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Examining intention to adopt to internet of things in healthcare technology products

Adem Karahoca, Dilek Karahoca, Merve Aksöz,

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Adem Karahoca
Department of Software Engineering, Bahcesehir Universitesi, Istanbul, Turkey
Dilek Karahoca
Department of Health Management, Bahcesehir Universitesi, Istanbul, Turkey, and
Merve Aksöz
Department of Software Engineering, Bahcesehir Universitesi, Istanbul, Turkey

Abstract

Purpose – The purpose of the study is to investigate critical factors affecting individuals' intention to adopt internet of things (IoT) products in healthcare.

Design/methodology/approach – An integrated model was developed based on technology acceptance model (TAM), innovation diffusion theory (IDT), technological innovativeness (TI), protection motivation theory and privacy calculus theory. The model was tested with 426 respondents (222 females, 204 males) using partial least square structural equation model with all data grouped by gender.

Findings – Based on the results of the complete model, perceived advantage (PA), image and perceived ease of use (PEOU) constructs have a significant effect on intention to adopt IoT healthcare technology products. The results show that for females, compatibility and trialability have more impact on PEOU whereas for males PA has more impact on PEOU. Image, perceived privacy risk, perceived vulnerability have more impact on males when compared to females.

Research limitations/implications – Research conducted only among Turkish people.

Originality/value – This study investigated adoption of future technology, "internet of things", products in healthcare from a behavioral perspective by integrating various theories. The reason is that before launching any technology into the market, its facilitative factors should be researched for the people who are going to use this in their daily routine.

Keywords Healthcare, Internet of things, Technology acceptance model, Adoption intention, Innovation diffusion theory, Partial least square-structural equation model, Technological innovativeness, Protection motivation theory, Privacy calculus theory

Paper type Research paper

1. Introduction

We hope for high quality healthcare services with low costs in our lifetime. Internet of Things (IoT) has the power to make this real. More sensor devices mean more patient monitoring for chronic issues, and more patient monitoring means fewer checkups and unnecessary appointments, all resulting in cost reduction. Early diagnoses and early interventions can be supported with IoT technologies to enhance the identification of the nature of an illness or other problems by examination of the symptoms. After the invention of the internet, IoT is expected to be the next pivotal digital revolution. IDC (2017) predicted that IoT-covered smart wearable devices will grow by 250 per cent in 2019. It means that digital revolution will be supported by IoT especially in healthcare products.

Kybernetes
© Emerald Publishing Limited
0368-492X
DOI 10.1108/K-02-2017-0045

This study focuses on adopting the intention of IoT healthcare products. Technology acceptance model was chosen to identify the mobile users' adoption intention of any emerging technology. Also, technological innovativeness was used to evaluate the individual's adoption to an innovation. An innovation diffuses via communication channels over time among the members of a social system. Thus, innovation diffusion theory was adopted to evaluate this impact on IoT-enabled healthcare products. For identifying the "threat and coping" of the innovation for individuals, protection motivation theory was taken into account, and privacy calculus theory was adopted to present anticipated benefits and perceived risks which affect an individual's decision to share information with others.

ITU report (2005) says that IoT is described as network connectivity between people and things from anywhere, anytime by anyone. IoT is the connectivity of everything (even dust) through wireless technologies by assigning an internet address to every single thing.

First generation of IoT (RFID and Sensors) starts with the tagged objects in EPCglobal, machine to machine (M2M) in oneM2M standard, and integration RFID with Wireless Sensor Networks (WSN). The second generation (Web Services and Internetworking) covers Internetworking with IETF 6LoWPAN, ROLL RPL, IEEE 802.15.4 standards, Web of Things with IETF CoAP, OASIS DPWS standards and Social Networks. Social Internet of Things, Semantic (W3C, SSN), Future Internet (IETF ICNRG), Cloud and RFID-IoT integration are constructs of the third generation (Social, Cloud and ICN) of the IoT (Atzori *et al.*, 2017).

Nowadays, IoT developments are actualized and accelerated almost in every area of life and industry. IoT is efficient, accurate and effective in operations. For instance; a parking application was developed to share timely information and reduce waiting time for parking via smart sensors in San Francisco (Cosgrave *et al.*, 2013).

We will discuss in this article the application of IoT in healthcare field. IoT plays a significant role in healthcare sector from managing to preventing chronic disease. An IoT-based healthcare system provides network connectivity between all available resources to perform healthcare activities such as remote surgeries over Internet, diagnosing and monitoring (Tarouco *et al.*, 2012). In health and wellbeing, the main contribution of the IoT includes monitoring people's health and quality of life by features such as pervasivity, transparency, wearability and security (Atzori *et al.*, 2017).

Medical devices are used for a number of purposes in elder patient care such as real-time location, patient data gathering, personal health tracking and chronic disease tracking. The geriatric population in the world is increasing day by day and this means that the society will suffer more from chronic disease such as diabetes, hypertension, dementia and in particular Alzheimer's disease. In Turkey, by 2020 Turkish Health Ministry expects that 44 million people will suffer from Alzheimer's disease. Thanks to IoT technology, daily schedule can be formulated by monitoring daily activities. In this way, inconsistencies can be detected and alerted for emergency services if necessary. In this paper, our main interest is personal IoT health devices such as health trackers, skin sensors, cardiac monitors, glucometers and ingestible smart pill, which are commonly used IoT devices that help individuals track their health metrics and get alerts about their latest status.

For example, thanks to sensors and sensor smartphone integration, unusual changes such as faster heartbeat, rise in blood pressure or blood sugar can be tracked and recorded, notifying persons about this unusual health condition. It is not just confined to notify, this IoT-based system can also suggest safety actions including personnel advice, informing your doctors, your family and friends (Bui and Zorzi, 2011).

Taking prescribed medicines regularly and on time requires effort. It is very natural for people to forget to take pills and/or overdose. For this issue, some IoT solutions including digestible pills have been proposed by some healthcare companies. These digestible pills can inform physicians whether their patients take their pills on time or not. It also reminds the patient to take medicine on time by text messages, flash lights, etc.

Another example for IoT-enabled device in healthcare is smart shirt. This shirt is equipped with lots of sensors that monitors the patient's vital signs and movements as heart rate, blood pressure and body temperature. This sensor-equipped shirt enables one to get an electrocardiogram. Also, this smart shirt can inform the location of the patient by means of GPS to healthcare providers in case of emergency such as heart attack and stroke.

In the very near future, the transition to IPV6 (Internet Protocol Version 6) will support the future internet. This means that more or less within 10 years almost everything will have an internet address. This technology improvement is inevitable, before any technology getting into the market; it can be useful to research facilitator factors for the people who are going to use it in their daily routine. Investigating and examining the adoption intention or acceptance of a new technology plays an important role for the industrial development for that technology. Many stunning IoT products have been developed by important users taking active involvement in both public and private sector (ITU Report, 2005). In any innovation diffusion process, the chasm point is stepped over by the lead users. Nowadays, user demand performs a prominent role in the process of innovation (Kidar and Vellera, 2013; Hippel *et al.*, 2009; Edquist and Hommen, 1999). Innovation is not confined to producing special, advanced products. Understanding the user demand and integration of potential adopters are essential in the earlier stages of research and development.

Individual consumers have an impact on shaping the technology market although Gartner researchers predict that IoT revenue will come from more enterprises, not from individual consumers by 2020. Readiness of individuals to embrace new services and products is a critical factor to make technologies more mature. If users' fears and concerns are not addressed appropriately, this readiness issue can be a bottleneck for technology diffusion process (ITU Report, 2005).

To diminish or avoid these potential shortcomings, it would be useful to evaluate factors for end users of new IoT technologies. For this purpose, in literature, a large number of studies examine these technology acceptance concepts (Hsu and Yeh, 2016; Lin *et al.*, 2016; Scuotto *et al.*, 2016; Prayoga and Abraham, 2016).

The purpose of this research study is to extensively examine and understand individuals' adoption intention towards IoT healthcare products so an integrated model has been developed and proposed that consists of technology acceptance, innovation diffusions, health behavior and privacy context from multiple perspectives. Examining the adoption intention of HIT products does not include just technology adoption process but also decision process related to health. The adoption of health information technology (HIT) products should be considered and distinguished from other technological products (Gao *et al.*, 2015; Sun *et al.*, 2013; Miltgen *et al.*, 2013; Holden and Karsh, 2010). According to some researchers, adoption intention of HIT products cannot be understood by examining it from just one perspective (Miltgen *et al.*, 2013; Sun *et al.*, 2013). Thus, Miltgen *et al.* (2013) studied user's acceptance of biometrics and Sun *et al.* (2013) studied health services adoption by integrating protection motivation theory (PMT) with TAM and UTAUT. It is suggested that researchers pay attention to healthcare context when developing a model about healthcare issues (Sun *et al.*, 2013; Holden and Karsh, 2010). Therefore, PMT is integrated into the proposed model. This study is not confined to explaining any kind of IoT-enabled product; this study specifically examines the adoption intention of IoT-enabled health technology products. PMT is used to investigate and predict health behaviors (Conner Norman, 2005). Meta analyses related to PMT find out that PMT antecedents are appropriate predictors of health-related behaviors in general (Floyd *et al.*, 2000, Milne *et al.*, 2000).

The rest of the paper is organized as follows; the models and theories covered in the study are given in Section 2. The research model and hypotheses are summarized in Section 3. Research methodology has been considered in Section 4. Results of the study and discussions and conclusions are followed in Section 5 and Section 6, respectively.

2. Background

In this study, adoption intention toward IoT healthcare products was examined using innovation diffusion theory, technology acceptance model, technological innovativeness, protection motivation theory and privacy calculus theory by creating a PLS-SEM model. The considered theories will be explained respectively.

Technology acceptance and adoption intention of any emerging technology are very prominent fields in Information Systems (IS). When literature is reviewed, it is possible to come across studies in which TAM and Roger' Innovation Diffusion Theory (IDT) and Technology Readiness Index (TRI) are used together (Sun *et al.*, 2013). TAM and IDT have some similar constructs and they are equivalent of each other to investigate adoption intention in IS field. Researcher points out that the constructs of TAM are basically a subset of perceived innovation characteristics, thus, combining these two theories could produce a more powerful model (Wu and Wang, 2005).

In literature, there is little research, combining IDT and TAM, carried out related to healthcare issues (Gao *et al.*, 2015; Miltgen *et al.*, 2013). In this sense, this study aims to fill this research gap through explaining underlying factors in adoption intention of any IoT healthcare product. In Turkey, this research study is a new perspective to examine adoption intention of new technological products in healthcare with various theories including TAM, IDT, protection motivation theory (PMT), privacy calculus theory (PCT) and cost issue.

2.1 Innovation diffusion theory

The most widely known source for IDT is Everett M. Rogers' research. Diffusion is the process as a means of an innovation diffuses by means of communication channels over time among the members of a social system (Rogers, 2003).

IDT has five significant characteristics which have a direct effect by means of consequence of innovation on individuals: compatibility, relative advantage, trialability, complexity and observability. It means that an innovation is perceived as better than the idea. Social prestige, convenience and satisfaction besides economical factors are important components to measure relative advantage. Compatibility is the status of an innovation that is perceived as being consistent with the existing values, past experiences and needs of potential adopters. Complexity is the degree of an innovation is perceived as difficult to understand and use. Trialability is the degree to which an innovation may be experimented with on a limited basis. Observability is the degree to which the results an innovation are visible to others.

IDT has applied widely to examine IT usage and adoption intention, in the past decade. For example, Chen *et al.* (2002) found compatibility, perceived usefullness (PU), perceived ease of use (PEOU) are the prominent factors to explain the attitude toward using virtual stores. Wu and Wang (2005) investigated factors which influence users' behavioral intention of user mobile commerce acceptance. They found that all factors except PEOU significantly affected user's behavioral intention adoption in mobile commerce. Among the factors, compatibility had the most significant influence.

2.2 Technology acceptance model (TAM)

The first technology acceptance models were introduced in the 1970s by Fishbein and Ajzen as theory reasoned action (TRA) and planned behavior theory (PBT). They tried to understand why people use technology and why believe drive intentions. In 1986, Fred Davis proposed the technology acceptance model (TAM). There are some comparative studies such as Todd and Taylor's study, the results of which show that TAM has more explanatory power than others like TRA and PBT. Although TRA and PBT can explain system utilization with subjective norms and perceived behavioral controls by means of attitudes toward technology utilization, TAM is more preferable and easy to apply for online works. TAM is specific for IS usage by taking easiness and usefulness into consideration (Chen *et al.*, 2011).

In TAM, there are two key factors: PEOU and PU. These two factors have a direct effect on individuals' attitude (AT) and behavioral intention (BI) in IS/IT usage (Hsiao and Tang, 2015). According to Davis (1989), perceived usefulness is defined as the perception degree of a person who believes that adopting/using a specific system/product can improve his/her job performance. Perceived ease of use is the perception degree of a person who believes that adopting/using a specific system/product can be easy to use.

2.3 Protection motivation theory (PMT)

PMT was originally proposed in 1975 by Rogers and the substantial elements of the Health Belief Model encompasses the cognitive processes mediating attitudinal and behavioral change to understand fear appeals (Prentice-Dunn and Rogers, 1986; Rogers, 1975). PMT comprises two evaluation processes: threat and coping. Threat evaluation is determined by perceived severity and perceived vulnerability (Armitage and Conner, 2000). Perceived severity is explained as the degree of harm from unhealthy behavior (Jones *et al.*, 2015; Champion and Skinner, 2008; Rogers, 1975). The severity of the health threat is described as how seriously the individual considers the health threats. Perceived vulnerability is one of the threat appraisal processes which assess how an individual personally perceives the given situation as a threat (Milne *et al.*, 2000).

2.4 Privacy calculus theory (PC)

PC perspective proposes that anticipated benefits and perceived risks affect an individual's decision to share information with other parts. Hence, individuals are expected to take the cost and benefits into consideration (Dinev and Hart, 2006). In the literature of privacy calculus, perceived risks mostly refer to "potential for loss associated with the release of personal information" (Smith *et al.*, 2011).

As it has been mentioned before, in literature there are various models for understanding and exploring the affecting factors in adoption, acceptance and use of the technology. When literature is reviewed, it is possible to come across research studies where TAM and other theories have been used together to explain technology adaptation including IDT and TRI (Sun *et al.*, 2013). TAM and IDT have some similar constructs and they are equivalent to each other to investigate adoption intention in IS field. Researchers point out that the constructs of TAM are basically a subset of perceived innovation characteristics; hence, combining these two theories could produce a more powerful model (Wu and Wang, 2005). There are lots of studies combining the original TAM with IDT (Chen *et al.*, 2002; Wu and Wang, 2005; Lee *et al.*, 2011; Miltgen *et al.*, 2013).

3. Research model and hypotheses

In this section, the proposed research model and its hypotheses that are derived from TAM, IDT, PMT and PCT for evaluating individuals' intention to adopt IoT products in healthcare are listed. Quantitative research method was used. The questionnaire of the integrated research model was applied on-line to 576 respondents who had at least one smart device as the target subjects – early adopter – because the target group member could use IoT healthcare products in the near future. In sum, 26 per cent of respondents were removed from dataset because of incompleteness, 74 per cent of respondents were selected for evaluation of the PLS-SEM model. A total of 426 responses were used in data analysis. Gender breakdown was dispersed almost equally; 222 respondents were females, and 204 respondents were males. The integrated research model was tested with a questionnaire consisting of three technological factors (key factors from TAM and technological innovativeness from TRI); five factors of IDT such as image, trialability, compatibility, attitude; two factors related to healthcare severity and vulnerability from PMT; a factor related to privacy issues from privacy calculus model and a factor related to cost issue.

3.1 Research model

We proposed an integrated research model encompassing technology acceptance, innovation diffusion, health behavior, privacy context and cost issue to explain and examine empirically individuals' adoption to IoT products in healthcare from multiple perspectives.

This research model covers two technological factors from TAM and one technological innovativeness factor from TRI; five factors from IDT such as image, trialability, compatibility, attitude; two factors related to healthcare severity and vulnerability from PMT; one factor related to privacy issue from PCT and one factor related to cost issue. The following Figure 1 gives a snapshot for this research model.

3.2 Hypotheses

In this section, the proposed model and its constructs have been summarized based on the hypotheses that are classified based on the related model and theories to evaluate individuals' intention to adopt IoT products in healthcare.

3.2.1 TAM factors. Technology acceptance model covers PU, PEU, AT and BI factors. Here hypotheses are explained from this viewpoint.

3.2.1.1 Attitude toward intention to adopt. In this study, the main dependent variable is BI. BI is defined by Ajzen and Fishbein (1980) as a measure of the likelihood that a person will get the given behavior. Attitude (AT) is the first determinant of BI to adopt and indicates the level of an individual who has a favorable or unfavorable evaluation of relevant behavior. Most contemporary social psychologists take a cognitive or information-processing approach to attitude formation. There are lots of studies which reveal that there is a positive relationship between the two constructs, AT and BI. Therefore, the following hypothesis was proposed:

H12. Attitude has a positive effect on the BI to adopt IoT healthcare products.

3.2.1.2 Perceived usefulness and perceived ease of use. PU and PEOU are two major utilitarian latent variables of TAM that reflect utilitarian motivation (Choi and Kim, 2016). According to Davis (1989), perceived usefulness is defined as the perception degree of a person who believes that adopting/using a specific system/product can improve his or her job performance. Many studies confirm the impact of PU and PEOU on both attitude and behavioral intention to use (Miltgen *et al.*, 2013; Kim, 2012; Wu and Wang, 2005; Chen *et al.*, 2002). Perceived ease of use is the perception degree of a person to believe that adopting/

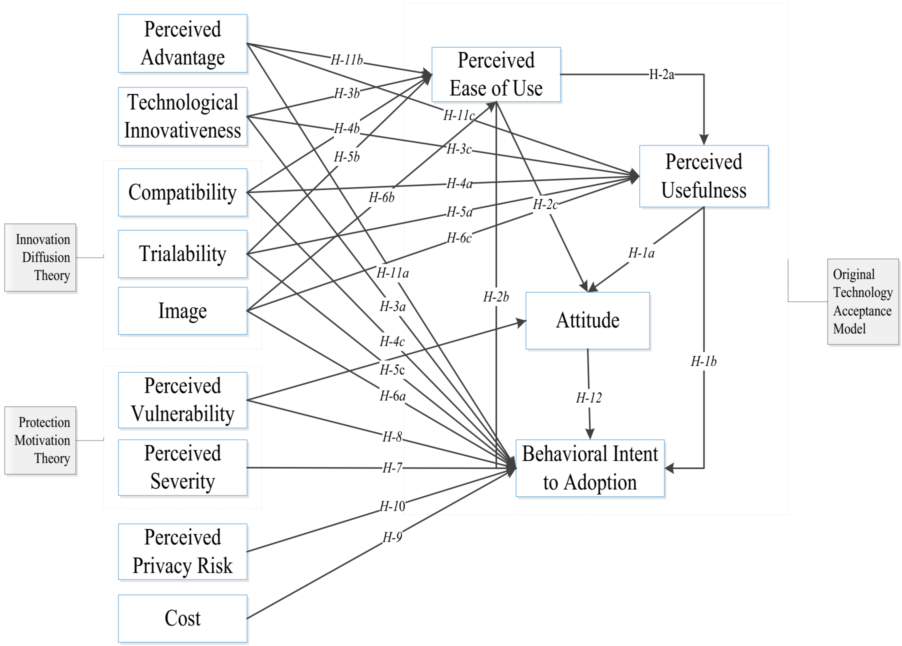

Figure 1.
Proposed research model

using a specific system/product can be easy to use. TAM affirms that perceived ease of use is a predictor of perceived usefulness and attitude toward use (Davis, 1989). According to Davis (1989), Venkatesh and Davis (2000), the relationship between PEOU and PU are explained in the following manner: if an individual perceives use of any technological product/system as easy to use and free of effort, he or she perceives that product/system is more useful. Therefore, following hypotheses are researched:

H1a. PU has a positive effect on the behavioral intention to adopt IoT healthcare products.

H1b. PU has a positive effect on the attitude to adopt IoT healthcare products.

H2a. PEOU has a positive effect on the PU of IoT healthcare products.

H2b. PEOU has a positive effect on the behavioral intention to adopt IoT healthcare products.

H2c. PEOU has a positive effect on the attitude to adopt IoT healthcare products.

3.2.2 Technological innovativeness. According to IDT, individuals react differently while adopting an innovation because of personal differences such as personal innovativeness. Many studies confirm that innovativeness is a significant determinant of technology acceptance (Miltgen *et al.*, 2013; Wu and Wang, 2005; Lewis *et al.*, 2003; Agarwal and Karahanna, 2000). Beyond TAM, early researches have proposed that the acceptance of mobile healthcare generally involves technological and behavioral aspects for personal use. Because of that, TAM alone is not sufficient to explain a potential adopter's behavioral intentions (Venkatesh and Davis, 2000). Therefore, innovativeness was integrated to this research model. The hypotheses for technological innovativeness (TI) in this study are as follows:

H3a. TI is associated with the behavioral intention to adopt IoT healthcare products.

H3b. TI is associated with the PEOU to adopt IoT healthcare products.

H3c. TI is associated with the PU to adopt IoT healthcare products.

3.2.3 IDT factors. Innovation diffusion theory has compatibility, trialability and image factors. Here, IDT and TAM factors interaction hypotheses are given.

3.2.3.1 Compatibility. In addition to other forementioned core latent variables of TAM, compatibility is suggested as one of the determinants of PU, PEOU and BI. In literature, there are many studies that reveal the effect of compatibility in individual technology acceptance (Kim and Choi, 2017; Wu and Wang, 2005; Hardgrave *et al.*, 2003; Chen *et al.*, 2002; Chau and Hu, 2001):

H4a. Compatibility has a positive effect on PU of IoT healthcare products.

H4b. Compatibility has a positive effect on PEOU of IoT healthcare products.

H4c. Compatibility has a positive effect on the behavioral intention to adopt IoT healthcare products.

3.2.3.2 Trialability. In literature, there is limited research about the effect of trialability in technological innovation adoption studies. However, a few researches confirm that trialability affects the behavioral intention to use the systems (Lee *et al.*, 2011; Yang, 2007). Accordingly, the following hypotheses were proposed:

H5a. Trialability has a positive effect on PU of IoT healthcare products.

H5b. Trialability has a positive effect on PEOU of IoT healthcare products.

H5c. Trialability has a positive effect on the behavioral intention to adopt IoT healthcare products.

3.2.3.3 Image. Moore and Benbasat (1991) proposed to extend innovation diffusion attributes by adding image, visibility, result demonstrability and voluntariness. At the beginning, some researchers including Rogers considered the image as an aspect of relative advantage. But Rogers (2003) also stated that "undoubtedly one of the most important motivations for almost any individual to adopt an innovation is the desire to gain social status". Therefore, image was also included in this research study. Accordingly, the following hypotheses were proposed:

H6a. Image has a positive effect on the behavioral intention to adopt IoT healthcare products.

H6b. Image has a positive effect on PEOU to adopt IoT healthcare products.

H6c. Image has a positive effect on PU to adopt IoT healthcare products.

3.2.4 Protection motivation theory (PMT) factors. The adoption of health information technology (HIT) products should be considered and distinguished from other technological products (Sun *et al.*, 2013; Holden and Karsh, 2010). Therefore, PMT was integrated to the proposed research model. PMT has better explanation power than other health behavior theories such as health behavior model, TRA, TPB and self-efficacy (Sun *et al.*, 2013;

Prentice-Dunn and Rogers, 1986). In literature, there are studies that reveal a positive relationship between health threat evaluation (that includes perceived severity and perceived vulnerability) and intention to adopt IT products in healthcare (Gao et al, 2015; Sun *et al.*, 2013; Mishra *et al.*, 2012). Accordingly, we hypothesize that:

H7. Perceived severity has a positive effect on the behavioral intention to adopt IoT healthcare products.

H8. Perceived vulnerability has a positive effect on the behavioral intention to adopt IoT healthcare products.

3.2.5 Privacy issue. Privacy issue is an important context in adoption of or continuation to use a technology. Compared with other type of information, such as demographic features and general transaction information, personal health information is more sensitive for individuals (Bansal *et al.*, 2010). If potential adopters feel that anyone can reach their healthcare data when using IoT health products, they can reject or give up using it. Accordingly, the following hypotheses were proposed:

H10. Perceived privacy is negatively associated with the intention to adopt IoT healthcare products.

3.2.6 Cost issue. Cost is simply defined as the money required to acquire something, and here refers to the money to be paid by consumers for IoT health products. Yahyapour and Nassab (2007) found out that cost was important to intention of adopting a new mobile messaging system. Accordingly, the following hypothesis was proposed:

H9. Cost is associated with the intention to adopt IoT healthcare products.

3.2.7 Perceived advantage. This construct has been added into the research model by researchers. This construct can be considered as relative advantage in IDT. Perceived advantage means that innovation brings greater benefits to potential adopters. In literature, there are studies confirms that relative advantage is a significant parameter in the technological adoption (Lee *et al.*, 2011). Accordingly, the following hypotheses were proposed:

H11a. PA has a positive effect on the BI to adopt IoT healthcare products.

H11b. PA has a positive effect on PEOU of IoT healthcare products.

H11c. PA has a positive effect on PU of IoT healthcare products.

4. Research methodology

4.1 Overview

To test the proposed research model and hypotheses, an online survey research method was used as quantitative research method. A summarized introduction of the IoT healthcare product was provided in the beginning of the survey questionnaire beause the respondents did not possess prior knowledge of the concept. Almost all measurement items had been derived from previous studies with minor differences to adapt the research context of IoT healthcare products. PLS-Structural equational model (PLS-SEM) method was used to analyze research model.

4.2 Measures

The survey questionnaire has two main parts as given in Appendix. The first part consists of six demographic questions such as age, gender, education, average income, profession field and one filter question: the ownership of any smart device. The second part consists of research-related 40 factor questions. The questionnaire was translated into Turkish and survey research scope was limited just with Turkish people who lived in Turkey. A seven-point Likert scale was used for all items in the second part of the questionnaire: 1 = Entirely Disagree, . . ., 7 = Entirely Agree. The research questions are adopted from previous studies in the literature. Just one scale has not been adopted from previous studies: perceived advantage is constructed by researchers. The items for compatibility, trialability, image, behavioral intention and attitude were adapted from Karahanna *et al.* (2000). Perceived severity and perceived vulnerability were adapted from Sun *et al.* (2013). Perceived usefulness and perceived ease of use were borrowed from Davis (1989). For technological innovation, instruments used by Parasuraman (2000) were taken into account. Perceived privacy risk was adapted from the study of Li (2004), and cost items were adapted from Yahyapour and Nassab (2007) study.

4.3 Data collection and sampling method

Random purposive sampling method has been found more appropriate for data sampling method of this research study. This method involves random sampling from purposefully selected target population. Tashakkori and Teddlie (2003) claim that the combination of random and purposive sampling increases the validity of the study. This method is based on searching for cases or individuals who meet a certain criterion. In literature, there are various studies used this method (Ho and Tai, 2012; Ahadzadeh *et al.*, 2015; Thorlby *et al.*, 2011). For this research study, the criterion was the ownership of any smart device. Because, people who have a smart device can be a potential user of any IoT healthcare product in the near future. It is expected that the sample is well representative for the research purpose.

Online survey tool, survey monkey was used to reach up the target group who had any smart device and they were over 18 years old. 576 people participated in the survey within 2 weeks (15th February 2016– 29th February 2016). The survey questionnaire was carried out online due to the fact that the online survey can be accessible from anywhere, anytime by anyone. Social networks such as Facebook, Twitter, social health forums, social IoT and technology Facebook groups, and e-mail contacts were used. Finally, a total of 426 responses (222 females, 2014 males) were used in data analysis. 81 per centage of the participants stated that they are interested in technological developments. Our sample is supposed to be representative for further analysis.

4.4 Data analysis

In order to test the proposed hypotheses, PLS-SEM was performed since the research data is distributed non-normally. PLS-SEM offers a great opportunity for SEM researchers especially in the management information system and marketing disciplines to execute various complex statistical analyses at once. As it can be understood from its name, PLS-SEM is a regression based approach that aims to minimize residual variances of endogenous variables (Hair *et al.*, 2011). A two-step approach to analysis the empirical data collected from online survey was employed. Firstly, the measurement model was examined and secondly the structural model was examined by assessing the path coefficients between constructs. For two step evaluation of data analysis SmartPLS 3.2.3 and XLSTAT were used. All data analysis steps for both measurement and structural model were illustrated in Figure 2.

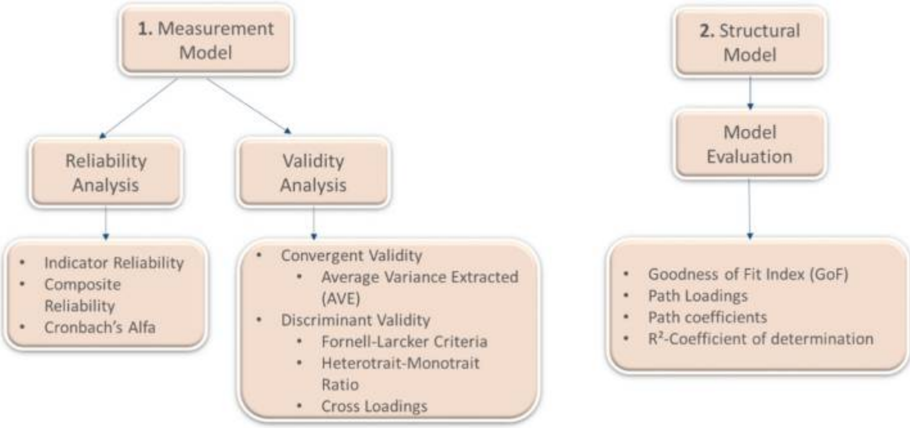

Figure 2.
Data analysis steps for PLS-SEM analysis

5. Results

This section argues reliability, validity, and convergence of the model. Also discriminant validity has been given. Then, goodness of fit index of the structural model is considered. Evaluation of the significance test of path coefficients between female and male was carried out by PLS-SEM accepted hypotheses are also listed.

5.1 Measurement model

Measurement model of this study is reflective so that Hair *et al.* (2012) suggests evaluating the model in terms of reliability and validity (convergent & discriminant validity). For construct reliability assessment, composite reliability and outer loadings are used respectively as an estimate of construct's internal consistency and indicator reliability. Table I shows the second evaluation of result summary of outer model. After removing low loading indicators, construct reliability is established. Some indicators which have <0.70 indicator reliability (AT3_, TI_1 and TI_2) were preferred to keep in the research model because of that, outer loadings of them are not so low. Convergent validity is examined to detect whether any unrelated measurement items in the measurement construct (Chan *et al.*, 2015). To examine convergent validity, average variance extracted (AVE) is calculated. A value of 0.70 or higher is preferred for indicator reliability, but 0.40 or higher is acceptable for an explanatory research (Hulland, 1999). For composite reliability, 0.70 is preferred, but 0.60 or higher is acceptable for an explanatory research (Bagozzi and Yi, 1988). Table I shows result summary of outer model.

Discriminant validity is carried out to check an observed variable which is empirically unique and represents best the related latent variable compared with other observed variables in the SEM (Hair *et al.*, 2011). According to the results of literature review in this context, for variance-based SEM, discriminant validity is evaluated in terms of three approaches:

(1) Fornell-Larcker criteria.

(2) Heterotrait-heteromethod ratio (HTMT) criteria.

(3) Cross loadings. The results of three of criteria indicate that discriminant validity is well established in this measurement model.

In Table II, Heterotrait-Monotrait Ratio result indicates that discriminant validity is well established. As mentioned above, HTMT values should be lower than 0.85, yet the value of

Latent variable	Indicator	Loadings	Indicator reliability (loadings^2)	Composite reliability	Cronbach's alfa	AVE
AT	AT_1	0.912	0.832	0.926	0.879	0.807
	AT_2	0.938	0.880			
	AT_3	0.843	0.711			
BI	BI_1	0.971	0.943	0.971	0.941	0.944
	BI_2	0.972	0.945			
COM	COM_1	0.884	0.781	0.928	0.884	0.812
	COM_2	0.918	0.843			
	COM_3	0.900	0.810			
COST	COST_1	0.942	0.887	0.925	0.84	0.861
	COST_2	0.914	0.835			
IM	IM_1	0.938	0.880	0.95	0.921	0.864
	IM_2	0.961	0.924			
	IM_3	0.887	0.787			
PA	PA_1	0.884	0.781	0.929	0.885	0.813
	PA_2	0.921	0.848			
	PA_3	0.899	0.808			
PEOU	PEOU_1	0.894	0.799	0.904	0.841	0.759
	PEOU_2	0.870	0.757			
	PEOU_3	0.850	0.723			
PPR	PPR_1	0.964	0.929	0.955	0.907	0.914
	PPR_2	0.948	0.899			
PS	PS_1	0.926	0.857	0.945	0.913	0.853
	PS_2	0.952	0.906			
	PS_3	0.891	0.794			
PU	PU_1	0.881	0.776	0.942	0.919	0.804
	PU_2	0.922	0.850			
	PU_3	0.901	0.812			
	PU_4	0.881	0.776			
PV	PV_1	0.857	0.734	0.912	0.854	0.775
	PV_2	0.919	0.845			
	PV_3	0.863	0.745			
TI	TI_1	0.776	0.602	0.887	0.83	0.663
	TI_2	0.738	0.545			
	TI_4	0.870	0.757			
	TI_5	0.864	0.746			
TR	TR_1	0.923	0.852	0.929	0.884	0.813
	TR_2	0.934	0.872			
	TR_3	0.847	0.717			

Notes: AT = Attitude; BI = Behavioral Intention; COM = Compatibility; IM = Image; PA = Perceived Advantage; PEOU = Perceived Ease of Use; PU = Perceived Usefulness; PPR = Perceived Privacy Risk; PS = Perceived Severity; PV = Perceived Vulnerability; TI = Technological Innovativeness; TR = Trialability

Table I.
Internal consistency and convergent validity

0.90 might also be acceptable. The reason why it does not well fit with the $HTMT_{0.85}$ is that PU and PA latent variables may have similar indicators (items/manifest variables).

According to the results of Fornell-Larcker criterion indicates that discriminant validity is well established, as it can be seen in Table III. Fornell and Larcker (1981) propose that the square root of AVE in each latent variable can be used to establish discriminant validity with the condition of that. This AVE value should be greater than other correlation values among the latent variables.

	AT	BI	COM	COST	IM	PA	PEOU	PPR	PS	PU	PV	TI	TR
AT													
BI	0.631												
COM	0.500	0.426											
COST	0.289	0.157	0.283										
IM	0.418	0.423	0.456	0.059									
PA	0.612	0.576	0.479	0.326	0.344								
PEOU	0.500	0.305	0.483	0.345	0.222	0.627							
PPR	0.060	0.031	0.152	0.174	0.026	0.052	0.076						
PS	0.336	0.302	0.471	0.370	0.284	0.403	0.451	0.077					
PU	0.613	0.489	0.528	0.339	0.402	0.868	0.716	0.058	0.443				
PV	0.355	0.286	0.311	0.300	0.239	0.254	0.237	0.121	0.364	0.269			
TI	0.282	0.327	0.474	0.210	0.370	0.377	0.478	0.081	0.344	0.321	0.227		
TR	0.459	0.351	0.617	0.421	0.261	0.527	0.500	0.122	0.504	0.492	0.310	0.417	

Notes: AT = Attitude; BI = Behavioral Intention; COM = Compatibility; IM = Image; PA = Perceived Advantage; PEOU = Perceived Ease of Use; PU = Perceived Usefulness; PPR = Perceived Privacy Risk; PS = Perceived Severity; PV = Perceived Vulnerability; TI = Technological Innovativeness; TR = Trialability

Table II. Heterotrait-monotrait ratio results for discriminant validity

	AT	BI	COM	COST	IM	PA	PEOU	PPR	PS	PU	PV	TI	TR
AT	*0.898*												
BI	0.574	*0.972*											
COM	0.442	0.388	*0.901*										
COST	0.250	0.141	0.249	*0.928*									
IM	0.379	0.396	0.415	0.055	*0.929*								
PA	0.540	0.526	0.424	0.284	0.315	*0.901*							
PEOU	0.432	0.273	0.420	0.296	0.201	0.542	*0.871*						
PPR	−0.033	−0.028	0.135	0.155	−0.024	−0.047	0.067	*0.956*					
PS	0.301	0.281	0.423	0.326	0.264	0.362	0.399	0.069	*0.923*				
PU	0.551	0.456	0.476	0.302	0.372	0.785	0.634	0.040	0.405	*0.897*			
PV	0.309	0.257	0.270	0.253	0.211	0.221	0.200	0.105	0.322	0.240	*0.880*		
TI	0.243	0.287	0.407	0.177	0.311	0.335	0.408	0.065	0.307	0.285	0.190	*0.814*	
TR	0.405	0.321	0.545	0.369	0.242	0.466	0.436	0.109	0.452	0.444	0.269	0.366	*0.902*

Notes: Boldfaced diagonal elements are the square roots of AVE. For discriminant validity, boldfaced elements should be larger than correlation elements in the same row and column; AT = Attitude; BI = Behavioral Intention; COM = Compatibility; IM = Image; PA = Perceived Advantage; PEOU = Perceived Ease of Use; PU = Perceived Usefulness; PPR = Perceived Privacy Risk; PS = Perceived Severity; PV = Perceived Vulnerability; TI = Technological Innovativeness; TR = Trialability

Table III. Fornell-Larcker criterion results for discriminant validity

Cross loadings generally indicate well-established discriminant validity, yet two indicators/manifest variables of perceived advantage (PA_2 and PA_3) have close high loadings with perceived usefulness as depicted in Table IV.

5.2 Structural model

At this second step, structural model was evaluated and hypotheses were tested. Firstly, the entire total model was evaluated. Then the data were grouped as per gender and tested to see if there was any significant difference between female and male potential adopters. For this research study, partial least squares multi-group analysis (PLS-MGA) was used for

	AT	BI	COM	COST	IMG	PA	PEOU	PPR	PS	PU	PV	TI	TR
AT_1	*0.912*	0.514	0.383	0.223	0.289	0.498	0.395	−0.022	0.243	0.483	0.287	0.209	0.360
AT_2	*0.938*	0.544	0.441	0.220	0.341	0.509	0.416	0.026	0.281	0.516	0.320	0.232	0.386
AT_3	*0.843*	0.486	0.364	0.233	0.394	0.446	0.350	−0.098	0.288	0.483	0.221	0.213	0.346
BI_1	0.567	*0.971*	0.365	0.138	0.371	0.502	0.255	−0.050	0.274	0.436	0.248	0.248	0.305
BI_2	0.548	*0.972*	0.390	0.136	0.398	0.520	0.274	−0.005	0.271	0.449	0.251	0.310	0.319
COM_1	0.408	0.353	*0.884*	0.259	0.346	0.355	0.354	0.105	0.407	0.409	0.270	0.340	0.496
COM_2	0.407	0.352	*0.918*	0.233	0.406	0.400	0.393	0.163	0.375	0.459	0.228	0.357	0.496
COM_3	0.380	0.345	*0.900*	0.183	0.368	0.390	0.386	0.095	0.362	0.417	0.233	0.403	0.481
COST_1	0.253	0.142	0.280	*0.942*	0.066	0.293	0.311	0.169	0.323	0.322	0.226	0.153	0.396
COST_2	0.207	0.117	0.173	*0.914*	0.033	0.229	0.232	0.115	0.280	0.231	0.246	0.179	0.278
IM_1	0.369	0.384	0.408	0.065	*0.938*	0.325	0.183	−0.024	0.251	0.363	0.168	0.308	0.264
IM_2	0.389	0.384	0.419	0.057	*0.961*	0.325	0.231	−0.017	0.272	0.378	0.199	0.303	0.255
IM_3	0.288	0.331	0.321	0.028	*0.887*	0.215	0.136	−0.027	0.206	0.287	0.230	0.251	0.140
PA_1	0.496	0.509	0.371	0.222	0.292	*0.884*	0.504	−0.046	0.302	0.673	0.208	0.307	0.433
PA_2	0.490	0.475	0.390	0.267	0.273	*0.921*	0.482	−0.049	0.307	*0.729*	0.197	0.293	0.414
PA_3	0.473	0.438	0.386	0.280	0.287	*0.899*	0.481	−0.031	0.371	*0.721*	0.193	0.305	0.413
PEOU_1	0.391	0.263	0.359	0.235	0.184	0.491	*0.894*	0.079	0.318	0.578	0.180	0.350	0.356
PEOU_2	0.355	0.219	0.325	0.233	0.148	0.440	*0.870*	0.060	0.283	0.481	0.188	0.357	0.314
PEOU_3	0.379	0.228	0.407	0.300	0.188	0.482	*0.850*	0.036	0.431	0.587	0.156	0.359	0.460
PPR_1	−0.033	−0.029	0.112	0.158	−0.029	−0.048	0.074	*0.964*	0.074	0.039	0.090	0.048	0.098
PPR_2	−0.029	−0.024	0.150	0.137	−0.016	−0.041	0.052	*0.948*	0.057	0.038	0.113	0.079	0.111
PS_1	0.306	0.263	0.392	0.310	0.253	0.364	0.355	0.043	*0.926*	0.371	0.288	0.284	0.429
PS_2	0.272	0.271	0.408	0.298	0.258	0.335	0.366	0.050	*0.952*	0.374	0.312	0.299	0.399
PS_3	0.256	0.242	0.369	0.296	0.218	0.304	0.386	0.102	*0.891*	0.380	0.291	0.266	0.427
PU_1	0.486	0.444	0.398	0.262	0.299	0.809	0.553	−0.020	0.370	*0.881*	0.219	0.256	0.432
PU_2	0.508	0.405	0.453	0.259	0.360	0.680	0.553	0.069	0.377	*0.922*	0.224	0.227	0.393
PU_3	0.478	0.399	0.420	0.313	0.351	0.666	0.569	0.076	0.404	*0.901*	0.227	0.299	0.391
PU_4	0.501	0.383	0.437	0.252	0.326	0.651	0.598	0.024	0.302	*0.881*	0.188	0.240	0.374
PV_1	0.245	0.219	0.202	0.199	0.152	0.138	0.121	0.113	0.260	0.159	*0.857*	0.166	0.209
PV_2	0.279	0.244	0.257	0.222	0.238	0.222	0.174	0.086	0.304	0.245	*0.919*	0.186	0.245
PV_3	0.292	0.216	0.251	0.248	0.162	0.222	0.234	0.080	0.284	0.225	*0.863*	0.150	0.257
TI_1	0.188	0.183	0.344	0.125	0.272	0.216	0.318	0.071	0.228	0.227	0.190	*0.776*	0.233
TI_2	0.189	0.285	0.299	0.105	0.415	0.167	0.220	0.075	0.161	0.180	0.136	*0.738*	0.229
TI_4	0.235	0.251	0.368	0.178	0.202	0.379	0.416	0.027	0.313	0.292	0.152	*0.870*	0.387
TI_5	0.173	0.222	0.309	0.158	0.169	0.289	0.345	0.051	0.273	0.211	0.146	*0.864*	0.314
TR_1	0.378	0.294	0.505	0.332	0.230	0.448	0.423	0.088	0.419	0.420	0.230	0.329	*0.923*
TR_2	0.386	0.319	0.496	0.362	0.236	0.411	0.397	0.119	0.418	0.389	0.278	0.353	*0.934*
TR_3	0.331	0.254	0.473	0.303	0.187	0.400	0.358	0.087	0.385	0.393	0.220	0.308	*0.847*

Notes: AT = Attitude; BI = Behavioral Intention; COM = Compatibility; IM = Image; PA = Perceived Advantage; PEOU = Perceived Ease of Use; PU = Perceived Usefulness; PPR = Perceived Privacy Risk; PS = Perceived Severity; PV = Perceived Vulnerability; TI = Technological Innovativeness; TR = Trialability; Italics show the sub items for each factor. These values such as at1 at2 and at3 are the sub items of the at. and these values individually have to greater than 0.50 to be significant

Table IV. Cross loading results for discriminant validity

evaluation of the significant difference between gender groups. This method is a non-parametric significance test. The p-value is examined to determine the significance of difference of group-specific path coefficients. A p-value smaller than 0.50 or larger than 0.95 is accepted as significant (Sarstedt *et al.*, 2011).

The essential evaluation criteria for the structural model is R^2 value, coefficient determinant, path coefficients' level and significance of the path coefficients. R^2 values of endogenous latent variables should be high because PLS-SEM aims to explain important latent constructs' variance. The evaluation of R^2 value varies in terms of particular research discipline. R^2 value of 0.20 is accepted high in social sciences whereas a R^2 value of 0.75 would be perceived high in more numerical studies. Chin (1998) describes R^2 values of 0.67, 0.33 and 0.19 in PLS path models as substantial, moderate and weak, respectively. Another measure to evaluate structural model is Goodness of Fit Index (GFI), which is based on the relative amount of variance and covariance in the sample covariance matrix.

T-statistics was used to test the significance of both inner and outer model by generating a procedure called bootstrapping. In this procedure, a great number of subsamples (e.g. 5,000) are taken from the original sample data set with the replacement by giving a bootstrap standard error; hence, this gives approximate T-values for significance testing of the structural path (Kwong and Wong, 2013).

Goodness of fit indexes for each complete model and each gender type are in acceptable ranges, as it is illustrated in Table V. It seems that male group GoF, GoF (Bootstrap) and standard error are substantially high when compared to female group.

Table VI and Table VIII summarize the research model with R^2, path coefficients and significant p level. For the complete model, The R^2 values of important constructs are 0.442 (Behavioral Intention), 0.314 (Attitude), 0.705 (Perceived Usefulness) and 0.386 (Perceived Ease of Use). To explain behavioral intention to adopt IoT healthcare products, the most important contribution comes from attitude (38 per cent) and perceived advantage (30 per cent). Other parameters' contribution is lower; Image (9 per cent), perceived ease of use (-7 per cent). The model equation for BI construct is:

$$\mathrm{BI} = 0.36 \times \mathrm{AT} + 0.31 \times \mathrm{PA} + 0.12 \times \mathrm{IM} - 0.14 \times \mathrm{PEOU}$$

(*Equation includes just the values which have significant path coefficients*).

Perceived usefulness has the greatest effect to explain attitude to adopt using IoT healthcare products. Its contribution to R^2 of AT is 65 per cent. The other parameters' contributions are relatively perceived vulnerability (15 per cent), perceived ease of use (13 per cent). The model equation for AT is:

$$\mathrm{AT} = 0.42 \times \mathrm{PU} + 0.17 \times \mathrm{PV} + 0.11 \times \mathrm{PEOU}$$

(*Equation includes just the values which have significant path coefficients*).

Perceived advantage has the greatest effect to explain perceived usefulness and perceived ease of use to adopt IoT healthcare products. Perceived ease of use, compatibility and image follow perceived advantage with the values relatively 25, 6 and 6 per cent, respectively. The impact of technological innovativeness and trialability, toward perceived advantage were found insignificant. The model equation is for PU is:

$$\mathrm{PU} = 0.58 \times \mathrm{PA} + 0.30 \times \mathrm{PEOU} + 0.10 \times \mathrm{COM} + 0.12 \times \mathrm{IM}$$

(*Equation includes just the values which have significant path coefficients*).

The other parameters which have impact on PEOU are technological innovativeness (19 per cent), compatibility (14 per cent). The impact of trialability and image on PEOU were found insignificant. The equation of the model for PEOU is:

$$\mathrm{PEOU} = 0.38 \times \mathrm{PA} + 0.20 \times \mathrm{TI} + 0.14 \times \mathrm{COM}$$

(*Equation includes just the values which have significant path coefficients*).

Table V.
Goodness of fit index results

GoF: goodness of fit index	Complete model			Female			Male		
	GoF	GoF (bootstrap)	Standard error	GoF	GoF (bootstrap)	Standard error	GoF	GoF (bootstrap)	Standard error
Absolute	0.598	0.618	0.030	0.596	0.608	0.043	0.664	0.673	0.043
Relative	0.942	0.938	0.026	0.944	0.898	0.039	0.949	0.918	0.038
Outer model	0.975	0.993	0.024	0.997	0.991	0.033	0.997	0.991	0.034
Inner model	0.966	0.945	0.009	0.947	0.906	0.017	0.952	0.926	0.014
Mean R^2	0.471			0.45		0.549			

Table VI. Model evaluation

		Complete model				Female				Male			
Latent variable	Type	R^2	Adjusted R^2	AVE	D.G. rho	R^2	Adjusted R^2	AVE	D.G. rho	R^2	Adjusted R^2	AVE	D.G. rho
PA	Exogenous			0.813	0.929			0.783	0.915			0.837	0.939
IM	Exogenous			0.864	0.950			0.849	0.944			0.88	0.956
TR	Exogenous			0.813	0.929			0.778	0.913			0.849	0.944
COM	Exogenous			0.812	0.928			0.795	0.921			0.825	0.934
PPR	Exogenous			0.356				0.868	0.952			0.871	0.953
COST	Exogenous			0.861	0.925			0.866	0.928			0.855	0.922
TI	Exogenous			0.595				0.629				0.543	
PS	Exogenous			0.853	0.945			0.847	0.943			0.859	0.948
PV	Exogenous			0.775	0.911			0.781	0.915			0.766	0.907
PEOU	Endogenous	0.386	0.38	0.759	0.904	0.356	0.344	0.736	0.893	0.493	0.482	0.78	0.914
PU	Endogenous	0.703	0.699	0.804	0.943	0.688	0.681	0.776	0.933	0.735	0.728	0.833	0.952
AT	Endogenous	0.354	0.346	0.807	0.926	0.303	0.286	0.803	0.924	0.448	0.434	0.811	0.928
BI	Endogenous	0.442	0.427	0.944	0.971	0.453	0.424	0.939	0.968	0.521	0.493	0.948	0.973
Mean		0.471		0.759		0.45		0.789		0.549		0.802	

Evaluation of the significance test of path coefficients between female and male was carried out through PLS-MGA and the results were illustrated in Table VII. According to these results, the paths that have the statistically significant difference between female and male are COM->PEOU ($p < 0, 05$), IM->BI ($p > 0, 95$), PA-> PEOU ($p > 0, 95$), PPR->BI (0, 95), PU->AT ($p > 0, 95$), PV-> BI ($p > 0, 95$), TI-> PU ($p > 0, 95$), TR->PEOU ($p < 0, 05$) Table VIII.

6. Conclusion and discussions

6.1 Discussion of results

The current study examined underlying factors affecting adoption intention of any emerging IoT technology product in healthcare. This research study extensively investigates factors that affect individual's adoption intention of IoT healthcare technology products from behavioral perspectives including technology, healthcare, innovativeness and privacy perspectives.

To examine and test the proposed integrated model, SEM-PLS, XLSTAT-PLSPM and SEM-PLS-MGA as estimation methods have been carried out. The proposed methodologies have been applied to a sample of 426 respondents through online survey. The integrated model encompasses 40 manifest variables and 13 latent variables to explain adoption intention of IoT healthcare technology products.

Paths	Path Coefficients diff (|GROUP_Gender (1.0) - GROUP_Gender(2.0)|)	p-Value (GROUP_Gender(1.0) vs GROUP_Gender(2.0))	Significance
AT -> BI	0.072	0.241	Not Significant
COM -> BI	0.077	0.230	Not Significant
COM -> PEOU	0.284	0.022	Significant*
COM -> PU	0.055	0.264	Not Significant
COST -> BI	0.019	0.425	Not Significant
IM -> BI	0.185	0.982	Significant**
IM -> PEOU	0.020	0.405	Not Significant
IM -> PU	0.020	0.368	Not Significant
PA -> BI	0.070	0.309	Not Significant
PA -> PEOU	0.316	0.969	Significant**
PA -> PU	0.064	0.732	Not Significant
PEOU -> AT	0.024	0.418	Not Significant
PEOU -> BI	0.130	0.109	Not Significant
PEOU -> PU	0.150	0.083	Not Significant
PPR -> BI	0.179	0.987	Significant**
PS -> BI	0.054	0.283	Not Significant
PU -> AT	0.189	0.957	Significant**
PU -> BI	0.197	0.916	Not Significant
PV -> AT	0.057	0.240	Not Significant
PV -> BI	0.268	0.999	Significant**
TI -> BI	0.210	0.017	Not Significant
TI -> PEOU	0.180	0.904	Not Significant
TI -> PU	0.143	0.970	Significant**
TR -> BI	0.004	0.479	Not Significant
TR -> PEOU	0.250	0.049	Significant*
TR -> PU	0.086	0.876	Not Significant

Notes: ***$p < 0.01$ = Significant; **$p < 0.05$ = Significant; *$p < 0.10$ = Significant

Table VII. Evaluation of difference between gender groups: PLS-MGA

Table VIII. Hypotheses test results

Hypotheses	Paths	Coefficients	*t* value	*p* value	Results
H1a	PU -> BI	−0.009	0.136	0.892	Not Supported
H1b	PU -> AT	0.428	7,781	<0.0005	Supported
H2a	PEOU -> PU	0.297	5,450	0.000	Supported
H2b	PEOU -> BI	−0.137	2,508	0.012	Supported
H2c	PEOU -> AT	0.124	2,179	0.029	Supported
H3a	TI -> BI	0.081	1,613	0.107	Not Supported
H3b	TI -> PEOU	0.200	3,012	0.003	Supported
H3c	TI -> PU	−0.109	3,495	<0.0005	Supported
H4a	COM -> PU	0.098	2,192	0.028	Supported
H4b	COM -> PEOU	0.135	1,839	0.066	Supported
H4c	COM -> BI	0.062	1,188	0.235	Not Supported
H5a	TR -> PU	0.002	0.044	0.965	Not Supported
H5b	TR -> PEOU	0.128	1,545	0.122	Not Supported
H5c	TR -> BI	−0.015	0.302	0.762	Not Supported
H6a	IM -> BI	0.124	2,803	0.005	Supported
H6b	IM -> PEOU	−0.069	1,607	0.108	Not Supported
H6c	IM -> PU	0.123	4,153	<0.0005	Supported
H7	PS -> BI	0.039	0.836	0.403	Not Supported
H8	PV -> BI	0.050	1,118	0.264	Not Supported
H9	COST -> BI	−0.053	1,122	0.262	Not Supported
H10	PPR -> BI	−0.001	0.032	0.975	Not Supported
H11a	PA -> BI	0.314	4,027	<0.0005	Supported
H11b	PA -> PEOU	0.380	4,123	<0.0005	Supported
H11c	PA -> PU	0.579	10,951	<0.0005	Supported
H12	AT -> BI	0.366	7,312	<0.0005	Supported

The majority of hypothesized relationships developed in this research study have been supported by the data. When the model is examined in terms of gender, health and privacy perspectives are found significant effect on adoption intention. Gefen and Straub (1997) states that gender construct has paid very little attention in TAM researches. Yet, in literature there recently are studies that examine and find significant gender difference in terms of technology acceptance (Zhang *et al.*, 2014; Yuen and Ma, 2002; Houtz and Gupta, 2001; Young, 2000; Venkatesh and Morris, 2000). In general, females tend to less confidence in computer abilities than males (Vekiri and Chronaki, 2008). In this research, it is observed that males concern more about privacy and healthcare vulnerability issues than females when deciding to adopt any IoT healthcare product.

For the complete model, privacy and healthcare perspectives have insignificant direct effect whereas healthcare perspective affects the adoption intention through attitude factor. From the technological perspective, whereas perceived ease of use and perceived advantage have a direct effect, perceived usefulness has indirect effect on attitude factor. From the diffusion of innovation perspective, perceived advantage and image have a direct effect while compatibility has indirect effect to adoption intention. Attitudes have the greatest effect to decide to adopt any IoT healthcare product. Besides, beneficialness is a salient factor to explain adoption intention. Technological innovativeness has an indirect effect on perceived ease of use whereas compatibility has an indirect effect on perceived usefulness. One important result is the significance correlation between perceived ease of use and perceived usefulness. As the original constructor of TAM proposes, perceived ease of use directly affects the perceived usefulness (Venkatesh, 2000). According to TAM, if use of a system is perceived as easy by an individual, the system is perceived more useful by the individual.

When explaining the impact of technological innovativeness on intention adoption whereas there is significant direct effect on females, there is no significant direct effect on males. It is observed that for males technological innovativeness is more significant factor to explain perceived usefulness compared to females.

Prayoga and Abraham (2016) analyzed user's technology acceptance from the perspective of TAM, integrating TAM with personality traits, facilitated appropriation and cultural value orientation. Main findings of their studies: i) PU had a significant effect on BI. ii) Facilitated appropriation predicts PU. They also investigated whether there is any correlation between age and BI- and PU-facilitated appropriation. They didn't find any correlation.

Miltgen *et al.* (2013) examined the individual acceptance of biometric identification techniques and found it to be voluntary. Miltgen and friends proposed an integrated model including elements from TAM, IDT, UTAUT and trusted privacy research fields. The study revealed that compatibility, perceived usefulness, facilitating conditions, privacy concern, technology trust and innovativeness had an influence on biometrics systems acceptance. The innovativeness construct had a significant effect on behavioral intention through compatibility. PEOU and social influence did not have a significant effect on behavioral intention. One more finding was that PEOU and PU affected compatibility.

Moores (2011) tested an integrated model of IT acceptance and compared the role of attitude use and compatibility in the acceptance. In this study, PU was defined in terms of information quality, while PEOU was defined in terms of factors that enable the user to make use of the system. Moores applied this model to hospital workers for adoption of a clinical management system and found strong support. It was found that facilitative factors help users to understand the system, whereas more experienced users take care of usefulness and compatibility.

Results show that mostly the factors related to technology acceptance and innovation diffusion would significantly affect individuals' decision to adopt IoT technology products in healthcare. It is observably seen that males give a lot of importance to image, privacy and health vulnerability issues compared to females. Findings also suggest that all individuals regardless of gender pay more attention to attitude, perceived advantage, and perceived ease of use in their adoption of IoT technology products in healthcare.

Our model confirms (Gao *et al.*, 2015; Sun *et al.*, 2013; Domingo, 2012) that empirical studies towards health information technology adoption should take into consideration factors from multiple perspective including health, technology, innovativeness, privacy, and cost perspectives.

6.2 Theoretical and practical implications

This study can make contributions in health information technology literature in several ways. First, this study is among the first to comprehensively investigate IoT healthcare technology issue from a behavioral perspective (Gao *et al.*, 2015; Sun *et al.*, 2013; Domingo, 2012). Potential benefits of the use of IoT-related products in healthcare can provide various advantages from reducing healthcare costs to improving healthcare efficiency and quality. The issue is not confined to invent an advanced technological product/service; the point of discussion is how to attract individuals to adopt these favorable fantastic technologies in their daily lives. For IS field, this is crucial to research. Various studies about users' technology adoption just conceptually state some critical factors or empirically examine a limited number of prominent factors from just technology perspectives (Prayoga and Abraham, 2016; Choi and Kim, 2016; Claes *et al.*, 2015; Miltgen *et al.*, 2013; Moores, 2011; Fraile *et al.*, 2010; Steele *et al.*, 2009). Different from others in literature, in this study, an integrated model has been developed to examine adoption intention of IoT healthcare technology products. After reviewing a large number of literatures about health information technology adoption, it merged four models to show how individuals' adoption intention toward IoT healthcare technology products is affected: TAM, IDT, PMT, and PCT. This integrated model provides a more comprehensive understanding of individual's decision to adopt an emerging healthcare technology products (such as internet of things healthcare products).

Second, this study proposes an integrated model to understand consumer health technology adoption rather than professional health technology or specific IoT-enabled health technology product. Different from other studies (Li, 2014; Johnson, 2014; Sun *et al.*, 2013; Huang *et al.*, 2012; Liang *et al.*, 2010; Or and Karsh, 2009; Bhattacherjee and Hikmet, 2007; Jia *et al.*, 2006; Chau and Hu, 2002), this study extensively investigates affecting factors of *consumers'* intention to adopt IoT-enabled health technology products from several perspectives: technology, healthcare and privacy. Regarding increase of IoT-enabled product development in healthcare, exploring factors that affect consumer's intention to adopt these products have become important. From this point of view, this study is a great example and theoretical foundation for future studies to investigate *consumer's* intention to adopt IoT-enabled products in healthcare.

In addition, we examined the acceptance of healthcare IoT-enabled devices in terms of gender which has been paid less attention in technology acceptance especially in healthcare. Results reveals that males give more importance to image, privacy and health vulnerability issues than females. This kind of comparative study approach provides a good example for future studies which examine the intention to adopt emerging technologies (such as IoT-enabled devices) in healthcare in terms of gender.

Furthermore, this research study also expresses several practical implications. First, the majority of hypothesized relationships are supported by the data. This current integrated model is proved to significantly explain consumer's intention to adopt IoT-enabled technology products in healthcare. Thus, the current study could help both business managers and social planners to regulate better policies and strategies to promote IoT technology diffusion in healthcare. Product managers and social planners should take into consideration technology, privacy, healthcare perspectives in order to increase the adoption of IoT-enabled health products. In order to increase the adoption an emerging technology product in healthcare, product managers and social planners should not just focus on technology perspective such as ease of use, compatibility, also they should take into consideration the healthcare and privacy perspectives. Second, it is found that relative advantage (in this study, it is PA) is an outstanding factor to explain the intention to adopt. From this point, it can be expressed that individuals desire to believe that start to adopt any IoT healthcare product should provide favorable effects onto their daily lives. Third, it is found that image, privacy and health vulnerability factors vary regarding gender. Males give a lot of importance to image, privacy and health vulnerability issues compared with females. Males believe that using any technological product can provide them more prestige in their social life and this can lead them to adopt more easily to any emerging technological product than females. Thus, these factors should be given more attention when designing a specific IoT healthcare technology product for male consumers. This information might be useful for marketing/sales people or academicians who study on these subjects. Fourth, compatibility and trialability have more significant effect on perceived ease of use for females compared to males. This result proves that compatibility and trialability have positive effect on the diffusion of any innovation (Koru and Norcio, 2014, Rogers, 2003). Females prefer to use any new emerging IoT healthcare technology products if they are compatible with their experiences, routines, and social norms.

This result also proves Tarde's logical law of imitation: "Why do few of innovations spread out while the rest of them not?" Compatibility and trialability factors are facilitator to adopt IoT healthcare technology products (Prayoga and Abraham, 2016; Moores, 2012; Lee *et al.*, 2011; Koru and Norcio, 2010; Bhattacherjee and Hikmet, 2007; Rogers, 2003; Fui-Hoon Nah *et al.*, 2001).

6.3 Limitations and future research

Although this study makes various theoretical and practical contributions, there are still some limitations in it. First, smart device owners and users were taken as the sample in the study because such kind of people would/could use IoT-enabled healthcare products in the near future. Research findings can't be generalized for all individuals in Turkey. Thus, the conclusions of the current study should be applied with the consideration of that. This study does not include not familiar any smart technological device. Second, the study was only conducted in Turkey, which has not examined cultural and technological differences between different countries. This research study would be extended by applying the current research model for different countries to examine consumer's intention to adopt IoT enabled products in healthcare between countries. Finally, although the research model has an acceptable explanatory power (47.1 per cent for intention), it can include additional factors to improve model's explanatory power in future research.

6.4 Concluding remarks

This research study proposed an integrated model that examines the outstanding factors of adoption intention toward IoT healthcare technology products from four different and complementary (of each other) theories: technology acceptance model, innovation diffusion theory, protect motivation theory and privacy calculus theory. How these factors differently affect individuals' intention to adopt in terms of gender is also provided. This study has pointed to understanding individuals' adoption intention of any emerging IoT-enabled product in healthcare. The majority of the developed hypotheses has been supported by the data. With our knowledge, this study is among the first that comprehensively investigates intention to adopt IoT healthcare technology issue from a behavioral perspective. On that sense, this study is a great example and theoretical foundation for future studies to investigate *consumers'* intention to adopt IoT-enabled products in healthcare.

Main finding of this study is that mostly the factors related to technology acceptance and innovation diffusion significantly affect individuals' decision to adopt IoT enabled products in healthcare. This information may help product designers to pay attention to all these factors when they design an IoT enabled healthcare product.

The other findings of the study reveal that all individuals regardless of gender pay more attention to attitude, perceived advantage and perceived ease of use in their adoption of IoT technology products in healthcare. From this finding, it can be expressed that Turkish people's perception drives their behaviors, not logical reasons. Maybe this is valid for all people not just for Turkish people. The world is what people see and understand of it, not the reality. Mostly, any innovation diffuses thanks to lead users who are innovators and early adopters according to the law of innovation diffusion (Kidar and Vellera, 2013; Hippel *et al.*, 2009; Rogers, 2003; Edquist and Hommen, 1999). Early majority do not start to adopt any innovation into their daily lives before they see the people around them use that new product (Rogers, 2003). Early majority wants to get feedbacks about the new emerging product that is used by others. The law of innovation diffusion tells us that if it is desired to reach mass market success or mass market acceptance of an idea, you cannot have it, until it crossed the chasm point which means between 15 and 18 per cent market penetration. Theses lead users buy or use any new emerging technology products just because they want and just because they believe that it is good to own that product. For the diffusion of IoT healthcare technology products this law is valid. IoT production (in any sector) is still in infancy for now these years. If marketing strategy is focused on "why people should adopt and accept IoT healthcare technology products" rather than "what features they have", IoT healthcare technology product would diffuse more easily and faster.

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Appendix

Measurement factors	Items
Demographics	Gender Age City Profession Field Average Monthly Income Education Status
Filter question	Are you interested in technological developments? Do you have smart devices (cellphone, tablet, watch and wearable technological products, etc.)?
Behavioral intention	I intend to adopt personal smart health technology products in my daily life within 6 months During the next 6 months, I plan to experiment with or regularly use personal smart health technology products in my daily life
Perceived advantage	Using personal smart health technology products would be useful in taking preventive actions related to my health Using personal smart health technology products would be useful in detecting early intervention states related to my health Using personal smart health technology products would provide the abililty to digitally manage and share the information about my health status with healthcare professionals (such as physician, nurse)
Attitude	To begin to use personal smart health technology products in my daily life within the next 6 months, it would be . . . . (Extremely bad-Extremely good) To begin to use personal smart health technology products in my daily life within the next 6 months, it would be . . . . (Extremely negative- Extremely positive) To begin to use personal smart health technology products in my daily life within the next 6 months, it would be . . . . (Extremely harmful- Extremely safe)
Perceived severity	If I suffered the stated problems, it would be severe If I suffered the stated problems, it would be serious If I suffered the stated problems, it would be significant
Perceived vulnerability	I am at risk for suffering the stated problems It is likely that I will suffer the stated problems It is possible for me to suffer the stated problems
Perceived usefulness	Using personal smart health technology products would enable me to take action related to my health more quickly Using personal smart health technology products would improve my deciding performance related to my health Using personal smart health technology products would enhance deciding effectiveness related to my health Using personal smart health technology products would make it easier to take decisions related to my health
Perceived ease of use	Learning to use personal smart health technology products would be easy for me It would be easy to use personal smart health technology products Having interaction between personal smart health technology products (smartphone, tablet, watch, etc.) and mobile devices would make my usage (being managable on mobile devices) easier
Technological innovativeness	Other people come to me for advice on new technology In general I am among the first in my circle of friends to acquire new technology when it appears

(*continued*)

Table AI.
Survey of the study

Measurement factors	Items
	It seems my friend learning more about newest technologies than I am
	I enjoy the challenge of figuring out high tech gadgets
	I keep up with the latest technological developments in my areas of interest
Image	If I were to adopt personal smart health technology products, it would give me high status around me
	If I were to adopt personal smart health technology products, I would have more prestige around me than who have not yet adopted it
	Having personal smart health technology products is a status symbol in the circle of me
Trialability	Before deciding on whether or not to adopt personal smart health technology products, I would like to try (be able to try) it on a trial basis
	Before deciding on whether or not to adopt personal smart health technology products, I would like to try (be able to try) it properly on a trial basis
	I would have a chance to try smart health technology products long enough to see what they can do
Compatibility	If I were to adopt personal smart health technology products, it would be compatible with my daily routine
	If I were to adopt personal smart health technology products, it would fit with my life style
	If I were to adopt personal smart health technology products, it would fit well the way I like to manage my daily routine
Perceived privacy risk	It would be risky to disclose my personal health information to vendors providing personal smart health technology products
	There would be high potential for loss associated with disclosing my personal health information to vendors providing personal smart health technology products
	There would be too much uncertainty associated with giving my personal health information to vendors providing personal smart health technology products
Cost	The amount of money I pay for personal smart health technology products has a direct effect on my intention to adopt it
	I prefer not to use personal health technology products if the money I pay for it costs me a lot, even if it provides me a lot of/many easiness/facilities in terms of my daily health management

Table AI.

Corresponding author
Adem Karahoca can be contacted at: akarahoca@gmail.com