IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received December 22, 2017, accepted February 11, 2018, date of publication February 22, 2018, date of current version March 15, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2808472

Internet-of-Things and Smart Homes for Elderly Healthcare: An End User Perspective

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ABSTRACT Although an Internet-of-Things-based smart home solution can provide an improved and better approach to healthcare management, yet its end user adoption is very low. With elderly people as the main target, these conservative users pose a serious challenge to the successful implementation of smart home healthcare services. The objective of this research was to develop and test a theoretical framework empirically for determining the core factors that can affect the elderly users' acceptance of smart home services for healthcare. Accordingly, an online survey was conducted with 254 elderly people aged 55 years and above across four Asian countries. Partial least square structural equation modeling was applied to analyze the effect of eight hypothesized predicting constructs. The user perceptions were measured on a conceptual level rather than the actual usage intention toward a specific service. Performance expectancy, effort expectancy, expert advice, and perceived trust have a positive impact on the behavioral intention. The same association is negative for technology anxiety and perceived cost. Facilitating conditions and social influence do not have any effect on the behavioral intention. The model could explain 81.4% of the total variance in the dependent variable i.e., behavioral intention. Effort expectancy is the leading predictor of smart homes for healthcare acceptance among the elderly. Together with expert advice, perceived trust, and perceived cost, these four factors represent the key influence of the elderly peoples' acceptance behavior. This paper provides the groundwork to explore the process of the actual adoption of smart home services for healthcare by the elderly people with potential future research areas.

INDEX TERMS Elderly, healthcare, smart homes.

I. INTRODUCTION

With an increase in age, the need for medical support also grows, which may lead to unplanned visits to the doctors frequently. The recent developments in Internet-of-Things (IoT) technology can play an important role in designing suitable healthcare systems for the elderly [1]. In most of the Asian countries, severe pressure on the public healthcare sector and lack of adequate facilities are driving the way in which health services are delivered to the patients [2], [3]. There is a paradigm shift from the once physician-centered environment to a more patient-centric healthcare system [4]. Smart homes, which integrate health and other ambient assisted living (AAL) technologies, can play a lead role in revolutionizing the way in which healthcare services are being provided to the elderly people [5]–[7]. In fact providing healthcare facility is one of the core functionalities offered by the smart homes that have been discussed in detail later in the literature review section of the paper.

Although a lot of work is being done on the technological aspects of smart homes, yet their adoption rate is very low mainly due to their disruptive nature and inherent conservativeness of the older people towards any new technology [8], [9]. Current research on IoT and smart homes point out towards the benefits of using such a system by the elderly along with a strong thrust in developing new underlying technologies and services [3], [10]–[12]. However, there is a lack of evidence of how the subjective opinion of the people can be influenced towards using these services/systems [10]. Understanding the entire process of how and why people tend to develop close relationships with certain technologies and services and make them an integral part of their life is the key to understanding the success of any new technology.

Physical and psychological needs of people change with age [13]. Older people tend to show certain specific behaviors that need to be taken into account during the development and commercialization of health-specific smart homes for this target group [14]. Understanding their basic needs, specific requirements, interaction with new technology and services along with the motivational factors that influence their decision making process are key to the success of the smart homes meant for their well-being. Clearly, there is a research gap in this aspect, which we aim to answer through this work.

The main objective of this study is to assess the interaction between elderly human factors and the success of smart homes in the health context by framing two main research questions: firstly, what are the factors influencing the older adults' acceptance behavior of smart homes for health and what is the underlying model? Secondly, how does such a model perform in an empirical setting?

The key challenge is to understand the behavior of the elderly people towards using a service that currently is not available on a commercial scale. Hence, there is a serious lack of a theoretical/conceptual approach in acceptance modelling as the current focus is on the underlying technologies and services rather than an end-user perspective [15]. In this study, we concentrate on the factors affecting the elderly acceptance of the smart homes for healthcare from a conceptual viewpoint rather than a specific product or service. Thus, the takeaway of this research is a framework that suitably explains the acceptance behavior of smart homes for healthcare among the elderly on a conceptual level that will provide the initial groundwork for potential future research.

The remaining paper has been divided into six sections. Section II provides the relevant literature review. In Section III, we propose the theoretical framework and the underlying hypotheses. Section IV provides the methodology, while the results are given in Section V. Finally, Section VI presents the discussions, while the conclusion and scope of future work is dealt with in Section VII.

II. LITERATURE REVIEW

Developments in IoT technology have resulted in the evolution of traditional homes to smart homes which according to Rosslin et.al. is defined as " *an amalgamation of technology and services through home networking that ensures a better quality of life for its inhabitants*" [16]. Fig. 1 shows the basic concept of the smart homes in a healthcare perspective. The sensors and actuators along with the backbone communication network (wired or wireless) form the core part of such smart homes. Artificial intelligent (AI) techniques are often used to gather and analyze the information of the occupants' health status and report any kind of abnormalities; thereby enabling to take certain decisions and provides recommendations. Fig. 1 also shows the key five areas of elderly healthcare that current research focuses on. Most of the studies provide specific solutions to address the needs of the patients/elderly people, such as chronic disease management, assistance in independent living, preventive care, etc. [17]–[20] or use

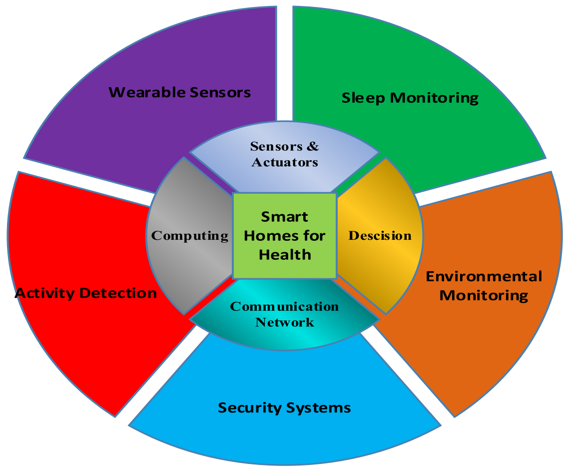

FIGURE 1. Smart homes from healthcare perspective.

specific technologies like mobile phones, web-applications, wearable sensors or software [21]–[24]. All these systems include a combination of sensors, software and networking technology to collect, process, analyze, and transfer the data either to the smart home service providers or to a remote healthcare center. TABLE 1 provides the detail of the literature review.

Although a lot of work is going on in the aspect of elderly healthcare and smart homes, yet the adoption of these services is quite low [3], [8], [40]. The main cause for such a low adoption rate is the lack of a holistic approach towards smart home systems for healthcare in general. Most of the ongoing research focus on the underlying technologies and services without talking into account the dependence of human characteristics on technology and the social background. Hence, there is a mismatch between the users' expectations and the services available [3], [40]–[42].

The concept of smart homes is relatively new and the engagement of the elderly users' with these systems/services is less probable, since traditionally they are reluctant to accept any new innovative solutions [43]. The older adults' adoption of technology is a complex issue that is affected by many factors [44]. In the present context, a proper understanding of the behavior, motivations, and decision-making by the elderly people represents the main challenge in the successful acceptance of the smart homes for healthcare among this target population [44]–[46].

Therefore, theories about technology acceptance should be used to study the factors that can affect the elderly intention. The Technology Acceptance Model (TAM) has been widely used in a variety of contexts to have an idea about the acceptance of any new technology [47]–[49]. Over the years, TAM has evolved to become a key model in predicting human behavior towards the potential acceptance or rejection of technology [50]. The Unified Theory of Acceptance and Use of Technology (UTAUT) is the latest derivative of TAM [51]. Since its inception, UTAUT has been tested extensively in a

TABLE 1. Overview of literature review.

Reference No	Who	What	How
[25]	Elderly people with dementia Sample size: Not mentioned	Provide assistance in remembering daily activities and promote self-independence	Use of multiple ICT technologies and help from care-givers
[26]	Elderly having age > 50 and mentally impaired Sample size: Not mentioned	Provide mechanisms to increase the participatory behavior and activity	Heterogeneous methods mainly by using a variety of sensors like door-openers, smoke-detectors, motion detectors, etc.
[27]	Normal elderly people with no specific disabilities or requirements Sample size: Not mentioned	Discovering and monitoring patterns of daily activity among the elderly	Gathering information from various kinds of sensors installed in the homes and subsequent data analysis using a variant of hidden Markov model
[28]	Normal elderly people with no specific disabilities or requirements Sample size: 70	Provide healthcare facilities for the elderly and trying to improve both mental and physical health	Design and implementation of field-trial of a robot "Matilda" that provides human-like assistive service and companionship
[29]	Normal elderly people with no specific disabilities or requirements Sample size: 28	Exploration of the issues of QoL being faced by the elderly people in relation to their experiences of and attitudes towards using ICT for healthcare needs	Using focus groups and supplementary questionnaires to collect qualitative data from older people and measure their attitudes
[30]	Normal elderly people with no specific disabilities or requirements Sample size: Not mentioned	Exploring the use of smart-home technologies by the elderly in a residential setup to improve their QoL and their perceptions of privacy that can inhibit their acceptance	Use of a qualitative study to gauge the user perception
[31]	Normal elderly people with no specific disabilities or requirements Sample size: 14	Assessing the older adult's perception towards using a smart-home (bed sensor, gait monitor, stove and motion sensors, etc.) that enhances their sense of security and monitors health condition	Conducting focus group sessions that are audio-taped and later used for content analysis
[32]	Normal elderly people with no specific disabilities or requirements divided into 3 groups depending upon age (mean age = 50, 68 and 75) Sample size: 22	Determination of the ergonomic and functional requirements of optical and wearable fall sensors for fall detection	Conducting a semi-structured interview across 3 focus groups and getting back the feedback from the users to judge if such systems can improve the elderly life
[33]	Normal elderly people with no specific disabilities or requirements Sample size: 15	A computer vision based fall detection system for the elderly that is used in a home environment	Vision (digital video camera) based method by transforming the video frame into certain features by using image processing techniques and then creating a classification model by using a Support Vector Machine (SVM) classifier
[34]	Elderly people suffering from dementia Sample size: 11	Provision for a continuous monitoring scheme both inside and outside the residence for conducting a stray prevention system for the elderly	Using radio frequency identification, GPS sensors and GIS for elderly monitoring and subsequent feedback about the system
[35]	Elderly people suffering from depression Sample size: 20	Implementation and testing of algorithms on sensor data collected from elderly homes that helps to detect depression	Use of neural network, C4.5 decision tree, Bayesian network and SVM classifiers to detect the severity of depressions
[36]	Normal elderly people with no specific disabilities or requirements Sample size: 19	Investigating different factors and attributes that can help in the design process of a smart home healthcare system	Conducting interviews across different households and identifying 15 empirically derived attributes that can help in the design process
[37]	Normal elderly people with no specific disabilities or requirements Sample size: Not mentioned	An indoor location tracking system that is used to locate and track an elderly very accurately	Using RFID technology to gather indoor location data and log it into the database for further analysis
[38]	Normal elderly people with no specific disabilities or requirements Sample size: 25	Various types of activity recognition (normal activity, bad night, fall, etc.) for the elderly in a home environment	Using a Case Based Reasoning (CBR) approach that is integrated with the smart homes to analyze the daily activities of the elderly using different algorithms like t-CNN, t-RENN, etc.
[39]	Normal elderly people with no specific disabilities or requirements Sample size: 49	Creating a robot '*Hobbit*' that supports the elderly living independently at home	Creation of a multi-modal interface including speech recognition, that enables daily interaction with the robot

variety of contexts including technologies related to health assistance [52], [53].

The UTAUT model has four independent core constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) as direct determinants of the dependent construct; Behavioral Intention (BI). This framework is often supplemented by additional factors that have moderating effects on the core constructs like age, gender, experience, voluntariness of use, etc. depending upon the usage context [51]. In addition to this, it is also common to add relevant external factors depending on the actual use-case [54]–[56]. The primary motive behind adding these additional contextual factors is to enable a better and more accurate understanding of the users' acceptance of technology. Based upon the literature review of smart homes for elderly healthcare, we have identified four external factors: Technology Anxiety (TA), Perceived Trust (PT), Perceived Cost (PC), and Expert Advice (EA) as potential factors to study and explain the user behavior. Thus, our model has two types of constructs: the original UTAUT constructs or the internal factors and the contextual constructs or the external factors.

The outcome of literature review clearly indicates that a lot of work is being done towards the elderly healthcare by utilizing the advantages of IoT technology. Typically, most of them are experimental projects that assume a technology based perspective. However, in order to promote and motivate the elderly people to use smart homes, it is very important to gauge their behavior and perception towards using these services. Accordingly, we propose our theoretical framework in the next Section.

III. THEORETICAL FRAMEWORK AND HYPOTHESES

In the core UTAUT model, Performance Expectancy (PE) and Effort Expectancy (EE) are closely related to the Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) constructs of the Technology Acceptance Model (TAM) [57]. A detailed description of all the constructs proposed is presented next:

A. PERFORMANCE EXPECTANCY (PE)

Venkatesh et.al defined PE as "the degree to which using a technology will provide benefits in performing certain activities" [51]. With respect to the elderly users' intention to use any new technology, the perception of the technology being beneficial and helpful plays a key role in its acceptance [58]. However, if these users' fear and doubt about the usefulness of the technology, it can create a negative influence and affect the adoption rate [59], [60]. Prior research establishes the relationship between usefulness and intention to use healthcare services [57], [61]. If the elderly users feel that using smart homes for health support will enable them to manage their health in a better manner, provide better access to healthcare facilities, and improve their overall life quality, then it can create a positive perception towards using these systems. Thus, for our context, PE is defined as " *the extent to which using smart homes will provide direct benefits to the elderly people with respect to their overall health*." The corresponding hypothesis is:

H_1: *Performance Expectancy affects the Behavioral Intention of the elderly users' to use the smart homes for healthcare purpose in a positive way.*

B. EFFORT EXPECTANCY (EE)

EE is defined as " *the degree of ease associated with the use of any system*" [51]. EE has a strong influence on the users' intention to use health information systems and has a positive effect on its acceptance. Especially, when a technology is new, the degree of ease associated with using it, strongly affects the acceptance behavior particularly in case of the elderly users' [57]–[59], [62].

In addition to the direct impact of PE and EE on BI, EE also affects PE i.e. the usefulness of any technology is determined by the degree to which the users' feel that the technology is easy to learn and use [57], [58]. We therefore hypothesize:

H_{2a}: *Effort Expectancy affects the Behavioral Intention of the elderly users' to use the smart homes for healthcare purpose in a positive way.*

H_{2b}: *Effort Expectancy has a positive influence on the Performance Expectancy of the elderly users'.*

C. SOCIAL INFLUENCE (SI)

When any technology is at its beginning stage, the users of such a system lack enough information regarding its usability. In those cases, the user may be influenced by the opinions or suggestions provided by their homecare nurse, friends and/or relatives [46], [63]. The positive relationship between SI and the usage intention has been verified in a number of previous studies [57], [59], [62]. We therefore hypothesize:

H_3: *Social Influence affects the Behavioral Intention of the elderly users' to use the smart homes for healthcare purpose in a positive way.*

D. FACILITATING CONDITIONS (FC)

FC is defined as " *the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system*" [51]. FC is a direct determinant of behavioral intention and use of technology [64]. This fact was further confirmed by Bhattacherjee et.al in the context of using a health information system [65]. In the context of elderly users' of health related ICT, ready access to and availability of technical support significantly increases the BI [59], [62], and [66]. Therefore, we hypothesize as:

H_4: *Facilitating Conditions affects the Behavioral Intention of the elderly users' to use the smart homes for healthcare purpose in a positive way.*

Next, we present the contextual constructs/external factors unique to our model:

E. TECHNOLOGY ANXIETY (TA)

Technology Anxiety is defined as " *the fear, apprehension and hope that people feel when considering use or* *actually using certain technology*" [67]. Studies show that technology anxiety, particularly in the context of computer related systems and information services are very common [68], [69]. This is especially true for the elderly people that we consider for our research. The older people tend to use those technology and services, which they are accustomed to, and using for a long period of time, rather than switching over to some new technology and platform [54], [70]. A higher level of TA, should therefore negatively affect the intention to use any technology. Therefore, we hypothesize as:

H$_5$: *Technology Anxiety affects the Behavioral Intention of the elderly users' to use the smart homes for healthcare purpose in a negative way.*

F. PERCEIVED TRUST (PT)

When smart homes are used for providing healthcare facilities, they can collect, manage, monitor, and analyze the personal health data belonging to the individuals. This raises severe security and trust issues that current literature reports and it can adversely affect the adoption of these smart homes by the end-users in general [3], [71], [72]. The elders also have negative views regarding the security aspect [45], [46], [58], [73]. Trust in technology also has a strong positive influence on the perceived usefulness [74]. In the present context, we define PT as " *the state of mind of the elderly people where they feel that their personal data will be safe, carefully protected, and anonymous."* The relevant hypotheses are:

H$_{6a}$: *An increase in Perceived Trust will increase the Behavioral Intention of the elderly users' to use the smart homes for healthcare purpose.*

H$_{6b}$: *An increase in Perceived Trust will increase the Performance Expectancy of the elderly users' to use the smart homes for healthcare purpose.*

G. PERCEIVED COST (PC)

The cost of affording any new technology is a crucial factor responsible for its success [75], [76]. If the cost associated with the healthcare services provided by the smart homes is high, it can lead to a negative effect on the elderly mindset. In the present context, we define PC as " *the price which the elderly users' considers to be an appropriate monetary sacrifice in return of the services that they get from using the smart homes."* Clearly, if the price if not reasonable, then the users' will show resistance in using those products/services [77], [78]. Thus, we hypothesize as:

H$_7$: *Perceived Cost affects the Behavioral Intention of the elderly users' to use the smart homes for healthcare purpose in a negative way.*

H. EXPERT ADVICE (EA)

The elderly users' are often conservative by nature and they tend to use heuristic methods in their decision making process [79]. Previous research reports that these groups of users' rely heavily on external experts' opinion like doctors, nurses, or pharmacists in taking decisions related to their health [80]. Therefore, in a healthcare perspective these users' tend to defer their decision to the expert's authority [81]. If the experts' feel and believe that using smart homes for healthcare will be beneficial, it will increase the perception of the technology as being useful among the elderly people [82]. Thus, we hypothesize:

H$_8$: *Expert Advice affects the Performance Expectancy of the elderly users' to use the smart homes for healthcare purpose in a positive way.*

The final construct that we measure is BI. Fig. 2 shows our proposed research model.

IV. METHODOLOGY

A. DATA COLLECTION AND SAMPLE CHARACTERISTICS

An online survey instrument has been developed to measure the perception of the elderly people in using smart homes for healthcare purpose. The target population is from India, Thailand, Indonesia, and Malaysia. Before distributing the questionnaire to the participants, opinion has been sought from two independent experts for ensuring the questionnaire validity and relevance. The survey instrument has been structured in two parts. Part 1 contains certain socio-demographic questions (respondent age, gender, household size, and household income) and a basic question on smart home awareness that has been used as a screening question. The screening question has been used in order to minimize the hypothetical response biases from those people who absolutely have no idea or prior knowledge about smart homes. The screening question used was "Do you know what smart home technologies are?" Response options ranged from "no idea", "vague idea", "general idea", "and good idea" to "already using some form of smart home technology/service." Respondents answering "no idea" were filtered out from the remaining survey. For all other respondents they moved on to part 2. In order to get sufficient number of subjects to generalize our model, the age group that we have considered for the elderly is 55 years and above instead of the 60 years and up criterion. In addition, in order to ensure that the questionnaire reaches out to as many elderly people as possible our contacted subjects were requested to further contact their friends or relatives matching the age criterion. 254 responses were obtained out of which 15 did not pass the screening requirement. Hence, for the final analysis we have data from 239 elderly people. The relevant descriptive statistics showing the respondents demographic information has been shown in Table 2.

B. MEASUREMENT INSTRUMENT

Part two of the survey contains open-ended questions that measure the intention of the respondents to use smart homes for healthcare. Table 3 gives the detail of the questions that has been administered. All the questionnaire items have been evaluated on a 5-point Likert scale (1 = "strongly disagree" to 5 = "strongly agree"). Since, UTAUT was originally used

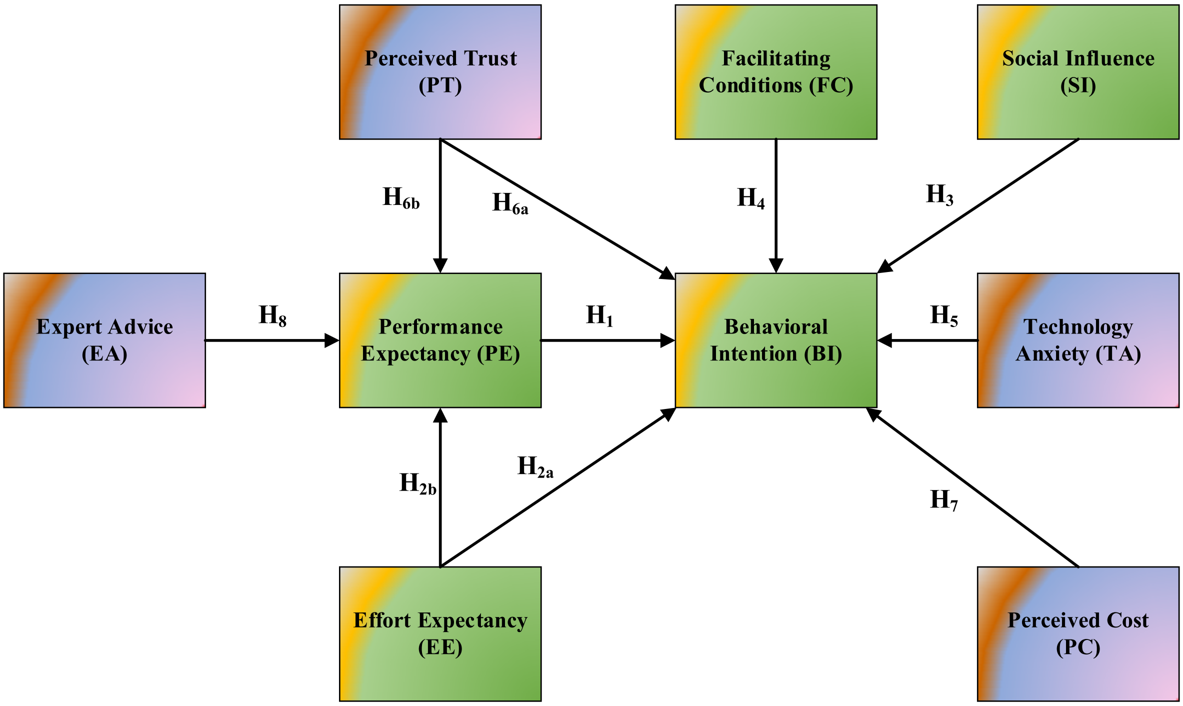

FIGURE 2. Proposed research model.

TABLE 2. Demographic information of the respondents.

Characteristics	Number (N)	N %
Age		
55-64	112	44.1
65-74	90	35.4
75 and above	52	20.5
Gender		
Male	167	65.7
Female	87	34.3
Number of family members		
1	62	24.4
2	69	27.2
3	71	28
4	30	11.8
More than 4	22	8.7
Home ownership status		
Owned	217	85.4
Rented	37	14.6
Education		
High school or below	21	8.27
Bachelor degree	164	64.56
Master degree or above	69	27.16
Household income		
Less than 15,000	7	2.75
15,001 – 30,000	40	15.75
30,001 – 40,000	139	54.72
More than 40,000	68	26.77
Country of stay		
India	104	40.9
Thailand	85	33.5
Indonesia	29	11.4
Malaysia	36	14.2

to measure the acceptance of technology in an organizational environment, the end-user perspective in a smart home for healthcare context, have to be considered when formulating the individual survey questions and measurement scale. The changes that are incorporated for every construct are represented in Table 3 under the references column. Table 4 shows the relevant descriptive statistics that has been carried out in SPSS 17.0.

TABLE 3. Details of measurement instrument used in our study.

Construct	Item No	Question	References
Performance Expectancy	PE1	Using smart homes allow me to monitor my health	[85-87]
	PE2	I find using smart homes for health purpose to be helpful in my daily life	
	PE3	Using smart homes for health purpose makes me feel safe overall	
	PE4	Smart homes enhance the capability to access medical care services when needed	
	PE5	Smart homes definitely help in independent assisted living	
	PE6	Overall, I think smart homes for health services are extremely useful	
Effort Expectancy	EE1	It is easy and clear for me to use the various smart devices present in my home	[85-87]
	EE2	Using various features and services provided by smart homes is simple and easy to learn	
	EE3	I can operate the smart home devices by myself	
	EE4	It is not difficult for me to use the smart devices present in my home	
	EE5	Overall, I think that using smart homes for healthcare purpose will be convenient	
Social Influence	SI1	I will use smart devices for healthcare in my house if my family members and friends do so	[88-89]
	SI2	I will use smart homes if media/government encourages to use them	
	SI3	People who are important to me will support my use of smart homes for healthcare	
Facilitating Conditions	FC1	I believe proper guidance will be available when using the smart homes for healthcare	[90-91]
	FC2	All my different smart home devices can inter-operate with each other	
	FC3	I believe proper service is available if I face difficulty in using the smart homes for healthcare	
Technology Anxiety	TA1	I have sufficient knowledge and ability to use the smart home services by myself	[92-93]
	TA2	The sophisticated technology behind smart homes makes me feel worried	
	TA3	I am very enthusiastic to learn about computers and new technology	
	TA4	I hesitate using computers and other ICT products for the fear of making mistakes	
Perceived Trust	PT1	I fear to use a smart home service due to loss of my personal data and privacy	[41, 94]
	PT2	The Internet offers a secure medium through which sensitive personal information can be send confidentially	
	PT3	I find it risky to disclose my personal details and health information to the smart home service providers	
Perceived Cost	PC1	The cost of investing into the various smart home products for healthcare are too expensive	[76-77]
	PC2	I need to pay a much lower price for doctor consultation than I have to do for subscribing to smart home services	
	PC3	Purchasing and maintaining a smart home is a burden for me	
Expert Advice	EA1	I trust my doctor's judgement more than the health related suggestions given by my smart home	[95]
	EA2	The experience that the healthcare professionals have likely makes them more accurate and trustworthy than smart systems	
	ES3	I trust my doctor's judgement regarding use of smart homes for healthcare purposes	
	EA4	Doctors and more responsible and intelligent than the smart home systems	
Behavioral Intention	BI1	I will definitely use smart homes for healthcare in the near future	[96-97]
	BI2	Given that I have access to smart home services for healthcare, I would use the services	
	BI3	I intend to invest and use smart home services as much as possible	

TABLE 4. Descriptive statistics of the research constructs.

Construct	Mean	Standard Deviation
Performance Expectancy	4.12	1.24
Effort Expectancy	3.95	0.66
Social Influence	4.01	0.62
Facilitating Conditions	4.13	0.86
Technology Anxiety	3.88	0.75
Perceived Trust	2.68	1.80
Perceived Cost	3.98	0.57
Expert Advice	4.24	1.33
Behavioral Intention	4.06	0.72

C. MATHEMATICAL TOOL

The data that is collected from the online questionnaire survey is analyzed using a Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM) approach to test our research model. CFA is conducted to test the convergent validity of each of the constructs used. The results have been provided in detail in the next section. While conducting the SEM, we have used specifically the Partial Least Square SEM (PLS-SEM) algorithm as it is best suited for exploratory studies like ours where there is less of a theoretical backing to the underlying concepts and hypothesis and where the sample size is small to medium [83], [84].

In case of PLS-SEM the error variables are not part of the model at all; hence they are un-correlated and uncovariated. It is a powerful technique as it assumes that the individual constructs are variated one by one with the rest in the model and the final model fit indices are monitored in the measurement part of the model. Although this technique enables us to create the measurement model, but it does not have any biased parameters for the variables.

TABLE 5. Internal consistency of the used questionnaire.

Construct	No. of Questions	Cronbach's Alpha
Performance Expectancy	6	0.91
Effort Expectancy	5	0.85
Social Influence	3	0.87
Facilitating Conditions	3	0.92
Technology Anxiety	4	0.80
Perceived Trust	3	0.83
Perceived Cost	3	0.82
Expert Advice	4	0.91
Behavioral Intention	3	0.94

TABLE 6. Convergent validity test.

Construct	Item	Factor Loading	Composite Reliability	Average Variance Extracted
Performance Expectancy	PE1	0.858	0.970	0.845
	PE2	0.948		
	PE3	0.946		
	PE4	0.915		
	PE5	0.926		
	PE6	0.920		
Effort Expectancy	EE1	0.932	0.971	0.726
	EE2	0.961		
	EE3	0.917		
	EE4	0.901		
	EE5	0.955		
Social Influence	SI1	0.925	0.954	0.874
	SI2	0.947		
	SI3	0.933		
Facilitating Conditions	FC1	0.882	0.911	0.774
	FC2	0.881		
	FC3	0.875		
Technology Anxiety	TA1	0.812	0.899	0.689
	TA2	0.838		
	TA3	0.838		
	TA4	0.834		
Perceived Trust	PT1	0.887	0.922	0.798
	PT2	0.904		
	PT3	0.891		
Perceived Cost	PC1	0.835	0.875	0.705
	PC2	0.821		
	PC3	0.862		
Expert Advice	EA1	0.886	0.932	0.775
	EA2	0.900		
	EA3	0.862		
	EA4	0.873		
Behavioral Intention	BI1	0.975	0.967	0.908
	BI2	0.934		
	BI3	0.950		

V. RESULTS

In this Section, we present the details of the results that are obtained from this study. SPSS 17.0 has been used to conduct the Confirmatory Factor Analysis (CFA), while Smart PLS 3.0 is used to test the proposed model and the corresponding hypotheses.

A. TESTS OF VALIDITY

The internal consistency for reliability of the used questionnaire has been measured by using the Cronbach's alpha values and presented in Table 5. For all the constructs that are used, the value of Cronbach's alpha obtained is greater than 0.7 that suggests a high degree of internal reliability [101].

In order to measure the convergent validity, the average variance extracted (AVE) and the composite reliability has been calculated for every construct. This is shown in Table 6. The corresponding factor loading for every construct exceeds the threshold value of 0.60, which is a minimum requirement criterion for the convergent validity test to pass [102]. In addition, for every construct, the value obtained for AVE is greater than the recommended level of 0.5 [103].

We also test for the discriminant/divergent validity in order to check whether the measurements that are not supposed to be related are actually unrelated. The result of the discriminant validity test is reported in Table 7. When examining the discriminant validity, the square root of the AVE for each construct should be greater than the correlational values

TABLE 7. Test for discriminant validity.

	PE	EE	SI	FC	TA	PT	PC	EA	BI
PE	**0.919**								
EE	0.567	**0.852**							
SI	0.668	0.623	**0.935**						
FC	0.525	0.447	0.489	**0.879**					
TA	-0.684	-0.642	-0.439	-0.633	**0.830**				
PT	0.652	0.616	0.525	0.206	-0.176	**0.893**			
PC	-0.719	-0.563	-0.338	-0.164	0.141	0.221	**0.839**		
EA	0.613	0.152	0.484	0.138	-0.121	0.386	0.334	**0.880**	
BI	0.677	0.692	0.586	0.474	-0.620	0.653	-0.730	0.416	**0.953**

TABLE 8. Pls-sem path analysis and test statistics.

Hypothesis No	Hypothesis/Path	Standardized Coefficient (β)	t-Statistics	p-Value	Hypothesis Status
H_1	PE -> BI	0.231	3.539	< 0.001	Supported
H_{2a}	EE -> BI	0.424	5.735	< 0.001	Supported
H_{2b}	EE -> PE	0.742	11.701	< 0.001	Supported
H_3	SI -> BI	0.045	0.729	0.466	**Not Supported**
H_4	FC -> BI	0.023	0.554	0.507	**Not Supported**
H_5	TA -> BI	-0.177	2.775	< 0.001	Supported
H_{6a}	PT -> BI	0.185	2.953	< 0.001	Supported
H_{6b}	PT -> PE	0.228	3.167	< 0.001	Supported
H_7	PC -> BI	-0.338	3.770	< 0.001	Supported
H_8	EA -> PE	0.479	6.327	< 0.001	Supported

between any two constructs. This is exactly what happens in our case as evident from Table 7, where all the diagonal elements (which represent the square root of AVE) have a higher correlation level between any two specific factors. Thus, the discriminant validity test is also sufficed for our model.

In case of PLS-SEM, Tenenhaus. et.al. has provided an alternative way to assess the goodness of fit (GoF) of any research model [101]. The GoF value is calculated with the AVE and R-square values of the structural model as per the formulae given in equation (1):

$$GoF = \sqrt{(averageAVE) \times (average - R^2)} \quad (1)$$

The recommended GoF value should be greater than 0.36 [101], [102]. We obtain a GoF value of 0.78, which shows the validity of the model.

B. HYPOTHESES TESTING

The hypothesis testing has been done in Smart PLS 3.0. For testing the significance level and obtaining the path coefficients, we followed the bootstrapping procedure [103]. In bootstrapping, subsamples are created with randomly drawn observations from the original set of data (with replacement). The sub-sample is then used to estimate the PLS path model. This process is repeated until a large number of random sub-samples have been created (we used a maximum iteration value of 300). Table 8 and Fig. 3 present the results of the research model.

Results show that all the hypotheses except H_3 and H_4 are supported and have a high level of statistical significance of $p < 0.001$. For each path, if the value of the β- coefficient is greater than 0.30, it indicates a strong impact on the dependent variable. Thus, for our case, relationships proposed by hypotheses H_{2a}, H_{2b}, H_7, and H_8 have a strong effect size, while the hypotheses H_1, H_5, H_{6a}, and H_{6b} have a moderate effect. EE, PT, and EA account for 73.6% of the variance in PE collectively, whereas PE, EE, PT, TA, and PC account for 81.4% of the variability in BI.

VI. DISCUSSIONS

In this study, we applied an extended UTAUT model to determine the elderly users' intention to use the smart homes for healthcare purpose in an Asian context. The analysis yielded eight significant predictors as a part of our research model, with 81.4% of the total variance being explained by the final measured construct BI. This indicates a strong predictive power of the model. The results also offer various useful insights into the acceptance behavior of the smart homes for healthcare among the elderly people.

A. THEORETICAL IMPLICATIONS

Previous research in the domain of smart healthcare systems, found PE to be a significant predictor of the actual system usage intention. For example, findings by authors in [62] and [104] reveals PE to be the most significant predictor of BI. However, the results that we obtain are quite different from the previous findings. In our case, although PE has a contribution to BI, the effect of EE on the actual system usage is far greater than PE. This variation can be attributed to the unique elderly population that we consider for this research. With an increase in age, there is a decline in the cognitive capability of a person in terms of the speed of information processing [79]. These group of people tend to use certain heuristic algorithms as a part of their decision

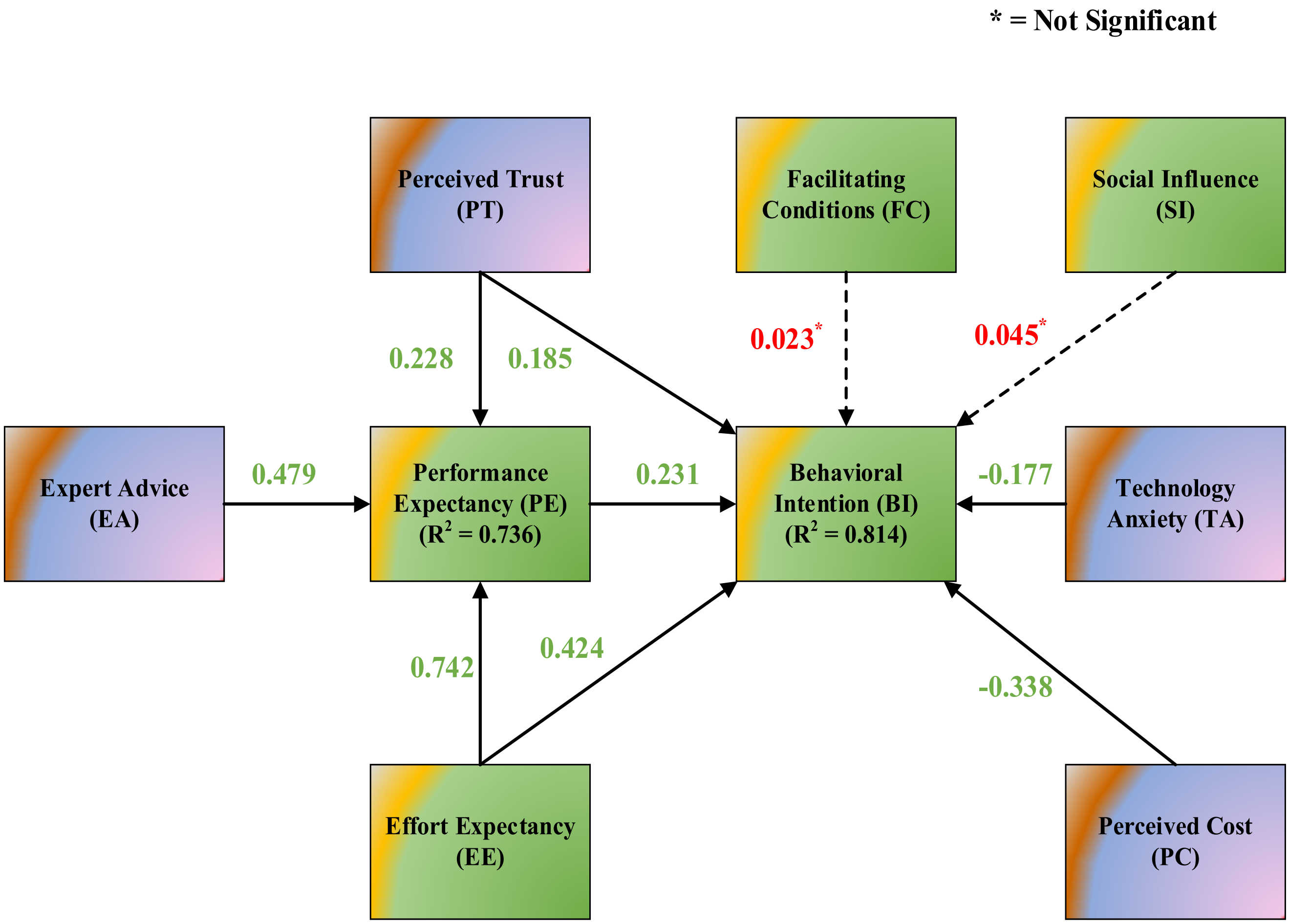

FIGURE 3. Summary of our research model.

making process [79]. Hence, for them the level of effort that goes into learning any new technology or service far outweighs the perceived benefit and overall usefulness of the system.

The effect of expert advice (EA) has not been taken into account in any previous research of smart healthcare systems. A moderately high β value of 0.479 indicates a significant role played by EA as a part of the overall research model. The elderly users tend to rely a lot on the diagnosis and advice from experts like doctors, pharmacists, etc. rather than relying on the smart systems alone. Therefore, assurance from the experts about the real benefits and advantages of using the various smart solutions for healthcare will definitely improve the system acceptance.

Perceived trust (PT) is another important construct that affects the entire system usage. The older users' are extremely concerned and sensitive about the privacy and security of the health data that the smart homes can collect. In addition, they worry about the data anonymity, meaning that they are reluctant to share their private health data with their close friends and relatives. This important factor must be kept in mind by the smart home service providers for healthcare, because they must be able to provide independent technical support and advice in real time to its customers. This can be done by opening of call centers and dedicated hotline numbers that can provide the elderly people with customized help as and when needed.

Quiet strangely, the effect of social influence (SI) on BI was found to be non-significant. This observation is in sharp contrast to the findings by the original UTAUT model and also by other researchers, where SI plays a significant role in determining the intention to actually use a system [46], [49], [59], [62], [63]. This means that the elderly users'' do not bother about the opinions from their peers, social status or other societal pressures and are more motivated to derive an emotional meaning from their life, rather than expanding one's horizon [105]. Non-significance of SI can also be attributed to the perceived trust PT construct that we discussed before. Since, the elderly users' want more data security and anonymity, hence they perceive the external social environment around them as a source of potential threat and thereby reluctant to share their personal sensitive health data with peers, friends or relatives. Thus, we find the effect of SI on BI to be non-significant.

The effect of facilitating conditions (FC) on BI is also non-significant. This observation is quiet surprising as previous studies have reported a positive relationship between FC and BI in technology adoption [59], [62], [64]–[66]. We attribute this fact, to the unique characteristics of the elderly population. Inherently, the elderly people tend to rely less on technology [43], [44]. IoT in general and the context of smart homes providing health support is a relatively new idea, the underlying technologies for which are still evolving. Consequently, the aged people perceive the current smart home technologies and services to be immature and in an early developmental state, due to which FC has a non-significant effect on the BI.

Technology anxiety (TA) affects BI in a negative way, as proposed by our hypothesis and established by previous research [67]–[70]. The elderly people are more resistant to changes and they prefer to use healthcare services as they have been doing so in the same manner without any radical changes.

Perceived cost (PC) is another major factor that affects the behavioral intention in a negative way. This implies that a high cost of smart home implementation can inhibit the elderly people to invest in such a service. The psychological mindsets of the elderly people are different from the early adopters of any new technology to whom a high price can be a less important factor [106]. Thus, the smart home device manufacturers must consider cost to be an important factor if they want the smart homes to be widely used by the elderly people for healthcare purpose.

B. METHODOLOGICAL IMPLICATIONS

This research provides a number of important insights into the acceptance behavior of smart homes for healthcare among the elderly people. There is very limited research towards acceptance modelling of smart homes for healthcare, as the major thrust lies on the underlying technological aspects rather than the psychological viewpoint of the users [15], [46]. This is the core essence of the research where we provide a theoretical framework to measure the perception of a non-existent service on a commercial scale among the elderly people.

C. MANAGERIAL AND POLICY IMPLICATIONS

The elderly people belong to a special age group and therefore there are certain factors, which are unique to them. In order to increase the adoption rates, the manufacturers should focus on designing systems that are simple to operate. This can be in the form of easy to understand user-interfaces or simple hardware actions that can trigger a specific function. While designing smart homes for the elderly, the focus should be on usage simplicity rather than various system functionalities. In addition, large-scale investments have to be made in the form of data centers and big data analyzing solutions that can track the smart home residents' lifestyle and provide them with the right type of health information when needed in a timely fashion. These recommendations should serve as a baseline for the various smart home stakeholders that will increase its chances of adoption by the elderly people.

VII. CONCLUSION, LIMITATIONS AND SCOPE OF FUTURE WORK

This is the first empirical study that assesses the intention of the elderly people to use smart homes from a healthcare perspective, which are still in an early stage of diffusion. In order to properly understand the elderly intention, we first conducted an in-depth literature review and identified five different healthcare scenarios on which current research focus upon. Nine constructs are then identified which are used to build our research model based upon the UTAUT framework. The model that we propose and validate is exclusively associated with the elderly people and includes features that are unique to such a population. The empirical results show that our framework has a good explanatory power with a R^2 value of 81.4%. This implies that the integration of UTAUT along with our proposed constructs is able to create a useful theoretical framework to explain the usage intention of smart homes among the elderly in a health context.

One of the limitations of our research is we measured the usage intention of a service that is currently not available on a commercial scale (future service). Therefore, this research should be followed up by further investigations into the actual acceptance of the system usage (the step following BI).

The issue of data privacy and overall trust in the smart home services for healthcare is an important factor that needs a more detailed analysis. More threat factors (if any) should be identified and subsequently a threat/risk model can be created that will enable the various smart home stakeholders to create better strategies and policies which can ensure a greater success of these services.

Another limitation of this work is the geographical distribution of the elderly subjects. All the elderly people are from India, Thailand, Indonesia, and Malaysia. However, more number of elderly people from across the globe should be included in order to test for any significant differences in opinion. In addition, we can extend our current findings by investigating the moderating effects of gender, cultural background, etc. that will be undertaken as a part of future work.

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