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Smart Home Adoption: The Impact of User Characteristics and Differences in Perception of Benefits

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Abstract: Despite the various benefits offered by smart homes, they have not yet been widely adopted by mainstream users. This study was designed to identify user perceptions in the association between smart home service preference and adoption and to identify factors affecting the adoption and service preferences of smart homes. In order to achieve the goal of the study, an online survey was conducted among 400 potential users in the Republic of Korea. The main findings are as follows: First, there were considerable needs for the services that can support the independent lives of residents, such as safety and convenience services, among all age groups. Second, the study findings suggested that those who preferred environmental control service most were more likely to become relatively active adopters. Third, a significant association between the preference for smart home services and the intention to use was identified. Finally, the study findings suggested that the number of service preferences and adoption was not directly proportional. The findings reported in this study can improve the overall understanding of the process of adopting smart homes, and can provide important insights into user-centered strategies to promote the adoption of smart home services.

Keywords: smart home; technology adoption; service preference; user characteristics; influencing factors

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1. Introduction

A smart home is an intelligent environment that supports various activities at home, such as housework, work, rest, and entertainment. Early smart homes were widely known for concepts such as home intelligence, ubiquitous computing, ambient intelligence, and home automation [1–4]. However, they were considered inconvenient new technologies due to the cost burden and were limited in their distribution. In contrast, the widespread use of networks, reduced sensor technology costs, and the popularization of smartphones have currently reduced consumer resistance to smart homes, and smart home technology is currently drawing attention worldwide due to advances in wired and wireless home networking, sensing technology, IoT home appliances, machinery and control engineering, and architectural engineering [5,6].

Smart homes enhance user convenience through network-connected intelligent technologies and services, and advances in smart home technology have also led to the diversification of services that can meet more consumer needs. Despite the various benefits offered by smart homes, they have not yet been widely adopted by mainstream users [7,8]. In view of this, studies are being conducted to determine the factors influencing the adoption of smart homes in order to identify the demand and expectations of potential users more clearly.

Prior studies have focused on the needs for smart homes, such as energy management or healthcare [9,10], measured overall user perceptions (e.g., benefits and risks) of the concept of smart homes [8,11], or considered the effect of the technical and functional characteristics of smart homes on adoption [12–15]. In particular, since exploring the needs and expectations of various user types is one effective approach to smart home adoption [16], many studies have measured the impact of user characteristics on adoption, such as gender, age, and experience of use. The common implication of prior studies was that, first, various factors affect adoption, second, expectations for smart homes vary depending on users, and third, the effectiveness of factors varies depending on users' different expectations. Prior studies have validated factors affecting smart home adoption from the user's perspective. However, very few studies have considered the impact of user perceptions of various types of services on adoption [17], especially, identifying user preferences depending on the types of subdivided services and analyzing the correlation with adoption.

This study was designed to measure different expectations for smart homes and determine their impact on adoption. In particular, this study identified intuitive user preferences for the four standard dimensions of smart home services i.e., convenience, safety, energy, and healthcare, and analyzed the correlation between service preferences and adoption. The main research questions were as follows: (1) the type of smart home services users preferred most, (2) whether service preferences affected the adoption of smart homes, and (3) what user characteristics were associated with service preferences and adoption.

The rest of this paper is organized into the following four sections. In Section 2, a review of the related literature is provided. In Section 3, the research methodology is explained. In Section 4, the study results are presented and discussed. Finally, Section 5 concludes this paper.

2. Literature Review

2.1. Benefits of Smart Home

Smart homes can improve residents' quality of life by providing various services that assist their daily lives. In general, smart home services can be classified into four types: convenience, security, energy, and healthcare [12,17].

First, convenience services support the lifestyle of residents to increase comfort. As a typical example, environmental control is the most theoretical and representative smart home function. Environmental control includes the ability to remotely control or automatically schedule components of the house, such as thermostats, ventilators, lighting equipment, kitchen appliances, and various household appliances [8,13]. It enables easy management of residential environments, effectively reducing household labor and providing comfort for residents.

Second, smart home safety services can assist residents to manage the security of their homes and prevent accidents. For example, security services detect movements in the house to identify potential intruders or to warn of open doors and windows [7].

Third, smart homes can effectively reduce the environmental and economic costs of housing by reducing energy consumption and maintenance costs. Energy management services provide residents with information that can reduce energy consumption in the house, or automatically optimize energy consumption without human intervention [10,12,18–20].

Finally, healthcare services can assist users to manage their health in their daily lives. The services offer effective management of individual health information through health-monitoring infrastructure (e.g., a smart thermometer, health data management platform, fall detection) or detect environmental information which could affect residents' health, such as air quality and pollution [21]. Moreover, smart homes can offer solutions to problems derived from socio-population changes, such as the increase in single households and the aging population [22–25]. Smart homes are expected to provide vulnerable households with greater independence and stability, enabling aging at home by monitoring the health conditions of the elderly, chronically ill, and disabled and automatically reporting unusual activities [24,26,27].

2.2. Factors Influencing Smart Home Adoption

As the technology cycle develops, technology adoption is increasingly considered a key issue to be addressed in the innovation of information technology. In order to increase the usage of innovative technologies by workers in the 1980s, Davis (1989) laid a theoretical basis for specifically measuring the decision factors regarding the adoption of the technology. Currently, technology adoption theory is being widely used across various research fields, including intelligent home technology, IoT appliances, smart city services, and smart homes, as a theoretical basis for identifying and examining users' intentions to use new information technologies [28–31].

Research theories have been expanded as various variables that affect the intention to use information technology have been newly identified in subsequent studies based on technology adoption theory, which have reported negative or positive effects of the perception of technology on usage intentions [32,33]. In particular, Kim et al. (2007) reported that adoption of technology was made to maximize its value and that different values of technology recognized by the adopter affected behavior [34]. They explained the adoption process of the technology based on the concept of perceived value that comprehensively considers both the sacrifices (e.g., technicality, perceived fee) and the benefits (e.g., usefulness, enjoyment) that accompany the use of the technology.

Despite the innovation and functional advantages of smart homes, there are various factors that discourage their adoption. The perceived sacrifices of smart home technology, which typically consist of difficult usability, cost burden, uncertainty about controllability, and risk awareness of security, are known to affect usage intent [12,35,36].

On the other hand, several studies have identified the effects of positive perceptions of technology on adoption [37,38]. Attitude has been considered a key factor affecting information technology adoption [30,39,40]. Likewise, as a form of expectation and attitude toward technology, preference is known to affect intention to use [41,42]. Positive attitudes and expectations in smart home adoption research have had a positive impact on intention to use [14,30,43,44]. Some studies have also reported the impact of different expectations of the "function" of smart home services on adoption [17,45]. These studies demonstrate that the effectiveness of factors influencing the adoption process can be controlled by the type of smart home service.

Other major influencing factors are user characteristics such as age, gender, residential types, and experience. The expectations and demands for smart homes have been found to vary depending on the user characteristics [7,45–47]. First, it is known that there are differences in the perception and needs of smart homes depending on the age of the users [16]. For example, although a smart home can provide a convenient and easy automation system, most people generally tend to want the system to be under their control rather than be fully automated or show a concern about the cost of automation [45,48]. On the other hand, some studies have shown that the elderly population generally tends to respond positively to most smart devices and sensors associated with health problems. Especially in the perception of automation, the elderly generally shows a positive attitude [49–51].

Gender differences have also been addressed in many studies. A study by Yang et al. (2017) showed that females had greater intention to use the smart home services than males [52]. Shin et al. (2018) revealed that the effect of factors affecting smart home adoption (e.g., perceived usefulness and compatibility) vary by gender [16], and Nikou (2019) also found that females are more affected by perceived costs in the smart home adoption process compared to males [53].

Differences in the level of education have been validated in some studies. It is generally known that users with higher education tend to pay more attention to the usefulness and benefits of innovative technologies [17]. Similarly, Shin et al. (2018) found differences between groups with high education levels and those with low education levels in their expectations and adoption of smart home devices [16].

However, the impact of income level presents a point of contention in this field of study. The cost burden of the initial purchase, installation, and maintenance of smart home services is a major barrier to the adoption of the services [12,26,54]. In particular, the cost burden caused by the structural changes in the space required for using new services has been reported to be one of the factors hindering smart home adoption [35]. For instance, Kim et al. (2017) revealed that the users' perception that structural and technical infrastructure must be prepared before using smart home services has a significant impact on the adoption of the services [30]. Overall, the cost burden is a key factor in adoption. Interestingly, on the other hand, the impact of income levels on the adoption of smart homes has been supported in very few studies. For example, in the study of Yang et al. (2017), income levels did not directly affect the adoption of smart homes [52]. Shin et al. (2018) found an indirect effect of income levels, but it did not reach statistical significance [16].

Additionally, smart home adoption is also affected by the type of housing (e.g., apartment/general home) that users currently reside in. Some studies noted that the needs and intention to use smart home services vary depending on the type of housing the respondents live in [47,55]. The researchers speculated that the difference may be due to different levels of infrastructure in place depending on the type of housing.

Finally, the adoption of technology can be influenced by users' related experiences [32,33,56]. Shih and Veatesh (2004) emphasized the effects of experience as one of the factors that accelerated the diffusion of innovations [57]. In the context of a smart home, likewise, some studies have confirmed that the user's relevant experiences affect the expectations and adoption of smart home services [53,55].

Overall, studies on smart home adoption suggested that there are several cognitive factors that influence users' decisions to adopt smart homes and that the process of the decision may vary depending on the user's characteristics and background conditions.

3. Research Method

3.1. Research Model and Hypotheses

User expectations for different functions in smart homes are known to affect adoption. This study assumes the impact of these diverse needs, namely service preferences, on the adoption of smart homes. The main variables in the research model reflect these preferences: convenience, safety, energy, and healthcare. The demographic characteristics of users are also included as control variables. The hypotheses of this study are as follows (Figure 1):

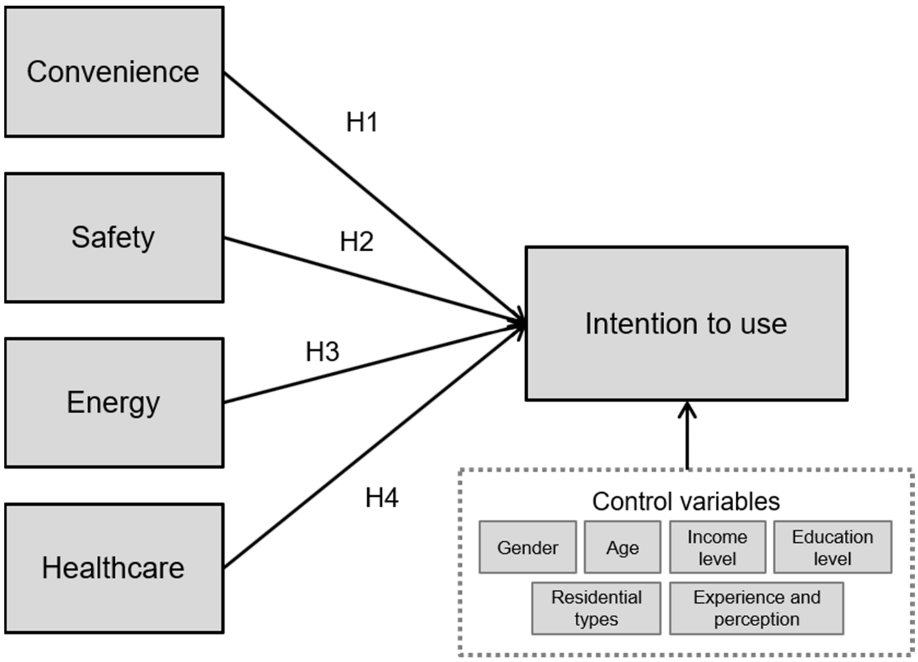

Figure 1. Research model and hypotheses.

Hypothesis 1 (H1). *Preference for convenience services will positively affect intention to use;*

Hypothesis 2 (H2). *Preference for safety services will positively affect intention to use;*

Hypothesis 3 (H3). *Preference for energy services will positively affect intention to use;*

Hypothesis 4 (H4). *Preference for healthcare services will positively affect intention to use.*

3.2. Questionnaire Items

A questionnaire composed of three parts was developed to investigate the factors influencing smart home service adoption. The first part was background questions consisting of six general questions about demographic characteristics. In the second part, one question was used to measure the preferences of smart home services. The question consisted of seven options covering all four types of smart home services: convenience, safety, energy, and healthcare. The options were selected based on both a targeted literature search of smart homes [12,14] and case studies about government-led building quality assessment tools for smart homes in the Republic of Korea, i.e., where the spatial scope of the survey was conducted to include a familiar category of services for respondents [58]. The options contained a variety of services, particularly those related to the management of residential environments. For example, in the case of healthcare services, health data management platforms stand out in relevant areas but were excluded because they only manage data on a human body and can be replaced by mobile devices such as smartwatches. The options also contained a detailed description of each service to help the respondents' understanding (Table 1). Especially, in order to induce an intuitive and clear response, respondents were required to choose only one type of service which they preferred or needed most. In the third part, the intention to use the service was measured in order to identify respondents' adoption of smart home services. This part consisted of four questions which were derived through prior studies [14,30,39,52]. The items were answered using a five-point Likert scale ranging from "Strongly disagree" to "Strongly agree".

Table 1. Options and descriptions of service preference questionnaire item.

Category	Option	Description
Convenience	Environmental control	A service that provides integrated management of house components, such as heating, ventilation, and lighting systems.
	Remote monitoring	A service that offers remote residential environment management connected anytime, anywhere, such as a remote door or window opener, home camera, voice-control devices for the home.
Safety	Visitor monitoring	A service that identities potential intruders or sends warning notifications to residents about the open state of doors and windows.
	Leak detection	A service that detects gas, electricity, or water leaks and automatically shuts down the system to prevent accidents.
Energy	Energy-saving and management	A service that reduces energy demand either directly or indirectly by monitoring energy consumption and promoting users' participation in eco-friendly energy utilization.
Healthcare	Air quality monitoring	A service that detects and manages air pollution information and air quality affecting users' health.
	Emergency call	A service that automatically sends an alarm to designated families or facilities if there is unusual activity for users, such as falls.

3.3. Data Collection

The potential respondents were recruited by a professional survey company in the Republic of Korea. After giving informed consent, respondents completed and submitted the anonymous survey online. All respondents were provided with a description of a smart home before the survey and were given incentives after completing the survey. Response quality filters were used to eliminate poor responses, e.g., (1) the survey was completed in a much shorter time than the average, (2) the survey had the same responses recorded for all items, and (3) the survey had incorrect responses for basic panel properties such as age, gender, and educational levels. Responses that failed to pass the filter were ignored and a total of 400 surveys were used for the final analysis.

The sample size adequacy was determined using G power ver. 3.1.9.7. Using a medium effect size of 0.15 [59,60], $\alpha = 0.05$, power = 0.95, and ten predictor variables (4 independent variables and 6 control variables), the minimum sample size N was calculated as 172. The collected survey responses were analyzed using IBM SPSS Statistics ver. 20.0.

4. Result

4.1. Demographic Characteristics of Respondents

The frequency analysis of the respondents' demographic characteristics and the cross-analysis results between the variables are shown in Table 2. There was a slightly higher percentage of female participants, i.e., 46% were male (N = 184) and 54% were female (N = 216). A total of 37.5% of respondents were 31–40 years old, and almost half of the participants responded that their average monthly income was between 2 million won and 4 million won. For education level, respondents with bachelor's degree or graduate degree accounted for most (81.3%), and 69.3% of the respondents lived in an apartment (N = 277). The average monthly income of wage earners in the Republic of Korea was 2.97 million won in 2018 [61], with the college entrance rate reaching 69.7%. In addition, households living in apartments accounted for 61.4% of all households [62].

Table 2. Demographic characteristics of questionnaire respondents (N = 400, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Variable			N	%	Cross-Tabulation Analysis (p)				
					Age	Income Level	Education Level	Residential Type	Experience of Use
Gender		Male	184	46.0	<0.05 *	<0.001 ***			
		Female	216	54.0					
Age		Under 20	0	0		<0.001 **		<0.05 *	·
		21–30	91	22.8					
		31–40	150	37.5					
		41–50	89	22.3					
		51 or above	70	17.5					
Income level		Less than 2 million won	85	21.3			<0.001 ***	<0.01 **	<0.05 *
		2 million won–4 million won	179	44.8					
		4 million won or more	136	34					
Education level		Up to high school	75	18.8				<0.01 **	<0.05 *
		Bachelor's degree/graduate degree	325	81.3					
Residential type	Apartment		277	69.3					
	Non-apartment	Single-family home	50	12.5					
		Studio-apartment	21	5.3					
		Mixed-use apartment	15	3.8					
		Other types	37	9.3					
Experience of use		Never experienced	380	95.0					
		Have experience	20	5.0					

In terms of the experience of use, only 5% (N = 20) of the participants responded that they had experiences with smart home services.

4.2. Service Preference

The results of the service preference test are shown in Figure 2. More than half of respondents (N = 220, 55%) preferred the safety service, which is composed of a leak detection service (N = 112) and visitor monitoring service (N = 108), and 31.8% (N = 127) would prefer to use a convenience service. On the other hand, the preference for energy and healthcare services was only 8.3% (N = 33) and 5% (N = 20).

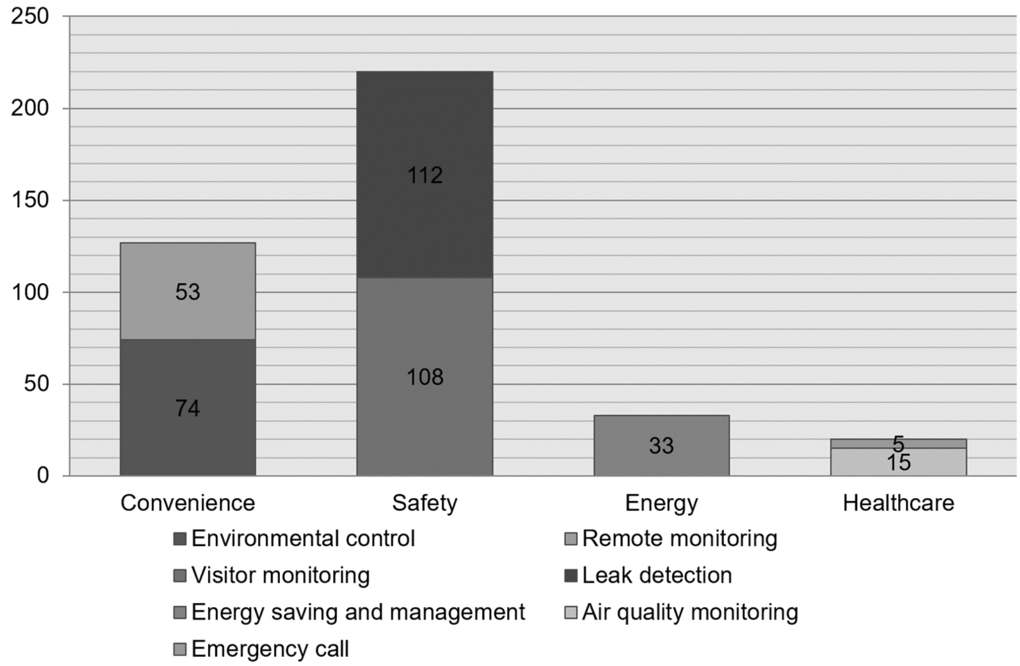

Figure 2. Results of the service preference test (N = 400).

Cross-tabulation analysis was conducted to analyze the frequency distribution of service preference by demographic characteristics (Table 3). A chi-square test and Fisher's exact test were performed to determine the significance of association between the variables. First, the association between gender and service preference was statistically significant ($p = 0.021$). While females preferred safety services most distinctly (62%, N = 134), males' responses showed little difference between safety (46.7%, N = 86) and convenience (38.6%, N = 71) services. Second, residential types were also significantly related to service preferences ($p = 0.007$). Since apartments are the most common type of housing in the Republic of Korea (Statistics Korea, 2019), which account for more than half of all households, the other residential types such as a single-family house, studio-apartment, and mixed-use apartment, were integrated into one response. A total of 49.8% (N = 138) of respondents living in an apartment preferred safety services, followed by 36.1% (N = 100) preference for convenience services. On the other hand, more than half of the respondents living in non-apartment properties preferred safety services the most (66.7%, N = 82), and only 22% (N = 27) preferred convenience services. In other words, the preference for safety services was found to be relatively high in the group who lived in non-apartment properties. Third, the association between experience of use and service preference was also statistically significant ($p = 0.001$). More than half of respondents who had never used smart home services before preferred safety services most, while 65 percent of respondents who had experience using the services preferred convenience services. The remaining characteristics, such as age, income level, education level, did not reach statistical significance.

4.3. Factors Influencing Intention to Use

As shown in Table 4, the mean value of respondents' intention to use smart home services was 3.8506. The independent t-test and one-way analysis of variance (ANOVA) were conducted to examine the factors influencing the intention to use. For the one-way ANOVA, Dunnett's T3 test and Scheffe test were applied, as an assumption of equal variances according to each variable (Table 5).

Table 3. Cross-tabulation analysis between service preferences and demographic characteristics (N = 400, * $p < 0.05$, ** $p < 0.01$).

Variable		Convenience	Safety	Energy	Healthcare	Total	χ^2	p
Gender	Male	71 (38.6)	86 (46.7)	17 (9.2)	10 (5.4)	184 (100.0)	9.777	<0.05 *
	Female	56 (25.9)	134 (62.0)	16 (7.4)	10 (4.6)	216 (100.0)		
Age	21–30	29 (31.9)	50 (54.9)	8 (8.8)	4 (2.7)	91 (100.0)	10.953	
	31–40	56 (37.3)	80 (53.3)	10 (6.7)	4 (2.7)	150 (100.0)		
	41–50	22 (24.7)	48 (53.9)	11 (12.4)	8 (9.0)	89 (100.0)		
	51 or above	20 (28.6)	42 (60.0)	4 (5.7)	4 (5.7)	70 (100.0)		
Income level	Less than 2 million won	24 (28.2)	53 (62.4)	5 (5.9)	3 (3.5)	85 (100.0)	5.387	
	2 million won–4 million won	56 (31.3)	100 (55.9)	16 (8.9)	7 (3.9)	179 (100.0)		
	4 million won or more	47 (34.6)	67 (49.3)	12 (8.8)	10 (7.4)	136 (100.0)		
Education level	Up to high school	20 (26.7)	43 (57.3)	8 (10.7)	4 (5.3)	75 (100.0)	1.517	
	Bachelor's degree/graduate degree	107 (32.9)	177 (54.5)	25 (7.7)	16 (4.9)	325 (100.0)		
Residential type	Apartment	100 (36.1)	138 (49.8)	22 (7.9)	17 (6.1)	277 (100.0)	12.200	<0.01 **
	Non-apartment	27 (22.0)	82 (66.7)	11 (8.9)	3 (2.4)	123 (100.0)		
Experience of use	Never experienced	114 (30.0)	217 (57.1)	30 (7.9)	19 (5.0)	380 (100.0)	15.385	<0.01 **
	Have experience	13 (65.0)	3 (15.0)	3 (15.0)	1 (5.0)	20 (100.0)		

First, the effects of demographic characteristics are as follows. For gender, the male respondents showed a slightly higher intention to use the services than females, but the difference did not reach statistical significance. Similarly, respondents aged 51 years or above showed the highest mean intention to use (3.9750). However, it was not statistically significant. On the other hand, the mean differences depending on income level, education level, residential type, and experience of use were statistically significant. Respondents with an average monthly income of less than 2 million won had a lower intention to use than other groups (3.4588), and income level provided a statistically significant difference ($F = 18.653$, $p < 0.001$). Regarding education level, respondents with lower education levels had lower intention to use than those with higher education levels ($t = -2.334$, $p < 0.05$). It was also found that people living in apartments had a higher mean intention to use than those living in non-apartment properties ($t = 2.779$, $p < 0.01$). Finally, the mean intention to use depending on previous experience had a statistically significant difference ($t = -4.872$, $p < 0.001$); thus, the respondents with past experience had a higher mean intention to use than those without experience.

Table 4. Mean of Intention to use.

Variable	Item	N	Min	Max	Mean	SD
IU 1	Using smart home services will be worthwhile.	400	1	5	3.92	0.878
IU 2	I would like to use smart home services as much as I can from now on.	400	1	5	3.95	0.997
IU 3	I will continue using smart home services or expect to use smart home services in the future.	400	1	5	3.92	0.904
IU 4	I will recommend smart home services to others.	400	1	5	3.61	0.935
Intention to use (Mean)		400	1.25	5.00	3.8506	0.78162

Table 5. T-test and ANOVA test results (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Variable		Intention to use						
		n	Mean	SD	t	p	F	Post-Hoc Test(p)
Gender	Male	184	3.9171	0.81457	1.573			
	Female	216	3.7940	0.74967				
Age	21–30	91	3.7720	0.81959			1.970	
	31–40	150	3.9133	0.76467				
	41–50	89	3.7275	0.81328				
	51 or above	70	3.9750	0.70602				
Income level	Less than 2 million won (a)	85	3.4588	0.92086		<0.001 ***	18.653	a < b (<0.01 **) a < c (<0.001 ***) b < c (<0.01 **)
	2 million won–4 million won (b)	179	3.8324	0.73428				
	4 million won or more (c)	136	4.1195	0.63023				
Education level	Up to high school	75	3.6267	0.96157	−2.334	<0.05 *		
	Bachelor's degree/graduate degree	325	3.9023	0.72587				
Residential type	Apartment	277	3.9224	0.76009	2.779	<0.01 **		
	Non-apartment	123	3.6890	0.80809				
Experience of use	Never experienced	380	3.8184	0.77875	−4.872	<0.001 ***		
	Have experience	20	4.4625	0.56356				
Service preference [1]	Convenience (a)	127	4.1083	0.69550		<0.001 ***	8.322	a > b (<0.001 ***) a > d (<0.01 **)
	Safety (b)	220	3.7375	0.77313				
	Energy (c)	33	3.8561	0.77316				
	Healthcare (d)	20	3.4500	0.98208				
Service preference (detailed) [2]	Environmental control (a)	74	4.1318	0.62923		<0.001 ***	5.182	a > d (<0.05 *) a > g (<0.05 *)
	Remote monitoring (b)	53	4.0755	0.78383				
	Visitor monitoring (c)	108	3.8032	0.78913				
	Leak detection (d)	112	3.6741	0.75549				
	Energy saving & management (e)	33	3.8561	0.77316				
	Air quality monitoring (f)	15	3.6500	0.98107				
	Emergency call (g)	5	2.8500	0.78262				

Homogeneous subset test results: (bcd = 1, abc = 2) [1], (dfg = 1, abcdef = 2) [2].

Subsequently, the effect of service preferences on the difference in intention to use was analyzed. First, the mean differences between the four types of smart home services were statistically significant (F = 8.322, $p < 0.001$). The mean of the group that preferred the convenience service most was the highest at 4.1083 and showed statistically significant differences from the mean of safety (3.7375) and healthcare (3.4500). Additionally, seven types of detailed services also significantly affected the intention to use (F = 5.182, $p < 0.001$). The respondents who preferred an environmental control service showed the highest intention to use (4.1318), while those who preferred the emergency call service had the lowest mean (2.8500). A posthoc Scheffe test was conducted to identify specific differences between group means. The results indicated that there are significant differences between environment control, leak detection, and emergency calls. Furthermore, subsets of homogeneous groups using Scheffe's method showed some interesting differences across service preferences. For example, healthcare and convenience formed different homogenous groups. Moreover, an emergency call was also separated into different homogeneous groups from visitor monitoring, energy-saving and management, remote monitoring, and environmental control. Intention to use depending on service preferences showed a statistically significant difference. In other words, the groups that preferred convenience services, especially environmental control services, tended to be more willing to use the services, while those who prefer healthcare services, especially emergency call services, were relatively less willing to use them.

4.4. Regression Analysis

A regression analysis was performed to test the hypothesis. Prior to the regression, a reliability analysis was conducted for the dependent variables consisting of multiple scales. For reliability, the internal consistency reliability was examined based on Cronbach's alpha, and its value was measured at 0.861. In general, a Cronbach's alpha of 0.6 or higher can be considered to represent internal consistency [63] and indicates that the reliability of the results is relatively high.

For the autocorrelation of the dependent variables, the Durbin-Watson statistic was used, in which a value between 1–3 is generally deemed to satisfy the independence assumption [64]. The Durbin-Watson value of the regression model was 2.007, thereby meeting this criterion. For multicollinearity, the variance inflation factors (VIFs) were less than 10, indicating that multicollinearity was not a concern.

To test the hypotheses, a hierarchical regression analysis was performed to study the effects of service preferences on intention to use after controlling for demographic characteristics. Before performing regression analysis, all categorical variables were converted into dummy variables. For analyzing income level, the group was divided into two with respect to a monthly average of 2 million won, which showed the clearest difference in the mean intention to use in this study (Table 5). In addition, for service preference variables, among the four types of services, the convenience service preference, which recorded the highest mean intention to use (Table 5), was considered as a reference group. The results of the hierarchical regression analysis on the effects of demographic characteristics and service preferences on the intention to use are reported in Table 6.

Model 1 examined the effects on intention to use by employing demographic characteristics as the control variables. Model 2 examined whether and how the independent variables affect the intention to use by controlling for exogenous variables after inputting the service preferences as independent variables. The results of Model 1 indicated that the variance accounted for R^2 with the control variable (demographic characteristics) was 0.116 (adjusted R^2 = 0.097), which was statistically significant (ΔF = 6.387, $p < 0.001$). Next, in Model 2, the change in variance accounted for ΔR^2 was 0.04, which was a statistically significant increase in variance (ΔF = 6.097, $p < 0.001$). In other words, the explanatory power of the model increased significantly by about 4%, and it was statistically significant for the independent variables to explain the dependent variables after inputting the control variables.

The results of Model 1 indicated the impact of demographic characteristics as control variables on the intention to use. Two of the demographic characteristics, income levels, and experience of use, were statistically significant. In other words, relatively low-income levels had a negative effect on the intention to use, while the experience of previous use had a positive effect on the intention to use.

Table 6. The results of regression analysis (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Variable		Model 1					Model 2				
		B	β	t	p	VIF	B	β	t	p	VIF
(constant)		3.894		31.684	<0.001 ***		4.153		29.355	<0.001 ***	
Gender (Male)		0.058	0.037	0.758		1.052	0.020	0.013	0.265		1.078
Age (21–30)		−0.048	−0.026	−0.396		1.890	−0.076	−0.041	−0.632		1.902
Age (31–40)		−0.039	−0.024	−0.353		2.034	−0.076	−0.047	−0.702		2.049
Age (41–50)		−0.233	−0.124	−1.954		1.788	−0.219	−0.116	−1.858		1.805
Income level (Less than 2 million won)		−0.423	−0.222	−4.342	<0.001 ***	1.154	−0.427	−0.224	−4.459	<0.001 ***	1.156
Education level (Up to high school)		−0.131	−0.066	−1.325		1.082	−0.124	−0.062	−1.271		1.086
Residential types (Apartment)		0.142	0.084	1.721		1.053	0.118	−0.070	1.436		1.082
Experience of use (Have experience)		0.475	0.133	2.727	<0.01 **	1.044	0.387	0.108	2.232	<0.05 *	1.077
Service preference	Safety						−0.283	-0.181	−3.345	<0.01 **	1.339
	Energy						−0.213	−0.075	−1.478		1.180
	Healthcare						−0.626	−0.175	−3.535	<0.001 ***	1.124
R^2		0.116					0.155				
adj.R^2		0.097					0.131				
ΔR^2		0.116					0.040				
$\Delta F(p)$		6.387 (<0.001)					6.097 (<0.001)				

Durbin-Watson: 2.007; Reference group: Gender * Female, Age * 51 or above, Income level * 2 million won or more, Education level * Bachelor's degree/graduate degree, Residential types * Non-apartment, Experience of use * Never experienced, Service Preference * Convenience.

The results of Model 2 reported that while service preferences had statistically significant effects on the intention to use, preferences for energy services did not reach statistical significance. In other words, H1, H2, and H4 were supported whereas H3 was rejected. Furthermore, the results of Model 2 indicated the relative impacts of service preferences on intention to use after controlling for demographic characteristics. For example, the unstandardized coefficient (B) of the regression model of safety service preferences and healthcare service preferences, which had secured statistical significance, were both recorded negatively. This suggests that convenience service preference, a reference group of service preference variables injected into the regression model, had the greatest impact on intention to use.

4.5. Discussion

This study identified the impact of smart home service preferences on intention to use. Of the four constructs of smart home services, convenience, safety, and healthcare influenced adoption, and the intention to use differed significantly depending on the type of service preferences.

These results suggest that identifying preferences for different types of services is effective in predicting the adoption of services. While the preference for safety services was the highest in the overall response, intention to use was highest for the group that preferred environmental control services, which ranked third in the overall preference assessment. This means that those who prefer and want to use environmental control services most are more likely to become relatively active adopters. On the other hand, the group that preferred healthcare, especially the emergency call service, showed they were less willing to use the service. Therefore, it was assumed that this group was sensitive to price, or did not believe they needed the service despite being aware of the importance of it.

Another type of factor identified that affects preferences and intentions to use smart home services was the demographic characteristics. First, gender affected service preferences. Female respondents were found to have a higher demand for safety in residential environments than males. On the other hand, the intention to use was slightly higher among male respondents, but not significant, which was different from prior studies that found the impact of gender on the adoption of smart homes [16,52].

Second, age did not affect either service preferences or intention to use, which is a remarkable result. Safety services were most preferred among all age groups, with no significant difference in intention to use over the ages. Many studies have focused on the elderly population as a major beneficiary of the automated technology of smart homes, and smart home research has generally focused on healthcare services for the elderly [23,49,50]. However, the results of this study show that there are considerable needs for other aspects of services that can support the independent lives of residents, such as safety and convenience, among all age groups. Therefore, future smart home adoption studies, especially those for the elderly, will have to consider both the various functions and needs of housing.

Third, both income and education levels have significant effects on the intention to use, while the preference was not affected. Respondents with low-income levels showed relatively low intention to use, and the result would support existing studies that reported the impact of the cost burden on the adoption of smart homes [12,35]. In addition, the results of this study have re-examined the significant impact of education levels on adoption, which have only been addressed in some studies [16].

Fourth, residential type has been considered only in some prior studies as an influencing factor in the adoption of smart homes. However, this study supported the findings of previous studies as the effects of residential type on both service preferences and intention to use were verified [16,55]. The study findings showed that respondents living in apartments had a relatively high preference for convenience services compared to respondents living in non-apartment properties, and their intention to use was also relatively high. These results suggest that the adoption behavior of smart homes can be affected by the physical environment characteristics such as the environmental and system infrastructure in which users reside. In other words, considering the conditions of the residential environment of the target user would be a valid design strategy to promote the adoption of smart home services.

Another factor supporting existing studies was the significant impact of experience on adoption. Since experience has been treated as a major influencing factor in terms of acceptance of innovative technologies, this result supports prior studies [33,57]. In addition, respondents who have experience of use tended to prefer convenience services over safety services. This result indicates that experienced respondents would have more strongly recognized and noted the effects of convenience services than safety services, compared with inexperienced respondents.

Demographic classification according to service preferences provides new insight for adoption research. For example, although the largest number of respondents expressed preferences for safety services, this preference had less of an impact on the intention to use than those with a preference for convenience services. These results show that the "amount" of preference for services is not directly related to the intention to use. In other words, the "most" preferred services are not necessarily the most adopted. This is in the same vein as the findings of Van Dijk et al. (2008), who found a gap between the preference of government Internet services and the actual usage of the services [42]. There are many potential causes for this. One obvious reason is that respondents have different service preferences depending on their demographic characteristics.

The demographic characteristics that most clearly affected the intention to use were shown by income levels and experience (Table 6). Cross-analysis of service preferences also showed that those with no experience of use had the highest preference for safety services, and those with usage experience have the highest preference for convenience services (Table 5). In other words, those without service experience felt that safety services were the most attractive, but expressed relatively low intention to use, while the convenience services preferred by the majority of respondents with service experience had the most positive impact on the intention to use. In particular, the results of ANOVA analysis showed the difference in intention to use between leak detection service preference and environmental control service preference. Similarly, residential types significantly affected service preferences and intention to use. Respondents who preferred safety services had a high proportion of non-apartment dwellers, and the mean intention to use by non-apartments dwellers was significantly lower ($p = 0.006$).

Another possible reason for the gap between the preference and intention to use is the effects of respondents' perceived comprehensive value judgments. Some studies on the adoption of information technology have reported that perceived sacrifices have a greater impact on adoption than perceived benefits [34,38]. That is, it can be assumed that respondents would have hesitated to adopt smart home services because the perceived sacrifices had a greater impact than the preference for smart home services. For this study, in-depth consideration will be required regarding the impact of income level, one of the factors that have formed a significant relationship with intention to use. Income levels formed a significant association with other demographic characteristics, such as gender, age, education levels, residential types, and experience (Table 2). In addition, relatively low-income levels were associated with relatively little experience, and the proportion of respondents living in non-apartment housing was high in groups of respondents with low-income levels. As mentioned above, both experience and residential types were factors that significantly affect preferences and intention to use. Thus, the results of this study suggest the need for in-depth research into the indirect effects of income levels on the service preferences, intention to use, and the comprehensive value-judging process of smart home adoption.

In conclusion, while the significant effects of some factors (e.g., education level, residential type, experience, preference) on smart home adoption is in line with the existing literature, the effects of other factors (e.g., gender, age, income level) were somewhat different from the existing literature. The findings of this study can not only improve the overall understanding of the process of adopting smart homes by verifying differences in adoption and preferences by user characteristics but also present a user-centered strategy to promote adoption. For example, respondents living in apartments and having experience in smart home service use had a relatively high preference for convenience services and a high willingness to use them. In other words, convenience services are likely to be recognized effectively by apartment dwellers or users with relatively high technology levels. In particular, since respondents who preferred convenience services had the highest intention to use, strategies to actively target these users are required to promote smart home adoption. On the other hand, it is also noteworthy that females preferred safety services the most, although gender did not have a direct impact on the intention to use. In other words, the findings may suggest that safety services are more likely to be chosen by females.

Furthermore, the results of this study suggest that discussions on the digital divide should be carried out in smart home adoption research. Van Dijk et al. (2008) noted that the significant impacts of preference and experience on the adoption of information technology-based services indicate that the problem of a digital divide is significant [42]. The dissemination of smart home technology can provide welfare to vulnerable residents, promote social participation, and ultimately realize environmental, economic, social sustainability and innovation at the urban level. Since the main benefits of smart homes are in close contact with ensuring the independent lives and safety of the vulnerable, the findings of this study can provide inspiration to improve accessibility for the users who are alienated from the benefits of technology. Factors that can cause a digital divide might include experience and technical skills, availability of spatial/technical infrastructure, and affordability. Likewise, some studies suggested that technology affordability, network infrastructure availability, residents' education level, income level, and cost burden should be considered at national or urban levels to facilitate the adoption of smart home technologies [65,66]. The results of this study indicate the need for policies and strategies to maintain the adoption of smart homes and enhance technology innovation. Therefore, making smart home services accessible to a wide range of users, especially those with low-wage, low-educated, and low-technical levels, should be the first step in promoting adoption. One example is to reduce costs through joint purchases or to provide pre-experience opportunities for services preferred by target users, generally safety services.

5. Conclusions and Limitation

Although the supply of smart home services is expanding, actual usage promotion is still small. This phenomenon could be described as the result of the comprehensive impact of users' perceptions, attitudes, experiences, and personal characteristics on the adoption of technology. From this perspective, this study validated how demographic characteristics and preferences of potential users influence the adoption of smart home services. The results of this study confirmed the impact of gender, residential type, and experience on service preferences and the impact of income level, education level, residential type, experience, and service preference on the adoption.

The findings of the present study provide both theoretical and practical implications. From a theoretical perspective, this study presents an improved comprehension of the process of adopting a smart home, by identifying the impacts of preference for different types of smart home services on the adoption. Moreover, the findings of the study offer insight and new issues on smart home adoption for future research. For example, while prior research was actively focused on energy efficiency in house and health care for the elderly, this study validated considerable demands for safety and convenience services that do not differ depending on age.

This study presented a demographic classification according to the adoption and preference of smart home services. A general conclusion that can be derived from this study is that the adoption of smart home services should be analyzed based on a detailed understanding of the target users for each service type. Based on the delicate classification of the service contents that might affect adoption, future research that deals with type-specific comparisons based on granular service types need to be followed, rather than combining smart home services into a single concept.

The study also suggests that smart home adoption can be associated with complex social phenomena such as income inequality. The Republic of Korea is known to have a relatively high penetration rate of information infrastructure. However, this study suggested that demographic characteristics could create various gaps in smart home adoption. This is not much different from the results of previous studies of smart technology adoption in developing countries with relatively low penetration of information infrastructure [65,66].

From a practical perspective, this study presents an example of adoption tendencies of smart home services in a housing context. In particular, the findings of the study can equip service providers and related industries, such as IT, engineering, and architecture, with useful information for designing effective services and selecting appropriate target users. For example, setting up a group of women, non-apartment residents, and inexperienced users as the primary target users of safety services, and controlling the direct and indirect impact of expected adoption inhibitors such as income levels, residential types, and experience might be a strategy that can increase service adoption.

Despite these contributions, there are some limitations of this study. First, the present study did not consider the interrelationship between demographic characteristics in testing the hypothesis. For example, demographic characteristics such as gender, income level, and education level are generally known to be closely related to each other. Therefore, precise verification of the independent effects of each characteristic will have to be followed by controlling for the effects of variables or targeting subdivided samples in consideration of socio-cultural contexts. Second, it is difficult to generalize the results to other countries since the sample of this study was limited to those living in the Republic of Korea, where public IT infrastructure is common and is expected to be relatively high in technology acceptance. Therefore, future research will need to ensure racial and geographical diversity in selecting samples. Finally, the scope of the study did not cover all types of services that make up the smart home market. Since the smart home market is rapidly evolving and changing, various services appear and disappear at the same time. Thus, future studies need to address the adoption and preferences of new types of services that will emerge as the market changes. In conclusion, future research should overcome these limitations and extend the present study findings to provide a more comprehensive understanding of the adoption of smart home technology.

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References

1. Weiser, M. The Computer for the 21st Century. *Sci. Am.* **1991**, *265*, 94–105. [CrossRef]
2. Lutolf, R. Smart home concept and the integration of energy meters into a home based system. In Proceedings of the Seventh International Conference on Metering Apparatus and Tariffs for Electricity Supply 1992, Glasgow, UK, 17–19 November 1992.
3. Friedewald, M.; Da Costa, O.; Punie, Y.; Alahuhta, P.; Heinonen, S. Perspectives of ambient intelligence in the home environment. *Telemat. Inform.* **2005**, *22*, 221–238. [CrossRef]
4. Alam, M.R.; Reaz, M.B.I.; Ali, M.A.M. A review of smart homes—Past, present, and future. *IEEE Trans. Syst. Man Cybern. Part C* **2012**, *42*, 1190–1203. [CrossRef]
5. Yamazaki, T. Beyond the smart home. In Proceedings of the 2006 International Conference on Hybrid Information Technology, Cheju, Korea, 9–11 November 2006. [CrossRef]
6. Chang, S.; Nam, K. Spatial Design Direction of Smart Home in IoT Paradigm. In Proceedings of the 2019 2nd World Symposium on Communication Engineering (WSCE), Nagoya, Japan, 20–23 December 2019. [CrossRef]
7. Coskun, A.; Kaner, G.; Bostan, İ. Is smart home a necessity or a fantasy for the mainstream user? A study on users' expectations of smart household appliances. *Int. J. Des.* **2018**, *12*, 7–20.
8. Wilson, C.; Hargreaves, T.; Hauxwell-Baldwin, R. Benefits and risks of smart home technologies. *Energy Policy* **2017**, *103*, 72–83. [CrossRef]
9. Dimitrokali, E.; Mackrill, J.; Jennings, P.; Khanna, S.; Harris, V.; Cain, R. Exploring homeowners' perception and experiences in using a domestic smart home heating controller. *Indoor Built Environ.* **2015**, *24*, 1010–1032. [CrossRef]
10. Koupaei, D.M.; Song, T.; Cetin, K.S.; Im, J. An assessment of opinions and perceptions of smart thermostats using aspect-based sentiment analysis of online reviews. *Build. Environ.* **2020**, *170*, 106603. [CrossRef]
11. Pal, D.; Funilkul, S.; Charoenkitkarn, N.; Kanthamanon, P. Internet-of-things and smart homes for elderly healthcare: An end user perspective. *IEEE Access* **2018**, *6*, 10483–10496. [CrossRef]
12. Balta-Ozkan, N.; Davidson, R.; Bicket, M.; Whitmarsh, L. Social barriers to the adoption of smart homes. *Energy Policy* **2013**, *63*, 363–374. [CrossRef]
13. Hubert, M.; Blut, M.; Brock, C.; Zhang, R.W.; Koch, V.; Riedl, R. The influence of acceptance and adoption drivers on smart home usage. *Eur. J. Mark.* **2019**, *53*, 1073–1098. [CrossRef]
14. Park, E.; Kim, S.; Kim, Y.; Kwon, S.J. Smart home services as the next mainstream of the ICT industry: Determinants of the adoption of smart home services. *Univers. Access Inf. Soc.* **2018**, *17*, 175–190. [CrossRef]
15. Shuhaiber, A.; Mashal, I. Understanding users' acceptance of smart homes. *Technol. Soc.* **2019**, *58*, 101110. [CrossRef]
16. Shin, J.; Park, Y.; Lee, D. Who will be smart home users? An analysis of adoption and diffusion of smart homes. *Technol. Forecast. Soc. Chang.* **2018**, *134*, 246–253. [CrossRef]
17. Baudier, P.; Ammi, C.; Deboeuf-Rouchon, M. Smart home: Highly-educated students' acceptance. *Technol. Forecast. Soc. Chang.* **2020**, *153*, 119355. [CrossRef]
18. Ford, R.; Pritoni, M.; Sanguinetti, A.; Karlin, B. Categories and functionality of smart home technology for energy management. *Build. Environ.* **2017**, *123*, 543–554. [CrossRef]
19. Khan, A.; Javaid, N.; Khan, M.I. Time and device based priority induced comfort management in smart home within the consumer budget limitation. *Sustain. Cities Soc.* **2018**, *41*, 538–555. [CrossRef]
20. Paetz, A.G.; Dütschke, E.; Fichtner, W. Smart homes as a means to sustainable energy consumption: A study of consumer perceptions. *J. Consum. Policy* **2012**, *35*, 23–41. [CrossRef]
21. Chan, M.; Campo, E.; Estève, D.; Fourniols, J.Y. Smart homes—current features and future perspectives. *Maturitas* **2009**, *64*, 90–97. [CrossRef]
22. Allameh, E.; Jozam, M.H.; de Vries, B.; Timmermans, H.; Beetz, J.; Mozaffar, F. The role of Smart Home in smart real estate. *J. Eur. Real Estate Res.* **2012**, *5*, 156–170. [CrossRef]
23. Reeder, B.; Chung, J.; Lyden, K.; Winters, J.; Jankowski, C.M. Older women's perceptions of wearable and smart home activity sensors. *Inform. Health Soc. Care* **2020**, *45*, 96–109. [CrossRef]
24. Thielke, S.; Harniss, M.; Thompson, H.; Patel, S.; Demiris, G.; Johnson, K. Maslow's hierarchy of human needs and the adoption of health-related technologies for older adults. *Ageing Int.* **2012**, *37*, 470–488. [CrossRef]
25. Wong, J.K.W.; Leung, J.K. Modelling factors influencing the adoption of smart-home technologies. *Facilities* **2016**, *34*, 906–923. [CrossRef]
26. Balta-Ozkan, N.; Amerighi, O.; Boteler, B. A comparison of consumer perceptions towards smart homes in the UK, Germany and Italy: Reflections for policy and future research. *Technol. Anal. Strateg. Manag.* **2014**, *26*, 1176–1195. [CrossRef]
27. Demiris, G.; Hensel, B.K. Technologies for an aging society: A systematic review of "smart home" applications. *Yearb. Med. Inform.* **2008**, *3*, 33–40.
28. Ziefle, M.; Himmel, S.; Wilkowska, W. When your living space knows what you do: Acceptance of medical home monitoring by different technologies. In Proceedings of the Symposium of the Austrian HCI and Usability Engineering Group, Graz, Austria, 25–26 November 2011. [CrossRef]
29. Yeh, H. The effects of successful ICT-based smart city services: From citizens' perspectives. *Gov. Inf. Q.* **2017**, *34*, 556–565. [CrossRef]

30. Kim, Y.; Park, Y.; Choi, J. A study on the adoption of IoT smart home service: Using Value-based Adoption Model. *Total. Qual. Manag. Bus. Excell.* **2017**, *28*, 1149–1165. [CrossRef]
31. Gaul, S.; Ziefle, M. Smart home technologies: Insights into generation-specific acceptance motives. In *Symposium of the Austrian HCI and Usability Engineering Group*; Springer: Berlin/Heidelberg, Germany, 2009; pp. 312–332.
32. Venkatesh, V.; Davis, F.D. A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Manag. Sci.* **2000**, *46*, 186–204. [CrossRef]
33. Venkatesh, V.; Morris, M.G.; Davis, G.B.; Davis, F.D. User acceptance of information technology: Toward a unified view. *MIS Q.* **2003**, 425–478. [CrossRef]
34. Kim, H.W.; Chan, H.C.; Gupta, S. Value-based adoption of mobile internet: An empirical investigation. *Decis. Support Syst.* **2007**, *43*, 111–126. [CrossRef]
35. Brush, A.B.; Lee, B.; Mahajan, R.; Agarwal, S.; Saroiu, S.; Dixon, C. Home automation in the wild: Challenges and opportunities. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Vancouver, BC, Canada, 7–12 May 2011; ACM Press: New York, NY, USA, 2011; pp. 2115–2124. [CrossRef]
36. Wilson, C.; Hargreaves, T.; Hauxwell-Baldwin, R. Smart homes and their users: A systematic analysis and key challenges. *Pers. Ubiquitous Comput.* **2015**, *19*, 463–476. [CrossRef]
37. Davis, F.D.; Bagozzi, R.P.; Warshaw, P.R. Extrinsic and intrinsic motivation to use computers in the workplace. *J. Appl. Soc. Psychol.* **1992**, *22*, 1111–1132. [CrossRef]
38. Lin, T.C.; Wu, S.; Hsu, J.S.C.; Chou, Y.C. The integration of value-based adoption and expectation–confirmation models: An example of IPTV continuance intention. *Decis. Support Syst.* **2012**, *54*, 63–75. [CrossRef]
39. Davis, F.D. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Q.* **1989**, *13*, 319–340. [CrossRef]
40. Wu, G. The mediating role of perceived interactivity in the effect of actual interactivity on attitude toward the website. *J. Interact. Advert.* **2005**, *5*, 29–39. [CrossRef]
41. Hsu, C.L.; Lin, J.C.C. Acceptance of blog usage: The roles of technology acceptance, social influence and knowledge sharing motivation. *Inf. Manag.* **2008**, *45*, 65–74. [CrossRef]
42. Van Dijk, J.A.; Peters, O.; Ebbers, W. Explaining the acceptance and use of government Internet services: A multivariate analysis of 2006 survey data in the Netherlands. *Gov. Inf. Q.* **2008**, *25*, 379–399. [CrossRef]
43. Aldossari, M.Q.; Sidorova, A. Consumer acceptance of Internet of Things (IoT): Smart home context. *J. Comput. Inf. Syst.* **2020**, *60*, 507–517. [CrossRef]
44. Parag, Y.; Butbul, G. Flexiwatts and seamless technology: Public perceptions of demand flexibility through smart home technology. *Energy Res. Soc. Sci.* **2018**, *39*, 177–191. [CrossRef]
45. Luor, T.T.; Lu, H.P.; Yu, H.; Lu, Y. Exploring the critical quality attributes and models of smart homes. *Maturitas* **2015**, *82*, 377–386. [CrossRef]
46. Mennicken, S.; Vermeulen, J.; Huang, E.M. From today's augmented houses to tomorrow's smart homes: New directions for home automation research. In Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing, Washington, DC, USA, 13–17 September 2014; pp. 105–115. [CrossRef]
47. Noh, M.J.; Kim, J.S. Factors influencing the user acceptance of digital home services. *Telecommun. Policy* **2010**, *34*, 672–682. [CrossRef]
48. Eggen, B.; Hollemans, G.; van de Sluis, R. Exploring and enhancing the home experience. *Cogn. Technol. Work.* **2003**, *5*, 44–54. [CrossRef]
49. Courtney, K.L.; Demeris, G.; Rantz, M.; Skubic, M. Needing smart home technologies: The perspectives of older adults in continuing care retirement communities. *Inform. Prim. Care* **2008**, *16*, 195–201. [CrossRef] [PubMed]
50. Demiris, G.; Rantz, M.J.; Aud, M.A.; Marek, K.D.; Tyrer, H.W.; Skubic, M.; Hussam, A.A. Older adults' attitudes towards and perceptions of 'smart home'technologies: A pilot study. *Med. Inform. Internet Med.* **2004**, *29*, 87–94. [CrossRef] [PubMed]
51. Pal, D.; Funilkul, S.; Vanijja, V.; Papasratorn, B. Analyzing the elderly users' adoption of smart-home services. *IEEE Access* **2018**, *6*, 51238–51252. [CrossRef]
52. Yang, H.; Lee, H.; Zo, H. User acceptance of smart home services: An extension of the theory of planned behavior. *Ind. Manag. Data Syst.* **2017**, *117*, 68–89. [CrossRef]
53. Nikou, S. Factors driving the adoption of smart home technology: An empirical assessment. *Telemat. Inform.* **2019**, *45*, 101283. [CrossRef]
54. Williams, T.; Bernold, L.; Lu, H. Adoption patterns of advanced information technologies in the construction industries of the United States and Korea. *J. Constr. Eng. Manag.* **2007**, *133*, 780–790. [CrossRef]
55. Yang, H.; Lee, W.; Lee, H. IoT smart home adoption: The importance of proper level automation. *J. Sens.* **2018**. [CrossRef]
56. Mamat, M.; Haron, M.S.; Razak, N.S.A. Personal interaction encounter, customer involvement, familiarity and customer service experience in Malaysian public universities. *Procedia Soc. Behav. Sci.* **2014**, *130*, 293–298. [CrossRef]
57. Shih, C.F.; Venkatesh, A. Beyond adoption: Development and application of a use-diffusion model. *J. Mark.* **2004**, *68*, 59–72. [CrossRef]
58. Ministry of Land, Infrastructure and Transport. Standards for Intelligent Home Network Installation and Technology. Available online: http://www.molit.go.kr/USR/I0204/m_45/dtl.jsp?idx=16461 (accessed on 21 August 2020).

59. Cohen, J. *Statistical Power Analysis for the Behavioral Sciences*; Lawrence Erlbaum Associates: Hillsdale, MI, USA, 1988.
60. Faul, F.; Erdfelder, E.; Buchner, A.; Lang, A.-G. Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behav. Res. Methods* **2009**, *41*, 1149–1160. [CrossRef] [PubMed]
61. Statistics Korea. Income Statistics of Wage Workers in 2018. Available online: http://kostat.go.kr/portal/eng/pressReleases/1/index.board?bmode=read&bSeq=&aSeq=380950&pageNo=1&rowNum=10&navCount=10&currPg=&searchInfo=srch&sTarget=title&sTxt=2018 (accessed on 25 August 2020).
62. Statistics Korea. 2018 Population and Housing Census. Available online: http://kostat.go.kr/portal/eng/pressReleases/1/index.board?bmode=read&bSeq=&aSeq=378503&pageNo=1&rowNum=10&navCount=10&currPg=&searchInfo=srch&sTarget=title&sTxt=2018+Population+and+Housing (accessed on 25 August 2020).
63. Hair, J.F.; Bush, R.P.; Ortinau, D.J. *Marketing Research: A Practical Approach for the New Millennium*; Irwin/McGraw-Hill: Boston, MA, USA, 2000.
64. Field, A. *Discovering Statistics Using SPSS: (and Sex and Drugs and Rock'N'Roll), 3rd ed*; SAGE: London, UK, 2009.
65. Tetteh, N.; Amponsah, O. Sustainable Adoption of Smart Homes from the Sub-Saharan African Perspective. *Sustain. Cities Soc.* **2020**, *63*, 102434. [CrossRef]
66. Soyinka, O.; Siu, K.W.M.; Lawanson, T.; Adeniji, O. Assessing smart infrastructure for sustainable urban development in the Lagos metropolis. *J. Urban Manag.* **2016**, *5*, 52–64. [CrossRef]