pISSN: 1906 - 6406 The Scholar: Human Sciences
eISSN: 2586 - 9388 The Scholar: Human Sciences
http://www.assumptionjournal.au.edu/index.php/Scholar

Key Determinants for Users' Intention To Use Smart Home Technology: A Case of Residents in Mianyang, Yibin and Wanzhou, China

Tianbin Mao*

Received: September 14, 2023. Revised: October 23, 2023. Accepted: October 31, 2023.

Abstract

Purpose: The objective of this research is to investigate the various determinants that affect residents' inclination to adopt smart home technology in the cities of Mianyang, Yibin, and Wanzhou, located in China. The conceptual framework encompasses factors such as perceived usefulness, perceived ease of use, personal innovativeness, trust, hedonic motivation, social influence, price value and intention to use. **Research design, data, and methodology:** In this study, the target population consisted of 500 smart home users. To ensure the content validity and reliability of the questionnaire, Item-Objective Congruence (IOC) and a pilot test of Cronbach's Alpha were employed before distribution. Data analysis was conducted using Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) to assess the model's goodness of fit and validate the causal relationships among variables for hypothesis testing. **Results:** All hypotheses were found to be supported. The variables of perceived usefulness, perceived ease of use, personal innovativeness, trust, hedonic motivation, social influence, and price value were discovered to significantly influence the intention to use smart home technology. Additionally, it was observed that perceived ease of use exerted a significant impact on perceived usefulness. **Conclusions:** In particular, it has important theoretical guidance and practical value for improving the user experience of Chinese residents using smart homes.

Keywords : Hedonic Motivation, Social Influence, Price Value, Intention to Use, Smart Home Technology

JEL Classification Code: E44, F31, F37, G15

1. Introduction

The concept of a smart home can be understood as an implementation of ubiquitous computing, it seamlessly integrates into individuals' daily routines and activities. In addition, there is an increasing desire for residences that offer convenience through the integration of household equipment and contents via ICT (Kim et al., 2017), in contrast to optimistic projections on the future expansion of the market. The smart home industry is now nascent and has encountered challenges in attaining widespread adoption (Greenough, 2016).

Smart Home Technology (SHT) is an exemplification of the practical implementation of Internet of Thing (IoT) technology. A smart home is a residential automation system that connects various components such as sensors, displays, interfaces, and devices with the IoT. According to Hong et al. (2017), the IoT sector is anticipated to experience significant growth soon. It is projected that the worldwide IoT industry will experience significant growth, reaching a value of USD 1.56 trillion by the year 2025. One notable example of an IoT service that has garnered significant interest is the smart home concept (Statista Research Department, 2023).

Smart home services have been driven in recent years by the fourth technological revolution, defined by the IoT, big data, cloud computing, and information technology (IT). Smart cities represent a strategic initiative undertaken by the Chinese government to attain sustainable development objectives. Promoting SHT to urban households is an important component of the Chinese government's blueprint for smart cities. The nation will endeavor to enhance the development of manufacturing, communication, and service

1*Tianbin Mao, School of Fine Arts and Design, Chengdu University, China. Email: 405012445@qq.com

industries associated with the IoT while also expanding the utilization of technology to establish a more extensive value chain (Li et al., 2016).

Chinese consumers have a limited degree of comprehension and willingness to embrace smart homes, rendering the concept still novel and detached from their everyday experiences. The limited adoption of smart home products and services among the general consumer population can be linked to the relatively short duration of development within the smart home industry. This has resulted in a restricted diffusion of such products and services, with just a few famous firms being exceptions to this trend. Despite numerous companies offering early iterations of such products and services, their widespread adoption has been hindered by technological disparities, the absence of standardized protocols, apprehensions regarding security and privacy, and various other factors.

The primary theoretical objective of this research is to provide an all-encompassing conceptual framework that elucidates the determinants impacting the adoption of SHT. The existing body of studies examining the adoption of sustainable housing and energy technologies (SHET) among urban inhabitants in China needs to be revised (Kim et al., 2017). For the academics, the paper proposed a conceptual model in the context of system technology focus for adopting smart homes in China.

2. Literature Review

2.1 Perceived Usefulness

Perceived usefulness describes how an individual is convinced that technology will improve performance (Davis et al., 1989). In other words, “having the potential to be advantageous” (Sponselee et al., 2008). The precise connotation of perceived usefulness refers to the user’s conviction that utilizing the system will enhance their work performance, as defined by Thi-Hong-Linh et al. (2018). The idea of perceived utility encompasses the extent to which individuals maintain the belief that using smart homes will augment users' overall quality of life (Shuhaiber & Mashal, 2019).

The technology acceptance model (TAM) states that important determinants of perceived usefulness a system/technology are perceived ease of use and perceived usefulness (Gao & Bai, 2014). In short, the degree to which a person believes that using the technology will improve his or her performance is perceived usefulness (Davis et al., 1989). According to Leeraphong et al. (2015), the TAM can facilitate this study. It posits that individuals who regard the smart home as highly valuable are more likely to have a favorable attitude towards its acceptance and demonstrate a preference for selecting and adopting it. The formulation of hypotheses regarding the desire to embrace smart home technology can be presented in the following hypothesis:

H1: Perceived usefulness has a significant influence on intention to use.

2.2 Perceived Ease of Use

The concept of perceived ease of use influences the acceptability of new technology advancements. The term “perceived ease of use” pertains to an individual’s evaluation of the effort required to effectively utilize a system, as described by Davis (1989). Venkatesh and Bala (2008) suggest that perceived ease of use pertains to an individual’s subjective perception regarding the little physical or cognitive exertion required to engage with smart homes (Shuhaiber & Mashal, 2019). The occurrence of participating in an excessive amount of physical or mental exertion. Previous research has demonstrated the importance of trust concerning the ease of use of IT systems, emphasizing its central role in shaping their acceptance (Venkatesh & Davis, 2000).

Previous studies have demonstrated that the perceived ease of use influences consumers’ inclination to adopt this specific set of technologies (Lee et al., 2012). Additionally, the study conducted by Gao and Bai (2014) revealed that the perceived ease of use significantly influenced the reported utility. Moreover, it is important to acknowledge that the aspect of perceived ease of use positively influences perceived usefulness, as emphasized in the research conducted by Shuhaiber and Mashal (2019). Hence, a hypothesis is developed:

H2: Perceived ease of use has a significant influence on intention to use.

H3: Perceived ease of use has a significant influence on perceived usefulness.

2.3 Personal Innovativeness

Schillewaert et al. (2005) have proposed a definition for individual innovation in IT. They describe personal innovativeness as a cognitive inclination or personal disposition that indicates individuals’ tendency to engage in independent experimentation and achieve novel advancements in IT. Personal innovativeness refers to how customers see a specific product and its influence on their inclination to adopt and utilize said technology (Hong et al., 2017).

This concept pertains to an individual’s inclination to explore and experiment with novel technologies, as well as the degree to which they are inclined to adopt these technologies before others (Sánchez-Franco et al., 2009). A substantial corpus of scholarly literature, comprising studies

undertaken by Kim and Shin (2015), has offered empirical evidence that supports the notion that perceptual innovation exerts a substantial influence on users' behavioral intention. Therefore, persons with higher levels of perceptual innovation are expected to demonstrate a greater inclination to adopt smart home technologies (Nikou, 2019). Therefore, this study concludes that:
H4: Personal innovativeness has a significant influence on intention to use.

2.4 Trust

Trust has been seen as a trade promotion factor between buyers and sellers, which can reduce the uncertainty and instability in trade (Doney & Cannon, 1997). Trust is the most effective method compared with other means because trust can reduce uncertainty, reduce risk, and improve the sense of security (Lin, 2011). When using smart homes, the user's trust in them is very important because it can help users overcome concerns about risks and reduce uncertainties in using smart homes (Shuhaiber & Mashal, 2019). Trust is universally defined as a state of being, that is, the existence of positive and confident expectations about one's own or another person's motives in the presence of risk. However, the conceptualization of trust varies in different fields of study (Siau & Shen, 2003).

The extent to which smart home technology is perceived to be trustworthy in performing its activities is measured by the trust structure. Trust significantly determines individuals' behavioral intentions toward technology adoption (El-Masri & Tarhini, 2017). In another recent work (Yang et al., 2017), An important factor that always influences smart home adoption is an individual's trust in the provider, as confirmed by studies. The researchers incorporated trust into the TAM to establish a favorable association between trust and the intention to use IOT technologies. This decision was made based on their recognition of the significance of trust in promoting the adoption of usage behaviors and mitigating risks. Thereby, this researcher refers a hypothesis:
H5: Trust has a significant influence on intention to use.

2.5 Hedonic Motivation

Hedonic motivation specifically refers to the degree of entertainment and pleasure consumers bring when using a certain technology (Gerhart et al., 2015). Hedonic motivation is an individual motivation in shopping where they believe that shopping is an activity that creates happiness, so they attach little importance to the benefits of the products or services they buy (Andini & Adiwijaya, 2021). Venkatesh et al. (2012) state that the specific definition of hedonic motivation usually comes from the pleasure or enjoyment brought by technology. Hedonic motivation refers to the degree to which consumers feel fun, excitement, and pleasure when using smart audio (Zaharia & Würfel, 2021). Davis et al. (1989) also proved that the hedonic factor plays a decisive role in the intention of technical behavior.

The role of hedonistic incentives in technology acceptance and usage has been empirically shown. The contemporary interpretation of hedonistic motivation encompasses the gratification and enjoyment of using technology. Hedonic motivation can be described as the experience of fun or enjoyment typically derived through technology. Interest and satisfaction in using technology is the definition of hedonic motivation (Thi-Hong-Linh et al., 2018). An important determinant of technology use and acceptance has been identified as the hedonic motive, especially in today's consumer context (Childers et al., 2001). Consequently, the researcher introduced hedonic drive as an additional variable to predict customers' behavioral intention toward technology adoption. Consequently, a hypothesis is set:
H6: Hedonic motivation has a significant influence on intention to use.

2.6 Social Influence

Social influence can be defined as the measure of the level of esteem. Individuals receive from their peers within social networks, as stated by Lin and Bhattacherjee (2010). Social influence refers to the occurrence in which an individual or a collective entity can change their behavior, either through direct or indirect methods, due to the influence produced by external sources. Social influence can be defined as the extent to which an individual's cognitive processes, emotional experiences, and behavioral patterns are influenced by the presence and conduct of others within a given social environment. Social influence is the belief that their significant other should accept and utilize a new system (Venkatesh et al., 2003).

Chong et al. (2012) emphasized the significant influence of social variables on individuals' propensity to adopt mobile commerce. Previous research has established that the phenomenon of social influence has a substantial role in shaping individuals' propensity to embrace new technical innovations. (Kijsanayotin et al., 2009; Zhou, 2012). The concept of social influence encompasses an individual's perception of the expectations held by significant others regarding their adoption of new technology. Additionally, social influence pertains to the influence exerted by external social pressures on an individual's behavioral choices concerning using technology. Prior research has also revealed that social factors significantly influence individuals' inclination to engage in a particular behavior (Aldosari et al., 2018). Therefore, this study hypothesizes that:
H7: Social influence has a significant influence on intention to use.

2.7 Price Value

Price value is the comprehensive assessment of consumers' usefulness of goods or services during the acquisition and payment process. In marketing research, it is common practice to assess the perceived value of a product or service by considering the cost of capital or price in conjunction with the product or service quality (Zeithaml, 1988). The concept of perceived value pertains to the significant aspects that impact consumers' subjective preferences and assessments of specific items, hence facilitating or impeding the achievement of their objectives (Woodruff, 1997). According to Kim et al. (2017), consumer behavior is influenced by many perceived values.

If the benefits of a technical advancement outweigh the costs connected with obtaining the required resources, then the pricing of that technology will positively influence persons' intentions. The findings of the study done by Venkatesh et al. (2012) provide clear evidence that price value has a significant influence on intention to use. The study conducted by Leong et al. (2017) presents empirical data that indicate the considerable influence of Price Value on individuals' inclination to utilize IOT technology in the context of smart cities. Thus, a hypothesis can be put forward:
H8: Price value has a significant influence on intention to use.

2.8 Intention to Use

The "intention to utilize a smart home" refers to a quantifiable measure or metric that evaluates the user's preparedness to engage with a smart home system. Based on a substantial body of empirical research, the variable of use intention has been identified as a suitable indicator due to its significant predictive capacity for future usage and consumer behavior (Lee et al., 2012). The construct of purpose is conceptualized as a dependent variable (Nikou, 2019). The assumption is that if users feel the technology is beneficial to them and they think it is simple to use, they will have a greater intention to use the technology (Brezavšček et al., 2014). Several notable researchers, including Hubert et al. (2017) in the domain of smartphone-based mobile shopping acceptance and Rocks-de Boer et al. (2020) in the realm of IoT acceptance in residential settings, have concluded that perceived usefulness plays a pivotal role in shaping the adoption of IT. Furthermore, recent research has revealed that the construct of perceived usefulness can elucidate a substantial percentage of the variability observed in individuals' propensities to embrace novel technological advancements (Fan et al., 2021).

3. Research Methods and Materials

3.1 Research Framework

The foundation of the theoretical framework in this research was built upon the examination of eight distinct factors. The study integrates these factors into three distinct variables: the independent variable, the mediator variable, and the dependent variable. As illustrated in Figure 1, the construction of the research model was informed by an analysis of three prior studies, specifically those conducted by Nikou (2019), Shuhaiber and Mashal (2019), and Baudier et al. (2020).

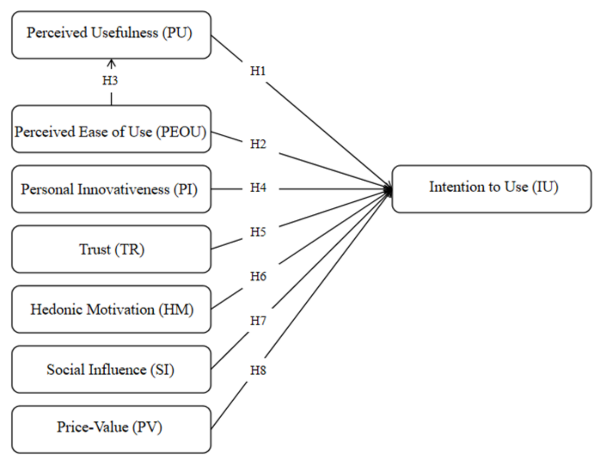

Figure 1: Conceptual Framework

H1: Perceived usefulness has a significant influence on intention to use.
H2: Perceived ease of use has a significant influence on intention to use.
H3: Perceived ease of use has a significant influence on perceived usefulness.
H4: Personal innovativeness has a significant influence on intention to use.
H5: Trust has a significant influence on intention to use.
H6: Hedonic motivation has a significant influence on intention to use.
H7: Social influence has a significant influence on intention to use.
H8: Price value has a significant influence on intention to use.

3.2 Research Methodology

This quantitative research employs a conceptual framework drawn from previous studies, encompassing eight variables and corresponding hypotheses. The study encompasses meticulously designed and standardized questionnaires, which include screening inquiries, demographic data, and measurement items. To ensure questionnaire robustness, the researcher conducts preliminary internal tests before distributing it to the target audience.

Data analysis relies on Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) to validate the model's goodness of fit and establish causal relationships among variables for hypothesis testing. Prior to data collection, the research instrument undergoes content validity assessment utilizing the Item-Objective Consistency Index (IOC). Furthermore, pilot tests involving 50 participants were conducted to gauge the reliability of each construct using the refined research instrument.

In this study, IOC ratings from three experts in the study's domain were solicited. Notably, five out of the 32 scale items failed to meet the minimum inter-item correlation (IOC) threshold of 0.6 and were consequently excluded from further analysis. In line with reliability standards, Straub (1989) posits that a Cronbach's alpha value exceeding 0.7 serves as the acceptable threshold, and this criterion was met.

3.3 Population and Sample Size

The study focuses on smart home users residing in Mianyang, Yibin, and Wanzhou, China. In accordance with Soper's (2023) recommendation of a minimum sample size of 444 for optimal results, this study has chosen a sample size of 500. This sample size is considered appropriate for the application of the statistical method known as Structural Equation Modeling (SEM).

3.4 Sampling Technique

Sampling is a methodology used to choose a representative subset from a larger population for the purpose of studying and analyzing the characteristics of the entire population (Zikmund, 2003). Initially, purposive sampling was employed to select smart home users located in Mianyang, Yibin, and Wanzhou, China. Subsequently, the population was stratified into multiple subgroups, as delineated in Table 1, using stratified random sampling. Additionally, convenience sampling, which involves selecting respondents based on their availability, was incorporated. As a result, this study utilizes online surveys as the data collection method.

Table 1: Sample Units and Sample Size

Smart Communities	Population Size	Proportional Sample Size
Shimao Yunjin Smart Community (Mianyang)	5351	109
Li Ya Jiang Chen Smart Community (Yibin)	8100	164
Wancui City Smart Community (Wanzhou)	11181	227
Total	**24632**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

Based on the provided demographic information in Table 2, there are 203 male respondents, constituting 40.6% of the total sample. This indicates that a substantial portion of the participants in this study are male. Female respondents make up the majority of the sample, with 297 individuals, accounting for 59.4% of the total. This suggests that there is a higher representation of females in the study.

Only a small proportion of the respondents, 10 individuals (2% of the total sample), fall within the 18-20 years old age group. This age group is the least represented in the study. The majority of the respondents, 154 individuals (30.8%), belong to the age group of 21-40 years old. This suggests that a significant portion of the participants falls within the younger to middle-age range. The age group of 41-60 years old comprises 183 respondents (36.6% of the total). This group represents a substantial portion of the study's participants and indicates a mix of middle-aged and older individuals. There are 153 respondents (30.6%) who are above 60 years old. This age group is also well-represented in the study and indicates a significant number of older participants.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	203	40.6%
	Female	297	59.4%
Age	18- 20 years old	10	2%
	21-40 years old	154	30.8%
	41-60 years old	183	36.6%
	Above 60	153	30.6%

Source: Constructed by author.

4.2 Confirmatory Factor Analysis (CFA)

In CFA, the Cronbach's Alpha values serve as indicators of the internal consistency of the construct when subjected to various reliability tests. It is generally accepted that values over 0.70 are considered acceptable (Nunnally, 1978). Additionally, the factor loadings of the constructs were greater than 0.5, ranging from 0.734 to 0.863. The overall reliability CR values ranged from 0.826 to 0.886, where all were greater than 0.7. The average extracted variance values AVE ranged from 0.582 to 0.660, all greater than 0.5. Based on the composite reliabilities, the constructs of this study had good internal consistency and acceptability.

Table 3: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived Usefulness (PU)	Nikou (2019)	4	0.858	0.749-0.829	0.859	0.604
Perceived Ease of Use (PEOU)	Nikou (2019)	4	0.884	0.767-0.863	0.886	0.660
Personal Innovativeness (PI)	Nikou (2019)	3	0.840	0.793-0.807	0.841	0.638
Trust (TR)	Shuhaiber and Mashal (2019)	4	0.863	0.734-0.829	0.864	0.613
Hedonic Motivation (HM)	Baudier et al. (2020)	3	0.807	0.757-0.770	0.807	0.582
Social Influence (SI)	Baudier et al. (2020)	3	0.829	0.763-0.831	0.830	0.619
Price Value (PV)	Baudier et al. (2020)	3	0.824	0.749-0.820	0.826	0.612
Intention to Use (IU)	Baudier et al. (2020)	3	0.825	0.760-0.798	0.826	0.613

In the researcher's statistical analysis, the data presented by the initial model consistently met all the predefined acceptable criteria, aligning with the outcomes of the validated factor analysis (CFA). Consequently, no adjustments to the model were deemed necessary. Table 4 provides a comprehensive listing of all the parameters derived from the initial model, each of which falls within the acceptable thresholds, including CMIN/DF = 1.306, GFI = 0.946, AGFI = 0.932, NFI = 0.941, CFI = 0.985, TLI = 0.983, and RMSEA = 0.025.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	386.552/296 or 1.306
GFI	≥ 0.85 (Sica & Ghisi , 2007)	0.946
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.932
NFI	≥ 0.80 (Wu & Wang, 2006)	0.941
CFI	≥ 0.80 (Bentler, 1990))	0.985
TLI	≥ 0.80 (Sharma et al., 2005)	0.983
RMSEA	< 0.08 (Pedroso et al., 2016)	0.025
Model Summary		**In harmony with empirical data**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker-Lewis index, and RMSEA = root mean square error of approximation

Fornell and Larcker (1981) introduced a criterion suggesting that a construct's validity can be considered acceptable when the coefficients between related constructs are smaller than the square root of the Average Variance Extracted (AVE). The square root of the AVE for each construct is listed along the diagonal of Table 5. Notably, these values are found to be greater than the correlation coefficients observed between different constructs. This discovery indicates that the discriminant validity is robust and meets the recommended criteria. Therefore, the results of this study offer empirical evidence confirming the strong discriminant validity of the structural framework.

Table 5: Discriminant Validity

	PU	PEOU	PI	TR	HM	SI	PV	IU
PU	**0.777**							
PEOU	0.195	**0.812**						
PI	0.091	0.206	**0.799**					
TR	0.146	0.324	0.254	**0.783**				
HM	0.188	0.137	0.123	0.244	**0.763**			
SI	0.229	0.187	0.235	0.211	0.150	**0.787**		
PV	0.174	0.176	0.170	0.174	0.181	0.151	**0.782**	
IU	0.368	0.389	0.422	0.411	0.331	0.372	0.334	**0.783**

Note: The diagonally listed value is the AVE square roots of the variables
Source: Created by the author.

4.3 Structural Equation Model (SEM)

The researchers assessed the fit of two sets of Structural Equation Models (SEM). In the initial dataset, the fit indices yielded the following results: CMIN/DF was 2.037, GFI was 0.903, AGFI was 0.884, NFI was 0.902, CFI was 0.947, TLI was 0.942, and RMSEA was 0.046. These findings collectively indicate that the model exhibits a strong fit, as evidenced by the favorable values across several indices. Notably, the values of CMIN/DF, GFI, AGFI, NFI, CFI, TLI, and RMSEA all fall within acceptable ranges, affirming the model's adequacy. The researchers have provided a comprehensive summary of the data in Table 6 for reference.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable	Statistical Values
CMIN/DF	< 3.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	643.830 / 316 or 2.037
GFI	≥ 0.85 (Sica & Ghisi , 2007)	0.903
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.884
NFI	≥ 0.80 (Wu & Wang, 2006)	0.902
CFI	≥ 0.80 (Bentler, 1990))	0.947
TLI	≥ 0.80 (Sharma et al., 2005)	0.942
RMSEA	< 0.08 (Pedroso et al., 2016)	0.046
Model Summary		**In harmony with empirical data**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker-Lewis index, and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

The outcomes of the Structural Equation Modeling (SEM) analysis offer compelling evidence in favor of the hypotheses under examination. Each hypothesis explored the association between a distinct factor and the intention to utilize a specific product or service. According to the results, all of these associations were determined to be statistically significant at an exceptionally high level of confidence ($p < 0.001$), thus affirming strong and well-supported backing for the formulated hypotheses.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: Perceived usefulness has a significant influence on intention to use.	0.274	5.547***	Supported
H2: Perceived ease of use has a significant influence on intention to use.	0.217	4.559***	Supported
H3: Perceived ease of use has a significant influence on perceived usefulness.	0.216	4.197***	Supported
H4: Personal innovativeness has a significant influence on intention to use.	0.343	6.900***	Supported
H5: Trust has a significant influence on intention to use.	0.246	5.165***	Supported
H6: Hedonic motivation has a significant influence on intention to use.	0.216	4.424***	Supported
H7: Social influence has a significant influence on intention to use.	0.229	4.770***	Supported
H8: Price value has a significant influence on intention to use.	0.206	4.298***	Supported

Note: *** p<0.001
Source: Created by the author

H1: The coefficient (β) of 0.274 with a t-value of 5.547*** indicates a strong positive relationship between perceived usefulness and the intention to use. This result suggests that when individuals perceive a product or service as useful, they are more inclined to have the intention to use it.

H2: With a coefficient (β) of 0.217 and a t-value of 4.559***, this hypothesis also finds strong support. It implies that perceived ease of use significantly impacts the intention to use, indicating that users are more likely to adopt technology or products that are easy to use.

H3: The coefficient (β) of 0.216 and a t-value of 4.197*** demonstrate that perceived ease of use significantly influences perceived usefulness. This suggests that when something is perceived as easy to use, it tends to be perceived as more useful.

H4: This hypothesis is strongly supported, with a coefficient (β) of 0.343 and a t-value of 6.900***. It implies that personal innovativeness significantly affects the intention to use, indicating that more innovative individuals are more inclined to adopt new technologies or products.

H5: With a coefficient (β) of 0.246 and a t-value of 5.165***, this hypothesis receives strong support. It suggests that trust is a significant factor influencing the intention to use, indicating that users are more likely to adopt technologies or products they trust.

H6: The coefficient (β) of 0.216 and a t-value of 4.424*** indicate a significant influence of hedonic motivation on the intention to use. This implies that factors related to pleasure and enjoyment play a role in the adoption of technology or products.

H7: With a coefficient (β) of 0.229 and a t-value of 4.770***, this hypothesis is strongly supported. It suggests that social influence significantly affects the intention to use, indicating that individuals are influenced by the opinions and behaviors of others.

H8: The coefficient (β) of 0.206 and a t-value of 4.298*** indicate a significant influence of price value on the intention to use. This suggests that the perceived value for the price paid plays a role in users' intentions to adopt a product or service.

In summary, all eight hypotheses have been strongly supported by the statistical analysis, with each demonstrating a significant influence on the intention to use. These findings highlight the importance of perceived usefulness, ease of use, personal innovativeness, trust, hedonic motivation, social influence, and price value in shaping individuals' intentions to adopt and use a product or service.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This research aimed to investigate the determinants influencing residents' adoption of smart home technology in the cities of Mianyang, Yibin, and Wanzhou, China, based on a conceptual framework comprising perceived usefulness, perceived ease of use, personal innovativeness, trust, hedonic motivation, social influence, price value, and intention to use.

The study, which involved a target population of 500 smart home users, employed rigorous methods to ensure the validity and reliability of its data. Both Item-Objective Congruence (IOC) and a pilot test of Cronbach's Alpha were utilized to validate the research instrument. Data analysis was conducted using Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) to evaluate model fit and establish causal relationships for hypothesis testing.

The outcomes of this research have several implications for both researchers and practitioners in the field of smart home technology adoption.

Firstly, the strong positive relationship found between perceived usefulness and the intention to use reaffirms the significance of designing and marketing smart home solutions that genuinely address users' needs and add value to their lives. Developers and manufacturers should prioritize features that enhance perceived usefulness to encourage adoption.

Additionally, the impact of perceived ease of use on perceived usefulness highlights the importance of user-friendly interfaces and intuitive designs. Simplifying the user experience can positively influence users' perceptions of technology's utility.

The presence of personal innovativeness as a significant factor suggests that targeting early adopters and individuals who are more open to innovation may be an effective strategy for promoting smart home technology adoption.

Trust is a critical factor, indicating that security and privacy concerns must be addressed to gain users' confidence. Developers should prioritize robust security measures to foster trust among potential users.

Hedonic motivation's role in adoption suggests that promoting the enjoyment and satisfaction derived from using smart home technology can be a persuasive marketing approach.

The impact of social influence underscores the importance of word-of-mouth recommendations and the role of social networks in shaping technology adoption. Leveraging social networks for marketing and advocacy efforts can be beneficial.

Lastly, the influence of price value suggests that offering competitive pricing and clear value propositions can positively affect users' intentions to adopt smart home technology.

Overall, the findings of this study provide valuable insights for businesses and policymakers looking to promote the adoption of smart home technology. Understanding the multifaceted nature of these determinants is crucial for developing effective strategies that encourage widespread adoption in the cities of Mianyang, Yibin, and Wanzhou, China, and beyond. Further research in this field can continue to refine our understanding of the complex factors influencing technology adoption in diverse contexts.

5.2 Recommendation

The rapid evolution of smart home technology presents exciting opportunities to transform the way we live. However, the adoption of these innovations in the cities of Mianyang, Yibin, and Wanzhou, China, is contingent on various factors. Building on the insights gained from our research, this essay offers a comprehensive set of recommendations aimed at promoting the adoption of smart home technology in these regions.

First and foremost, developers and manufacturers must prioritize user-centric design and innovation. To enhance the perceived usefulness of smart home technology, it is imperative to address real user needs and pain points. By conducting user-centered research and feedback sessions, companies can align their products and services with the preferences and expectations of residents in these cities.

The user experience is a critical factor influencing adoption. Thus, improving the perceived ease of use is paramount. User-friendly interfaces, intuitive designs, and user training resources should be developed to ensure that residents can easily navigate and operate smart home systems. Simplifying the user experience can significantly boost adoption rates.

Identifying and targeting innovators and early adopters can accelerate adoption efforts. These individuals are inherently more open to embracing new technologies. Collaborative partnerships with local influencers or tech enthusiasts can help promote the benefits of smart home technology and create a buzz within the community.

One of the key takeaways from our research is the critical role of trust in technology adoption. Building and maintaining user trust is imperative. To achieve this, companies should invest heavily in security and privacy measures. Transparent data handling practices and robust cybersecurity protocols will help reassure residents that their information is safe.

The enjoyment and satisfaction derived from using smart home technology should be at the forefront of marketing strategies. Stories and testimonials showcasing the positive experiences of users can be persuasive. Demonstrating how these technologies can enhance everyday life, reduce stress, and provide convenience can be compelling.

Word-of-mouth marketing and social influence are potent tools in driving adoption. Encouraging users to share their positive experiences with friends and family can lead to a ripple effect. Engaging with local communities and influencers can amplify the impact of social networks.

Affordability and perceived value are critical factors in technology adoption. Companies should offer competitive pricing while clearly communicating the value propositions of their products and services. Residents need to see a clear benefit in adopting these technologies.

Education and awareness campaigns should be employed to inform potential users about the advantages and capabilities of smart home technology. Addressing misconceptions and concerns through informative content and workshops can alleviate uncertainties and encourage adoption.

Local preferences and cultural factors should be taken into account when designing marketing strategies. Tailoring campaigns to resonate with the unique characteristics of Mianyang, Yibin, and Wanzhou will yield more significant results.

Collaboration with government bodies to establish regulatory frameworks that ensure the security and privacy of smart home users is essential. Regulatory support can boost user confidence and create a conducive environment for technology adoption.

To ensure the sustained adoption of smart home technology, companies should develop strategies for long-term user engagement. Regular updates, improvements, and value-added services will maintain user interest and loyalty.

Highlighting the sustainability and energy efficiency benefits of smart home technology can appeal to environmentally-conscious residents. Demonstrating how these technologies can contribute to both cost savings and environmental conservation can be a compelling selling point.

In conclusion, the adoption of smart home technology in Mianyang, Yibin, and Wanzhou, China, is within reach, but it requires a strategic and user-focused approach. By heeding these recommendations, stakeholders can pave the way for a connected future, where residents can enjoy the benefits of convenience, efficiency, and improved quality of life through smart home technology adoption.

5.3 Limitation and Further Study

While this study provides valuable insights into the determinants of smart home technology adoption in Mianyang, Yibin, and Wanzhou, China, it is essential to acknowledge its limitations and suggest areas for future research to build upon our findings. First, this research focused exclusively on the cities of Mianyang, Yibin, and Wanzhou. Future studies can expand the scope to include a more diverse range of regions in China, taking into account potential variations in adoption determinants across urban and rural areas. Second, while this study primarily employed quantitative methods, qualitative research techniques such as interviews and focus groups can provide a more in-depth understanding of residents' perceptions, motivations, and barriers to adoption. Last, although this study included 500 smart home users, a larger and more diverse sample may provide more robust insights. Ensuring a representative sample that accounts for demographic diversity is crucial.

References

Aldosari, M. A., Aljabaa, A. H., Al-Sehaibany, F. S., & Albarakati, S. F. (2018). Learning style preferences of dental students at a single institution in Riyadh, Saudi Arabia, evaluated using the VARK questionnaire. *Advances in medical education and practice, 9*, 179-186. https://doi.org/10.2147/AMEP.S157686

Al-Mamary, Y. H., & Shamsuddin, A. (2015). Adoption of Management Information Systems in Context of Yemeni Organizations: A Structural Equation Modeling Approach. *Journal of Digital Information Management, 13*(6), 429-444.

Andini, N. D., & Adiwijaya, K. (2021). What factors do influence the adoption of internet of things (Smart Home) in Indonesia. *International Journal of Business and Technology Management, 3*(2), 84-97. http://myjms.mohe.gov.my/index.php/ijbtm

Awang, Z. (2012). *A Handbook on SEM Structural Equation Modelling: SEM Using AMOS Graphic* (5th ed.). Universiti Teknologi Mara Kelantan.

Baudier, P., Ammi, C., & Deboeuf-Rouchon, M. (2020). Smart home: Highly-educated students' acceptance. *Technological Forecasting and Social Change 153*, 119355.

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin, 107*(2), 238-246. https://doi.org/10.1037/0033-2909.107.2.238

Brezavšček, A., Šparl, P., & Žnidaršič, A. (2014). Extended technology acceptance model for SPSS acceptance among Slovenian students of social sciences. *Organizacija, 47*(2), 116-127. https://doi.org/10.2478/orga-2014-0009

Childers, T. L., Carr, C. L., Peck, J., & Carson, S. (2001). Hedonic and utilitarian motivations for online retail shopping behavior. *Journal of Retailing, 77*(4), 511-535.

Chong, A. Y.-L., Chan, F. T., & Ooi, K.-B. (2012). Predicting consumer decisions to adopt mobile commerce: Cross country empirical examination between China and Malaysia. *Decision Support Systems, 53*(1), 34-43.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982-1003.

Doney, P. M., & Cannon, J. P. (1997). An examination of the nature of trust in buyer-seller relationships. *The Journal of Marketing, 61*(2), 35-51.

El-Masri, M., & Tarhini, A. (2017). Factors influencing the adoption of e-learning systems in Qatar and USA: Extending the unified theory of acceptance and use of technology 2 (UTAUT2). *Educational Technology Research and Development, 65*(3), 743-763.

Fan, X., Duangekanong, S., & Xu, M. (2021). Factors Affecting College Students' Intention to Use English U-learning in Sichuan, China. *AU-GSB E-JOURNAL, 14*(2), 118-129. https://doi.org/10.14456/augsbejr.2021.20

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50. https://doi.org/10.1177/002224378101800104

Gao, L., & Bai, X. (2014). A unified perspective on the factors influencing consumer acceptance of internet of things technology. *Asia Pacific Journal of Marketing and Logistics, 26*(2), 211-231. https://doi.org/10.1108/APJML-06-2013-0061

Gerhart, N., Peak, D., & Prybutok, V. (2015). Searching for new answers: The application of task-technology fit to e-textbook usage. *Decision Sciences Journal of Innovative Education, 13*(1), 91-111.

Greenough, J. (2016, April 23). *The US Smart Home Market has been struggling- Here's how and why the market will take off.* Business Insider. http://www. businessinsider. com/the-us-smart-home-marketreport-adoption-forecasts-top-products-and-the-cost-and-fragmentation-problems-that-could-hindergrowth-2015-9

Hong, J. C., Lin, P. H., & Hsieh, P. C. (2017). The effect of consumer innovativeness on perceived value and continuance intention to use smartwatch. *Computers in Human Behavior, 67*, 264-272.

Hubert, M., Blut, M., Brock, C., Backhaus, C., & Eberhardt, T. (2017). Acceptance of smartphone-based mobile shopping: mobile benefits, customer characteristics, perceived risks, and the influence of application context. *Psychology & Marketing, 34*(2), 175-194.

Kijsanayotin, B., Pannarunothai, S., & Speedie, S. M. (2009). Factors influencing health information technology adoption in Thailand's community health centers: Applying the UTAUT model. *International Journal of Medical Informatics, 78*(6), 404-416.

Kim, K. J., & Shin, D. H. (2015). An acceptance model for smart watches: Implications for the adoption of future wearable technology. *Internet Research, 25*(4), 527-541.

Kim, Y., Park, Y., & Choi, J. (2017). A study on the adoption of IOT smart home service: Using value-based adoption model. *Total Quality Management, 28*(9-10), 1-17. http://dx.doi.org/10.1080/14783363.2017.1310708

Lee, Y.-K., Park, J.-H., Chung, N., & Blakeney, A. (2012). A unified perspective on the factors influencing usage intention toward mobile financial services. *Journal of Business Research, 65*(1), 1590-1599.

Leeraphong, A., Papasratorn, B., & Chongsuphajaisiddhi, V. (2015, November 23-24). *A Study on Factors Influencing Elderly Intention to Use Smart Home in Thailand : A Pilot Study* [Paper Presentation]. The 10th International Conference on e-Business (iNCEB2015), Bangkok, Thailand.

Leong, G.-W., Ping, T.-A., & Muthuveloo, R. (2017). Antecedents of behavioral intention to adopt internet of things in the context of smart city in Malaysia. *Global Business and Management Research, 9*(4), 442-456.

Li, S., Tryfonas, T., & Li, H. (2016). The Internet of Things: a security point of view. *Internet Research, 26*(2), 337-359. https://doi.org/10.1108/IntR-07-2014-0173

Lin, C.-P., & Bhattacherjee, A. (2010). Extending technology usage models to interactive hedonic technologies: A theoretical model and empirical test. *Information Systems Journal, 20*(2), 163-181. https://doi.org/10.1111/j.1365-2575.2007.00265.x

Lin, H.-F. (2011). An empirical investigation of mobile banking adoption: The effect of innovation attributes and knowledge-based trust. *International Journal of Information Management, 31*(3), 252-260.

Nikou, S. (2019). Factors driving the adoption of SHT: An empirical assessment. *Telematics and Informatics, 45*, 1-10. https://doi.org/10.1016/j.tele.2019.101283

Nunnally, J. C. (1978). *Psychometric theory* (2nd ed.). McGraw-Hill.

Pedroso, R., Zanetello, L., Guimaraes, L., Pettenon, M., Goncalves, V., Scherer, J., Kessler, F., & Pechansky, F. (2016). Confirmatory factor analysis (CFA) of the crack use relapse scale (CURS). *Archives of Clinical Psychiatry, 43*(3), 37-40. https://doi.org/10.1590/0101-60830000000081

Rocks-de Boer, P., Deursen, A. J. A. M., & Van Rompay, T. (2020). Internet-of-Things Skills Among the General Population: Task-Based Performance Test Using Activity Trackers. *JMIR Human Factors, 7*(4), e22532. https://doi.org/10.2196/22532

Sánchez-Franco, M. J., Villarejo-Ramos, Á., & Martín-Velicia, F. (2009). The moderating effect of gender on relationship quality and loyalty toward Internet service providers. *Information & Management, 46*(3), 196-202. https://doi.org 10.1016/j.im.2009.02.001

Schillewaert, N., Ahearne, M. J., Frambach, R. T., & Moenaert, R. K. (2005). The adoption of information technology in the sales force. *Industrial Marketing Management, 34*(4), 323-336.

Sharma, S., Pradhan, K., Satya, S., & Vasudevan, P. (2005). Potentiality of earthworms for waste management and in other uses- a review. *Journal of American Science, 1*(1), 4-16.

Shuhaiber, A., & Mashal, I. (2019). Understanding users' acceptance of smart home. *Technology in Society, 58*, 101110.

Siau, K., & Shen, Z. (2003). Building customer trust in mobile commerce. *Communications of the ACM, 46*(4), 91-94.

Sica, C., & Ghisi, M. (2007). The Italian versions of the Beck Anxiety Inventory and the Beck Depression Inventory-II: Psychometric properties and discriminant power. In M. A. Lange (Ed.), *Leading-edge psychological tests and testing research* (pp. 27-50). Nova Science Publishers.

Soper, D. (2023). *Calculator: A-priori Sample Size for Structural Equation Models. Daniel Soper.* https://www.danielsoper.com/statcalc/calculator.aspx?id=89

Sponselee, A., Schouten, B., Bouwhuis, D., & Willems, C. (2008). Smart Home Technology for the Elderly: Perceptions of Multidisciplinary Stakeholders. In M. Mühlhäuser, A. Ferscha, & E. Aitenbichler (Eds.), *Constructing Ambient Intelligence.* (pp. 314-326). Springer. https://doi.org/10.1007/978-3-540-85379-4_37

Statista Research Department. (2023, July 11). *Smart home control & connectivity penetration rate by country.* https://bg.qianzhan.com/report/detail/459/190724-0905885f.html

Straub, D. W. (1989). Validating instruments in MIS research. *MIS Quarterly, 13*(2), 147– 169. https://doi.org/10.2307/248922

Thi-Hong-Linh, N., Minh-Hung, D., Hai-Dang, N., Dang-HongNgan, V., DuyPhuong-Trinh, V., & Hoanh-Su, L. (2018). Key determinants for users' intention to use smarthome devices in Vietnam. *Journal of Multimedia Information System, 5*(4), 283-290. http://dx.doi.org/10.9717/ JMIS.2018.5.4.283

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences, 39*(2), 273-316.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186-204.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478.

Venkatesh, V., Thong, J., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157-178.

Woodruff, R. B. (1997). Customer value: The next source for competitive advantage. *Journal of the Academy of Marketing Science, 25*(2), 139-153.

Wu, J. H., & Wang, Y. M. (2006). Measuring KMS Success: A Respecification of the DeLone and McLean's Model. *Journal of Information & Management, 43*(6), 728-739. http://dx.doi.org/10.1016/j.im.2006.05.002

Yang, H., Lee, H., & Zo, H. (2017). User acceptance of smart home services: an extension of the theory of planned behavior. *Industrial Management & Data Systems, 117*(1), 68-89, https://doi.org/10.1108/IMDS-01-2016-0017

Zaharia, S., & Würfel, M. (2021). Voice commerce - studying the acceptance of smart speakers. In T. Ahram, R. Taiar, K. Langlois & A. Choplin (Eds.), *Human interaction, emerging technologies and future applications III* (pp.449-454). Springer.

Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: A means–end model and synthesis of evidence. *Journal of Marketing, 52*(3), 2-22.

Zhou, T. (2012). Examining location-based services usage from the perspectives of unified theory of acceptance and use of technology and privacy risk. *Journal of Electronic Commerce Research, 13*(2), 135-144.

Zikmund, W. G. (2003). *Business research methods* (7th ed.). Thomson/ South-Western.