Smart Home Technology Acceptance: An Empirical Investigation

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Abstract. Recent technological advances have contributed to the development of smart homes, embedded with artificial intelligence, which aim to provide tailored services to residents. Smart home technologies benefit people daily and improve the environment in the long-term perspective. Despite the great interest of the research community in smart homes, the adoption rate is still low. The purpose of this study is to develop the research model, which can explain the acceptance of smart homes by users. Along with the relationship of technology acceptance factors with use behaviour, this study analyses the importance of individuals' belief and values. Structural equational modelling has been employed to test the proposed hypotheses using a sample of 422 smart home users. The analysis revealed the significance of the relationships between values and perceived technology-fit, while the technology acceptance factors had a strong correlation with use behaviour leading to satisfaction.

Keywords: Technology acceptance model · Smart home technology · Smart technology · Use behaviour

1 Introduction

A smart home is defined as a "*residence equipped with computing and information technology, which anticipates and responds to the needs of the occupants, working to promote their comfort, convenience, security and entertainment through the management of technology within the home and connections to the world beyond*" [1]. The current research focuses mostly on the examination of benefits that smart homes make possible [2, 3]. However, compared to other technologies, the pervasive nature of smart homes undermines users' trust and raises concerns related to privacy. Technologies utilised in a private context have largely been overlooked in technology acceptance studies. Moreover, the examination of psychological factors of users, perceived outcomes of use and beliefs is of paramount importance as they may underpin the utilisation of such technologies [4]. Similarly, the use of technology in homes is heavily contingent on potential risks that users perceive in relation to personal data misuse and financial losses [1, 3, 5]. Therefore, studying technology acceptance from the perspective of potential risks and benefits perceived by users is more important when it comes to private spaces compared to public or mixed settings. This study will address

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the gap in the literature on the acceptance of technologies in private settings by pursuing two objectives. First, the study will examine the acceptance of technologies with the focus on users of smart homes. Second, the study will empirically investigate underlying attitudes towards technology utilisation, such as perceived benefits and risks.

2 Literature Review and Hypothesis Development

This study adopts the Task-Technology Fit (TTF) model as a baseline theoretical framework. The TTF model examines the dependence of users' behaviour on the perceived fit between technology functionality and task requirements of residents. The model assumes that a higher degree of fit indicates higher technology performance. Although the "fit" factor has been proved to be crucial in technology acceptance, the prior research has mostly studied it implicitly [6]. In this study, we combine TTF with perceived usefulness and perceived ease of use from the Technology Acceptance Model (TAM), which refer to the users' perception of technology performance [7].

2.1 Antecedents of Task-Technology Fit

TTF is defined as "*the degree to which technology assists an individual in performing his or her portfolio of tasks*" [6]. The theory that underlines task-technology fit suggests that individuals determine the fit between technology and task requirements based on their utilitarian and hedonic needs [6, 8]. The perception of the technology is dependent on the degree to which perceived values of the technology use satisfy individuals' needs [8, 9]. The essence of the hedonic value is the achievement of self-fulfilment. When it comes to the information systems context, hedonic value is defined as an individual's subjective perception of the extent to which a product or service brings fun and enjoyment [8, 10]. In contrast, utilitarian value implies an instrumental utility of technology use, such as enhanced task performance or efficiency [8]. Based on the above, we propose that there is a correlation between behavioural beliefs and users' perception of task-technology fit. Based on the literature on the smart home domain, smart home technology makes it possible to save on utility bills and improve the operational efficiency of daily tasks, thus satisfying users' utilitarian values [3, 5], as well as helping improve hedonic experiences by bringing fun and enjoyment [5]. Therefore, the first hypothesis states that:

H1: Utilitarian and Hedonic beliefs are positively correlated with consumers' perception of task technology fit.

There is a stream in the literature heavily focused on the perceived risks of using technology [11, 12]. Those risks can refer to two main categories: privacy and financial risks [11, 12]. Individuals perceive high risk when they are uncertain on the outcome of the technology use [13]. Following the definition, task-technology fit results from the consistency between the technology characteristics and an individual's belief that it is able to satisfy their requirements and assist in fulfilling particular tasks [8, 14]. Consequently, the perception that technology fits individuals' requirements can be inhibited by high perceived risks. In line with the research on the smart home domain, individuals have raised concerns that the use of technology may result in privacy intrusion, security breaches and the inability to reduce financial spending on energy consumption [1, 3, 5]. Therefore we hypothesise that:

H2: Financial and privacy risks are negatively correlated with an individual's perception of task technology fit.

2.2 The Effects of Task-Technology Fit

TTF has been used in combination with other technology acceptance models aiming to examine individuals' attitudes underlying technology adoption, the perception of performance and intention to continuously use technology [15–17]. The perception of fit between task and technology is an underlying factor of innovation adoption [15, 16]. The TTF model found implications in various contexts, including online learning systems, mobile insurance and mobile banking [16, 18]. When examining the adoption of online learning courses, users stressed the importance of task-technology fit in evaluating the usefulness and ease of use of online systems [16]. However, previous research found variance in the significance of TTF dimensions (i.e. data quality, authorisation, locatability, timeliness, training, compatibility, relationship with users and system reliability) for users. For example, Lee, Cheng [18] argued that data quality was the main factor underpinning the adoption of mobile insurance services. Another study found that the relationship between TTF and the impact of mobile banking performance varies across different age groups. Particularly, the effect was significant only for older respondents, but not for the younger generation [17]. Conflicting results in prior research can be explained by the difference in the purpose of online systems' use and users' IT skills. For example, TTF can play a more important role in the context of online learning, as online systems can be the only solution to achieve the task. When it comes to mobile banking, users are usually provided with other alternatives that aim to increase the convenience of the use of banking services. Secondly, TTF can be insignificant for younger users because they are more knowledgeable about the technology and more efficient in use. In addition, some studies focused on the outcomes of technology use in the form of satisfaction. The literature provides evidence of both an indirect and a direct effect of task-technology fit on satisfaction [19, 20]. The studies examining a direct relationship between TTF and satisfaction concluded that satisfaction is strongly and positively affected by perceived fit, and leads to continuous use intention [20, 21]. Based on the above, we hypothesise that:

H3: The perceived task technology fit is positively correlated with use behaviour and satisfaction.

There has been evidence in the literature about the correlation between TTF and PEOU [15]. The study compared the strength of the effect of constructs in two scenarios: (1) when TTF was examined as a stand-alone model and (2) when TTF was combined with TAM. The results demonstrated that TTF has a stronger effect when it was integrated with TAM constructs [15]. A similar finding was provided by another recent study that integrated TAM and TTF and concluded that an extended model has a better explanatory power [16]. Also, a higher effect of TTF was observed when the model was integrated with UTAUT constructs, such as effort expectancy and performance expectancy [22, 23]. Performance expectancy and perceived usefulness have a great deal of similarity. Similarly, both effort expectancy and perceived ease of use measure users' belief that using information systems is effortless [24]. By confirming a strong correlation between TTF constructs, effort expectancy and performance expectancy, the findings conclude that the combination of TTF with behavioural beliefs gives a better explanation of the utilisation and adoption of IT systems. Also, technology characteristics had an influence on effort expectancy, while performance expectancy was directly affected by TTF [23]. Based on the aforementioned, the next hypothesis states:

H4: The perceived task technology fit has a significant direct and indirect effect on (a) perceived usefulness and a direct effect on (b) perceived ease of use.

2.3 Perceived Usefulness and Perceived Ease of Use

Perceived usefulness is defined "*as the degree to which an individual believes that using the system will help him or her attain gains in job performance*" [24, 25]. Due to technology acceptance theories, such as TAM and UTAUT, perceived usefulness and perceived ease of use constructs have received wide attention in information systems research [7, 26]. The theories propose that the degree to which technology performance is perceived positively is dependent on the perception of the usefulness of the technology for users. Therefore, high perceived usefulness leads to use behaviour and influences the perception of the technology performance outcome [27]. Further research tested the construct in different cultural and geographical contexts and provided consistent results supporting the original findings [28, 29]. This means that perceived usefulness has an invariant effect on use behaviour. Based on the prior research, our next hypothesis is:

H5: Perceived usefulness is positively correlated with use behaviour.

Perceived ease of use can be defined "*as the degree of ease associated with the use of the system*" [24, 25]. Perceived ease of use refers to the key psychological belief underlying technology acceptance [25, 30]. Numerous studies have confirmed a significant relationship between perceived ease of use and behavioural intention in voluntary as well as mandatory settings [7, 26]. It was found that the construct has both an indirect and a direct relationship with the use behaviour. For example, it was found that perceived ease of use serves as one of the main motivational factors predicting the perceived relevance of information systems and technology satisfaction. Drawing upon the above, the next hypothesises of the paper is the following:

H6: Perceived ease of use is positively correlated with perceived usefulness.

2.4 Outcomes of Use Behaviour

A lot of attention has been paid to studying the relationship between technology use and satisfaction [31–33]. It was found that satisfaction plays a crucial role in technology adoption by consumers. Particularly, satisfaction acted as a mediator between the adoption of online platforms and actual use behaviour [34]. In the context of mobile internet services, satisfaction was used to examine the effect of user experience using a multidimensional construct. Experience represented the composite scale measuring hedonic, functional and overall performance expectations. The results of the study provided evidence that the strongest predictor of satisfaction was confirmed expectations, whereas the outcome of satisfaction is an intention to use services continuously [35]. A few studies tried to explain the antecedents of the individual's satisfaction by developing conceptual models [33]. However, there is inconsistency in the findings of research that examined the effect of technology use on stress and satisfaction [31]. While the general technology use construct was found to have a significant influence on satisfaction, there are contradictory findings when it comes testing the effect of the frequency of use [32]. Moreover, there was a variance in the level of satisfaction across respondents. For example, the literature provides evidence that the use of technology positively correlates with satisfaction levels [31]. Another stream of research argued that technology use positively correlates with the arousal of stress [36, 37]. For instance, a study focusing on technology acceptance in higher education found that technology use had a significant effect on anxiety, which led to dissatisfaction [38]. Drawing on the smart home literature, we propose that given the ability of smart homes to provide health-related, environmental and financial benefits, the technology use will more likely result in positive outcomes. Hence, we hypothesise the following:

H7: Smart home use is positively related to satisfaction.

3 Methodology

3.1 Data Collection and Sampling

The proposed model was examined using a quantitative approach. Before embarking on the collection of data, a pilot study was carried out with the purpose of testing the adequacy and feasibility of the data collection tools, the design of the questionnaire and the survey approach. The questionnaire comprised three parts. The first one contained screening questions which aimed to filter out respondents who had never used smart home technology. In the second part, individuals provided answers to general questions in order to build a descriptive profile of the survey respondents (i.e. socio-demographic data). In the third part of the questionnaire, respondents were provided with model-specific questions. The questionnaires were distributed online to consumers in the United States. The analysis was based on 422 responses. The sample was balanced in terms of gender with 53.6% of females and 46.4% of males. Out of those, 59.3% of the participants were married. The majority of the respondents were full-time employed (43.3%), had an annual income ranging from 25,000 to 74,999 US dollars (53.6%), had a college degree or were at least attending some college courses (50%) and living in urban or urbanized areas (71.3%). When it comes to age, the largest group, which constituted over 40%, were individuals from 60 to 69.

3.2 Measurement Items

For examining the research model, nine multi-item scales were adopted. To ensure content validity all scales derived from the prior literature and were validated. For the accuracy and precision of the measurement of latent variables, seven-point Likert scales were used [39]. ***Antecedents of task-technology fit*** were measured by privacy risk, financial risk, hedonic value and utilitarian value. *Privacy* and *financial risks* were adapted from the study by Featherman and Pavlou [11]. To measure privacy risk respondents were asked questions such as “What are the chances that using smart home technology will cause you to lose control over the privacy of your payment information?”. Financial risk measurement included questions, like “What are the chances that you stand to lose money if you use smart home technologies?”. The answers ranged from 1 = very low to 7 = very high. *Hedonic value* and *utilitarian value* items were adapted from the study by Babin et al. [9] and used the scale range from 1 = strongly disagree to 7 = strongly agree. The items, like “Using smart home technologies truly felt like an escape” measured hedonic value, and the statements like “I accomplished just what I wanted to during the use of smart home technologies” measured utilitarian value. ***Task-technology fit*** items were adopted from the study by Lin and Huang [40] (e.g. “Smart home technologies fit my requirements in daily life”), with answers ranging from 1 = strongly disagree to 7 = strongly agree. To examine the ***outcomes of task-technology fit***, this study used (1) the *use behaviour* scale adapted from the study by Taylor and Todd [41] with the scale points from 1 = strongly disagree to 7 = strongly agree (e.g. “I believe I could communicate to others the consequence of using smart home technologies”), and (2) the *satisfaction* scale derived from the study by Spreng and Mackoy [42] measuring the overall experience of using smart home technologies by four scales (1 = very dissatisfied to 7 = very satisfied, 1 = very displeased to 7 = very pleased, 1 = very frustrated to 7 = very contented, 1 = terrible to 7 = very delighted). ***Perceived usefulness*** and ***perceived ease of use*** were measured using the adapted version of the scales developed by Venkatesh and Morris [43]. For measuring perceived usefulness respondents were asked to indicate the degree to which they agree with statements like “I would find smart home technologies useful in my daily life”. Perceived ease of use was measured by statements such as “My interaction with smart home technologies is clear and understandable” using a scale ranging from 1 = strongly disagree to 7 = strongly agree.

3.3 Data Analysis

The analysis of data was in line with the strategy proposed by Hair Jr and Lukas [44]. SPSS v.24 and SPSS AMOS v.24 were employed to examine the relationships between variables. To ensure that the measured constructs meet construct validity and reliability requirements, confirmatory factor analysis was run. The CFA analysis showed a satisfactory model fit ($X^{(288)} = 605.198$ CMIN/DF = 2.101, CFI = .980, RMSEA = .0.51). As the results of the reliability test all indices were satisfactory, including the factor loading (> 0.8), construct reliability (C.R. > 0.8), average variance expected (AVE > 0.7) and Cronbach’s α (>0.8) [44]. Also, a convergent validity test showed no validity concerns (Table 1).

Table 1. Convergent validity

		1	2	3	4	5	6	7	8	9
1	**UB**	0.891								
2	**PR**	−0.095	0.928							
3	**FR**	−0.086	0.821	0.877						
4	**HV**	0.764	−0.208	−0.173	0.942					
5	**UV**	0.792	−0.179	−0.162	0.903	0.929				
6	**TTF**	0.770	−0.244	−0.224	0.852	0.874	0.959			
7	**EoU**	0.787	−0.147	−0.171	0.797	0.787	0.745	0.932		
8	**PU**	0.736	−0.213	−0.178	0.864	0.845	0.869	0.815	0.936	
9	**Sat**	0.724	−0.264	−0.241	0.79	0.808	0.834	0.714	0.747	0.930

Note: Figure in the diagonal represents the square root of the average variance extracted (AVE); those below the diagonal represent the correlations between the constructs.

4 Results and Discussion

4.1 Path Analysis

The proposed model aimed to examine the factors underpinning the use of smart home technology and subsequent outcomes. The results of structural equation modelling showed that all model fit criteria were satisfactory and the model explained sufficient variance, as presented by R^2 coefficients in Table 2. All the hypotheses except 2a and 2b were supported.

Table 2. The results of hypothesis testing

Hypotheses	R^2	Standardised path coefficient	t-values
H1a: Hedonic value → Task technology fit	0.821	0.347	5.402$^{(***)}$
H1b: Utilitarian value → Task technology fit		0.562	8.525$^{(***)}$
H2a: Privacy risk → Task technology fit		−0.038	−0.794$^{(ns)}$
H2b: Financial risk → Task technology fit		−0.042	−0.866$^{(ns)}$
H3a: Task technology fit → Use behaviour	0.615	0.569	7.134$^{(***)}$
H3b: Task technology fit → Satisfaction	0.723	0.732	13.752$^{(***)}$
H4a: Task technology fit → Perceived usefulness	0.824	0.618	15.267$^{(***)}$
H4b: Task technology fit → Perceived ease of use	0.590	0.768	20.397$^{(***)}$
H5: Perceived usefulness → Use behaviour		0.235	2.968 $^{(**)}$
H6: Perceived ease of use → Perceived usefulness		0.343	8.759$^{(***)}$
H7: Use behaviour → Satisfaction		0.146	2.827 $^{(**)}$

Note: SEM (H1–7): Model Fit $X^{2(307)}$= 850.025 CMIN/DF = 2.769, CFI = 0.966, RMSEA = 0.065

4.2 Discussion

Antecedents of Task-Technology Fit: The current study examined antecedents of task-technology fit in the form of hedonic and utilitarian values, and inhibiting factors, such as privacy risk and financial risk. As a result of testing relationships, the first hypothesis suggesting a significant effect of values on task-technology fit was supported. This means that prior beliefs about utilitarian and hedonic outcomes directly affect the perception of the match between users' household tasks and technology characteristics, and indirectly affect use behaviour. However, utilitarian value was found to have a stronger effect. A possible explanation could be that individuals are mostly concerned with the ability of smart home technology to reduce costs on energy, deliver operational convenience and reduce waste production [45]. Remarkably fewer studies confirmed that users tried to satisfy hedonic needs, such as fun and enjoyment when using smart homes [8, 9, 46]. This finding contributes to the current literature by shedding light on the relative importance of utilitarian and hedonic values in perceiving task-technology fit and their indirect influence on behaviour. Prior studies did not examine the relationship between values and task-technology fit [16, 23] and an indirect effect of values on use behaviour [8, 9, 46]. The second hypothesis suggesting the negative affect of perceived privacy and financial risks on task-technology fit was not supported. This contradicts the findings in the prior literature that showed evidence of the inhibiting role of perceived risks in technology acceptance and adoption [47].

The Effects of Task-Technology Fit: By supporting proposed hypotheses 3 and 4, the findings of the study confirm a significant correlation between task-technology fit, perceived usefulness, PEOU, use behaviour and satisfaction. First, the study provides evidence of a significant influence of task-technology fit on use behaviour, which is in line with the previous literature [15, 23]. This means that in order to use smart home technology, users must perceive the high relevance of technology characteristics and its capability to implement specific tasks in hand. Second, the study found a significant and strong effect of task-technology fit on perceived usefulness, which is consistent with previous research [22, 23]. Third, in line with the study conducted by Dishaw and Strong [15], PEOU is conditioned by the perception of high task-technology fit. Compared to the relationship between fit and perceived usefulness, the influence on PEOU is stronger. The potential interpretation is that users' requirement of smart home technology is to achieve higher efficiency of technology performance by simplifying daily routines [1, 5]. Fourth, the result of path analysis shows that perceived task-technology fit predicts satisfaction, which corresponds to the findings of the study by Lin [21] and contradicts the paper by Lu and Yang [48].

Perceived Usefulness, Perceived Ease of Use and Outcomes of Use Behaviour: The study supported hypotheses 5 and 6, confirming the direct effect of perceived usefulness on use behaviour, as well as an indirect effect of PEOU on use behaviour through perceived usefulness. Results of path analysis support the findings of prior literature [28, 29, 47]. The effect of perceived usefulness is weaker, which can be explained by the focus of the study on smart home technology. Smart home users try to make the performance of technology more efficient by decreasing the input of effort to implement household tasks [1, 5]. In addition, the results of path analysis make it possible to accept the seventh hypothesis, proposing a positive correlation between use behaviour and satisfaction. This is in contrast to other findings on the smart home domain that proved that the use of technology leads to dissatisfaction and stress [36, 37]. Contradictory findings can be explained by the difference in the conditions underpinning the technology use and settings. For example, the studies confirming that technology use caused dissatisfaction and stress focused on organisational settings, where the use of technology was not voluntary and was not aimed at satisfying individuals' needs [31]. In contrast, smart homes are used voluntarily, and the use is driven by hedonic or utilitarian needs. Hence, satisfaction is a more likely outcome.

5 Conclusion

The paper has examined the acceptance of smart home technologies by exploring the effect of behavioural belief factors and task-technology fit on use behaviour and satisfaction. This study addressed the gap in the literature on the acceptance of technologies in private settings by focusing on smart home users. The paper theorised and empirically investigated the relationship between underlying attitudes towards technology utilisation, such as perceived benefits and risks, the beliefs about technology performance and technology compatibility with users' requirements. The model produced robust results, supporting the relationships between the majority of the proposed constructs. The findings of the study add value to the current literature by providing insight into the acceptance of smart home technology. Secondly, the study contributes to the literature examining the acceptance of pervasive technology in private residential spaces from the perspective of users.

This paper is not without limitations. Research focusing on smart home technology is still scarce and to have a more comprehensive insight future research studies need to extend the model with additional constructs. For example, further research could examine the direct and indirect effect of normative beliefs on use behaviour. Also, this study has not tested the moderating role of psychological traits, which can potentially cause a variance in the strength of model relationships. Finally, future research could test the model in other geographical locations, which would help generalise the findings of the present study.

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