Determining the Factors Affecting the Acceptance of Systems Providing the Integration of Big Data Analysis and Mobile Applications: Enhanced Technology Acceptance Model

Yıldız Yılmaz Güzey
Professor of Business Administration (EN)
Faculty of Economics and Administrative Sciences
Beykent University
Istanbul, Turkey
yildizguzey@beykent.edu.tr

Öznur Dal
Istanbul, Turkey
oznurdal83@gmail.com

Abstract

Due to mobile healthcare (mHealth) applications, consumers have more control over their health decisions. The integration of Big Data Analysis (BDA) and mHealth applications can facilitate discovery of new information, early diagnosis of diseases, preventing pandemics, providing personalized healthcare services. In Turkey, Life Fits into Home (HES) mHealth application is a method used to inform citizens on Covid-19 in the battle with the pandemic. In HES, pandemic data is analyzed and the spread of the pandemic is visualized in real time. Additionally, users are given individual codes to provide personalized service and participation in healthcare. This study investigates the factors affecting the acceptance of information systems providing the integration of BDA and mHealth applications by users. A model is presented using the variants Theory of Planned Behavior, DeLone and McLean Model of Information Systems Success, and Technology Acceptance Model (TAM). The study is significant in terms of obtaining results on the usage of TAM and improves technology adoption literature. Data of 400 individuals were tested by structural equation modeling within the scope of the research. The research revealed that the perceptions of users about subjective norm, behavioral control, system quality, information quality, usefulness, and ease of use have a positive effect on intention to use. The results of the study will be instructive in developing applications displaying the effects of BDA on public. Determining the factors influencing consumer behavior can encourage designers to create improved services, and support health industry to design work models.

Key Words
Mobile Health, Big Data, Healthcare Services, Technology Acceptance Model

1. Introduction

Due to scientific and technological advancements, digital technologies have become a great part of our lives. The increase of the usage of digital devices, such as smart phones, tablets, sensors, and mobile applications, produce structured, unstructured, and semi-structured immense data stacks (Sivarajah et al. 2017; Constantiou and Kallinikos 2014). Studies claim that data volume will double biennially (Gantz and Reinsel 2012; Sivarajah et al. 2017), more than 80% of all digital content is unstructured (Gupta and George 2016), and 68% of digital information is created by consumers (Gantz and Reinsel 2012).

BDA is defined as increase in (3V) volume (huge amount of data), velocity (temporality of big data), and variety (data types) of data (Chen and Zhang 2014). Universal criteria do not exist, as these notions vary depending on the size of company, sector, location, and time (Gandomi and Haider 2015; McAfee and Brynjolfsson 2012). In later studies, value and veracity (5V) (Gupta and George 2016; Chen and Zhang 2014), variability and visibility (7V) variables were added to 3V (Seddon and Currie 2017). McAfee and Brynjolfsson (2012) define big data as “management revolution”, whereas Gartner describes it as high-volume, high-velocity and high-variety information assets that demand cost-effective, innovative forms of information processing (Raguseo 2018). Big data incorporates storage, analysis, and visualization of various types of data sets. At the end, data gain meaning by being processed and valuable information is obtained. Some studies describe BD as huge data stacks difficult to process, store, and analyze with conventional data processing methods (Constantiou and Kallinikos 2014). The variety and magnitude of data rendered conventional data processing methods insufficient; therefore, investment in new technologies is required in order to survive and compete in this era of information.

BDA provides a number of advantages for companies such as lowering costs, making better decisions faster, improving product and services, and competitive advantage (Raguseo 2018). It may provide valuable information from hidden data (Gantz and Reinsel 2012), facilitate timely response (Sivarajah et al. 2017), increase company performance (Fosso Wamba et al. 2018), convert gathered information into business advantage (McAfee and Brynjolfsson 2012), expedite decision making through providing real-time analyses (Gandomi and Haider 2015). Additionally, by allowing high speed capturing, discovery, and analysis, it may also increase economic value (Gantz and Reinsel 2012; Chen and Zhang 2014). BDA has been implemented successfully in various fields such as healthcare services, logistics and supply, retail sales, and astronomy (Chen et al. 2015; Lai et al. 2018). Behaviors, emotions, and mental states of individuals can be predicted by BDA so that product and services can be improved (George et al. 2014). BDA is a process in which the infrastructure of the organization is altered (Günther et al. 2017) and is deemed as innovation on company level (Kwon et al. 2014). Internal and external environment data can be analyzed to predict future conditions and outcomes. It can allow the current situation to be analyzed and to predict customer behavior (McAfee and Brynjolfsson 2012; Tabesh et al. 2019).

Digital devices such as electronic health records, telemedicine, mHealth, personal health records create immense data stacks (Aceto et al. 2020; Murdoch and Detsky 2013). BDA may improve healthcare services (Aceto et al. 2020; Mehta and Pandit 2018; Ward et al. 2014) and financial performance (Ward et al. 2014), help making effective decisions (Mehta and Pandit 2018; McAfee and Brynjolfsson 2012; Murdoch and Detsky 2013). Moreover, it may support the development of new medicine and provide personalized services (Szlezák et al. 2014). It can enhance quality of care, provide early diagnosis of risky and costly patients, and track spread of diseases (Raghupathi and Raghupathi 2014). By providing fast and correct diagnosis, it may present benefits in caretaking and management of public health (Raghupathi and Raghupathi 2014; Mehta and Pandit 2018). Cloud-based systems have been used to track and keep under control epidemics such as Ebola (Jagadeeswari et al. 2018), Zika (Sareen et al. 2017), and H1N1 (Sandhu et al. 2016).

mHealth information systems are one of the big data sources in healthcare services. Healthcare service users employ mHealth applications to obtain better, faster, and cost-effective health service (Duarte and Pinho 2019), to enhance life quality (Balapour et al. 2019), and to participate in healthcare management. mHealth applications allow users to easily access health information anywhere, anytime (Zhao et al. 2018), and to communicate with healthcare professionals effortlessly (Zhang et al. 2020). Introducing BDA to users can transform healthcare services (Murdoch and Detsky 2013). Individuals can be encouraged to maintain themselves healthy, decide consciously, and participate in healthcare (Mehta and Pandit 2018; Raghupathi and Raghupathi 2014). Individuals adopt healthy behavior more easily (Mehta and Pandit 2018). Feedback from healthcare professionals and patients can affect service presentation and product design (Aceto et al. 2020). In case of an epidemic, disease spread can be controlled by informing people what steps to take (Jagadeeswari et al. 2018). Systems enabling the integration of BDA with mHealth applications can analyze data in real-time and present them to users. Presenting analyzed health data to users is essential for preventive and personalized medicine.

Literature scan revealed that studies on adoption and acceptance of BDA are scanty. Research often focuses on software, hardware, and characteristics of BDA. Sample groups of studies examining adoption of BDA in companies usually consist of big data analysts or experts. Studies on BDA adoption in healthcare sector are limited. The aim of the research is to determine factors affecting the user adoption of systems providing the integration of BDA and mHealth applications in healthcare services. With this purpose, a model has been developed utilizing Theory of Planned Behavior (TPB), Technology Acceptance Model (TAM), and DeLone and McLean Model of Information Systems Success. In addition, the study obtains results on the applicability of TAM, and enhances technology adoption literature. Unlike other research, this study focuses on users of systems providing the integration of BDA and mHealth.

Research questions are as follows:

1. Do system quality, information quality, subjective norm, perceived ease of use, perceived usefulness, and perceived behavioral control affect the intention to use mHealth systems?
2. Do mHealth system users adopt the information provided through BDA systems?

Literature scan has been conducted in Chapter 2. Research model and hypotheses are presented in Chapter 3. Chapter 4 comprises research methodology. Research results and discussions take place in Chapter 5. Finally, conclusions and inferences drawn from the findings are declared.

2. Literature Review

2.1 Research for Behavioral Intention on Using mHealth Applications

mHealth applications are information technologies providing citizens health information anytime, anywhere, overcoming geographical and temporal obstacles (Miao et al. 2017). Adopting or using a health technology is considered as a health behavior (Zhang et al. 2020). mHealth designers need to evaluate behavioral intention of consumers in order to improve products and services (Miao et al. 2017). Designs should promote development of health behavior and maintaining a healthy life (Deng 2013). Researchers applied numerous theories in order to determine behavioral intention of consumers regarding mHealth systems and groups of professionals (Wu et al. 2007; Wu et al. 2011) and users (Duarte and Pinho 2019; Zhang et al. 2020; Lin 2011; Hung and Jen 2012; Deng 2013; Sun et al. 2013; Shareef et al. 2014; Nisha et al. 2019; Dwivedi et al. 2016; Zhao et al. 2018; Saheb 2020) were worked on. Adopting mHealth on an individual level reduces economic burden on patients and accelerates the cultural and social change of the nation (Shareef et al. 2014; Miao et al. 2017). Studies on adoption of mHealth systems reveal that perceived usefulness (PU) has significant impact on behavioral intention (Hung and Jen 2012). Furthermore, studies have been conducted focusing on the influence of perceived information quality (PIQ) (Nisha et al. 2019), perceived system quality (PSQ) (Nisha et al. 2019), perceived usefulness (Wu et al. 2007; Wu et al. 2011; Lin 2011; Hung and Jen 2012; Deng 2013; Shareef et al. 2014), perceived ease of use (PEU) (Wu et al. 2007; Wu et al. 2011; Lin 2011; Hung and Jen 2012; Deng 2013; Sun et al. 2013; Shareef et al. 2014), subjective norm (SN) (Zhang et al. 2020; Wu et al. 2011; Sun et al. 2013; Dwivedi et al. 2016), and perceived behavioral control (PBC) (Wu et al. 2011) on intention to use (IU).

It is claimed that the integration of big data with mHealth applications is highly important in discovery of new information, providing real-time personalized healthcare service, and prevention and control of diseases (Saheb 2020; Jagadeeswari et al. 2018). Real-time analysis of big health data can be used to keep epidemics under control. Cloud-based systems were designed to keep Zika and H1N1 viruses under control, and to prevent them. Data were gathered through cell phones and uploaded to the cloud, each user was given an identity and classified either as infected or uninfected (Sareen et al. 2017; Sandhu et al. 2016). Information technologies were also used to prevent the spread of the pandemic during COVID-19. Pandemic data were analyzed and quickly visualized, the spread was geographically tracked, and regional projections were made (Zhou et al. 2020). Saheb (2020) investigated the influence of social media and big data with mTechnologies on the adoption behavior. Presenting big data through mHealth applications can lead to users developing healthy behavior and participating in their own health management. Dwivedi et al. (2016) claimed that adopting mHealth varies among countries. mHealth should reflect each country's cultural characteristics. In their study, Dwivedi et al. replaced ease of use with effort expectancy, and performance expectancy is similar to the usefulness variable.

2.2 Technology Acceptance Model (TAM)

Davis (1986) developed TAM in order to measure the acceptance and use behavior for any technology, and it has become one of the most commonly employed models in studies on information technologies adoption. TAM comprises five structures (PU, PEU, attitude toward using, behavioral intention to use and actual system use). According to TAM, PU and PEU are the most important belief variables. PU represents the perception that using a particular system increases work performance. PEU is the belief level whether a particular system will be effortless to use. The positive or negative emotions of an individual about performing the expected behavior reflect the person's attitude toward the system. The system using situation of an individual is influenced by their behavioral intention to use. According to the model, PU and PEU influence the attitude toward use, and the attitude influences the behavioral intention toward use (Davis 1989).

2.3 Theory of Planned Behavior (TPB)

Ajzen (1986) proposed Theory of Planned Behavior to explain behavior types in information systems studies (Ajzen and Madden 1986). According to the theory, behavioral intentions are determined by three factors, namely, attitude toward the behavior, subjective norm (SN) and perceived behavioral control (PBC). The more a person is willing to perform a behavior, the more they will have the intention to adopt that system. SN represents the social pressure toward performing the behavior. PBC refers to the difficulty or easiness of performing the behavior. PBC impacts the behavior in two ways; indirect effect through intention, and direct effect on behavior. The theory argues that the more positive the attitude toward engaging in a behavior and SN is, the stronger the intention to perform the behavior will be, and, thus, the behavior will be performed (Ajzen 1991).

2.4 DeLone and McLean Model of Information Systems Success

DeLone and McLean (1992) developed Model of Information Systems Success to measure the success of information systems. The model claims that information quality and system quality affect system usage and user satisfaction. System use impacts individual users and causes organizational impacts. The model was updated later in 2003 and service quality variable was added to the model. Individual and organizational impacts were replaced by net benefits. As a result, six categories were identified in the model (Information quality, system quality, service quality, intention to use/use, user satisfaction and net benefits). According to the model, system quality measures technical success, information quality measures semantic success of a system. Use/user satisfaction and net benefits measure effectiveness success (DeLone and McLean 2003).

3. Research Model and Hypothesis Development

Suggested research model is exhibited in Figure 1. In the research model PU, PEU and IU variables were extracted from TAM; SN and PBC variables from TPB; PIQ and PSQ variables from DeLone and McLean Model of Information Systems Success. Perceived ease of use (PEU) represents the degree to which a person believes that using a particular system would be free from effort (Davis 1989). Using a new technology should be perceived as clear, comprehensible, not requiring mental effort, and easy. Various studies examined the relationship between PEU and PU (Yi et al. 2006; Wu et al. 2011; Wixom and Todd 2005; Hung and Jen 2012; Shareef et al. 2014; Deng 2013; Saheb 2020). Research on adopting mHealth investigated the impact of PEU on PU (Miao et al. 2017; Deng 2013). Studies on healthcare information systems obtained findings about this impact (Pai and Huang 2011; Moores 2012). Pai and Huang (2011) stated that the largest impact on IU is PEU. Verma et al. (2018) asserted in their study that PEU has insignificant impact on PU. This result indicates that even the system usage is perceived as easy, company executives are unaware of PU. Although the system usage is easy, the benefits it will create are ignored. A technology can be perceived as beneficial when its usage is easy, and perceived as effortless (Verma et al. 2018). The less effort is given, the more work performance there will be to use that system.

If the user believes they can use the technology effortlessly, they will have the intention to adopt that technology (Verma et al. 2018). However, if the system use is mandatory, insignificant relationship with constructs may emerge (Moores 2012). Numerous studies were conducted investigating the relationship between PEU and IU (Miao et al. 2017; Pai and Huang 2011; Saheb 2020; Yi et al. 2006; Hung and Jen 2012; Nisha et al. 2019). Sun et al. (2013) researched the acceptance of mHealth by consumers and determined that PEU has an important impact on IU. Some studies claimed that PEU and effort expectancy have the same meaning and that the relationship with IU is significant and positive (Nisha et al. 2019). There are, on the other hand, research suggesting the relationship between PEU and IU is insignificant (Yi et al. 2006). Results of the research revealed that although healthcare professionals perceived a new technology as complicated, they had the intention to adopt it.

PU is the perception of users believing that using a certain technology will increase performance (Davis 1989). Believing a new technology will increase work performance and productivity leads to positive intention to adopt (Verma et al. 2018). The relationship between PU and IU were researched for mHealth (Miao et al. 2017; Zhao et al. 2018; Wu et al. 2011; Deng 2013) and other healthcare information technologies (Pai and Huang 2011; Chau and Hu 2002) and the results showed that PU has positive effect on IU.

SN is the social pressure on individuals causing them engaging or not engaging in a certain behavior (Ajzen 1991). People tend to adopt a behavior according to the opinions of people they care about (Venkatesh and Davis 2000; Pai and Huang 2011). Numerous studies indicated that social impact shapes behavioral intention of the user (Miao et al. 2017; Yi et al. 2006; Dwivedi et al. 2016; Duarte and Pinho 2019; Wu et al. 2011; Sun et al. 2013). The increase in using mHealth applications will lead to people adopting the technology. However, some studies showed that SN has negative effect on IU (Miao et al. 2017; Chau and Hu 2002; Nisha et al. 2019). This result stems from the target users in the studies. PBC refers to the perceived easiness or difficulty in engaging in the expected behavior (Ajzen

1991). Certain skills, resources, and information are required, in order to enact a behavior (Yi et al. 2006; Wu et al. 2011). PBC has positive impact on behavioral intention and use for system usage (Yi et al. 2006; Wu et al. 2011; Chau and Hu 2002).

PIQ refers to the perception about the accurateness, up-to-dateness, and credibility of the presented information in the information system (Nelson et al. 2005). If the information provided by the information system does not satisfy the needs, the user will not tend to use that technology. Studies were conducted examining the impact of a person's information quality perception of an information system on the intention to adopt that system (Wixom and Todd 2005; Nelson et al. 2005; Pai and Huang 2011; Saheb 2020; Moores 2012; Verma et al. 2018; Zheng et al. 2013; Nisha et al. 2019). It is expected that the information provided by information technologies to be accurate, reliable, complete, and timely (Verma et al. 2018). PSQ is the perceptions about an information system in terms of technical features (Verma et al. 2018). It consists of accessibility, reliability, flexibility, timeliness, privacy, and integration (Nelson et al. 2005; Wixom and Todd 2005). If a certain information system is perceived as of good quality, the intention to adopt and use that system will be high. Perceived system quality represents the perceptions about the systems features on its performance (Zheng et al. 2013; Nelson et al. 2005). Several studies investigated the impact of the PIQ variable (Pai and Huang 2011; Nisha et al. 2019; Moores 2012; Verma et al. 2018).

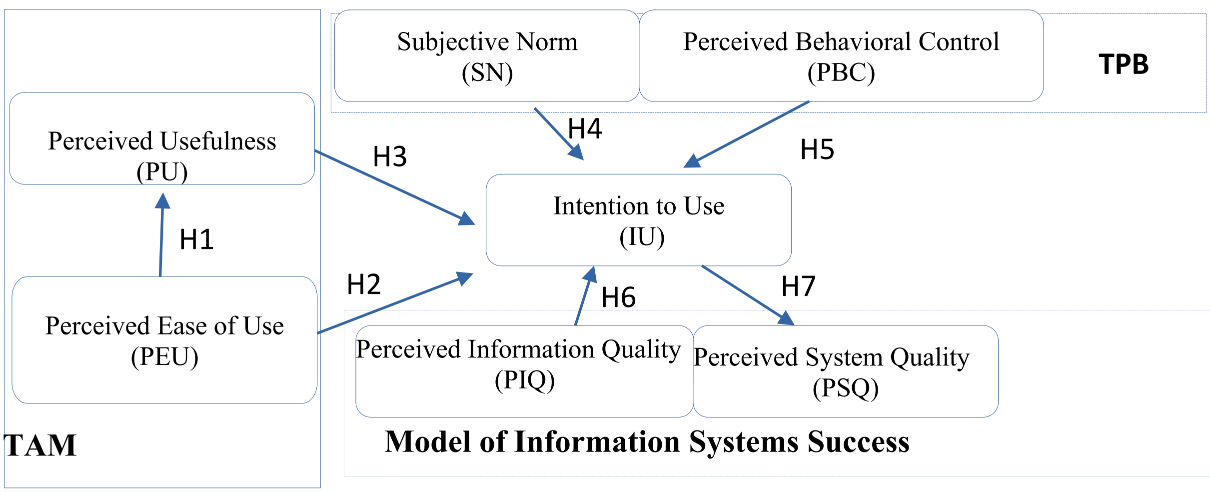

Figure 1. Proposed research model

H1. PEU has positive effect on PU in terms of using mHealth.
H2. PEU has positive effect on behavioral intention in terms of using mHealth.
H3. PU has positive effect on behavioral intention in terms of using mHealth.
H4. SN has positive effect on behavioral intention in terms of using mHealth.
H5. PBC has positive effect on behavioral intention in terms of using mHealth.
H6. PIQ has positive effect on behavioral intention in terms of using mHealth.
H7. PSQ has positive effect on behavioral intention in terms of using mHealth.

4. Research Methodology
4.1 Questionnaire Design
A comprehensive literature scan about TAM, TPB, and Model of Information Systems Success was conducted prior to the research. An empirical research was carried out to evaluate the proposed hypotheses of the study. The study was designed toward mHealth application users and participation is on voluntary basis. With this purpose, the questionnaire was electronically prepared by Google forms and consists of two parts and 35 questions. Except for the demographic questions, the questionnaire comprises 31 5-point Likert type questions with options varying from strongly agree to strongly disagree. As shown in Table 1, the measurement items in this research were adapted from previous studies.

Table 1. Research constructs and measurements

Constructs	**Item**	**Measurement Item**	**Reference**
PU	PU1	Using the mHealth application allows me to be more in control about my health.	Davis (1989)
	PU2	The mHealth application satisfies my information need.	
	PU3	Using the mHealth application saves me time.	
	PU4	Using the mHealth application helps me manage health-related conditions faster.	
	PU5	Using the mHealth application decreases the time I spend for inefficient activity.	
	PU6	Using the mHealth application helps me take care of health-related issues.	
	PU7	In general, I find the mHealth application useful.	
PEU	PEU1	My interaction with the mHealth application is clear and comprehensible.	Venkatesh and Bala (2008)
	PEU2	Using the mHealth application does not require much mental effort.	
	PEU3	I find it easy to use the mHealth application.	
	PEU4	Having the mHealth application do what I need is easy.	
	PEU5	Learning to operate the mHealth application is easy for me.	Davis (1989)
SN	SN1	People who have influence on my behavior think that I should use the mHealth application.	Venkatesh and Davis (2000)
	SN2	People who are important for me think that I should use the mHealth application.	
	SN3	People whose opinions I care about prefer me to use the mHealth application.	Dwivedi et al. (2016)
PBC	PBC1	I have control about using the mHealth application.	Venkatesh et al. (2000)
	PBC2	I have the necessary resources to use the mHealth application.	
	PBC3	I have the necessary knowledge to use the mHealth application.	
PSQ	PSQ1	The mHealth application operates reliably.	Wixom and Todd (2005)
	PSQ2	The mHealth application facilitates access to information.	
	PSQ3	The mHealth application combines information from diverse resources.	
	PSQ4	The mHealth application provides information timely.	
PIQ	PIQ1	The mHealth application provides me a complete information set.	Wixom and Todd (2005)
	PIQ2	Information provided by the mHealth application is well organized.	
	PIQ3	Information provided by the mHealth application is displayed on the screen clearly.	
	PIQ4	Information provided by the mHealth application is correct.	
	PIQ5	Information provided by the mHealth application is always up-to-date.	
	PIQ6	The mHealth application presents me the latest information.	
IU	IU1	I plan to use the mHealth application to preserve my health.	Balapour et al. (2019)
	IU2	I believe I will continue using the mHealth application to preserve my health.	
	IU3	If any healthcare service provider asks me to send my health records through a mobile device, I will do it.	

4.2 Data Collection

The sample group of the study comprises 18-year-old and above Life Fits into Home (HES) mHealth application users residing in Istanbul. As demonstrated in Figure 2, the HES application shows the density of the pandemic and daily pandemic situation table in Turkey. HES has become a mandatory tool in the fight against the pandemic in Turkey. HES is a system in which big data is integrated with mHealth applications and users are provided a personalized service with an individual code. Citizens without a HES code are not permitted to use public space such as public transport, schools, cinema, shopping malls, and restaurants. Data was gathered in Turkey in the city of Istanbul through online questionnaire. Potential participants were selected by convenience sampling method and were sent e-questionnaires. The online questionnaire was published via social media, in platforms such as Facebook and Instagram. The questionnaire was applied to 400 people between March 2021 and May 2021. 72.7% (n=291) of the participants were female, 27.3% were male. The distribution of the age groups are: 32.3% (n=129) ages 18-25, 31.8% (n=127) ages 26-33, 21.3% (n=85) ages 34-41, and 14.8% (n=59) ages 42 and above. 9.8% (n=39) of the participants have high school degree, 7.5% (n=30) have associate degree, 40.5% (n=162) have Bachelor's degree, and 42.3% (n=169) have Master's/doctoral degree. 18.0% (n=72) of the participants have been using the HES application for less than 6 months, 53.8% (n=215) have been using it for 6 -12 months, and 28.5% (n=113) have been using it for 12 months and more.

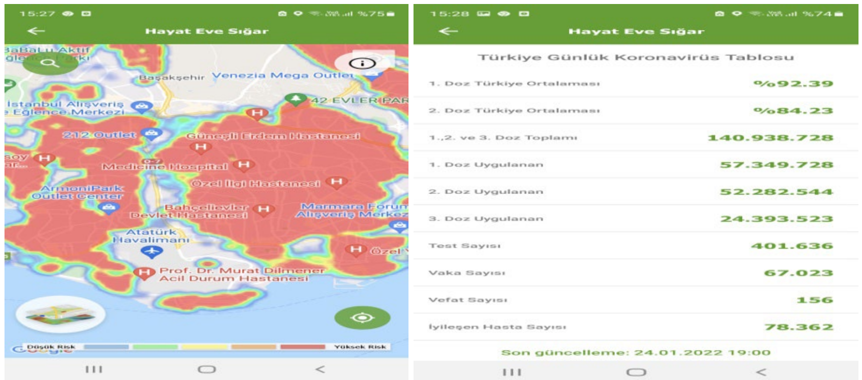

Figure 2. Screen shots of HES mHealth application

Table 2. Mean, standard deviation, inter-correlations and reliability scores

Construct	Mean±SD	CA	CR	AVE	PU	PEU	SN	PBC	PSQ	PIQ	IU
PU	3.49±0.86	0.93	0.93	0.56	1	0.261**	0.494**	0.200**	0.621**	0.634**	0.654**
PEU	4.2±0.54	0.88	0.88	0.60		1	0.192**	0.517**	0.310**	0.331**	0.368**
SN	3.34±1.03	0.92	0.89	0.74			1	0.191**	0.433**	0.483**	0.519**
PBC	4.31±0.56	0.85	0.86	0.67				1	0.357**	0.276**	0.368**
PSQ	3.76±0.79	0.93	0.92	0.75					1	0.799**	0.598**
PIQ	3.53±0.8	0.94	0.94	0.71						1	0.624**
IU	3.68±0.82	0.79	0.80	0.58							1

r=Pearson Correlation **p<0.01 *p<0.05
Note: SD = Standard deviation, CA = Cronbach's alpha, CR = Composite reliability and AVE = Average variance extracted.

5. Results and Discussion
5.1 Measurement Model
Confirmatory factor analysis was conducted to test the reliability and validity of the measurement model. Composite reliability (CR) and Cronbach's α were used to assess reliability. Cronbach's α values are above 0.70 in Table 2. Cronbach's alpha being above 0.70 indicates the measurement model is reliable (Afthanorhan 2013). CR value should be 0.60 or above (Hair et al. 2019). As CR values are between 0.804 and 0.937 in Table 2, it is supportive for construct reliability. While CR manifests the internal consistency of constructs, AVE shows the amount of imputed variance. An AVE value equal to or above 0.5 indicates adequate convergent validity (Afthanorhan 2013). Discriminant validity was examined by controlling correlation of each factor. All correlations between variables are observed to be positive and significant. Convergent validity is assessed by factor loadings. The factor loadings should exceed 0.50 (Yaşlıoğlu 2017). All indicators in this study are statistically significant.

5.2 Structural model and testing results
Structural equation modeling (SEM) analysis is examined by controlling path coefficients. Path coefficients show the degree of correlation between dependent and independent variables. R^2 value indicates to what degree the independent variable explains the observed variance (Verma et al. 2018). SEM not only assesses measurement

errors, but also errors that may emerge in the structural equation (Hair et al. 2019). SEM reveals how well the theory fits data. The results of the structural model are presented in Figure 3 and Table 3.

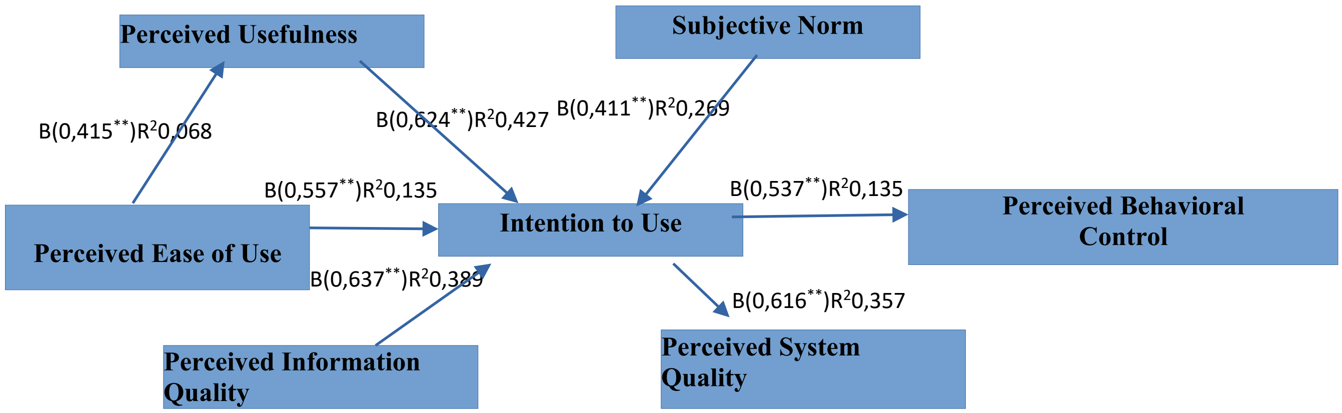

Figure 3. Results of the Research Model

Table 3 presents the results of hypotheses testing. The regression model between PEU and PU proves to be significant (p=0.001; p<0.01; Adjusted R^2: 0.068). PEU has a 41.5% unit positive impact on PU. The regression model between PEU and IU is significant (p=0.001; p<0.01; Adjusted R^2 : 0.135) and has a 55.7% unit positive impact. The regression model between PU and IU is significant (p=0.001; p<0.01; Adjusted R^2 : 0.427) and has a 62.4% unit positive impact. The regression model between SN and IU is significant (p=0.001; p<0.01; Adjusted R^2: 0.269) and has a 41.1% unit positive impact. The regression model between independent variable PBC and dependent variable IU is significant (p=0.001; p<0.01; Adjusted R^2: 0.135) and has a 0.537% unit positive impact. The regression model between independent variable PIQ and dependent variable IU is significant (p=0.001; p<0.01; Adjusted R^2: 0.389) and has a 63.7% unit positive impact. The regression model between independent variable PSQ and dependent variable IU is significant (p=0.001; p<0.01; Adjusted R^2: 0.357) and has a 61.6% unit positive impact. As a result, 7 hypotheses were constructed and all of them were supported.

Table 3. Results of hypotheses testing

Hypothesis	Hypothesized Path	Standardized B	Standard Error	t value	P value	Adjusted R^2	Support
H1	PEU PU	0.415	0.077	5.404	0.001**	0.068	Yes
H2	PEU IU	0.557	0.071	7.891	0.001**	0.135	Yes
H3	PU IU	0.624	0.036	17.239	0.001**	0.427	Yes
H4	SN IU	0.411	0.034	12.099	0.001**	0.269	Yes
H5	PBC IU	0.537	0.068	7.896	0.001**	0.135	Yes
H6	PIQ IU	0.637	0.040	15.932	0.001**	0.389	Yes
H7	PSQ IU	0.616	0.041	14.872	0.001**	0.357	Yes

**p<0.01

5.3 Discussion

The findings of this research provide a preliminary testing of the applicability of the model with the purpose of presenting BDA with mHealth applications to users. Enhanced TAM was presented by using TPB and Model of Information Systems Success. The study contributes to the adoption of a new information system literature by helping mHealth application users to comprehend the benefits of BDA. The focus of the research is on the contributions of BDA in developing mHealth applications and the impacts of services on user behavior. BDA provides presenting personalized service to mHealth users. The usage of these applications needs to increase, in order to improve health and promote being healthy. These are services that guide people in staying healthy.

Research findings demonstrate that perceived usefulness has a positive and significant impact on intention to use. This result is consistent with other studies confirming the impact of perceived usefulness on intention to use (Miao et al. 2017; Zhao et al. 2018; Shareef et al. 2014; Pai and Huang 2011; Sun et al. 2013; Hung and Jen 2012; Nisha et al. 2019). If the person believes that they can use the BDA integrated mHealth application effortlessly, they will engage in behavior to use the system. Therefore, the information system should be clear, comprehensible, and easy. Ease of use of devices can be provided by furnishing users with system-related training and help. A user believing that using a particular information system is easy, may perceive that system as useful. Research findings confirmed the impact of perceived ease of use on perceived usefulness, consistent with numerous study results (Miao et al. 2017; Yi et al. 2006; Hung and Jen 2012; Shareef et al. 2014; Pai and Huang 2011; Wu et al. 2011). If users anticipate that they will have more control over their health by using a system, they will have the intention to adopt that system. A system might be perceived as useful if it satisfies the user's needs, facilitates health management, and saves the user time. Research findings display that perceived usefulness has a direct impact on intention to use, consistent with various study results (Miao et al. 2017; Wu et al. 2011; Yi et al. 2006; Hung and Jen 2012; Pai and Huang 2011; Nisha et al. 2019; Shareef et al. 2014). By delivering information in real time, BDA will enable providing personalized service.

When adopting a new technology, social pressure also plays a role for individuals. Research findings confirmed that subjective norm positively impacts use behavior. This impact was observed in many studies (Wu et al. 2011; Sun et al. 2013; Dwivedi et al. 2016; Yi et al. 2006). However, some studies recognized no impact of subjective norm on intention to use (Miao et al. 2017; Chau and Hu 2002; Nisha et al. 2019). This result is based on the characteristics of targeted users in the study. The targeted users group was less influenced by social norm. A person will adopt a system, in case they presume they have necessary resources, skills, and control over using the system. Perceived behavioral control is linked to behavioral intention. This finding is supported by previous studies (Wu et al. 2011; Yi et al. 2006; Chau and Hu 2002). According to the research findings, information provided by BDA is perceived as accurate, up-to-date, and complete. If the user perceives information provided via mHealth application as of high quality, they will have the intention to adopt the system. Studies on information quality verify this conclusion (Nisha et al. 2019; Verma et al. 2018; Saheb 2020; Pai and Huang 2011; Moores 2012). The quality perception toward the system's technical features impacts the behavioral intention of system usage (Pai and Huang 2011; Verma et al. 2018; Nisha et al. 2019). A well designed and developed system can be perceived of high quality. Designers and developers should design system features well to provide a seamless, timely service.

6. Conclusion

The research propounds the importance of big data for mHealth designers, and offers salient information. Product and service designers need to distinguish the factors impacting user intention to adopt. Discerning user behavior can help designers to provide good service and healthcare service industry to reconstruct their business models. Research results suggest that users are inclined to use systems that integrate BDA with mHealth applications. Providing users analyzed big health data by mobile applications can increase use of mHealth applications and can help companies obtain value from big data. The results of this research can provide guidance for developing applications in which BDA can be appealing to whole public and for implementing BDA successfully. Presenting information obtained from BDA to users via mHealth applications can have influence on users in making decisions about their health and can encourage them to keep themselves healthy. In addition to academic contribution, research results will steer companies toward focusing on the factors used in the model. Enhanced TAM was tested within the context of the integration of mHealth and big data. The research will contribute to the literature of information system adoption by helping to understand the benefits of a new information system (BDA). The limitation of this study is that it was conducted toward the use of a single technology. To verify the model of this research, studies for diverse technologies and with bigger sample groups should be conducted. Other factors need to be taken into consideration as well.

References

Aceto, G., Persico, V. and Pescapé, A., Industry 4.0 and health: Internet of things, big data, and cloud computing for healthcare 4.0, *Journal of Industrial Information Integration*, 18, 100129, pp. 1-9, 2020.

Afthanorhan, W. M. A. B. W., A Comparison of Partial Least Square Structural Equation Modeling (PLS-SEM) and Covariance Based Structural Equation Modeling (CBSEM) for Confirmatory Factor Analysis, *International Journal of Engineering Science and Innovative Technology,* 2(5), pp. 198-205, 2013.

Ajzen, I. and Madden, T. J., Prediction of goal-directed behavior: Attitudes, intentions, and perceived behavioral control, *Journal of Experimental Social Psychology,* 22(5), pp. 453–474, 1986.

Ajzen, I., The theory of planned behaviour, organizational behaviour and human, *Decision Processes,* 50 (2), pp. 179-211, 1991.

Balapour, A., Reychav, I., Sabherwal, R., Azuri, J., Mobile technology İdentity and self-efficacy: Implications for the adoption of clinically supported mobile health apps, *International Journal of Information Management,* 49, pp. 58–68, 2019.

Chau, P. Y. K. and Hu, P. J.-H., Investigating healthcare professionals' decisions to accept telemedicine technology: An empirical test of competing theories, *Information & Management,* 39(4), pp. 297–311, 2002.

Chen, C. L. P. and Zhang, C.-Y., Data-intensive applications, challenges, techniques and technologies: a survey on big data, *Information Sciences*, 275, pp. 314-347, 2014.

Chen, D. Q., Preston, D. S. and Swink, M., How the use of big data analytics affects value creation in supply chain management, *Journal of Management Information Systems*, 32(4), pp. 4–39, 2015.

Constantiou, I. D. and Kallinikos, J., New games, new rules: big data and the changing context of strategy, *Journal of Information Technology*, 30(1), pp. 1-14, 2014.

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

DeLone, W. H. and McLean, E. R., Information systems success: The quest for the dependent variable, *Information Systems Research,* 3(1), pp. 60–95, 1992.

DeLone, W. H. and McLean, E. R., The DeLone and McLean Model of Information Systems Success: A ten-year update, *Journal of Management Information Systems,* 19(4), pp. 9-30, 2003.

Deng, Z., Understanding public users' adoption of mobile health service, *International Journal of Mobile Communications*, 11(4), pp.351-373, 2013.

Duarte, P. and Pinho, J. C., A mixed methods UTAUT2-based approach to assess mobile health adoption, *Journal of Business Research*, 102, pp. 140–150, 2019.

Dwivedi, Y. K., Shareef, M. A., Simintiras, A. C., Lal, B., Weerakkody, V., A generalised adoption model for services: A cross-country comparison of mobile health (m-health), *Government Information Quarterly,* pp. 174-187, 2016.

Fosso Wamba, S., Akter, S. and Bourmont, M., Quality dominant logic in big data analytics and firm performance, *Business Process Management Journal*, 24(4), pp. 923-942, 2018.

Gandomi, A. and Haider, M., Beyond the hype: Big data concepts, methods, and analytics, *International Journal of Information Management*, 35(2), pp. 137–144, 2015.

Gantz, J. and Reinsel, D., The digital universe in 2020: big data, bigger digital shadows, and biggest growth in the far east, *Idc Iview Idc Anal Future*, pp. 1–16, 2012.

George, G., Haas, M. R. and Pentland, A., Big data and management, A*cademy of Management Journal,* 57(2), pp. 321–326, 2014.

Günther, W. A., Rezazade Mehrizi, M. H., Huysman, M., Feldberg, F., Debating big data: A literature review on realizing value from big data, *The Journal of Strategic Information Systems,* 26(3), pp. 191–209, 2017.

Gupta, M. and George, J. F., Toward the development of a big data analytics capability, *Information & Management,* 53(8), pp. 1049-1064, 2016.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., Multivariate Data Analysis (8), *CENGAGE,* 2019.

Hung, M. C. and Jen, W. Y., The adoption of mobile health management services: an empirical study, *Journal of Medical Systems*, 36, pp. 1381-1388, 2012.

Jagadeeswari, V., Subramaniyaswamy, V., Logesh, R. and Vijayakumar, V., A study on medical internet of things and big data in personalized healthcare system, *Health Information Science and Systems,* 6(14), pp. 1-20, 2018.

Kwon, O., Lee, N. and Shin, B., Data quality management, data usage experience and acquisition intention of big data analytics, *International Journal of Information Management*, 34(3), pp. 387–394, 2014.

Lai, Y., Sun, H. and Ren, J., Understanding the determinants of big data analytics (BDA) adoption in logistics and supply chain management: An empirical investigation, *The International Journal of Logistics Management*, 29(2), pp. 676–703, 2018.

Lin, S. P., Determinants of adoption of mobile healthcare service, *International Journal of Mobile Communications*, 9(3), pp. 298-315, 2011.

McAfee, A. and Brynjolfsson, E., Big data: the management revolution, *Harvard Business Review*, pp. 1-9, 2012.

Mehta, N. and Pandit, A., Concurrence of big data analytics and healthcare: A systematic review, *International Journal of Medical Informatics*, 114, pp. 57–65, 2018.

Miao, R., Wu, Q., Wang, Z., Zhang, X., Song, Y., Zhang, H., Sun, Q., Jiang, Z., Factors that influence users' adoption intention of mobile health: A structural equation modeling approach, *International Journal of Production Research*, 55(19), pp. 5801–5815, 2017.

Moores, T. T., Toward an integrated model of it acceptance in healthcare, *Decision Support Systems,* 53(3), pp. 507-516, 2012.

Murdoch, T. B. and Detsky, A. S., The inevitable application of big data to health care, *JAMA,* 309(13), pp. 1351-1352, 2013.

Nelson, R. R., Todd, P. A. and Wixom, B. H., Antecedents of information and system quality: An empirical examination within the context of data warehousing, *Journal of Management Information Systems,* 21(4), pp. 199–235, 2005.

Nisha, N., Iqbal, M. and Rifat, A., The changing paradigm of health and mobile phones, *Journal of Global Information Management*, 27(1), pp. 19–46, 2019.

Pai, F.-Y. and Huang, K.-I., Applying the technology acceptance model to the introduction of healthcare information systems, *Technological Forecasting and Social Change,* 78(4), pp. 650–660, 2011.

Raghupathi, W. and Raghupathi, V., Big data analytics in healthcare: Promise and potential, *Health Information Science and Systems,* 2(1), pp. 1-9, 2014.

Raguseo, E., Big data technologies: An empirical investigation on their adoption, benefits and risks for companies, *International Journal of Information Management,* 38(1), pp. 187–195, 2018.

Saheb, T., An empirical investigation of the adoption of mobile health applications: Integrating big data and social media services, *Health and Technology,* 10, pp. 1063-1077, 2020.

Sandhu, R., Gill, H. K. and Sood, S. K., Smart monitoring and controlling of pandemic influenza a (H1N1) using social network analysis and cloud computing, *Journal of Computational Science,* 12, pp. 11-22, 2016.

Sareen S, Sood S.K. and Gupta S.K., Secure internet of things-based cloud framework to control zika virus outbreak, *International Journal of Technology Assessment in Health Care*, 33(1), pp. 1–8, 2017.,

Seddon, J. J. J. M. and Currie, W. L., A model for unpacking big data analytics in high-frequency trading, *Journal of Business Research*, 70, pp. 300-307, 2017.

Shareef, M. A., Kumar, V. and Kumar, U., Predicting mobile health adoption behaviour: A demand side perspective, *Journal of Customer Behaviour,* 13(3), pp. 187–205, 2014.

Sivarajah, U., Kamal, M. M., Irani, Z., Weerakkody, V., Critical analysis of Big Data challenges and analytical methods, *Journal of Business Research*, 70, pp. 263-286, 2017.

Sun, Y., Wang, N., Guo, X. and Peng, Z., Understanding the acceptance of mobile health services: A comparison and integration of alternative models, *Journal of Electronic Commerce Research,* 14(2), pp. 183-201, 2013.

Szlezák, N., Evers, M., Wang, J., Pérez, L., The role of big data and advanced analytics in drug discovery, development, and commercialization, *Clinical Pharmacology & Therapeutics*, 95(5), pp. 492–495, 2014.

Tabesh, P., Mousavidin, E. and Hasani, S., Implementing big data strategies: A managerial perspective, *Business Horizons,* 62(3), pp. 347-358, 2019.

Venkatesh, V. and Bala, H., Technology Acceptance Model 3 and a research agenda on interventions, *Decision Sciences,* 39(2), pp. 273–315, 2008.

Venkatesh, V. and Davis, F. D., A theoretical extension of the Technology Acceptance Model: Four longitudinal field studies, *Management Science,* 46(2), pp. 186–204, 2000.

Venkatesh, V., Morris, M.G. and Ackerman, P.L. A longitudinal field investigation of gender differences in individual technology adoption decision-making processes, *Organizational Behavior and Human Decision Processes,* 83(1), pp. 33–60, 2000.

Verma, S., Bhattacharyya, S. S. and Kumar, S., An extension of the technology acceptance model in the big data analytics system implementation environment, *Information Processing & Management,* 54(5), pp. 791-806, 2018.

Ward, M. J., Marsolo, K.A. and Froehle, C. M., Applications of business analytics in healthcare, *Business Horizons*, 57(5), pp. 571–582, 2014.

Wixom, B. H. and Todd, P. A., A theoretical integration of user satisfaction and technology acceptance, *Information Systems Research,* 16(1), pp. 85-102, 2005.

Wu, I. L., Li, J. Y. and Fu, C. Y., The adoption of mobile healthcare by hospital's professionals: An integrative perspective, *Decision Support Systems,* 51(3), pp. 587-596, 2011.

Wu, J. H., Wang, S. C. and Lin, L. M., Mobile computing acceptance factors in the healthcare industry: A structural equation model, *International Journal of Medical Informatics,* 76(1), pp. 66-77, 2007.

Yaşlıoğlu, M., Sosyal Bilimlerde Faktör Analizi ve Geçerlilik: Keşfedici ve Doğrulayıcı Faktör Analizlerinin Kullanılması, *İstanbul Üniversitesi İşletme Fakültesi Dergisi*, pp. 74-85, 2017.

Yi, M. Y., Jackson, J. D., Park, J. S. and Probst, J. C., Understanding information technology acceptance by individual professionals: Toward an integrative view, *Information & Management,* 43(3), pp. 350–363, 2006.

Zhang, X.,Liu, S., Wang, L., Zhang, Y. and Wang, J., Mobile health service adoption in china: Integration of theory of planned behavior, protection motivation theory and personal health differences, *Online Information Review*, 44(1), pp. 1-23, 2020.

Zhao, Y., Ni, Q. and Zhou, R., What factors influence the mobile health service adoption? A meta-analysis and the moderating role of age, *International Journal of Information Management*, 43, pp. 342-350, 2018.

Zheng, Y., Zhao, K. and Stylianou, A., The impacts of information quality and system quality on users' continuance intention in information-exchange virtual communities: An empirical investigation, *Decision Support Systems,* 56, pp. 513–524, 2013.

Zhou, C., Su, F., Pei, T., Zhang, A., Du, Y., Luo, B., Cao, Z., Wang, J., Yuan, W., Zhu, Y., Song, C., Chen, J., Xu, J., Li, F., Ma, T., Jiang, L., Yan, F., Yi, J., Hu, Y., Liao Y., Xiao, H., COVID-19: Challenges to GIS with big data, *Geography and Sustainability,* 1(1), pp. 77-87, 2020.

Biographies

Öznur Dal, earned her MSc degree in Hospital and Healthcare Management Department from Beykent University in 2013. She received her BSc in Business Administration from Istanbul University in 2018. She worked as a civil servant in affiliated institutions of Ministry of Health. She earned her Ph.D. in Business Administration from Beykent University in 2021.

Yıldız Yılmaz Güzey, received the B.A., MBA., M.Sc., and PhD. Degrees in Management and Organization and Business Policy from University of Istanbul, Turkey, and Management, HRM, Project Management Professional development degrees from Portland State University, USA. Her work experience includes, extensive management consulting in Industrial corporations, teaching and research. She has served as a visiting scholar at Portland State University, Engineering and Technology Management Program. She is currently Professor of Economics and Administrative Science Faculty and Head of Women Studies Research Center at Beykent University, Istanbul.