use AMAN MH-App. It would not be possible for people to continue using AMAN MH-App unless the individual was already inspired or had the discipline or commitment. Ultimately, it is the intrinsic commitment and determination of a person who will decide whether they will choose to use the app for health gain or behavior change. The app might directly provide the information, or it might be generated and shared on the app. Using different types of information is recommended so that individuals with special needs may be able to find relevant information such as voice messages or sign language used by deaf people. Additional technical issues should also be considered when developing mobile health applications such as phone storage, phone battery, system quality, and more.

8. Limitation and Future Work

There are some drawbacks to the research that we encourage potential studies to overcome. Our goal in this analysis was to investigate the factors that positively impact users' behavioral intention to use AMAN MH-App. The research sample was limited to the context of young people who already use AMAN MH-App. Thus, future work is researching the multigroup analysis such as gender, education level, age, income, work experience, and more. Future research recommendations are to conduct additional research on the same topic but include the various segments of people from different cities in Jordan. Finally, this study was only limited to six variables, but in future work it is recommended to include other factors that could affect the users' behavioral intentions to use AMAN MH-App in Jordan, such as technology Anxiety, trust, compatibility, Self-Efficacy, Risk, and perceived trust. Also, this study suggested to use Machine Learning techniques (Almasri, Alkhawaldeh, and Celebi 2020; Almasri, Celebi, and Alkhawaldeh 2019) and Deep Learning methods (Alkhawaldeh 2022) to predict the user's intention to use mobile health Apps.

9. Conclusion

The mobile health applications (MH-apps) enhanced our lives, especially for their services, such as treatment, diagnosis, and follow-up. MH-apps enable people to control and manage diseases using built-in technology. AMAN Mobile Health Application (AMAN MH-App) is one of the health-tech solutions used to detect virus exposure using GPS and later Bluetooth technology. However, the acceptance of AMAN MH-App is not fully witnessed among people in Jordan. Therefore, this study aimed to explore the factors that affect the usage of AMAN MH-App among young people using the quantitative method. The findings showed that all independent variables (Perceived Usefulness, Perceived Ease of Use value, Subjective Norms, Perceived Behavioral Control, Information Credibility, and Optimism) positively impact on the dependent variable (Behavioural Intention to use AMAN MH-App). The results also indicated that Information Credibility is the most vital and direct determinant of intention, followed by perceived ease of use and perceived behavioral control. Accordingly, the results of this research can be applied to similar context and applications in different countries.

References

Agag, G., & El-Masry, A. A. 2016. Understanding consumer intention to participate in online travel community and effects on consumer intention to purchase travel online and WOM: An integration of innovation diffusion theory and TAM with trust. Computers in Human Behavior 60 (3): 97-111.

Ajzen, I. 1991. The theory of planned behavior. Organizational behavior and human decision processes 50 (2): 179-211.

Ajzen, I. 2002. Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior 1. Journal of applied social psychology 32 (4): 665-683.

AlBar, A. M., & Hoque, M. R. 2019. Patient acceptance of e-health services in Saudi Arabia: An integrative perspective. Telemedicine and e-Health 25 (9): 847-852.

Alkhawaldeh, R.S., Alawida, M., Alshdaifat, N.F.F. et al. 2022. Ensemble deep transfer learning model for Arabic (Indian) handwritten digit recognition. Neural Comput & Applic 34 (1):705-719.

Almasri, A., Alkhawaldeh, R.S. & Çelebi, E. 2020. Clustering-Based EMT Model for Predicting Student Performance. Arab J Sci Eng 45 (1): 10067–10078.

Ammar Almasri, Erbug Celebi, Rami S. Alkhawaldeh 2019. EMT: Ensemble Meta-Based Tree Model for Predicting Student Performance. Scientific Programming 2019)1):1-13.

Almasri, A. K. M. 2014. The influence on mobile learning based on technology acceptance model (Tam), mobile readiness (Mr) and perceived interaction (Pi) for higher education students. International Journal of Technical Research and Applications 2 (1): 05-11.

Almasri, A. K. M. 2015a. A hybrid proposed framework based on Quality Factors (QF) and Technology Acceptance Model (TAM) for mobile learning process: Higher education students in Jordanian universities. International Journal of Information, Business and Management 7 (3): 200-212.

Almasri, A. K. M. 2015b. Readiness and mobile learning process for higher education students in Jordanian universities. ZENITH International Journal of Multidisciplinary Research 5 (1): 85-96.

Ammenwerth, E. 2019. Technology Acceptance Models in Health Informatics: TAM and UTAUT. Studies in health technology and informatics 263 (1): 64-71.

Anderson, J. C., & Gerbing, D. W. 1988. Structural equation modeling in practice: A review and recommended two-step approach. Psychological bulletin 103 (3): 411-423.

Babic-Hodovic, V., Arslanagic-Kalajdzic, M., & Imsirpasic, A. 2017. Perceived quality and corporate image in mobile services: the role of technical and functional quality. The South East European Journal of Economics and Business 12 (1): 114-125.

Bae, Y. S., Kim, K. H., Choi, S. W., Ko, T., Jeong, C. W., Cho, B., et al. 2020. Information Technology–Based Management of Clinically Healthy COVID-19 Patients: Lessons From a Living and Treatment Support Center Operated by Seoul National University Hospital. Journal of Medical Internet Research 22 (6): 1-49.

Bassi, A., Arfin, S., John, O., & Jha, V. 2020. An overview of mobile applications (apps) to support the coronavirus disease-2019 response in India. Indian J Med Res 151 (5): 468-473.

Chen, X., Tao, D., & Zhou, Z. 2019. Factors affecting reposting behaviour using a mobile phone-based user-generated-content online community application among Chinese young adults. Behaviour & Information Technology 38 (2): 120-131.

Cheon, J., Lee, S., Crooks, S. M., & Song, J. 2012. An investigation of mobile learning readiness in higher education based on the theory of planned behavior. Computers & education 59 (3): 1054-1064.

Chi, T. 2018. Understanding Chinese consumer adoption of apparel mobile commerce: An extended TAM approach. Journal of Retailing and Consumer Services 44 (1): 274-284.

Davis, F. D. 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS quarterly 13 (3): 319-340.

Ekong, I., Chukwu, E., & Chukwu, M. 2020. COVID-19 mobile positioning data contact tracing and patient privacy regulations: Exploratory search of global response strategies and the use of digital tools in Nigeria. JMIR mHealth and uHealth 8 (4): 1-21.

Erfannia, L., Barman, M. P., Hussain, S., Barati, R., & Arji, G. 2020. How mobile health affects primary healthcare? Questionnaire design and attitude assessment. Digital Health 6 (1): 1-13.

Fornell, C., & Larcker, D. F. 1981. Evaluating structural equation models with unobservable variables and measurement error. Journal of marketing research 18 (1): 39-50.

Gefen, D., Karahanna, E., & Straub, D. W. 2003. Trust and TAM in online shopping: An integrated model. MIS quarterly 27 (1): 51-90.

Guo, R., Berkshire, S. D., Fulton, L. V., & Hermanson, P. M. 2019. Predicting intention to use evidence-based management among US healthcare administrators: Application of the theory of planned behavior and structural equation modeling. International Journal of Healthcare Management 12 (1): 25-32.

Hair Jr, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. 2016. A primer on partial least squares structural equation modeling (PLS-SEM): Sage publications.

Hew, J.-J., Lee, V.-H., Ooi, K.-B., & Lin, B. 2016. Mobile social commerce: The booster for brand loyalty?. Computers in Human Behavior 59:142-154.

Ghose, A., Guo, X., Li, B., & Dang, Y. 2021. Empowering patients using smart mobile health platforms: Evidence from a randomized field experiment. Forthcoming at MIS Quarterly 46:151-192.

Ketikidis, P., Dimitrovski, T., Lazuras, L., & Bath, P. A. 2012. Acceptance of health information technology in health professionals: an application of the revised technology acceptance model. Health informatics journal 18 (2): 124-134.

Kodali, P. B., Hense, S., Kopparty, S., Kalapala, G. R., & Haloi, B. 2020. How Indians responded to the Arogya Setu app?. Indian journal of public health, 64 (6): 228-230.

Ku, WT., Hsieh, PJ. 2018. Understanding the Acceptance of Health Management Mobile Services: Integrating Theory of Planned Behavior and Health Belief Model. Communications in Computer and Information Science 850:247-252.

Lowry, P. B., & Gaskin, J. 2014. Partial least squares (PLS) structural equation modeling (SEM) for building and testing behavioral causal theory: When to choose it and how to use it. IEEE transactions on professional communication 57 (2): 123-146.

Lu, Y., Cao, Y., Wang, B., & Yang, S. 2011. A study on factors that affect users' behavioral intention to transfer usage from the offline to the online channel. Computers in Human Behavior 27 (1): 355-364.

McKnight, D. H., & Kacmar, C. J. 2007. Factors and effects of information credibility. Proceedings of the ninth international conference on electronic commerce 2007: 423-432.

MoH. 2020. Aman. from https://corona.moh.gov.jo/en (Accessed January 3, 2020).

Moon, J.-W., & Kim, Y.-G. 2001. Extending the TAM for a World-Wide-Web context. Information & Management 38 (4): 217-230.

Munoz-Leiva, F., Climent-Climent, S., & Liébana-Cabanillas, F. 2017. Determinants of intention to use the mobile banking apps: An extension of the classic TAM model. Spanish Journal of Marketing-ESIC, 21 (1): 25-38.

Pan, X. B. 2020. Application of personal-oriented digital technology in preventing transmission of COVID-19, China. Irish Journal of Medical Science 189 (4):1145-1146.

Parasuraman, A., & Colby, C. L. 2015. An updated and streamlined technology readiness index: TRI 2.0. Journal of service research 18 (1): 59-74.

Pilav-Velić, A., Černe, M., Trkman, P., Wong, S. I., & Kadić-Abaz, A. 2021. Digital or Innovative: understanding "Digital Literacy–Practice–Innovative Work Behavior" Chain. The South East European Journal of Economics and Business 16 (1): 107-119.

Pulia, M. S., Heckmann, D. J., Glazer, J. M., Barclay-Buchanan, C., Kuehnel, N., Ross, J., et al. 2020. Electronic Health Record-Based Surveillance for Community Transmitted COVID-19 in the Emergency Department. Western

Journal of Emergency Medicine: Integrating Emergency Care with Population Health 21 (4): 748-751.

Ren, X., Zhai, Y., Song, X., Wang, Z., Dou, D., & Li, Y. 2020. The Application of Mobile Telehealth System to Facilitate Patient Information Presentation and Case Discussion. Telemedicine and e-Health 26 (6): 725-733.

Shen, X.-L., Cheung, C. M. K., & Lee, M. K. O. 2013. What leads students to adopt information from W ikipedia? An empirical investigation into the role of trust and information usefulness. British Journal of Educational Technology 44 (3): 502-517.

Sun, Y., Wang, N., Guo, X., & Peng, Z. 2013. Understanding the acceptance of mobile health services: a comparison and integration of alternative models. Journal of electronic commerce research 14 (2): 183-200.

Timmers, T., Janssen, L., Stohr, J., Murk, J. L., & Berrevoets, M. 2020. Using mHealth to support COVID-19 education, self-assessment, and symptom monitoring: An observational study in The Netherlands. JMIR Mhealth Uhealth 8 (6): 1-29.

Umezuruike, C., Nwankwo, W., Tibenderana, P., Assimwe, J. P., & Ronald, M. 2020. Corona virus disease (COVID 19): Analysis and design of an alert and real-time tracking system. International Journal of Emerging Trends in Engineering Research 8 (5): 1854-1859.

Vokinger, K. N., Nittas, V., Witt, C. M., Fabrikant, S. I., & von Wyl, V. 2020. Digital health and the COVID-19 epidemic: an assessment framework for apps from an epidemiological and legal perspective. Swiss medical weekly 150:1-9.

Walczuch, R., Lemmink, J., & Streukens, S. 2007. The effect of service employees' technology readiness on technology acceptance. Information & Management 44 (2): 206-215.

Wang, S., Ding, S., & Xiong, L. 2020. A New System for Surveillance and Digital Contact Tracing for COVID-19: Spatiotemporal Reporting Over Network and GPS. JMIR mHealth and uHealth, 8 (6): 1-6.

Wathen, C. N., & Burkell, J. 2002. Believe it or not: Factors influencing credibility on the Web. Journal of the American society for information science and technology 53 (2): 134-144.

World Health Organization. 2020. Considerations for quarantine of individuals in the context of containment for coronavirus disease (COVID19). URL: https://tinyurl.com/y8smo4pe (accessed April 3, 2020).

World Health Organization Writing Group, Bell D, Nicoll A, Fukuda K, Horby P, Monto A, et al. 2006. Non-pharmaceutical interventions for pandemic influenza, national and community measures. Emerg Infect Dis 12 (1): 88-94.

Wu, J.-H., Wang, S.-C., & Lin, L.-M. 2007. Mobile computing acceptance factors in the healthcare industry: A structural equation model. International journal of medical informatics 76 (1): 66-77.

Wu, P., Zhang, R., Zhu, X., & Liu, M. 2022. Factors Influencing Continued Usage Behavior on Mobile Health Applications. Healthcare 10 (2): 1-18.

Wynne, C. W. 1998. Issues and opinion on structural equation modelling. Management Information Systems quarterly 22 (1): 1-8.

Xia, M., Zhang, Y., & Zhang, C. 2018. A TAM-based approach to explore the effect of online experience on destination image: A smartphone user's perspective. Journal of Destination Marketing & Management 8:259-270.

Ye, Q., Zhou, J., & Wu, H. 2020. Using Information Technology to Manage the COVID-19 Pandemic: Development of a Technical Framework Based on Practical Experience in China. JMIR Med Inform 8 (6): 1-23.

Zamberg, I., Manzano, S., Posfay-Barbe, K., Windisch, O., Agoritsas, T., & Schiffer, E. 2020. A Mobile Health Platform to Disseminate Validated Institutional Measurements During the COVID-19 Outbreak: Utilization-Focused Evaluation Study. JMIR Public Health Surveill 6 (2): 1-24.

Zhang, X., Geng, G., & Sun, P. 2017. Determinants and implications of citizens' environmental complaint in China: Integrating theory of planned behavior and norm activation model. Journal of Cleaner Production 166:148-156.