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DEVELOPING A MODEL OF SMART HOME USAGE AMONG IT SPECIALISTS: THE ROLE OF MACHINE LEARNING

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Models of smart home usage dominate in developed countries, while in developing countries, they are still lacking. Technology Acceptance Model (TAM) is widely used in the context of smart home, and few studies examined other technology acceptance theories. The purpose of this study is to examine the experience of using smart home by Information Technology (IT) specialists in the Gulf Cooperation Council (GCC). The study deploys existence theories and proposes that the effect of relative advantage, convenience, accessibility, and cost on the intention to use smart home is positive. In addition, it was suggested that intention to use, as well as facilitating condition, directly affects the actual use of smart home. The knowledge of machine learning was proposed as a moderator between intention to use and actual use. The data were collected from IT specialists in the GCC using purposive sampling. The analysis was conducted using the Analysis of moment structures (AMOS). The findings showed that convenience, accessibility, and relative advantage have a positive effect, while cost has a negative effect on the intention to use smart home. The intention to use and facilitating condition affected positively the actual use. Knowledge in machine learning moderated positively the effect of intention to use on actual use. Decision makers are recommended to enhance the benefits of using the Internet of Things smart home and create a customized plan to enable using smart home at all levels. The knowledge of machine learning is critical for smart home usage, and customized courses in this regard are critical to boost the usage of smart home

Keywords: GCC, Internet of Things, relative advantage, smart home, technology acceptance model

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1. Introduction

The Internet of Things (IoT) represents a fundamental transformation in how people interact with technology in their everyday lives, as well as in all facets of commerce and education. Its growth throughout the preceding decade has resulted in significant shifts in both personal and professional practices. It has the potential to link everything and anybody, at any time and in any location, and it spawns the development of new and creative applications and services [1, 2]. IoT has been referred to by its proponents as a "new industrial revolution" that will lead to an increase in productivity and a healthier population, an improvement in public transportation and a reduction in energy consumption, as well as a solution to the climate change problem, increased security and safety, and the achievement of more sustainable production and consumption [1–3].

IoT is a system that connects physical items, software, and hardware so that they can communicate with one another. This indicates the increasing importance of machine learning and the integration of this technology with the IoT to enhance the effectiveness of services provided by the IoT [4, 5]. The IoT was implemented in a variety of domains, including industry, manufacturing, healthcare, and other areas. When compared to other industries, the IoT is used less in smart homes (SH) [6–8]. The integration between SH and machine learning is a promising field [9] because it can enhance the services and the monitoring of the home, and is also important for healthcare application in the home, reducing energy consumption, and observing the behavior of the inhabitants [1, 10, 11].

SH is a new technology that aims to automate household appliances and every tool in the house for the convenience of users [12, 13]. Knowledge in machine learning is required for effective management of the SH [14]. Prior literature was more into the adoption by normal users for IoT applications. However, there is still limited adoption of the technology worldwide, and the limitation among individuals is high [15–18]. As a proposed solution, using IT specialists as target respondents can solve the issue of knowledge related to IoT usage. However, privacy and security issues are still critical predictors of IoT SH usage [19–21].

Among the theories related to SH usage are the technology acceptance model (TAM) and unified theory of acceptance and use of technology (UTAUT). However, these theories were highly criticized for not including social and technological factors [22]. An important social factor is the social influence of others on an individual's decision to use the technology. In addition, the usage of SH is costly, and affordability could be a critical factor for the usage. The convenience of using the technology could be a triggering factor for the usage.

Since cost is a determining factor, this study will be conducted in high-income countries. The Gulf Cooperation Council (GCC) is characterized by high incomes of citizens. This group of people can pretty much afford to use SH. However, there are other technical and behavioral factors that might hinder the usage.

Therefore, the study examining the usage of SH by IT specialists in GCC is of interest. Moreover, developing a model that can be used by policy makers in these countries to support the usage of SH by IT specialists in GCC is relevant.

2. Literature review and problem statement

The paper [23] examined the usage of SH. The paper was built upon the idea that users are not effectively utilizing SH. The paper stated that there are several unrevealed factors that deserve further investigation. Similarly, the paper [24] related the issue of SH usage to the privacy and security of the technology. However, the paper did not refer to other factors that might explain the usage of the technology. The work [25] suggested that there is an issue related to the user instruction or the service provider of the SH. The paper [26] agreed with [25] and suggested that the convenience of using the SH has the potential to affect the use of this technology. In both [25, 26], other important predictors were neglected.

Based on the issues identified by prior literature, knowledge of users is one of the main challenges for using SH. The paper [27] suggested that recently, there has been a discernible spike in interest across a very wide variety of application areas in the field of machine learning [27]. In [28], the findings agreed with [27] and referred to the importance of machine learning in the SH environment. Both [27, 28] attempted to solve the issue of using ML from the technical perspective. Similar to them is the study [29], which indicated that algorithms ensure biotechnology-based authentication and authorization, as well as anomaly detection. The paper [30] noted that ML is a subfield of artificial intelligence (AI) that studies the algorithms and statistical models based on patterns and inference that are used by computers to achieve their objectives. The paper [31] pointed out that the use of ML is still limited.

In agreement with [31], the research [32] noted that there is a lack of studies that have used ML to mitigate the risk of security and privacy in the context of SH. The research [33] noted the importance of applying and using ML in this context but also pointed out that there is a lack of studies. The functioning of the system proposed in [34] has been improved by the research [35], which recognizes the context and features of the problems in [33] to gain knowledge from them. The study [35] concluded that ML involves the performance of tasks that call for previously acquired information. These tasks can be categorized as reinforcement learning, unsupervised learning, or supervised learning.

Prior literature discussed above noted that the use of ML in SH is limited. In addition, most of ML studies are technology-based while behavioral studies are still in the early stage. Further, the use of IT specialists as respondents has been examined in limited studies. Therefore, to solve the problem, this study examines the SH and includes the knowledge of machine learning as a moderating variable in the context of SH usage by IT specialists in GCC.

To address the behavioral issue of using SH and ML in the context of IoT, several behavioral theories can be used to explain the usage of IoT SH. These include the TAM, which has variables such as perceived ease of use (PEOU) and perceived usefulness (PU), as well as attitude, which acts as a mediating variable [36]. UTAUT was developed by [37]. The model sums up eight well-established theories to come up with four variables that are performance expectancy (PE), which is similar to PU in TAM, effort expectancy (EE), which is similar to PEOU in TAM, social influence, and facilitating condition. The two models (TAM and UTAUT) were criticized due to the absence of technological and social factors [22].

RA is similar to PU in TAM and PE in UTAUT [37]. Several studies examined the effect of RA in the context of IoT usage. RA was found to have a significant effect on the usefulness and IU IoT [38]. [39] found that RA has a significant effect on the adoption of IoT. Similarly, [40] found that RA is critical for IoT usage. In this research, RA is expected to have a significant effect on the IU IoT SH.

H1: RA affects positively the IU SH.

Convenience is one of the important reasons for using the IoT SH [23]. Few studies examine the impact of convenience on the usage of IoT in general and SH in particular. Convenience is one of the enablers of using the IoT in healthcare [40]. It also positively affects the use of IoT for marketing purposes [41]. In this study, convenience is expected to affect positively the IU SH.

H2: Convenience affects positively the IU SH.

Accessibility is a critical factor for enabling the usage of IoT SH. Several studies referred to the importance of accessibility to encourage users to use IoT applications. Studies found that the accessibility of the technology encourages IoT usage [42]. Accessibility affected positively the usage of IoT technology such as smart board usage [43]. Accessibility is also critical for smart cities, schools and building application and usage [44]. In this study, accessibility is expected to affect the IU IoT. Accordingly, the following is hypothesized:

H3: Accessibility affects positively the IU SH.

Cost is one of the essential factors when deciding whether to use the IoT SH. The study [16] demonstrated a negative correlation between perceived cost and IoT adoption among Korean consumers. The study [45] looked at the impact of cost on IoT adoption and found that cost is in fact influential in the decision to use the IoT. [46] noted that the cost of implementing IoT in the healthcare industry is a significant barrier to widespread adoption. Small and medium-sized businesses in India are more likely to use IoT if they can save money in the process. IoT SH adoption is also negatively affected by the cost [47]. Thus, the following is hypothesized:

H4: Cost affects negatively the IU SH.

Theories such as TAM and UTUAT proposed a direct link between intention and AU. The higher the IU a technology, the more likely that the AU will occur [36, 37].

Accordingly, this study proposes a positive impact between IU and AU. Thus, the following is hypothesized:

H5: IU affects positively the AU of IoT.

Facilitating condition is proposed in UTAUT to directly affect the AU. Similarly, in this study, a direct effect is expected between the facilitating condition and the AU. Several studies that utilized the UTAUT model proposed and tested the effect of facilitating condition on IoT usage and found a direct and positive link [39, 48–50]. In this study, facilitating condition is expected to affect the AU of IoT SH.

H6: Facilitating condition affects positively the AU of IoT SH.

ML has become an integral part of IoT because it involves machine-to-machine communication. Knowledge in ML encourages individuals to use the technology because they understand the process and procedures of using the technology. Few studies examined machine learning as a variable. For instance, [51] examined the moderated mediated effect of machine learning in the context of COVID-19. In this study, the following is proposed:

H7: Knowledge of machine learning moderates the effect of IU on AU of SH.

The findings showed that there is a moderated mediation effect. Product knowledge moderated the effect of innovativeness on the use of robotic restaurant [52].

3. The aim and objectives of the study

The aim of this study is to examine the usage of SH by IT specialists in GCC. This will make it possible to develop a model that can be used by policy makers in these countries to support the usage of SH by IT specialists in GCC.

To achieve this aim, the following objectives are accomplished:

– to examine the effect of relative advantage, convenience, accessibility, and cost on the intention to use IoT SH;

– to examine the effect of IU and FC on the AU of SH;

– to examine the moderating role of knowledge of ML between IU and AU.

4. Materials and methods

The research object is SH usage among IT specialists in GCC.

The research subject is to identify the factors that affect SH usage among IT specialists in GCC and to examine the role of ML. Several hypotheses were developed in this study. To fulfill the objectives, the research follows a quantitative approach in which the population is users of the SH or those who intend to use the SH in the GCC area.

To select the most related respondents, a question was asked "do you use or intend to use SH". Those who answered "Yes" were asked to proceed with the questionnaire and those who answered "No" were asked to refrain from answering the questionnaire. This research utilized purposive sampling to select only those who use or intend to use the SH and those who have a decent knowledge of machine learning. Accordingly, the respondents are IT specialists in the field. A questionnaire was used to collect the data. Validation was conducted using the input of three experts. Next, a pilot study was conducted prior to the data collection. The measurement of the variables was adopted from several sources. Measurement of RA from [53], measurement of convenience was adopted from [41], measurement of accessibility, cost and knowledge of machine learning was adopted from [54], and measurement of facilitating condition, IU and AU was adopted from [55].

The data were collected by sending emails to 509 respondents, and they were asked to forward the questionnaire to those who fit the inclusion criteria (users or those intending to use SH with adequate knowledge of machine learning). The data were collected from 309 respondents. Table 1 shows the results of normality and multicollinearity.

Table 1

Results of Normality and Multicollinearity

Variable	Skewness<1	Kurtosis<1	Tolerance>0.20	VIF<5
Relative advantage	–0.088	–0.553	0.835	1.197
Convenience	–0.562	–0.316	0.652	1.535
Accessibility	–0.702	–0.301	0.385	2.600
Cost	–0.724	–0.474	0.324	3.083
Intention to use	0.474	–0.515	0.715	1.399
Facilitating Condition	–0.821	–0.020	0.468	2.135
Machine Learning	–0.467	–0.528	0.400	2.503
Actual Use	–0.912	0.117	–	–

The missing value was checked using frequency analysis in SPSS, and four responses were removed. In addition, the outliers were checked, and 11 responses were considered outliers. The data are normally distributed, and there are no high correlations among the variables, which eliminates the problem of multicollinearity as shown in Table 1.

A total of 294 respondents have participated in this study. Most of the respondents are males (81 %) while females are 19 % of the sample. This might be due to the fact that men predominate among IT specialists. The age of the majority of respondents (73 %) ranged from 35 to 45 years. This is because this segment is more aware of the technology and its usage since they are a technology-born generation. The respondents are holders of a bachelor's degree (76 %), which is logical since they are IT specialists, the other 24 % are holders of a master's and PhD degree. The working experience of the respondents is more than 10 years (72 %). This is also logical since their age ranged between 35 and 45 years, and they have been working after completing their first-degree education.

CFA is one of the stages to assess the goodness of AMOS analysis. It includes the check of indices, factor loading (FL), reliabilities and validities. Based on [56], the achievement of three of the indices is sufficient for the analysis. In this study, all the indices such as relative chi-square, IFI, TFI, CFI were achieved except for GFI. Table 2 shows the results of CFA.

Some items were removed due to low factor loading (less 0.60) or high correlation among the items. The Cronbach's Alpha (CA) was calculated using SPSS while the Composite reliability (CR) and the average variance extracted (AVE), as well as the cross loading, were calculated using excel sheet provided by [57]. As shown in Table 2, the reliabilities and validities were achieved.

Table 2

Results of CFA

Variable	CA	CR	AVE	RA	CO	ACC	COST	IU	FC	KML	AU
Relative advantage (RA)	0.93	0.94	0.78	0.88	–	–	–	–	–	–	–
Convenience (CO)	0.94	0.95	0.79	0.43	0.87	–	–	–	–	–	–
Accessibility (ACC)	0.95	0.96	0.75	0.62	0.69	0.91	–	–	–	–	–
Cost	0.94	0.95	0.79	0.69	0.42	0.44	0.91	–	–	–	–
Intention to use (IU)	0.93	0.94	0.85	0.66	0.70	0.42	0.62	0.90	–	–	–
Facilitating Condition (FC)	0.88	0.91	0.73	0.41	0.57	0.65	0.66	0.64	0.89	–	–
Machine Learning (KML)	0.94	0.96	0.86	0.64	0.73	0.60	0.68	0.62	0.41	0.92	–
Actual Use (AU)	0.93	0.95	0.83	0.66	0.69	0.60	0.69	0.64	0.65	0.32	0.85

5. Results of the proposed smart home usage modeling

5. 1. Effect of relative advantage, convenience, accessibility, and cost on the intention to use the Internet of Things smart home

Fig. 1 shows the structural model of this study.

Following the suggestions of [56, 58], the mean scores of the variables were used for testing the hypotheses. Table 3 shows the results of testing the hypotheses of this study. Table 3 shows the D. V, path, I.V, estimate, S.E, C.R, P, and Label.

Table 3

Results of Hypotheses Testing

H	D.V	Path	I.V	Estimate	S.E.	C.R.	P	Label
H1	IU	<---	RA	0.178	0.045	3.998	***	Supported
H2	IU	<---	CO	0.238	0.053	4.446	***	Supported
H3	IU	<---	ACC	0.214	0.054	3.962	***	Supported
H4	IU	<---	Cost	–0.228	0.050	-4.591	***	Supported

Table 4

Results of Hypotheses Testing of FC and IU

H	D.V	Path	I.V	Estimate	S.E.	C.R.	P	Label
H5	AU	<---	IU	0.525	0.034	15.444	***	Supported
H6	AU	<---	FC	0.210	0.038	5.495	***	Supported
H7	AU	<---	KML	0.215	0.042	5.120	***	Supported
	AU	<---	KML*IU	0.113	0.041	2.332	0.005	Supported

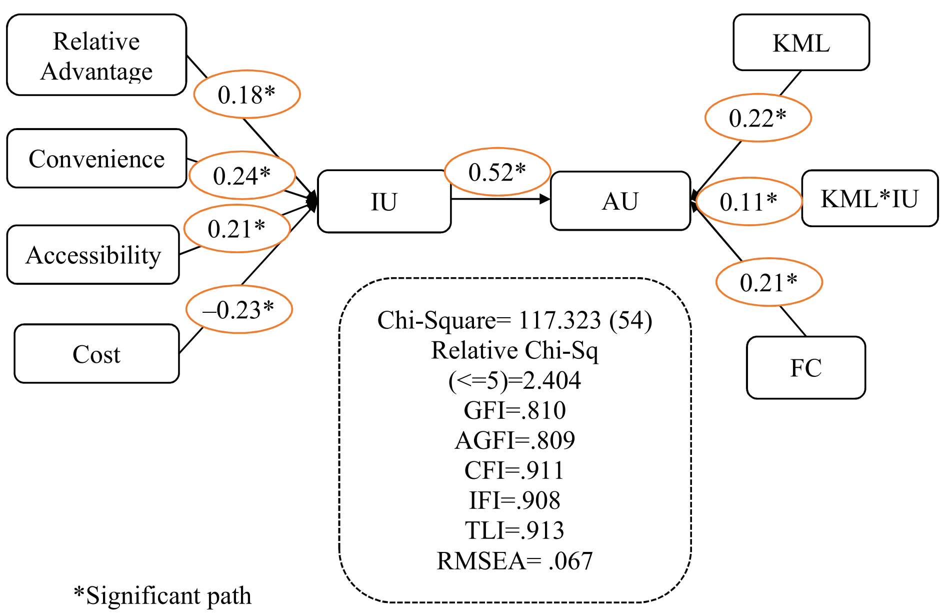

Fig. 1. Structural Model

The results of hypotheses testing as shown in Table 3 indicate that the effect of RA on IU is positive (estimate=0.178, P<0.001). Therefore, H1 is supported. Similarly, the effect of convenience (CO) and accessibility (ACC) on IU is positive and significant at an estimate of 0.238, and 0.214, respectively. Thus, H2 and H3 are supported. For the effect of cost on IU, the effect is negative and significant at an estimate of –0.228 and p-value less than 0.05. Thus, H4 is supported.

5. 2. Effect of intention to use and Facilitating Condition on the actual use of smart home

The results of testing the effect of FC and IU are shown in Table 4.

For H5, the effect of IU on AU is supported. Similarly, the effect of FC on AU is significant (estimate=0.210, P<0.001). Thus, H6 is supported.

5. 3. Moderating role of knowledge of machine learning between intention to use and actual use

For the moderating effect of machine learning (ML), the moderator is significant. The results of testing the moderating effect are shown in Table 5.

The increase in ML knowledge increases the positive effect between IU and AU as shown in Fig. 2.

The increase in the moderator (ML) enhances the positive effect of IU on AU. Therefore, H7 is supported. Additional findings shown in Table 3 indicate that ML itself is a positive predictor of the AU.

Table 5

Results of Hypotheses Testing

H	D.V	Path	I.V	Estimate	S.E.	C.R.	P	Label
H7	AU	<---	KML	0.215	0.042	5.120	***	Supported
	AU	<---	KML*IU	0.113	0.041	2.332	0.005	Supported

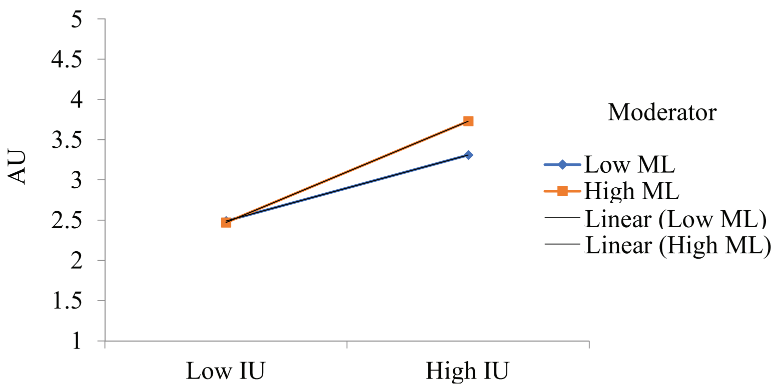

Fig. 2. Two-Way Interaction

6. Discussion of the results of the proposed smart home usage modeling

SH is a new trendy technology that is being widely used by the rich for their convenience. The wide spread of the technology is still limited, and this could be due to several issues related to the perception of users, knowledge and cost. This study examined the effect of RA, CO, ACC, and cost on IU. As shown in Table 3, the study found that RA, CO, and ACC have a positive effect on IU while cost has a negative effect. Convenience is the most critical factor followed by accessibility and RA. Customizing the house as desired by the owner is one source of convenience, and the ability to remotely control the appliances in the house contributes to the convenience of using the SH. In line with these findings, the study [39, 40] referred to the importance of RA for the decision to use the IoT. Similarly, researchers [41, 42] also indicated that convenience is critical for SH usage. The authors [43, 44] highlighted the role of accessibility in achieving the maximum usage of smart buildings, cities and universities, as well as SH. The impact of cost is in line with prior literature that indicated the importance of cost in making a decision to use the SH [45, 47].

The effect of FC and IU on the AU was found positive and significant as shown in Table 4. This indicates that respondents with positive IU toward the SH will be using the technology. The existence of FC, such as assistance from service providers, as well as hardware and software, is critical to facilitate the usage of SH. In agreement with these results, the findings of prior literature [36, 37] noted the importance of IU to AU. In addition, [48–50] concluded the criticality of the FC to the actual usage of SH.

For the moderating effect of ML, the findings shown in Table 5 and Fig. 2 indicated that the increase in ML as a moderator will increase the positive effect of IU on AU. This moderating effect agreed with the prior literature [52].

Limitations of this study include the following. The findings are limited to IT specialists in GCC. Purposive sampling was used to select suitable respondents who are aware of the technology. This highlighted the role of knowledge in ML but limited the findings to this group of respondents. The findings are also limited to GCC. The disadvantage of this study is the use of behavioral rather than technical aspects. However, the behavioral aspect is lacking, and this could justify the use of this approach in conducting this study. A methodological difficulty was encountered in collecting the data due to the busyness of IT specialists and the need to follow up with them to answer the questionnaire.

This study has contributed to the body of knowledge by examining SH usage by IT specialists. The studies related to this field are still emerging with the majority focusing on the technicality rather than the behavioral approach of the users. The study contributed to the field in emerging economies where the growth potential of this market is high while research is still limited.

7. Conclusions

1. The regression analysis indicated that the effect of RA, CO and ACC, as well as cost, is critical for the IU. In particular, IU was positively affected by RA, CO, and ACC, but negatively impacted by cost. After accessibility and RA, convenience is the most important aspect. One form of convenience stems from the capacity to tailor the home to the owner's preferences, while another comes from the ability to remotely manage the home appliances. Based on the findings, decision-makers in GCC have to enhance the perception of the advantages that can be gained from using the SH. The population is aging everywhere, and the use of SH helps in monitoring the health of the elderly in the house and provide more security and privacy for the inhabitants.

2. The results of regression analysis using the quantitative method showed that both FC and IU were found to have a statistically and positively significant impact on AU. This means that those who have a favorable opinion of the SH in terms of IU will really employ the technology. FC, including service provider support and hardware and software, is essential for making SH accessible. The FC and IU are critical for the AU. Having beneficial SH that is accessible and provides convenience at low cost will enhance the IU while providing continuous assistance will improve the FC, which in turn will lead to better actual usage.

3. The favorable impact of IU on AU was amplified by an increase in ML as a moderator indicating that decision-makers are recommended to enhance the accessibility of the SH using the Internet and other off-line methods. In addition, cost is a critical factor in this process. Therefore, decision-makers are recommended to customize the cost so that those with low budgets can afford to install the SH. The role of machine learning is critical for encouraging the respondents to use the SH. Decision makers are recommended to set up courses that can suit the educational level of all users. Simplifying the information and control of the SH will bring more users.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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