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HYBRID PLS-ANN APPROACH FOR SMART HOME HEALTHCARE SERVCIE ADOPTION PREDICTION: A HOUSEHOLD CASE STUDY

O.M. Almutairi [1] M.N. Yusoff [2] A. Mahmud [3] A.A. Bahaddad [4]

1. Computer Science Department, Shaqra University, Shaqra, Saudi Arabia, oalmutairi@su.edu.sa
2. School of Computer Sciences, Science University of Malaysia, Penang, Malaysia, najwadi@usm.my
3. Faculty of Sciences and IT, Daffodil International University, Dhaka, Bangladesh, arif.cse@diu.edu.bd
4. Faculty of Computing and IT, King Abdul-Aziz University, Jeddah, Saudi Arabia, dbabahaddad10@kau.edu.sa

Abstract- The healthcare industry is undergoing a paradigm shift, with a greater focus on preventative measures. The use of smart technology in health care is giving rise to new tools for monitoring vital signs in the general population. Citizens' acceptability and willingness to pay for mobile health technology is a widely disputed topic in the literature, particularly when the services offered are preventative rather than curative. The current healthcare and support systems are facing challenges due to the tremendous growth of the elderly population across the globe. This area has quickly become the leading option for the Internet of Things (IoT) and associated technologies. The healthcare industry is undergoing a sea change as traditional systems embrace new technology to become smart healthcare ecosystems. Nevertheless, achieving its broad acceptance remains an aspirational goal. The purpose of the proposed investigation was to identify the crucial factors that influence people's intentions to use smart healthcare services. The research model was developed by using the expanded diffusion of innovation (DOI) model with several external factors. The suggested model was tested using a multi-analytical technique, namely a partial least square (PLS)-artificial neural network (ANN). The findings of the hybrid analysis revealed that the most essential aspect for people to embrace SHHS is perceived relative advantage. Other factors such as innovativeness, perceived risk, compatibility, and privacy also influenced the behavioral intention of SHHS adoption. This research delves further into the theoretical, practical as well as methodological contributions of the SHHS in Saudi Arabia. Finally, the limitations of current findings and future research paths are highlighted.

Keywords: Smart Home Healthcare, Partial Least Square, Artificial Neural Network, Hybrid Approach, Adoption of Smart Healthcare Service.

1. INTRODUCTION

"Smart home health care" refers to residential health care that uses ubiquitous computing and IoT technologies [1]. Moreover, Smart homes provide options for pleasant and secure living; they additionally help the elderly and handicapped by improving their quality of life and extending their independence at home. Such technologies offer an amazing infrastructure for healthcare reasons, allowing the aged and handicapped to get certain available healthcare treatments in the comfort of their own homes [2]. Recently, there have been cases of developed countries utilizing healthcare in smart homes and planning to utilize more SHHS in the future. SHHS has already been used in advanced nations, such as the United States, the United Kingdom, Japan, and Europe, to enhance healthcare delivery. For instance, in the United States, firms such as Philips, Qualcomm, and AT&T have built smart home healthcare mechanisms that track patients' health information and transfer the data to medical care experts. In Japan, Fujitsu has launched an app that utilizes AI to track the health situations of elderly patients and inform healthcare experts of any abnormalities. In Europe, tech companies such as Tunstall, Vodafone, Epworth, and Telstra have launched SHHS, which tracks patients' situational signs and medical improvements. These examples demonstrate how developed countries have already embraced SHHS and how they are planning to utilize more SHHS in the future.

However, this is clear evidence of insufficient utilization of SHHS's applications in the undeveloped world, especially in Saudi Arabia, where SHHS remains limited research. Figure 1 displays the changes in Saudi Arabia's population age groups (in thousands) from 1950 to 2050 [3]. There has been a noticeable acceleration in the growth rate of the age groups 60–79 and 80+. Throughout the years 1950-2015, this percentage stayed around 5%. But from now to 2050, it will grow significantly. Compared to the growth of elderly population of Saudi Arabia, the healthcare sector is advancing swiftly; consequently, there is an urgent need to embrace SHHS to enhance medical care services. Thus, it is essential to look at the causes of the limited adoption of home IoT technologies and related SHHS.

In the Saudi Arabian context, SHHS can also enhance healthcare performance by enabling patients to access personalized healthcare services. Personalized healthcare

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services enhance patients' medical performances by matching healthcare services to the specific medical requirements of each patient. SHHS can assist patients by rendering personalized healthcare services, like medical management, disease management, and healthcare consultation that improves patients' health conditions. Smart home devices constitute a substantial portion of the consumer Internet of Things (IoT) market, but they come with inherent security risks. Security becomes a critical consideration when deploying networks on a large scale.

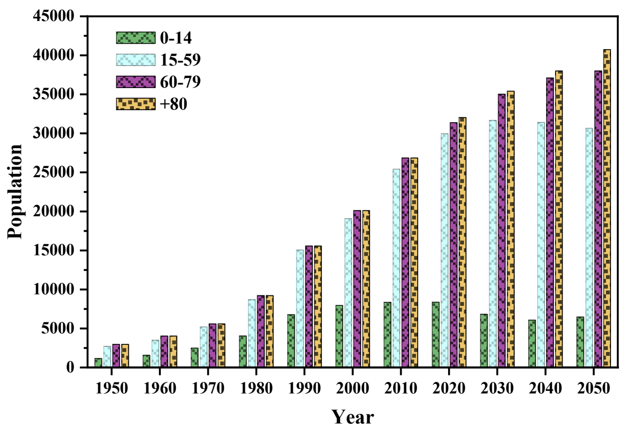

Figure 1. Generational distribution of Saudi Arabians in thousands

However, privacy and security apprehensions serve as significant obstacles to the widespread adoption of Smart Home Technology (SHT). In the realm of IoT-based healthcare systems, which handle data directly linked to individuals, even information collected innocuously from wearable sensors becomes susceptible to notable privacy concerns [4]. SHHS adoption rates in Saudi Arabia are still low, notwithstanding the potential advantages of SHHS technologies. There are many factors that contribute to the low adoption rate, including privacy and security concerns, lack of trust in technology, perceived risk, lack of awareness and education, and complexity of technology.

Because smart healthcare services are still in their early stages of commercialization, there is a lack of study exploring the individual's purpose for the adoption of SHHS, despite the functionality and large projected advantages. Alaiad and Zhou [5] found that while many individuals were interested in SHHS, only a small percentage actually used smart home technology (SHT) with wearable devices. This finding is consistent with the results of this study. Smart healthcare service providers may benefit much from a better adoption rate of SHT if they can increase awareness of the elements that impact consumers' intentions to embrace SHHS.

Using a novel hybrid research approach, this study analyzes the main elements that impact the choice to adopt SHHS and forecasts people's behavior intention, filling gaps in the previous literature. What makes this study's model unique is that it incorporates elements that have been studied in a limited number of studies-perceived privacy, relative advantage, and compatibility-in addition to well-known predictors like perceived innovativeness and perceived risk. Therefore, the purpose of this research was to determine the determinants of SHHS adoption and the relative importance of each. When it comes to predicting people's actions, traditional statistical methods often miss the mark since they only look for linear relationships between variables.

To solve this problem, we used an artificial neural network (ANN) to determine the weight of important variables; these networks are able to deduce complicated nonlinear correlations. Previous studies have failed to adequately forecast the elements that influence people to adopt the SHT, which is the main reason for this study [1]. To remedy this, we want to provide a model that does just that. Applying the PLS-ANN model also helped with understanding the right research procedure and maximizing the advantages of an integrated approach. At last, by explaining the previous works and identifying research gap as well as importance of SHHS in Saudi Arabia we can state the objectives of our study as follows:

- To identify potential factors that influence the behavioral intention of adopting SHHS in Saudi Arabian region.
- To prioritize the key characteristics influencing consumers' intention to embrace SHHS using a hybrid PLS-ANN approach.
- To discuss the acceptability of the analysis and how it can help to implement SHHS theoretically, practically and methodologically.

The paper's structure is organized as follows: The literature review of previous research on the adoption of SHHS is presented in Section 2. Section 3 presents the hypothesis and model developments. Section 4 explains the approach implemented, and Section 5 outlines the results of the study. Section 6 evaluates the ANN analysis. Sections 7 and 8 provide information on both the contributions and limitations. Lastly, Section 9 explains conclusions of the whole study.

2. LITERATURE REVIEW

DOI was developed using similar elements of existing technology acceptance and usage models with comparable roles, as was stated in the previous section. Technology is the most significant factor affecting consumer acceptance of new technologies. The individual consumer's perceptions of the features of SHT can be used to explain their decision to use it [6]. DOI has been used in SHT to describe factors like perceived usefulness, perceived convenience, perceived compatibility, and social influence that affect the consumers' intention to adopt SHHS.

To explain the uptake and spread of technological advances and the forecasting of organizational effects, Rogers and Kim [7] devised the DOI. According to some studies, diffusion of innovation is "the process by which an innovation is disseminated through time, among the members of a social system, using specific channels." The DOI model combines three key elements: the innovation-decision process, adopter characteristics, and features of an innovation. Four components comprise an invention's parts: the creation itself, particular linkages to other things, social norms, time, and system. DOI contains an innovation-decision process, innovation characteristics, adopter characteristics, and opinion leadership.

Rogers, et al. [8] claims that the diffusion of innovation is a procedure wherein innovation is disseminated throughout the members of a social system via particular routes. The adoption rate, correlated with many innovation aspects, determines the dissemination rate. From the perspective of the potential user, the following five attributes of innovation are interconnected: relative advantage, complexity, compatibility, trialability, and observability of innovation. However, observability and trialability were not widely applied in SHT studies.

As seen in previous studies, many studies have used DOI integration in SHT and healthcare service systems. Using a web-based survey to collect data from Finnish homeowners, Nikou [9] employed DOI to empirically examine the factors impacting the adoption of innovative home devices. The results showed that compatibility has an impact on the adoption of SHT. The intention to utilize is significantly impacted negatively by perceived expense. Many authors intend to look at the factors that affect a person's decision to employ IoTHD. According to that research, UTATU and DOI variables may explain behavioral intention. The findings showed that performance expectations are influenced by social influence, technological complexity, and fun.

Some studies implemented a structural equation modeling with ANN in order to foretell what factors will lead to the widespread use of wearable healthcare products. According to the structural equation modeling, factors such as initial trust, health interest, consumer innovativeness, and so on are the most influential in determining the adoption of wearable health devices. In addition, the neural network's output from structural equation modeling revealed that customers' perceptions of the wearable health devices' ease of use is a key predictor of their adoption. Another study was conducted by Bettiga, et al. [10] where the data was examined using structural equation modeling, a technique that may estimate the interdependent dependencies of the constructions in a single study. They demonstrated that the propensity to pay for smart health care technologies for preventative purposes is directly affected by social influence and perceived utility. Contrarily, it seems that perceived ease of use cannot increase willingness to pay on its own, but it does promote adoption. Additionally, the Table 1 below summarizes the works conducted on relevant fields of smart healthcare.

Table 1. Previous studies on SHHS adoption

Author	Method of analysis	Survey sample size	Key features
Rehman, et al. [11]	SEM-ANN dual stage	473	Investigate what influences customers' plans to use wearable smart health devices and offers a model that has been tested and shown to be 64.5% accurate in predicting their actions
Pan, et al. [12]	Technology transfer adoption	484	Investigates the motivation of doctors to use smart healthcare services by means of an expanded TAM rooted on a technology transfer viewpoint. Reframes the antecedents of TAM features, builds a theoretical framework from the viewpoint of technology transfer, and uses survey data to empirically support those constructs
Bettiga, et al. [10]	Structural equational modelling	212	Provides novel perspectives on the factors influencing the use of smart technologies for preventative mHealth, a rapidly expanding area of study that will occupy the attention of tech entrepreneurs and healthcare administrators
Alzawamri, et al. [13]	Combination of UTAUT, PCT and TAM	279	Results in the creation of a meticulously organized survey on the adoption of smart cities related to privacy issues, which is the first of its type in the health sector in Oman
Potnis, et al. [14]	Extended UTAUT	300 ~ 350	Focuses on the adoption of wearable technology in healthcare with some innovative factors like facilitating conditions, social influence, performance expectancy
Chau, et al. [15]	PLS-SEM	310	Helps to clarify how users' adoption intentions are formed in relation to healthcare wearable devices, which in turn helps managers and developers to implement more effective business development strategies for boosting users' adoption intentions
Ganji and Parimi [16]	ANN based predictive model	Selective survey	Conducted specially based on COVID-19 pandemic and aims to assess the rising need for healthcare systems, digital technologies, and the internet of things (IoT), particularly in the context of pandemics

3. HYPOTHESES AND RESEARCH MODEL

3.1. Hypotheses

Numerous studies have consistently shown that behavioral intentions are the most reliable predictors of actual behavior. Smart home technology is still in its infancy in terms of acceptance; hence this research chose to focus on behavioral intention rather than actual usage as a dependent variable for SHHS adoption.

3.1.1. Innovativeness (INV)

According to Rogers and Shoemaker [17], a creative person is one who is relatively earlier in adopting new ideas than the average member of his social system. Individuals' propensity and readiness to be attracted by novel goods and technologies was defined by Steenkamp as INV. Prior research has shown that INV has a significant impact on BI. Users who score higher on the innovativeness scale are better equipped to deal with uncertainty and are more likely to intend to embrace new technologies. New products, services, or technology use BI is impacted by innovativeness, according to another research. The current users of smart health technology are likely to be early adopters due to the novelty of the technology; hence, INV may have a significant role in the intention to adopt. The lack of perceived innovation regarding SHHS in the Saudi Arabia healthcare sector significantly contributes to SHHS's low adoption. However, the Saudi Arabian healthcare industry is perceived to be conventional that is resisting technological change. Therefore, we postulate that, in the planned investigation.

- H1: Innovativeness influences the acceptance of the Behavioral intention.

3.1.2. Privacy Concern

One of the primary factors for the low adoption of SHHS in Saudi Arabia is privacy and security anxieties. Patients are reluctant to share their personal health information with healthcare professionals because of fears of data breaches or misuse in Saudi Arabia. According to Alshammari, et al. [18], privacy and security apprehensions are one of the primary hurdles to the low adoption of e-health services in Saudi Arabia. The research discovered that patients are anxious about the privacy of their private health data and the likelihood of it being retrieved by unauthorized private. According to various survey outcomes, 79.7% of respondents express apprehension regarding privacy and security regulations. The findings reveal that 78.8% of participants harbor anxieties about utilizing smart home devices to access private data and monitor user behavior. Public awareness and functionality levels are persistently at the forefront of users' concerns. In general, user privacy emerges as a significant worry, stemming from their perceived inability to control personal and private information. Hence, we construct our hypothesis as below:

- H2: PC influence the acceptance of the Behavioral intention.

3.1.3. Perceived Compatibility

Rogers, et al. [19] defines compatibility as "the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters." According to many authors, consumers' behavioral intention for technology adoption is significantly impacted by compatibility, which is seen as a key component for innovation uptake. Knowledge sharing, mobile payment, adoption of e-learning, and mobile commerce are just a few areas where further research has shown that compatibility significantly impacts BI. Thus, compatibility was defined in this research as the extent to which SHT are functionally compatible with other items. However, we emphasize that:

- H3: PCO influence the acceptance of the Behavioral intention.

3.1.4. Perceived Risk

Additionally, the perceived SHHS risk hampers the adaptation of SHHS in Saudi Arabia. According to a study by Arfi, et al. [20], perceived risk is one of the main hurdles hampering the adoption of SHHS services. The study found that patients are concerned about the potential harm that may result from using SHHS, such as incorrect diagnosis or treatment. Adoption and usage of healthcare IT by doctors is also fraught with danger and uncertainty. When it comes to smart healthcare, physicians could be hesitant to explore new services if their perceived risk makes patients feel bad. Previous consumer behavior empirical research has provided support for the hypothesis of a negative correlation between PR and attitude. Hence, we hypothesise that:

- H4: PR influence the acceptance of the Behavioral intention.

3.1.5. Perceived Relative Advantage

In the context of SHHS adoption, perceived relative advantage refers to an individual's assessment of the superiority of a new technology over existing alternative. Many authors highlight that individuals are more inclined to adopt innovations when they perceive them as offering significant advantages compared to established practices. Perceived Relative Advantage (PRA) is a key construct influencing Behavioral Intention (BI) in the adoption of innovations. Users are more likely to express an intention to adopt when they perceive the new technology as superior, efficient, and providing clear benefits. Studies, including the Diffusion of Innovations (DOI) model, have consistently found that the perceived relative advantage strongly influences the behavioral intentions of individuals. In the context of smart health technology adoption, the perceived relative advantage would manifest in terms of improved healthcare outcomes, enhanced efficiency, and convenience. In Saudi Arabia's healthcare sector, the low adoption of Smart Home Healthcare Services (SHHS) can be attributed to a perceived lack of relative advantage, suggesting that potential users may not see clear benefits that outweigh traditional healthcare practices. Overcoming this perception hurdle is vital for fostering greater acceptance and utilization of SHHS in the Saudi Arabian healthcare landscape. Thus, we develop a hypothesis as follows:

- H5: PRA influence the acceptance of the Behavioral intention.

In order to investigate the elements that impact, the research model for the proposed study has been constructed, as shown in Figure 2.

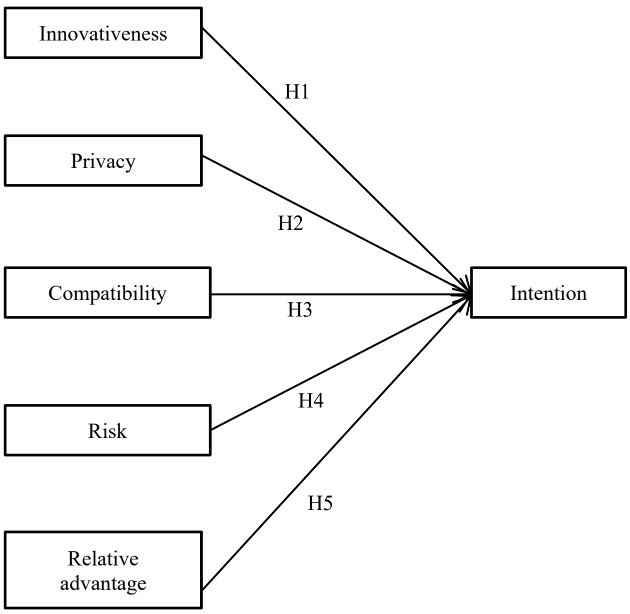

Figure 2. Research model

4. METHODOLOGY

4.1. The Multi-Analytical PLS-ANN Approach

This research used a two-pronged multi-analytical strategy, including analyses using both artificial neural networks (ANNs) and partial least squares (PLS). We used the PLS to examine our suggested conceptual model with the help of the SmartPLS tool (version 3.3.3). This allowed us to evaluate our research hypotheses and determine the factors that influence the adoption of smart home healthcare services. Nevertheless, the PLS was used to confirm variables that significantly impact SHHS adoption in the first stage of the research. later on, in the second phase, we used ANN analysis to provide more precise predictions of important elements influencing SHHS uptake. Users' decisions to embrace new technologies may be complicated, and the PLS technique, which relies only on statistical modeling for the liner model, can oversimplify this process. To address this issue, we examined the linear and nonlinear relationships between adoption variables and the choice to embrace wearable health technology using the ANN analytical technique. More accurate predictions compared to conventional regression methods are also achievable with the help of ANN. Further comprehensive understanding and substantial methodological contribution from an analytical standpoint can be obtained by the two-stage PLS-ANN technique, which is a predictive analytical approach.

4.2. Data Collection

Using an expert sampling variant of the purposive sampling approach, data was gathered from Saudi Arabian respondents. Respondents from public universities and contracting and trade firms were contacted online for the study. Individuals were also contacted via their social media connections to distribute the surveys. Respondents in several cities in Saudi Arabia, mostly Riyadh, were also sent hard copies of the poll. The correct sample considerations for PLS and ANN approaches are necessary since this work employs a PLS-ANN methodology. In least squares multiple regression, Stevens (2002) suggests using 15 examples per predictor construct. Our hybrid PLS-ANN models were able to employ a sample size of 274, which is sufficient. The respondent characteristics are given below in Table 2.

Table 2. Respondent's characteristics

Factors	Frequency (%)
Gender	
Male	57.65
Female	42.35
Age	
≤ 25	29.04
26-40	65.37
≥ 41	5.59
Education	
University	81.14
College	5.09
Higher degree	14.77
Occupation	
Professionals	6.18
University students	79.59
Researchers	14.23

4.2. Data Preparation

Using SPSS version 26, missing data, common method variance, and outliers were evaluated. There was no risk from common method variance, as shown by the figure of 37.876% that Harman's single factor produced. On the other hand, information was gathered utilizing online forms that needed to be fully filled out by the user. Therefore, the lack of data did not present any problems. However, the effect of outliers was reduced by maintaining a small difference between the original mean and the 5% trimmed mean.

Table 3. Validity and reliability

Variables	Items	Factor loading	Variance inflation factors	Composite Reliability	Average Variance Extracted
Behavioral Intention	BI1	0.908	3.186	0.924	0.754
	BI2	0.927	3.865		
	BI3	0.888	2.855		
	BI4	0.736	1.612		
Innovativeness	INV1	0.922	3.727	0.947	0.818
	INV2	0.852	2.443		
	INV3	0.923	3.771		
	INV4	0.919	3.987		
Privacy Concern	PC1	0.902	3.544	0.947	0.818
	PC2	0.938	4.853		
	PC3	0.923	4.659		
	PC4	0.852	3.074		
Perceived Compatibility	PCO1	0.919	4.000	0.943	0.805
	PCO2	0.913	3.850		
	PCO3	0.912	3.553		
	PCO4	0.842	2.038		
Perceived Risk	PR1	0.931	4.776	0.970	0.891
	PR2	0.942	4.386		
	PR3	0.954	4.224		
	PR4	0.948	4.911		
Perceived Relative Advantage	PRA1	0.876	2.707	0.943	0.805
	PRA2	0.913	3.922		
	PRA3	0.908	3.931		
	PRA4	0.893	2.946		

5. RESULTS

5.1. Assessment of Measurement Model

The measuring model of the constructs was tested for appropriate validity and reliability using a two-step approach. Composite reliability (CR), average variance extracted (AVE), factor loading, and variance inflation factors were used to assess the validity and reliability of constructs. Table 3 shows that the factor loading for the constructs varied between 0.736 and 0.954, which is higher than the suggested score and over the acceptable range of 0.5. Every single one of the constructs had CR scores higher than the cutoff of 0.70, and their AVE values were higher than the recommended 0.5.

The guidelines, an evaluation of discriminant validity was conducted. According to this method, the squared correlation of a variable cannot be larger than its average extracted variance. To determine discriminant validity, the square root of AVE was used. The results demonstrated that the square root of AVE was higher than the correlations between this construct and the other constructs, approving the constructs' discriminant validity. Table 4 displays the discriminant validity of the measurement items. Given these evaluation results, the measurement model for reliability and validity construction was found to be acceptable and to meet the recommended values.

Table 4. Discriminant Validity

Variables	BI	INV	PC	PCO	PR	PRA
BI	0.868					
INV	0.720	0.905				
PC	0.124	0.150	0.904			
PCO	0.666	0.692	0.040	0.897		
PR	0.142	0.253	0.832	0.052	0.944	
PRA	0.790	0.753	0.128	0.704	0.191	0.897

5.2. Assessment of Structural Model

In the second phase, after confirming the measurement model's reliability and validity, the structural model should be evaluated. The predictive capacity of the structural model was assessed using the coefficients of determination (R^2) and predictive relevance (Q^2) as shown in Table 5.

Table 5. R^2 and Q^2

Variables	R Square	R Square Adjusted	Q Square
BI	0.674	0.668	0.491
INV	0.088	0.085	0.070
PC	0.662	0.661	0.525
PCO	0.022	0.018	0.014
PR	0.701	0.700	0.618
PRA	0.041	0.038	0.030

When effects have values larger than or equal to 0.35, 0.15, 0.02, and 0.01, respectively, they are categorized as considerable, medium, minor, and very little effects. According to the data tabulated in Table 6, two relationships have a considerable impact, one medium, five minor, and two very little effects.

Table 6. Effect size

Relationships	F^2 values	Remarks
INV → BI	0.073	Minor effect
PC → BI	0.014	Very little effect
PCO → BI	0.021	Minor effect
PR → BI	0.015	Very little effect
PRA → BI	0.298	medium effect
PS → INV	0.096	Minor effect
PS → PC	1.959	Considerable effect
PS → PCO	0.022	Minor effect
PS → PR	2.340	Considerable effect
PS → PRA	0.043	Minor effect

Table 7 displays the results of the structural model evaluation for the hypotheses. This study found evidence for five of the five hypotheses put forth for consideration. Each of the hypotheses of the model is significant as per Table 7. Innovativeness, privacy, compatibility, risk, and relative advantage are the factors that influence intention. Figure 3 also depicts the results of the structural model.

Table 7. Hypotheses Results

Hypotheses	Relationships	Original Sample (O)	Sample Mean (M)	Standard Deviation (σ)	T Statistics	P Values	Remarks
H1	INV → BI	0.259	0.262	0.065	3.983	0.001	Significant
H2	PC → BI	0.124	0.125	0.063	1.973	0.049	Significant
H3	PCO → BI	0.126	0.125	0.056	2.239	0.026	Significant
H4	PR → BI	-0.132	-0.133	0.054	2.429	0.015	Significant
H5	PRA → BI	0.515	0.513	0.063	8.153	0.001	Significant

6. ANALYZING PROPOSED MODEL BY ARTIFICIAL NEURAL NETWORK (ANN)

Conduct the ANN analysis, we used a multi-layer perception ANN with input, hidden, and output layers, using the statistical tool SPSS 26. ANNs are big algorithms that can learn new things and apply what they've learned in the future. The synaptic weights, or connection strengths between interneuron neurons, are where new information is stored after learning. The neuron nodes in the hidden layer are able to predict the output node because they learn to make the input layer's nodes seem straightforward.

In an effort to achieve deeper learning, this research used an artificial neural network (ANN) design with two hidden layers for every output neuron. To address the issue of overfitting, we used a ten-fold cross validation method. The neural network model was trained using 90% of the data, and its prediction accuracy was tested using the remaining 10%. We generated the number of hidden layers automatically and utilized the sigmoid activation function for both the hidden and output layers. The validation results are tabulated in Table 8. By analyzing the data, we claim that the forecast is quite accurate and reliable because the data fits the model adequately.

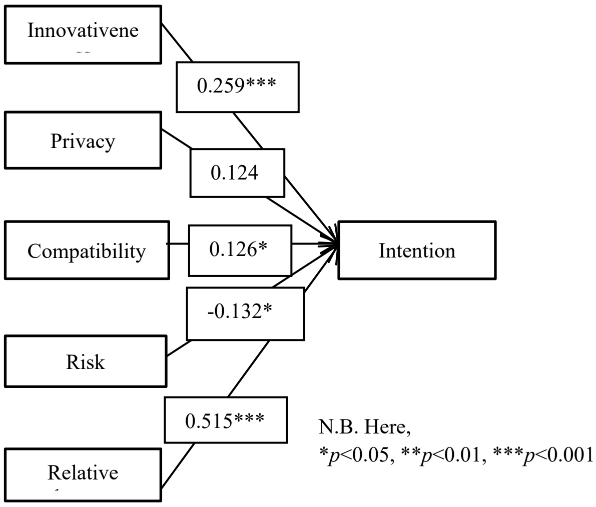

Figure 3. Outcomes of the proposed research model

Table 8. Validation results

N1	SSE	RMSE	N2	SSE	RMSE	N1+N2
248	43.761	0.420	26	3.179	0.350	274
243	43.840	0.425	31	4.308	0.373	274
239	48.214	0.449	35	4.694	0.366	274
245	41.724	0.413	29	5.562	0.438	274
241	36.585	0.390	33	5.404	0.405	274
249	42.554	0.413	25	1.995	0.282	274
246	49.874	0.450	28	3.599	0.359	274
247	46.476	0.434	27	2.157	0.283	274
239	42.530	0.422	35	3.420	0.313	274
246	38.860	0.397	28	3.341	0.345	274
Mean	43.442	0.421		3.766	0.351	
Std. Dev.	4.030	0.020		1.223	0.050	

To assess the strengths of each input neuron's predictive power, we did sensitivity analysis and reported the results in terms of normalized significance as shown in Table 9. According to Table, relative advantage is the most important predictor of intention followed by innovativeness, compatibility, risk, and privacy.

Table 9. Normalized variable importance

	Average importance	Normalized importance (%)
INV	0.26	56.31
PC	0.08	17.01
PCO	0.10	21.56
PR	0.09	20.02
PRA	0.47	100.00

6.1. Comparison between PLS and ANN Model Data

Table 10 compares partial least squares and artificial neural networks to show the relative contributions of each independent variable. The table's rankings of compatibility and risk do not line up. As it is seen, among five factors, the ranking from PLS matched with ANN analysis. However, the ranking of ANN for perceived risk and perceived compatibility didn't align with the ranking obtained from PLS. Unobserved traits may influence how these variables behave. Another defense is that, from a linear perspective, partial least squares cannot adequately capture the relationships between the variables.

Table 10. Comparison between partial least square and artificial neural network

Relationships	$\lvert\beta\rvert$ value	Rank	Normalized Importance	Rank	Remarks
INV → BI	0.259	2	56.31	2	Matched
PC → BI	0.124	5	17.01	5	Matched
PCO → BI	0.126	4	21.56	3	Not matched
PR → BI	0.132	3	20.02	4	Not matched
PRA → BI	0.515	1	100.00	1	Matched

7. CONTRIBUTION (THEORETICAL, METHODOLOGICAL AND PRACTICAL)

From a theoretical standpoint, this study adds to the literature on IT acceptability in several ways. As a first and main point, this research is one of the first to examine the purpose of smart healthcare service customers to accept such services. The authors are unaware of any prior studies that have examined the intent to use smart healthcare services for adoption considering some unique factors like perceived relative importance, perceived compatibility etc. The current research adds to the existing body of theory by using the experience of utilizing SHT as an antecedent to explore its link with consumers' BI on smart healthcare services.

From the point of methodological implication, this hybrid approach introduces a new innovative framework to analyze and correlate the influencing factor and behavioral intention of end users to adopt smart healthcare system. As it is seen from previous studies, most of the study choose technological acceptance model or structural equation model to predict the influence of the factors. Very few studies were conducted which incorporate partial least square with artificial neural network to develop the framework. Thus, this study will open a new door to further enhance and extend the use of this hybrid method in this field. Furthermore, the study's implications lie in its potential to offer more accurate and reliable predictions for the adoption of smart home healthcare services. The PLS approach accurately extract and rank relevant factors, while the ANN enhance the model's ability and make additional relationships in the output data.

Additionally, practitioners might benefit from the practical implications of this research's empirical results. First, healthcare service providers and marketers should prioritize reaching out to physicians who have expertise utilizing mHealth. In order to increase sales of smart healthcare via market segmentation, they can try to forge closer ties with physicians using mHealth. Secondly, in order to attract new customers and increase the market, it is important to identify the main variables that impact the desire to embrace smart healthcare services and to create distinct marketing strategies for physicians in various departments.

8. LIMITATION AND FUTURE WORKS

The fact that we were able to recruit residents only in Saudi Arabia (Riyadh) further limits our ability to draw conclusions about global trends in technology and culture. Therefore, it is crucial to examine the findings in other nations. Consequently, this research will also be carried out as a comparative study of smart home technology adoption across different nations. Furthermore, additional individual-level antecedents for SHT adoption, such as UTAUT, SEM, and TPB, could not be included in this research. Thus, researchers may use another theory of adoption to explore SHT predictors in the future.

9. CONCLUSIONS

The study's overarching objective was to identify possible factors of consumer adoption of SHHS and rank them in order of importance. An individual's intention for the adoption of smart healthcare technology in Saudi Arabia's Riyadh city was explored within the model that postulated the casual association of consumer innovativeness, privacy concern, perceived compatibility, perceived risk, perceived relative advantage. As stated in second objective, the findings of the partial least square (PLS) revealed that the most important aspect for people to embrace the SHHS is perceived relative advantage. As for the second important aspect influencing consumers' intentions to embrace the SHT, it was determined to be consumer innovativeness. Previous research on the topic of healthcare wearable technology found that customers' propensity for innovation might potentially boost their desire to purchase health technology. According to the PLS analysis, the perceived risk is the third important component. When consumers perceive more danger, they are less likely to be interested in or make plans to use new SHT.

However, from the results of the analysis it can say that, professionals may get something beneficial from the real-world consequences of the findings. This study also makes good impact on theoretical and methodological contribution as well which fulfil our third objectives. In addition, organizations may take use of the potential opportunities presented by the suggested research to alter the new product's characteristics in response to mixed reviews and increase its adoption. The hybrid approach offers more profound insights when both linear and non-linear relationships are present in the model. By weighing the relative relevance of each substantial construct, the method ranks the elements that impact behavioral intentions to adopt smart healthcare technology. Statistics pertaining to the implementation and maintenance of SHT may benefit from the PLS-ANN hybrid method, which represents a novel statistical analytical strategy. This research gives practitioners and manufacturers crucial advice about the features and characteristics of healthcare systems based on the study's results.

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BIOGRAPHIES

Name: **Omar**
Middle Name: **Mutheeb**
Surname: **Almutairi**
Birthday: 28.10.1984
Birthplace: Riyadh, Saudi Arabia
Bachelor: Computer Science, Computer Science Department, Umm Alqura University, Mecca, Saudi Arabia, 2007
Master: Advanced IT, School of IT, QUT University, Brisbane, Australia, 2016
Doctorate: Department of Computer Science, Science University of Malaysia, Penang, Malaysia, 2021
The Last Scientific Position: Academic Lecturer, Computer Science, Shaqra University, Shaqraa, Saudi Arabia, Since 2013
Research Interests: Internet of Things, Healthcare Technologies, Cybersecurity
Scientific Publications: 2 Papers

Name: **Mohd Najwadi**
Surname: **Yusoff**
Birthday: 03.06.1987
Birthplace: Penang, Malaysia
Bachelor: ICT, Faculty of Technology and Information Science, Petronas University of Technology, Perak, Malaysia, 2009
Master: School of Computer Science, Science University of Malaysia, Penang, Malaysia, 2011
Doctorate: Security in Computing, Faculty of Computer Technology and Information Technology, University of Putra Malaysia, Selangor, Malaysia, 2016
The Last Scientific Position: Senior Lecturer, Computer Science, Science University of Malaysia, Penang, Malaysia, Since 2013
Research Interests: Cyber Security, Cyber Threat Intelligence (AI), Blockchain, Quantum Cryptography, Software Vulnerabilities
Scientific Publications: 14 Papers
Scientific Membership: Research Center of Science University of Malaysia, Malaysia Board of Technologists (MBOT)

Name: **Arif**
Surname: **Mahmud**
Birthday: 23.04.1984
Birthplace: Dhaka, Bangladesh
Bachelor: Computer Engineering, Department of Computer Engineering, American International University, Dhaka, Bangladesh, 2004
Master: Computer Engineering, School of Computer Engineering, Mid Sweden University, Sundsvall, Sweden, 2009
Doctorate: School of Information Systems, Science University of Malaysia, Penang, Malaysia, 2023
The Last Scientific Position: Assist. Prof., Computer Science, Daffodil International University, Dhaka, Bangladesh, Since 2011
Research Interests: Privacy, Internet of Things, Healthcare Technologies, CyberSecurity
Scientific Publications: 14 Papers

Name: **Adel**
Middle Name: **Aboud**
Surname: **Bahaddad**
Birthday: 01.07.1976
Birthplace: Jeddah, Saudi Arabia
Bachelor: Computer Science, Computer Science Department, King Abdul-Aziz University, Jeddah, Saudi Arabia, 2002
Master: IT, School of Information and Communication Technology, Griffith University, Gold Coast, Australia, 2011
Doctorate: School of Information and Communication Technology, Griffith University, Gold Coast, Australia, 2017
The Last Scientific Position: Assist. Prof., Computer Science, King Abdul-Aziz University, Jeddah, Saudi Arabia, Since 2008
Research Interests: Technology Adoption, Internet of Things, Healthcare Technologies, CyberSecurity
Scientific Publications: 20 Papers