

A comprehensive acceptance model for smart home services

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CHRONICLE

ABSTRACT

Article history:

Received: June 21, 2021
Received in revised format: July 28, 2021
Accepted: October 19, 2021
Available online: October 19, 2021

Keywords:

Smart Home Services
Technology Acceptance Model
Innovation Diffusion Theory
Theory of Planned Behavior

Smart home services (SHSs) afford users an effective lifestyle management system, which provides human-oriented networking of smart devices and applications that enable users to control their homes from anywhere at any time. Despite the benefits of SHSs, however, their acceptance is very low. There remains a gap in the literature in terms of a comprehensive model that addresses users' intention to use SHSs. To address this gap, the present study explored the factors that influence SHS acceptance among users based on well-established theoretical frameworks, such as the technology acceptance model, innovation diffusion theory, and the theory of planned behavior. To this end, the study integrated four additional factors, namely, perceived convenience, perceived connectedness, perceived cost, and perceived privacy risk, into the exploration and carried out structural equation modeling to quantitatively determine the effects of these factors. Questionnaires were administered to 750 users. The findings indicated that perceived compatibility, perceived convenience, perceived connectedness, perceived cost, perceived behavioral control with perceived usefulness, and perceived ease of use directly and indirectly exerted a significant influence on users' intention to use SHSs.

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1. Introduction

The Internet of Things (IoT) refers to the worldwide network of billions of smart objects connected through the Internet (Park et al., 2017). These smart objects are equipped with core computing and communication capabilities and features that enable them to interact with the environment, humans, and other objects, thereby improving work efficiency and quality of life (Hsu & Lin, 2016; Shuhaiber, 2018). IoT technologies have begun to be integrated into a wide range of new information and communication technology (ICT) products and services (Park et al., 2017). In terms of economic and social growth, most industrial countries participating in the global ICT sector have shown that IoT has broadly emerged and expanded (Park et al., 2017). This innovation presents many possible benefits for all areas of daily life (Shuhaiber, 2018), among which one of the most promising is smart home services (SHSs) (Kim et al., 2017; Stojkoska & Trivodaliev, 2017).

Many industries have progressed toward the development of SHSs by transforming these offerings into effective lifestyle systems that reduce excessive heating, air conditioning, and electricity consumption. SHSs can also save property and human lives from threats, such as robbery, fire, and flooding (Y. Kim et al., 2017; Tomlinson, 2010). Park et al. (2018) described SHSs as a collection of technologies that offer human-oriented networking of devices and software in homes, while, more recently, Marikyan et al. (2019) defined smart homes as residences fitted with smart technologies that provide personalized services.

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Similar to all emerging technologies, SHSs can succeed only if users accept them (Bao et al., 2014; Nikou, 2019). Despite the benefits of SHSs, the acceptance of these innovations is very low. According to Venkatesh et al. (2003), researchers must select factors from models comprising various options. Therefore, researchers have recently started incorporating acceptance theories into models and examining their interrelationships, asserting that each theory can contribute to our understanding of technology acceptance from a unique perspective; that is, combining theories leads to new knowledge (Bao et al., 2014; Nikou, 2019). The problem is that a gap remains in the literature in terms of a comprehensive model that addresses users' intention to use SHSs (Bao et al., 2014; Nikou, 2019).

To fill this void, the current work explored the factors that influence users' acceptance of SHSs to develop and validate a comprehensive model on the basis of the most commonly used and verified acceptance theories, namely, the technology acceptance model (TAM) (Davis, 1989), innovation diffusion theory (IDT) (Rogers, 2003), and the theory of planned behavior (TPB) (Ajzen, 1991). The concepts of perceived usefulness (PU), perceived ease of use (PEOU), and attitudes toward using services (ATT) were adopted from the TAM. Perceived compatibility (PCOM) was adopted from IDT, and perceived behavioral control (PBC) was adopted from TPB. In addition to these well-validated concepts, four additional factors that play a vital role in SHS acceptance were included in the analysis: perceived convenience (PCV), which was conceived by Yoon and Kim (2007); perceived connectedness (PCON), which was developed by Shin (2010); perceived cost (PC), which was formulated by Tornatzky and Klein (1982); and perceived privacy risk (PPR), which was developed by Featherman and Pavlou (2003). The contribution of this study to the acceptance literature is twofold: It developed a comprehensive theoretical model to explore SHS acceptance and identified the factors that influence it (i.e., PU, PEOU, ATT, PCOM, PBC, PCV, PCON, PC, and PPR), and it examined the effects of such factors on the acceptance of and intention to use SHSs.

The remainder of this paper is organized as follows: Section 2 introduces the theoretical background of the study, and Section 3 presents a review of the literature on SHS adoption models and the hypotheses formulated in this work. Sections 4 and 5 discuss the research model and research methodology, respectively. Section 6 details the data analysis, while Section 7 centers on the discussion of the findings and the conclusions drawn from them. Section 8 concludes the paper with limitations and future work.

2. Theoretical Background

As previously stated, this study combined the TAM, IDT, and TPB. The TAM was adopted initially from the theory of reasoned action (TRA) to predict and explain users' acceptance and rejection of computer-based technology (Davis, 1989). The TAM serves as a basis for inquiring into the effects of external variables on user behaviors by identifying essential determinants of computer acceptance. The model suggests that PU and PEOU, as particular beliefs, determine computer acceptance behaviors, with external variables influencing these two constructs. Davis (1989) defined PU as "the degree to which a person believes that using a particular system would enhance his or her job performance." PEOU is "the degree to which a person believes that using a particular system would be free of effort."

The TAM also maintains that PEOU influences PU and that both determine users' ATT. Davis (1989) defined ATT as "the degree to which a person has a favorable or unfavorable evaluation or appraisal of the behavior in question." Aside from this, ATT and PU determined the Behavioral Intention (BI), which determined the actual system use (Davis, 1989). According to Davis (1989), BI is "the strength of one's intention to perform a specified behavior."

Although TAM examines various factors explaining technology acceptance, such as user demographic and psychographic factors, the factors discussed in IDT focus solely on technology-related determinants (Hubert et al., 2019). IDT explains the entire diffusion of the innovation process that passes from innovation development to form the user's attitudes and the final decision of adoption or rejection (Rogers, 2003). Rogers (2003) identified five key attributes relevant from a potential user's perspective: relative advantage, complexity, compatibility, trialability, and observability of the innovation. This study adopted from IDT the third key attribute that is compatibility, which is defined by Rogers (2003) as "the degree to which an innovation is perceived as being consistent with the existing values, past experiences, and needs of potential adopters."

As an extension of TRA, TPB considers situations where one may not have complete volitional control over behavior and adds the PBC factor from the individual capabilities' perspective. According to Ajzen (1991), a person's actual behavior when performing a specific action is directly influenced by his or her behavioral intention and determined by three kinds of specific beliefs about the behavior: attitude, subjective norm, and PBC. This study adopted from TPB the third factor that is PBC, which is defined by Ajzen (1991) as "the perceived ease or difficulty of performing the behavior and it is assumed to reflect past experience as well as anticipated impediments and obstacles."

3. Literature Review and Hypotheses Development

The robustness of TAM, IDT, and TPB have been tested in the SHSs. In addition, many studies were found in the literature that used an enhanced version of these acceptance theories with additional factors, depending on the technology being studied (Alaiad & Zhou, 2017; Bao et al., 2014; Dong et al., 2017; Gross et al., 2020; Guhr et al., 2020; Hojjati & Khodakarami, 2016; Hubert et al., 2019; Kim et al., 2017; Nikou, 2019; Pal et al., 2018; Park et al., 2018, 2017; Sequeiros et al., 2021; Shuhaiber & Mashal, 2019; Yang et al., 2017). A detailed description of all factors proposed is presented in the following subsections.

3.1 Perceived Usefulness and Perceived Ease of Use

TAM has been empirically tested in many studies. The outcomes of these studies confirmed that PU affects ATT (Gross et al., 2020; Hojjati & Khodakarami, 2016; Park et al., 2017, 2018; Shuhaiber & Mashal, 2019) and BI (Alaiad & Zhou, 2017; Bao et al., 2014; Dong et al., 2017; Guhr et al., 2020; Hojjati & Khodakarami, 2016; Nikou, 2019; Pal et al., 2018; Park et al., 2017, 2018; Shuhaiber & Mashal, 2019). Similarly, the outcomes of these studies confirmed that PEOU has an effect on PU (Bao et al., 2014; Dong et al., 2017; Gross et al., 2020; Hojjati & Khodakarami, 2016; Nikou, 2019; Pal et al., 2018; Park et al., 2017, 2018; Shuhaiber & Mashal, 2019) and ATT (Hojjati & Khodakarami, 2016; Park et al., 2017, 2018; Shuhaiber & Mashal, 2019). In addition, they confirmed that ATT affects BI (Gross et al., 2020; Hojjati & Khodakarami, 2016; C. Kim et al., 2010; Y. Kim et al., 2017; Park et al., 2017, 2018; Shuhaiber & Mashal, 2019; Yang et al., 2017). This research, therefore, proposed the following hypotheses:

H₁: *PU has a positive direct effect on ATT.*

H₂: *PU has a positive direct effect on BI.*

H₃: *PEOU has a positive direct effect on PU.*

H₄: *PEOU has a positive direct effect on ATT.*

H₅: *ATT has a positive direct effect on BI.*

3.2 Perceived Compatibility

The PCOM factor originated from IDT. PCOM is defined as “the degree to which an innovation is perceived as being consistent with the existing values, past experiences, and needs of potential adopters” (Rogers, 2003). In conjunction, some researchers include the PCOM factor into TAM as the determinant of PU, PEOU, and BI. In a study in South Korea to study the user adoption of SHSs, an extended TAM was conducted. The results showed that PCOM was a significant determinant of PU (Park et al., 2018). In another study in South Korea, an extended TAM was implemented to study the users working on IoT technologies in a smart home environment. They found that PCOM was a significant determinant of PU and PEOU (Park et al., 2017). Also, the acceptance of a mobile smart home was studied among potential home buyers and home users in China. The outcomes proved that PCOM was a significant determinant of PEOU and BI (Bao et al., 2014). Moreover, the acceptance of smart home technology was studied among households in Finland. They found that PCOM was a significant determinant of PU and PEOU (Nikou, 2019). In addition to that, the acceptance of a smart home was studied among scholars in social sciences in Germany (Hubert et al., 2019). The outcomes identified that PCOM was a significant determinant of PU and PEOU. Thus, the following hypotheses are proposed:

H₆: *PCOM has a positive direct effect on PU.*

H₇: *PCOM has a positive direct effect on PEOU.*

3.3 Perceived Convenience

The PCV factor, adopted from Yoon and Kim (2007), was defined as “the level of convenience toward time, place, and execution that one feels during participation when using the system.” Some researchers included the PCV factor in TAM as the determinant of PU in many domains, including SHSs. Group of researchers in China (Dong et al., 2017) have tried to confirm that TAM, enhanced with certain other factors, could be the best model to explain the user acceptance of SHSs. They enhanced TAM with PCV and found that PCV was a significant determinant of PU. Hence, the following hypothesis is introduced:

H₈: *PCV has a positive direct effect on PU.*

3.4 Perceived Connectedness

The PCON factor was adopted from Shin (2010) and was defined as “the degree to which users are emotionally connected with the world, its resources and people.” Some studies included the PCON factor in TAM as the determinant of PEOU. In a study in South Korea, TAM was extended to study the user adoption of SHSs (Park et al., 2018). The results showed that PCON was a significant determinant of PEOU. In another study in South Korea, TAM was extended to study the users who were working on IoT technologies in a smart home environment (Park et al., 2017). They found that PCON was a significant determinant of PU and PEOU. The following hypothesis is therefore proposed:

H₉: *PCON has a positive direct effect on PEOU.*

3.5 Perceived Cost

The PC factor originated from Tornatzky and Klein (1982), which “refers to the system cost whether it is expensive or not according to the user’s financial resources.” Much research includes the PC factor in TAM as the determinant of BI. A study was conducted to explore older people’s acknowledgment of SHSs in four Asian countries: India, Thailand, Indonesia, and Malaysia (Pal et al., 2018). The results of the study confirmed the significant effects of PC on BI to utilize home automation systems. In a study in South Korea, TAM was extended to determine the user adoption of SHSs (Park et al., 2018). The results showed that PC was a significant determinant of BI. In another study in South Korea, TAM was extended to study the users who were working on IoT technologies in a smart home environment (Park et al., 2017). They found that PC was a significant determinant of BI. In another study in the United States that confirmed the validity of TAM, a model was proposed for

studying the factors affecting the acceptance of mobile applications in smart homes (Alaiad & Zhou, 2017). The outcomes showed that PC was a significant determinant of BI. In addition to that, the acceptance of a mobile smart home was studied among potential home buyers and home users in China (Bao et al., 2014). The outcomes identified no significant correlation between PC and BI. TAM was used to study individuals’ adoption of SHSs in South Korea, including technology users and service consumers (Y. Kim et al., 2017). They found that BI was influenced by PC. Also, they found that ATT was influenced by PC. Moreover, the acceptance of smart home technology was studied among households in Finland. The results showed that PC was a significant determinant of BI (Nikou, 2019). In another study in the United States that confirmed the validity of TAM, a model was proposed for studying the factors affecting the acceptance of SHSs (Sequeiros et al., 2021). The outcomes showed that PC was a significant determinant of BI. The present research proposes the following hypothesis:

H₁₀: *PC has a negative direct effect on BI.*

3.6 Perceived Privacy Risk

The PPR factor was adopted from Featherman and Pavloub (2003) study, which defines PPR as “Potential loss of control over personal information, such as when information about you is used without your knowledge or permission.” Much research includes the PPR factor in TAM as the determinant of BI. A study tested the main factors of TAM with PPR to explain the acceptance of SHSs in the United States. Their findings showed that PPR had a significant effect on BI (Alaiad & Zhou, 2017). Another study extended TAM with PPR to test the acceptance of a smart home among potential customers of SHSs in Korea (Yang et al., 2017). They found that PPR had a significant effect on ATT. Additionally, a Chinese research group has tried to confirm that TAM, enhanced with certain other factors, could be the best model to explain the user acceptance of SHSs (Dong et al., 2017). They enhanced TAM with PPR and found that PPR was a significant determinant of PU and BI. Also, the acceptance of SHSs was studied among potential users (Guhr et al., 2020). The outcomes proved that PPR was a significant determinant of BI. The following hypothesis is thus proposed:

H₁₁: *PPR has a positive direct effect on BI.*

3.7 Perceived Behavioral Control

The PBC factor was adopted from TPB (Ajzen, 1991), which “refers to the perceived ease or difficulty of performing the behavior and it is assumed to reflect experience as well as anticipated impediments and obstacles.” Some researchers included the PBC factor in TAM as the determinant of BI. The acceptance of a smart home was studied among potential customers of SHSs in Korea. The researchers tested TAM with PBC (Yang et al., 2017). They found that PBC had a significant effect on BI. In addition to that, the acceptance of SHSs was studied among potential users (Guhr et al., 2020). The outcomes proved that PBC was a significant determinant of BI. Therefore, this study established the following hypothesis:

H₁₂: *PBC has a positive direct effect on BI.*

4. Research Model

This study developed a comprehensive theoretical model to examine factors that influence users’ acceptance of SHSs. The research model in Fig. 1 was developed based on the literature review and the hypotheses development.

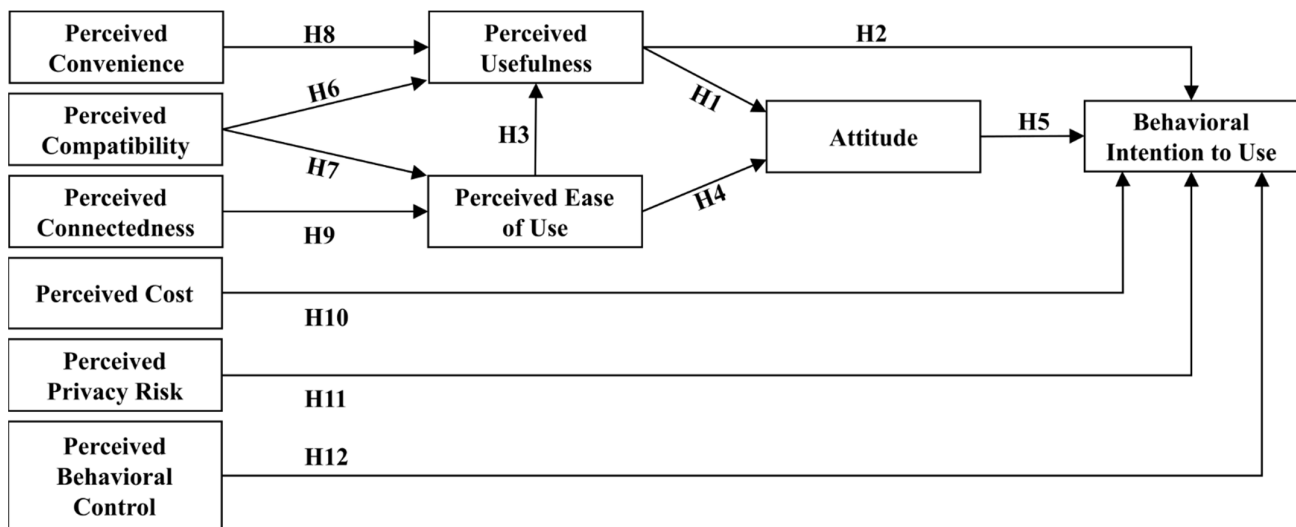


Fig. 1. Research Model and Hypotheses

4.1 Research Methodology

Critical steps were required to implement this work. Hence, the data collection and the statistical tools used were crucial determinants for the research outcomes (Walker, 1997).

4.2 Research Context

Based on the Department of Statistics (2016) estimates, the current population of Jordan was 9,531,712. Jordan is divided into three geographical regions with substantial proportions as following: north 2,733,245, middle 6,053,305, and south 745,162, constituting 28.7%, 63.5%, and 7.8% of the total population respectively. Therefore, the population of Jordan, including the three regions, was chosen to be the scope of this study.

4.3 Data Collection

This study used a cross-sectional survey, and the data was gathered at one point in time using a self-administered questionnaire as the instrument for collecting data. Regarding the questionnaire, this study adopted the measurement from eight studies (Davis, 1989; Featherman & Pavloub, 2003; Ghany et al., 2009; C. Kim et al., 2010; Moore & Benbasat, 1991; Ram & Sheth, 1989; Shin, 2010; Tornatzky & Klein, 1982).

4.4 Questionnaire Design

The questionnaire has been designed based on the factors and measurement items, as shown in Table 1. Additionally, a seven-point scale with anchors ranging from “strongly disagree” to “strongly agree” was used in the questionnaire.

Table 1
Measurement of factors

Factor	Code	Measurement Dimensions of Factors
Perceived Usefulness (Davis, 1989)	PU1	Using SHSs in my home would enable me to accomplish tasks more quickly.
	PU2	Using SHSs would improve my performance in my home.
	PU3	Using SHSs in my home would increase my productivity.
	PU4	Using SHSs would enhance my effectiveness in my home.
	PU5	Using SHSs would make it easier to do my task in my home.
	PU6	I would find SHSs useful in my home.
Perceived Ease of Use (Davis, 1989)	PEOU1	Learning to operate SHSs would be easy for me.
	PEOU2	I would find it easy to get SHSs to do what I want it to do.
	PEOU3	My interaction with SHSs would be clear and understandable.
	PEOU4	I would find SHSs to be flexible to interact with.
	PEOU5	It would be easy for me to become skillful at using SHSs.
	PEOU6	I would find SHSs easy to use.
Perceived Compatibility (Moore & Benbasat, 1991)	PCOM1	Using the system is compatible with most aspects of my life.
	PCOM2	Using the system fits my lifestyle.
	PCOM3	Using the system fits well with the way I like to interact with the components in my
Perceived Convenience (Kim et al., 2010)	PCV1	SHSs is convenient because I can use them at any time.
	PCV2	SHSs is convenient because I can use them in any place.
	PCV3	SHSs are convenient because they are not complicated.
Perceived Connectedness (Shin, 2010)	PCON1	I feel good because I can access the components in my house anytime via the system.
	PCON2	I feel like being connected to the components in my house because I can take any infor-
	PCON3	I feel emotionally comforted because I can interact with the components in my house via
Perceived Cost (Ram & Sheth, 1989; Tornatzky & Klein, 1982)	PC 1	Using the system is expensive overall.
	PC 2	Installing and operating the system is a burden to me.
	PC 3	There is a financial barrier to maintaining and repairing the system.
Perceived Privacy Risk (Featherman & Pavloub, 2003)	PPR1	Using the system will cause me to lose control over the privacy of my personal infor-
	PPR2	Using the system would lead to a loss of privacy for me because my personal information
	PPR3	Someone might take control of my personal information if I used the system.
Perceived Behavioral Control (Ajzen, 2002)	PBC1	For me to use the system is always possible.
	PBC2	If I want, I always could use the system.
	PBC3	It is mostly up to me whether or not to use the system.
	PBC4	I believe that there are much control I have to use the system.
Attitude (Davis, 1989)	ATT1	I think using SHSs is a good idea.
	ATT2	I would have positive feelings toward SHSs in general.
	ATT3	It is a wise idea to use SHSs, as opposed to other services.
Behavioral Intention to Use (Davis, 1989)	BI1	I intend to use SHSs.
	BI2	I predict that I would use SHSs.
	BI3	I plan to use SHSs.

4.5 Sampling

Data was collected from Jordanian citizens in the three regions. Among the population, random sampling was used. According to Zikmund et al. (2013), if the population size is greater than or equal to 500,000 subjects, the minimum sample size is equal to 544 subjects. Therefore, the sample size of this study was equal to 750 subjects, and the questionnaire was distributed among the three regions considering the proportion of each region.

4.6 Piloting the Questionnaire

Piloting the instrument was fundamental to guarantee the questions asked what they should and ensure that there was no problem with the wording and measurements from respondents' comprehension. In other words, piloting was used to purify measurements before confirmatory testing by refining or deleting measurements to avoid these issues when the final model was analyzed (Hair et al., 2014).

According to Hair et al. (2014), the minimum adequate sample size should be equal to the larger of the following: (a) 10 times the number of formative indicators or (b) 10 times the number of structural paths directed at a particular latent construct in the structural model. In this study, ten times the number of formative indicators was 90, and 10 times the number of structural paths directed at a latent construct was 120. Thus, the minimum sample size was 120, distributed as follows: 35 questionnaires in the north region, 76 questionnaires in the middle region, and 9 in the south region.

To examine the reliability of the measurement items, the Cronbach's alpha test was used. The results in Table 2 show that Cronbach's alpha values for all factors were larger than 0.6 and close to 1. Therefore, all the factors were considered reliable and could be included in the questionnaire (Sekaran & Bougie, 2016).

Table 2
Reliability of Pilot Test Questionnaire

Factor	Cronbach's Alpha
PU	0.961
PEOU	0.960
PCOM	0.942
PCV	0.971
PCON	0.942
PC	0.952
PPR	0.975
PBC	0.941
ATT	0.958
BI	0.963

In determining the validity, content validity was tested using expert judgment (Hair et al., 2014). Therefore, several Ph.D. holders reviewed the first draft of the questionnaire as expert judges. Based on their comments, the revised version of the questionnaire was designed.

4.7 Data Handling

The questionnaires were distributed to 750 subjects from the three regions: 215 (28.7%), 476 (63.5%), and 59 (7.8%) questionnaires from north, middle, and south, respectively. At the same time, the responses were 208, 440, and 59 questionnaires from north, middle, and south, respectively, with a response rate of 94.3%.

4.8 Data Analysis

In this study, data were analyzed using SPSS and AMOS version 26.0 to perform Structural Equation Modeling (SEM). SPSS was used for data screening and treatment, normality assessment, sample adequacy, reliability, and validity of the measurement items. SEM was used to test models with multiple independent factors, even if there were correlations between different independent factors and correlations between different dependent factors. It could examine complex models with mediating factors. Moreover, the hypotheses were then tested using the structural model.

4.9 Data Screening and Treatment

Data screening were carried out based on three steps: The first step intended to detect incorrectly entered values to assure the data was entered correctly based on the scale measurement (between 1 and 7). Then, the second step is intended to detect and handle missing values. According to Pirker (Pirker, 2009), the recommended handling of missing values was imputation by replacing missing values using the remaining data values. The mean could be used for the imputation (Lemieux & McAlister, 2005; Sekaran & Bougie, 2016). As we considered the recommendation, this study replaced the missing values in each item by using the mean values of the respective items. Then, the non-integer values that were not convenient with the scale of data were rounded to the nearest integer to obtain an integer value by using one as the rounding denomination (Allison, 2001; Enders, 2010). Finally, the third step was detecting and handling the outlier values, for instance, extreme values that lie outside the normal range of the rest of the data (Kwak & Kim, 2017; Miles & Shevlin, 2001). To manage this, a boxplot was used. Then one of the most efficient techniques to handle outliers employed in this study was trimming (Bollinger & Chandra, 2005; Ramsey & Ramsey, 2007; Relles & Rogers, 1977). Technically, trimming means removing questionnaires that represent the outliers to enhance the statistical power and reduce the effect of outliers on statistical analysis (Bollinger & Chandra, 2005; Ramsey & Ramsey, 2007; Relles & Rogers, 1977). Consequently, the number of respondents after data screening and treatment was 678.

4.10 Profiles of Respondents

Fig. 2 displays the profiles of respondents after data screening and treatment. The results showed that more than half of the respondents were male (59.7%), and about 40.3% were female. Generally, the respondents fell in the age group of 25 to 45 years old (68.6%), live in the middle region (63.4%), and earn a monthly income of 500 JD to 1500 JD (700 USD to 2100 USD) (66.8%). Overall, the respondents have a bachelor's degree level of education (84.2%), have available internet service at home (92.3%), and have greater use of social media websites (62.5%).

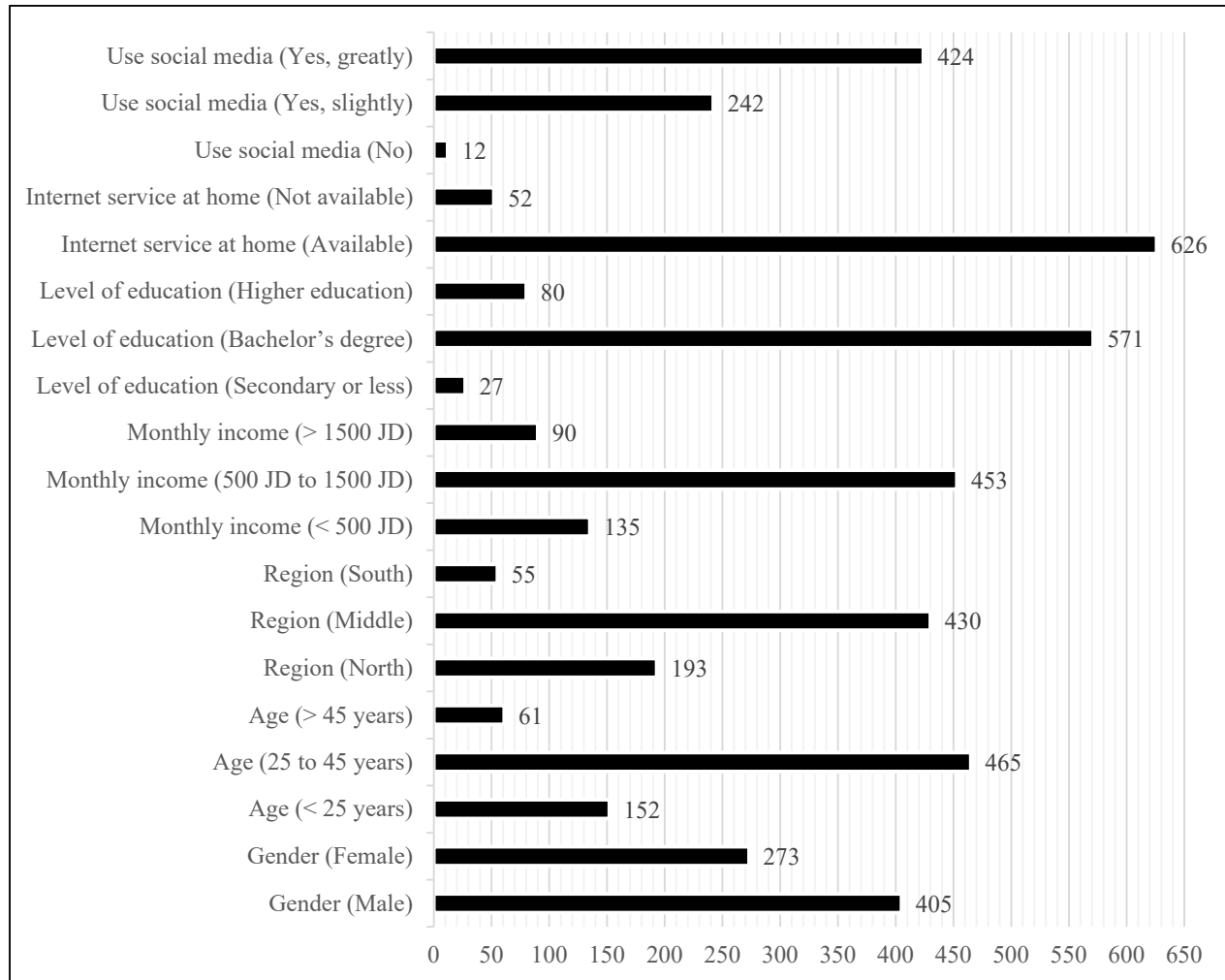


Fig. 2. Profiles of Respondents

4.11 Normality Assessment

The normality assessment of the measurement items was carried out to all measurement items using the skewness and kurtosis testing. The measurement items were deemed normally distributed if the skewness and kurtosis values were less than three (Corrado & Su, 1996). Therefore, all measurement items for PU, PEOU, ATT, PCOM, PCV, PCON, PC, PBC, PPR, and BI were normally distributed in this study.

4.12 Sample Adequacy

The sample was considered adequate if Kaiser Meyer Olkin's (KMO) value was larger than 0.6 (Coakes et al., 2006). The sample in this study was considered adequate because the value of KMO was 0.931.

4.13 Reliability and Validity of the Measurement Items

To test the reliability of the measurement items, the loading factor values, composite reliability, and Cronbach's alpha were tested. In addition, two kinds of validity tests were conducted: convergent and discriminant validity.

According to Bohrnstedt (1970), a common threshold criterion is that the factor should explain more than 50% of a measurement item's variance. Therefore, items with loading values larger than 0.7 are acceptable (Bohrnstedt, 1970). In this study, all factor loadings were more than 0.7. Thus, none of the items were removed. Moreover, the reliability was also examined using composite reliability and Cronbach's alpha tests (Hair et al., 2014; Sekaran & Bougie, 2016). Composite reliability is used to

test “how well a factor is measured by its measurement items” (Gotz et al., 2010). According to Fornell and Larcker (1981), composite reliability (CR) in a measurement model is calculated as $\text{composite reliability} = (\text{square of the summation of the factor loadings}) / ((\text{square of the summation of the factor loadings}) + (\text{summation of error variances}))$. Theoretically, the composite reliability is between 0 and 1, in which values larger than 0.6 are acceptable (Bagozzi & Yi, 1988). In this study, all values were larger than 0.6, which means they were significant enough. Cronbach’s alpha is similar to composite reliability, but it includes the actual factor loading, whereas the alpha uses equal weighting (Gotz et al., 2010). The values for Cronbach’s alpha are between 0 and 1; essentially, values larger than 0.6 are acceptable (Hair et al., 2014; Sekaran & Bougie, 2016). In this study, all values were suitable to uphold the requirements. Table 3 shows all the results of reliability values.

Table 3
Results of Reliability Values

Factors	Items	Loading Factor	Composite Reliability	Cronbach’s Alpha
PU	PU1	0.821	0.925223	0.938
	PU2	0.851		
	PU3	0.834		
	PU4	0.809		
	PU5	0.796		
	PU6	0.812		
PEOU	PEOU1	0.791	0.924812	0.934
	PEOU2	0.854		
	PEOU3	0.833		
	PEOU4	0.815		
	PEOU5	0.803		
	PEOU6	0.822		
PCOM	PCOM1	0.872	0.928036	0.926
	PCOM2	0.956		
	PCOM3	0.872		
PCV	PCV1	0.94	0.944953	0.944
	PCV2	0.966		
	PCV3	0.859		
PCON	PCON1	0.925	0.930869	0.927
	PCON2	0.963		
	PCON3	0.82		
PC	PC1	0.826	0.939856	0.938
	PC2	0.981		
	PC3	0.935		
PPR	PPR1	0.949	0.968975	0.969
	PPR2	0.981		
	PPR3	0.935		
PBC	PBC1	0.856	0.929097	0.927
	PBC2	0.95		
	PBC3	0.909		
	PBC4	0.779		
ATT	ATT1	0.835	0.924775	0.926
	ATT2	0.963		
	ATT3	0.888		
BI	BI1	0.915	0.947033	0.956
	BI2	0.938		
	BI3	0.923		

Alternatively, two kinds of validity tests were executed in this study to examine factor validity, convergent validity and discriminant validity (Hair et al., 2014; Sekaran & Bougie, 2016). Mainly, convergent validity is based on the correlation between responses acquired by various methods of measuring the same construct (Peter, 1981). According to Fornell and Larcker (1981), convergent validity is measured by the Average Variance Extracted (AVE), which is defined as $\text{AVE} = (\text{average of the square of the factor loadings})$. AVE values larger than 0.5 are acceptable (Fornell & Larcker, 1981). In this study, all values were suitable to uphold the requirements, as shown in Table 4.

Table 4
The results of AVE values

Factors	AVE
PU	0.673539833
PEOU	0.672267333
ATT	0.804379333
PCOM	0.811568000
PCV	0.851545667
PCON	0.818464667
PC	0.839620667
PBC	0.767089500
PPR	0.912395667
BI	0.856332667

Meanwhile, according to Fornell and Larcker (1981), discriminant validity is proven if the square root of AVE for each factor is larger than the squared correlations between factors. In this study, all square roots of AVE values were larger than R² values, as shown in Table 5, which means that all the factors were different from each other.

Table 5
The results of square root of AVE and R-Square values

Factor	PU	PEOU	ATT	PCOM	PCV	PCON	PC	PBC	PPR	BI
PU	0.820695									
PEOU	0.63686944	0.819919								
ATT	0.34938621	0.399088	0.896872							
PCOM	0.22402614	0.262718	0.140729	0.900871						
PCV	0.36604315	0.434388	0.310344	0.331472	0.922792					
PCON	0.3840095	0.439162	0.321353	0.352475	0.709331	0.90469				
PC	0.00753042	0.021336	0.001314	0.017177	0.004191	0.001656	0.916308			
PBC	0.25892832	0.299222	0.164468	0.29343	0.250873	0.292326	0.040092	0.875836		
PPR	0.00228723	0.010087	0.000581	0.005203	0.000161	0.000981	0.239194	0.060502	0.955194	
BI	0.23577628	0.247208	0.182065	0.303689	0.27139	0.326775	0.061132	0.411207	0.034279	0.925382

4.14 Hypothesis Testing

The determination coefficient (R²) is the level of the variance explained by the factors. Therefore, the value of R² is a logical metric to evaluate the structural model between 0 and 1. Chin (1998) categorized the R² into weak (R² ≥ 0.19), moderate (R² ≥ 0.33), and substantial (R² ≥ 0.67). This study involved four dependent factors. In detail, the first factor was PU that was affected by PEOU, PCOM, and PCV; the second factor was PEOU that was affected by PCOM and PCON; the third factor was ATT that was affected by PU and PEOU; finally, the fourth factor was BI that was affected by PU, ATT, PC, PPR, and PBC. A hypothesis is accepted if the level of significant (p) value is less than 0.1, 0.05, or 0.01 (Iacobucci, 2018; Sharma, 1996). Table 6 shows the results of the hypothesis testing. The initial model revised with the R², β, and p values of the relationships are depicted in Fig.3.

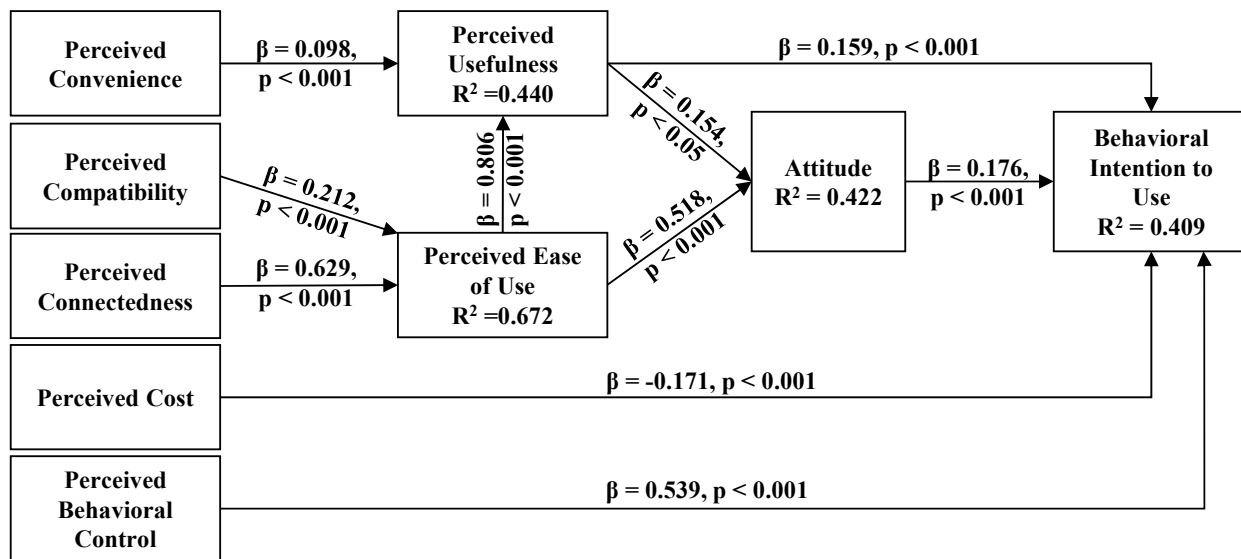


Fig. 3. An Extended Acceptance Model for SHSs

Table 6
The results of testing the hypotheses

Hypotheses	Factor		β	p-value	Hypotheses Status
	Independent	Dependent			
H1	PU	ATT	0.154	p < 0.05	Supported
H2	PU	BI	0.159	p < 0.001	Supported
H3	PEOU	PU	0.806	p < 0.001	Supported
H4	PEOU	ATT	0.518	p < 0.001	Supported
H5	ATT	BI	0.176	p < 0.001	Supported
H6	PCOM	PU	0.034	p > 0.05	Not Supported
H7	PCOM	PEOU	0.212	p < 0.001	Supported
H8	PCV	PU	0.098	p < 0.001	Supported
H9	PCON	PEOU	0.629	p < 0.001	Supported
H10	PC	BI	-0.171	p < 0.001	Supported
H11	PPR	BI	0.015	p > 0.05	Not Supported
H12	PBC	BI	0.539	p < 0.001	Supported

5. Discussions and Conclusion

This study aims to explore the factors that influence users' acceptance of SHSs to develop and test a comprehensive model based on the most commonly used and validated acceptance theories which are the Technology Acceptance Model (TAM), Innovation Diffusion Theory (IDT), and Theory of Planned Behavior (TPB). The literature review suggested ten possible factors that might have influenced the acceptance of SHSs. These factors were perceived usefulness (PU), perceived ease of use (PEOU), Attitudes Toward using the services (ATT), perceived compatibility (PCOM), perceived behavioral control (PBC), perceived convenience (PCV), perceived connectedness (PCON), perceived cost (PC), and perceived privacy risk (PPR).

Previous studies show that PU, PEOU, ATT, PCOM, PBC, PCV, PCON, PC, and PPR have not been tested together in SHSs. In addition to that, the previous studies also explicitly exhibited that PCOM, PCON, PC, PCV, PPR, and PBC affected the PU, PEOU, ATT, and BI of the applications. Additionally, the previous studies also showed that integrating different acceptance theories could provide more understanding and explanation of the users' acceptance. Thus, this study developed a comprehensive acceptance model, and the relationships between factors were identified by formulating 12 hypotheses. To identify the strength of each relationship, the researchers conducted a survey to test the model with citizens who were distributed in three geographical regions in Jordan: north, middle, and south.

The results clarified that PU had a positive direct effect on ATT (H1), consistent with previous user acceptance studies (Gross et al., 2020; Hojjati & Khodakarami, 2016; Park et al., 2017, 2018; Shuhaiber & Mashal, 2019). Also, PU had a positive direct effect on BI (H2), which was consistent with previous user acceptance studies (Alaiad & Zhou, 2017; Bao et al., 2014; Dong et al., 2017; Guhr et al., 2020; Hojjati & Khodakarami, 2016; Hubert et al., 2019; Nikou, 2019; Pal et al., 2018; Park et al., 2017, 2018; Shuhaiber & Mashal, 2019). Therefore, to increase the intention to use SHSs, the PU factor should be given more attention. PU can be improved by adding innovative applications, appropriate features, and functional capabilities to the SHSs, focusing more on enhanced quality and speed services. As a result, it could better enable users to accomplish daily tasks more quickly, improve their daily task performance, increase their productivity, enhance their effectiveness inside their homes, make it easier to do their daily tasks, and finally find SHSs useful in their lifestyle. In addition, guidance and training must be provided to understand the SHSs and perceive it to be compatible with their values and past experiences.

In the same manner, PEOU had a direct positive influence on PU (H3), which was consistent with previous user acceptance studies (Bao et al., 2014; Dong et al., 2017; Gross et al., 2020; Hojjati & Khodakarami, 2016; Nikou, 2019; Pal et al., 2018; Park et al., 2017, 2018; Shuhaiber & Mashal, 2019). Aside from this, PEOU had a direct influence on ATT (H4), which was consistent with previous user acceptance studies (Hojjati & Khodakarami, 2016; Park et al., 2017, 2018; Shuhaiber & Mashal, 2019). This means that the users found it easy to get SHSs to do what they wanted. They found SHSs to be flexible to interact with, and they found SHSs would be clear and understandable. They found it easy to become skillful at using SHSs, and they found SHSs easy to use. This means that when users believed that SHSs were easy to use, they perceived it as useful, and their attitude changed in favor of using SHSs.

Furthermore, ATT had a positive direct effect on BI (H5), which was consistent with previous user acceptance studies (Gross et al., 2020; Hojjati & Khodakarami, 2016; C. Kim et al., 2010; Y. Kim et al., 2017; Park et al., 2017, 2018; Shuhaiber & Mashal, 2019; Yang et al., 2017). This means that the users thought that using SHSs was a good and wise idea, and they had positive feelings toward SHSs in general.

Additionally, the results explained that PCOM had no positive direct effect on PU (H6), which was not consistent with previous user acceptance studies conducted by Hubert (2019), Park et al. (2017, 2018), and Nikou (2019). This means that users saw that using SHSs was not compatible with most aspects of their lives and did not fit their lifestyle and how they liked to interact with the components in their homes (Park et al., 2018). Therefore, providing compatible technologies with traditional services and devices is one of the core issues in determining the usefulness of SHSs (Park et al., 2017).

Also, PCOM had a positive direct effect on PEOU (H7), which was consistent with previous user acceptance studies conducted by Hubert (2019), Park et al. (2017, 2018), and Nikou (2019). This means that there was a need to ensure that all different devices and appliances could function well and be integrated together, allowing the integration of some of their existing home appliances. If the assortment of devices and appliances are not compatible with each other, users might find SHSs lacking ease of use, thus, obstructing their decisions to adopt SHSs (Park et al., 2017, 2018).

Moreover, the results found that PCV had a positive direct effect on PU (H8), which was consistent with a previous user acceptance study conducted by Dong et al. (2017). This means that users saw that using SHSs was convenient because they were not complicated and could be used at any time and in any place. Therefore, if the users found that SHSs was convenient, they will also find it useful.

It was also found that PCON had a positive direct effect on PEOU (H9), which was consistent with previous user acceptance studies conducted by Park et al. (2017, 2018). This means that users saw that they could access, connect to, and interact with the components in their houses anytime via the system. Additionally, this implies that the users' acceptance was associated with not only providing more reliable connected SHSs but also suggesting well-connected functionalities among the components in the SHSs (Park et al., 2017, 2018). Therefore, if the users find that SHSs were well-connected with the components, they will find it easy to use.

In addition, PC has a negative direct effect on BI (H10), which is consistent with previous user acceptance studies (Alaiad & Zhou, 2017; Y. Kim et al., 2017; Nikou, 2019; Pal et al., 2018; Park et al., 2017, 2018; Sequeiros et al., 2021). This means that the users find that SHSs were expensive in addition to the financial barrier to maintaining and repairing the SHSs. Furthermore, this implies that the PC of the technologies is important in the market success and is considered as one of the prominent barriers to the BI. This barrier can be reduced by the advancement and development of the technologies (Park et al., 2017). Additionally, this denotes that the high cost of SHSs can prevent the user from investing in such a service. Moreover, because the monthly income of most participants in the survey was between 500 JD and 1500 JD (700 USD to 2100 USD), which is moderate, they were more likely to have financial issues with buying and using SHSs. Thus, the smart home device manufacturers must consider cost as an important factor if they want smart homes to be widely used (Pal et al., 2018). Moreover, SHSs designers should focus on making SHSs affordable, and service providers should discuss the initial cost of the SHSs in light of its potential long-term benefits (Alaiad & Zhou, 2017). Furthermore, this means that possible customers accept a new type of service only when the cost investment leads to sensible results (Y. Kim et al., 2017).

It was also found that PPR did not have a direct effect on BI (H11), which was not consistent with previous user acceptance studies (Alaiad & Zhou, 2017; Dong et al., 2017; Guhr et al., 2020). This means that the users find that the system would not lead to losing control over the privacy of their personal information because their personal information would not be used without their knowledge. This implied that the enthusiasm of users to use new technologies might make them pass over the seriousness and riskiness of losing control over the privacy of their personal information. Therefore, there is a need to spread awareness in the community about the importance of buying and using systems that guarantee control over the privacy of their personal information. This issue can be solved by providing and describing privacy policies regarding information collection, storage, and use (Alaiad & Zhou, 2017), as well as applying advanced encryption technologies to protect the privacy of personal information (Alaiad & Zhou, 2017).

Finally, the results found that PBC had a positive direct effect on BI (H12), which was consistent with previous user acceptance studies (Guhr et al., 2020; Yang et al., 2017). This demonstrates that users believe they always could use the SHSs and they believe they have ample control when using SHSs. Therefore, when potential users perceive more controllability than obstacles, they feel able to adopt SHSs (Yang et al., 2017).

6. Limitations and Future Work

There was some notable limitation that was faced by the researchers during this study. First, because the survey described in current study was conducted in Jordan, the results cannot be directly applied to other nations. Second, the model is restricted to chosen theoretical founded factors of the behavioral intention to use SHSs.

For future research, effects (e.g., gender, age, income, regions, Internet availability) will be taken when exploring the research model, considering that several studies have shown that user adoption of innovative and recent technologies is significantly related to their individual characteristics (Staddon & Chow, 2008). Additionally, this model could be tested with other users in various countries. Former researches have shown that user adoption patterns could be significantly associated based on cultural and national similarities and differences (Carter & Weerakkody, 2008). In addition, this model could be tested to study user acceptance in other IT applications such as smart building and smart city, so the model could be generalized in the IT domain. Moreover, this model could be tested with additional factors that might affect the acceptance of SHSs.

Acknowledgments

The authors are grateful to the Applied Science Private University, Amman, Jordan, for their support in conducting this research.

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