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Factors Influencing Consumer Adoption of AI-Based Smart Home Energy Management Systems in Vietnam

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Abstract: This research paper presents a case study on customer acceptance of AI-based smart home energy management systems in Vietnam. With the escalating focus on energy efficiency and sustainable living, the adoption of smart technologies has gained substantial popularity. Drawn upon the integration of three frameworks: Technology Acceptance Model (TAM), Innovation Diffusion Theory (IDT) and Artificially Intelligent Device Use Acceptance (AIDUA) model, this study explores the willingness of Vietnamese customers to accept AI-based smart home energy management systems. The research findings, derived from 307 responses of Vietnamese customers, reveal an increasing interest in smart home energy management systems in Vietnam and identifies Perceived Compatibility as the most crucial factor influencing both Perceived Usefulness and Perceived Ease of Use. Furthermore, both Perceived Usefulness and Perceived Ease of Use are proven antecedents to Emotions, which eventually influences Customer's Intention to Use. The insights derived from this research can aid policymakers, technology developers, and marketers in formulating effective strategies to promote widespread adoption of AI-based smart home energy management systems, thereby fostering sustainable energy consumption, and contributing to a greener future for households in Vietnam.
Keywords: Artificial intelligence, Behavioral intention, Higher Education, AI in higher education

1. Introduction

The modern world stands at a pivotal crossroads where technological innovation intersects with pressing environmental concerns. In Vietnam, the energy consumption is escalating with rapid growth. It is widely indicated that household electricity consumption has been steadily increasing due to rising living standards, urbanisation, and the proliferation of electrical appliances. Moreover, according to the Vietnam Energy Efficiency Outlook Report 2019, the residential sector in Vietnam is a significant contributor to overall energy consumption. The report highlights that households consume approximately 24% of the total energy used in the country. Therefore, the National Power Development Plan for the period of 2021-2030 with a vision to 2045 (known as PDP8) aims to promote energy efficiency and renewable energy sources in Vietnam's energy mix. This plan recognizes the importance of reducing energy consumption in the residential sector through the adoption of energy-efficient technologies and practices. In this context, the convergence of Artificial Intelligence (AI) and smart home technologies emerges as a beacon of hope for sustainable living. AI-based smart home energy management systems (hereinafter referred to as AI-SHEMS) encompass a range of technologies that utilise artificial intelligence to optimise energy consumption and improve overall energy efficiency within residential settings. These systems transcend traditional energy conservation approaches by employing AI algorithms to optimise energy consumption, thereby mitigating wastage and reducing costs. As Onwusinkwue et al. (2024) emphasise, AI's analytical capabilities are harnessed to interpret complex usage patterns, enabling proactive adjustments to energy usage. This AI-based system has been used widely and successfully in many countries such as Singapore, Australia, Thailand, etc. However, amidst the promise of innovation, a chasm emerges - the gap between technological potential and user acceptance, especially in Vietnam where this system is sort of new to Vietnamese users. The surge in smart technology adoption does not uniformly extend to AI-driven energy management systems due to concerns like compatibility, data privacy and complexity (Muniandi et al., 2024). This study seeks to investigate customer acceptance of AI-SHEMS, with Vietnam as the contextual backdrop. As digital intelligence intertwines with household energy management, understanding the factors that impact customer attitudes and behaviours becomes an imperative stride toward a more energy-efficient future.

For the purposes of this research, an AI-SHEMS encompasses an integrated network of AI-powered devices, sensors, and algorithms designed to optimise energy consumption within a household. Our focus narrows onto the Vietnamese customers, aiming to glean insights from consumers' perspectives within this specific cultural and economic landscape.

The adoption of AI-SHEMS holds significant implications, particularly in the context of residential energy consumption and sustainability. As homes become smarter and more connected, AI-driven systems have the potential to revolutionise energy management practices. These systems promise to enhance energy efficiency, reduce costs, and contribute to a more sustainable energy future (Smith et al., 2020). However, the key question arises: Will homeowners in Vietnam embrace AI-SHEMS powered by artificial intelligence, and what factors will influence their acceptance or rejection of these systems?

Drawing upon the Theory of Reasoned Action (Fishbein and Ajzen, 1975), which posits that intentions and willingness are primary determinants of actual behaviour, it is imperative to investigate the factors that significantly impact homeowners' willingness to adopt these innovative technologies. Previous research has proposed various determinants that influence customers' willingness to either adopt or reject the use of new technology devices. Among those, the earliest findings go to Davis, Bagozzi and Warshaw (1989) which emphasises "ease of use" and "perceived usefulness" as primary determinants of customer adoption of technology. Extended from this, other determinants have been taken to consideration, such as "perceived compatibility" and "relative advantage" (Rogers, 2003), "perceived complexity", "trialability" and "social influence" (Venkatesh et al., 2020), "effort" and "performance expectancy" (Gursoy et al., 2019), "user experience and design" (Venkatesh et al., 2020). There are also studies from Lin et al. (2020) and Boonsiritomachai&Pitchayadejanant (2017) which brought "hedonic motivation" to discussion. "Anthropomorphism" and "Emotions" are also significant antecedents to customer acceptance of new technology devices, as opined by Kim et al. (2018), Qiu et al. (2019) and Gursoy et al. (2019).

Prior research on customer acceptance of AI-based devices has yielded valuable insights into the factors influencing users' decisions. Venkatesh and Davis (2000) introduced the Unified Theory of Acceptance and Use of Technology (UTAUT), emphasising the significance of perceived usefulness and ease of use as key determinants of AI technology acceptance. Building on this foundation, Bagozzi et al. (2018) focused on AI-powered virtual assistants, revealing the pivotal role of users' emotional attachment in shaping acceptance. In the healthcare context, Liang et al. (2019) examined AI chatbots and identified the critical influence of users' trust in chatbots, along with perceived privacy and security concerns. Gursoy et al. (2019) researched AI-driven recommendation systems, highlighting the central importance of trust and perceived usefulness, particularly in the context of e-commerce. These studies collectively underscore the multidimensional nature of AI acceptance and provide a solid framework for understanding the adoption of AI-based devices across various domains (Venkatesh & Davis, 2000; Bagozzi et al., 2018; Liang et al., 2019; Gursoy et al., 2019). However, despite the extensive literature on technology adoption, limited attention has been given to understanding customer willingness to use AI-based devices in the context of deploying a smart home energy management system. Furthermore, the willingness to adopt such a system in Vietnam remains an underexplored area, which leaves a significant literature gap for this study.

This article embarks on a journey to uncover the underpinnings of customer acceptance or resistance to AI-SHEMS within Vietnam. The central objective is to unravel the intricate web of factors that shape consumer perceptions and decisions. By doing so, we intend to provide practical insights for policymakers, industry stakeholders, and researchers, facilitating the integration of cutting-edge technology into everyday lives.

The article's structure is as follows: Theoretical framework: An integration of four frameworks: Theory of Reasoned Action, Innovation Diffusion Theory, Cognitive Appraisal Theory, and Artificially Intelligent Device Use Acceptance model; Methodology: An exposition of the research approach, detailing the case study design, data collection methods, and analytical tools employed; Findings and Discussion: Presentation and interpretation of the case study's outcomes, elucidating consumer sentiments, concerns, and patterns related to AI-SHEMS; Implications: An exploration of the practical implications drawn from the study, with recommendations for stakeholders to bolster technology acceptance. By dissecting the nexus between technology and consumer acceptance, this article aspires to contribute to the discourse surrounding energy efficiency and AI's transformative potential.

2. Theoretical Framework

To date, scholarly investigations into the acceptance of Information Technology (IT) and Information Systems (IS) collectively fall under the purview of Innovation Adaptation Research (Al-Rahmi et al., 2019). In accordance with the seminal works of Rogers (1995) and Davis et al. (1989), the two foremost theoretical frameworks underpinning research in innovation adaptation are the Innovation Diffusion Theory (IDT) and the Technology Acceptance Model (TAM). These models have gained widespread utilisation among academicians and researchers for the comprehensive exploration of diverse facets pertaining to the adoption of various forms of novel technology. Rogers (1995) and Davis et al. (1989) posit that both of these research paradigms share a foundational premise, which posits that an individual's acceptance of a new product or technology is contingent upon their perception of its inherent attributes. Specifically, if the new product or technology exhibits more favourable characteristics, it is more likely to garner acceptance and adoption. Moreover, antecedent studies rooted in these two models have concurred that factors influencing technology acceptance can be categorised into two principal groupings: (1) value-oriented determinants encompassing perceived usefulness and relative advantage, and (2) effort-oriented determinants encompassing perceived ease of use, complexity, and compatibility (Al-Rahmi et al., 2019). Scholars contend that while IDT comprehensively addresses the multifaceted factors shaping users' technology acceptance, TAM furnishes a more succinct theoretical framework elucidating users' perceptions and behaviours (Zhang et al., 2008). Consequently, integrating the two models, TAM and IDT, is posited to engender heightened efficacy in innovation adaptation research. Numerous studies have underscored the efficacy of this integration, notably exemplified by Hameed et al.'s (2012) investigation into the adoption of information technology applications in businesses and Puklavec et al.'s (2014) inquiry into factors impacting the deployment of business intelligence systems in small and medium enterprises.

Nevertheless, in the ever-evolving technological landscape, particularly amid the pervasive influence of the Fourth Industrial Revolution, the emergence of novel technologies necessitates researchers to adapt and evolve their research frameworks. Both the Technology Acceptance Model (TAM) and the Innovation Diffusion Theory (IDT) have served as fundamental theoretical underpinnings in innovation adaptation research, offering invaluable insights into users' decision-making processes regarding new technology adoption. However, these time-tested models have revealed notable limitations when confronted with nascent technology paradigms such as Artificial Intelligence (AI), Virtual Reality (VR), Augmented Reality (AR), etc. Furthermore, their applicability has become incongruous with contemporary users' heightened technological literacy levels. Specifically, empirical studies have underscored the inadequacy of TAM and IDT in explicating the acceptance and utilisation of emerging technologies. For instance, in the examination of AI adoption, Venkatesh and Morris (2000) demonstrated that factors like relative benefits, paramount in IDT, may lack efficacy in assessing intricate AI systems effectively. Similarly, a 2019 study by Gursoy et al. illuminated that while TAM factors lay a foundational premise for elucidating user intentions regarding specific products or technologies, certain constructs, such as anthropomorphism, prove inadequate in elucidating behaviours linked to advanced technological applications like AI. These factors overemphasise users' comprehension of new technology and human-like attributes. Additionally, Ribeiro et al. (2021), in their investigation of user acceptance in relation to AI-driven automated vehicles, highlighted that acceptance of high-tech products hinges upon users' beliefs and perceptions of associated risks, elements hitherto unaccounted for in the conventional TAM and IDT frameworks. Moreover, these models traditionally presuppose users' technological literacy levels (Maruping et al., 2017). However, considering the ubiquity of technology in daily life, contemporary users exhibit a diverse spectrum of technological users, spanning from the highly proficient to neophytes.

In light of these limitations, recent studies have proposed the consideration of models such as the Cognitive Appraisal Theory (CAT) and the Artificially Intelligent Device Use Acceptance (AIDUA) model. CAT accentuates the role of users' emotions and mental appraisals in their technology adoption decisions, while AIDUA extends the Technology Acceptance Model (TAM) to accommodate novel and intricate technologies such as Artificial Intelligence (AI).

Specifically, CAT, a psychological model developed by Lazarus (Lazarus, 1991a, 1991b), elucidates how individuals assess and process information in emotionally charged situations. This model centres on the human cognitive appraisal process in generating emotional states and responsive behaviours. According to CAT, individuals do not directly respond to events they experience but rather to how they evaluate and interpret those events. The core components of CAT encompass "appraisal," which involves individuals assessing the significance and meaning of specific events or situations to them, "emotions," resulting from these appraisals, such as happiness, anger, fear, and joy, and "responsive behaviours," where emotions subsequently drive responsive behaviours, i.e., how individuals react or respond to the situation. CAT can be applied to comprehend users' decisions regarding technology acceptance and use. In this context, users' cognitive appraisals of technology can predict whether they will accept and use it.

On the other hand, AIDUA is a model developed for investigating the acceptance and use of Artificially Intelligent (AI) devices (Gursoy et al., 2019). This model extends the TAM framework to align with emerging, complex technologies like AI. Key components of AIDUA, in addition to the two TAM factors of perceived usefulness and perceived ease of use, include "trust," reflecting users' confidence in the functionality and performance of AI devices; "perceived risk," encompassing users' concerns about risks associated with AI device use, including security and privacy risks; and "emotions," capturing users' emotional states and moods regarding AI devices, including joy, anxiety, and happiness (Gursoy et al., 2019). The AIDUA model provides a comprehensive framework for understanding users' decisions regarding the acceptance and use of AI devices and can be applied to study the acceptance of new technology within this domain.

The integration of these novel models may help address some of the limitations inherent in TAM and IDT when examining the acceptance and use of emerging technologies. Moreover, it aligns more effectively with the diverse contexts of contemporary users. In summary, to address the specific challenges and nuances of AI-SHEMSs in Vietnam, this study proposes the integration of the Technology Acceptance Model (TAM), Innovation Diffusion Theory (IDT), and the Artificially Intelligent Device Use Acceptance (AIDUA) model, under the psychological concepts of Cognitive Appraisal Theory (CAT).

3. Hypotheses Development & Proposal of Research Model

A summary of the proposed research model is stated below.

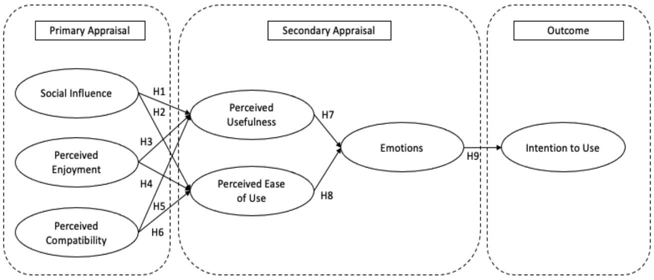

Fig. 1: Proposed research model (Source: Authors's compilation)

***Primary appraisal:**

Primary appraisal, as per the Cognitive Appraisal Theory (CAT), refers to the initial cognitive process where individuals evaluate a situation or stimulus to determine its relevance and significance to their well-being (Lazarus, 1991a, 1991b). In the context of this study on customer acceptance of AI-SHEMS, primary appraisal involves customers' initial assessments of this AI-based technology concerning its perceived relevance, importance, and potential benefits in managing their home energy consumption.

In line with the AIDUA model, social influence, as defined by Venkatesh, Thong, and Xu (2012), pertains to the extent to which consumers perceive that people having significant impact on customers (e.g., family and friends) believe they should use a particular technology. For AI-SHEMS, social influence refers to the degree to which an individual's social circles (e.g., family, friends, social networks) believe that adopting AI-SHEMS for managing home energy consumption is relevant and aligns with their group norms. As proposed by AIDUA, social influence is a crucial factor that likely plays a pivotal role during the primary appraisal of AI-SHEMS. Existing research has shown that social norms and beliefs regarding the social appropriateness of a technology in a given context can significantly impact customers' willingness to adopt (Bansal and Kockelman, 2018; Zhang et al., 2020). Therefore, it is hypothesised that social influence directly influences customers' perceptions of the usefulness of AI-SHEMS. If social norms suggest that AI-SHEMS can enhance energy efficiency and align with group norms, individuals are more likely to perceive it as useful. Thus, we posit the following hypothesis:

H1: Social Influence has a positive impact on Perceived Usefulness of AI-SHEMS

Building on the AIDUA model, it is posited that social influence also plays a crucial role in shaping individuals' perceptions of how easy it is to use AI-SHEMS. Similar to the primary hypothesis, social influence reflects the extent to which a person's social networks view AI-SHEMS adoption as congruent with group norms. If individuals receive positive feedback and encouragement from their social circles regarding the ease of using AI-SHEMS for managing home energy, it is expected that this social influence will directly impact their perception of the system's ease of use. Thus, we posit the following hypothesis:

H2: Social Influence has a positive impact on Perceived Ease of Use of AI-SHEMS

Perceived compatibility refers to the degree to which individuals believe that a technology is consistent with their existing values, needs, and requirements. It is an essential element introduced in the Technology Acceptance Model (TAM) by Davis (1989). Previous research in various technological contexts has consistently shown that perceived compatibility positively influences users' perceptions of usefulness. According to Davis (1989), when users perceive that a technology aligns with their needs and fits well within their existing routines, they are more likely to believe that the technology will enhance their performance and effectiveness.

In the context of AI-SHEMSs (AI-SHEMS), it can be hypothesised that individuals who perceive AI-SHEMS as compatible with their energy management needs and lifestyle will also perceive it as useful. This is based on the premise that compatibility fosters the belief that AI-SHEMS can effectively assist in managing home energy consumption, making it more efficient and valuable. Therefore, we propose:

H3: Perceived Compatibility has a positive impact on Perceived Usefulness of AI-SHEMS

Perceived compatibility reflects users' perceptions of how well a technology aligns with their existing routines and needs. Prior research has consistently shown that perceived compatibility positively influences users' perceptions of the ease of using a technology. Davis (1989) argued that when users perceive a technology as compatible with their current practices, they are more likely to find it simple and straightforward to use. Up to date, this has been continuously emphasised in previous studies, with adaptation to various contexts such as e-marketing (Kanchanatanee et al., 2014); mobile payment services (Moti and Walla, 2020); chatbot in banking (Alt et al., 2021), etc.

In the context of AI-SHEMS, it is postulated that individuals who perceive AI-SHEMS as compatible with their lifestyle and energy management needs will also find it easy to use. This is based on the idea that compatibility fosters the belief that AI-SHEMS seamlessly integrates into their daily routines, making it less complex and more user-friendly. Therefore, we propose:

H4: Perceived Compatibility has a positive impact on Perceived Ease of Use of AI-SHEMS

***Secondary appraisal**

During this stage, customers will engage in a comprehensive evaluation of the advantages and disadvantages associated with adopting AI-SHEMS in their homes, focusing on their perception of the usefulness and ease of use of AI-SHEMS (Gursoy et al., 2019). As an extension of the AIDUA model, this study incorporates the consideration of perceived usefulness and perceived associated with the adoption of AI-SHEMS into the secondary appraisal process.

Perceived Usefulness, as defined by Venkatesh et al. (2003), pertains to the extent to which individuals believe that using a technology will enhance their overall experience. In the context of AI-SHEMS, Perceived Usefulness can be interpreted as the extent to which customers believe that implementing these systems will lead to improved energy management and cost savings. Perceived Ease of Use refers to the extent to which customers believe that using AI-SHEMS will be free from effort, as adapted from Segars and Grover (1993).

It is hypothesised that during the secondary appraisal process, customers will consciously evaluate the perceived benefits (Perceived Usefulness) and ease of use (Perceived Ease of Use) of implementing AI-SHEMS in their homes, which will influence their emotional response toward AI-SHEMS. In specific, we propose that:

H5: Perceived Usefulness has a positive impact on customers' Emotions towards AI-SHEMS

H6: Perceived Ease of Use has a positive impact on customers' Emotions towards AI-SHEMS

***Outcome**

In accordance with the appraisal patterns outlined in the CAT and AIDUA model, emotions towards the use of AI-SHEMS will significantly influence users' behavioural intentions regarding their adoption. Previous research in the context of automatic vehicles (Gursoy et al., 2019), hospitality services (Roy et al., 2020) have shown that emotions play a crucial role in shaping users' intentions towards technology adoption.

Following the principles of the AIDUA model, the willingness to use AI-SHEMS represents users' intentions to utilise such systems in their homes (Lin et al., 2020; Zhang et al., 2019). Although AI-SHEMS offers various advantages, users may have reservations regarding their safety, reliability, and potential disruptions to their current energy management habits. Previous studies have highlighted that one of the key challenges in the adoption of AI-based technologies is related to incompatibility in the technology integration itself (Raue et al., 2019).

In the context of AI-SHEMS, individuals may be inclined to embrace this technology due to its potential benefits such as energy efficiency and cost savings, while simultaneously harbouring concerns about its reliability and the potential loss of control over their energy consumption habits. This duality of emotions, as suggested by CAT, will influence users' willingness to adopt AI-SHEMS and their inclination to object to its implementation in their homes.

Taking these insights into consideration, we propose the following hypothesis:

H7: Emotions positively impact customers' intention to use AI-SHEMS.

4. Methodology

4.1. Research method

This study employs a methodological approach combining analysis and synthesis to establish the theoretical framework. Furthermore, it utilises a quantitative research method by collecting survey responses from residents of Vietnam, specifically those interested in AI-SHEMS. The data collected will be subjected to statistical analysis using SPSS 20 and AMOS 24 software. The analysis will encompass various statistical procedures, including Cronbach's Alpha coefficient for assessing scale reliability, exploratory factor analysis (EFA) for initial scale validation, confirmatory factor analysis (CFA) for further scale refinement, and structural equation modelling (SEM) to test the research model's validity.

4.2. Sampling Methodology

Determining an appropriate sample size is critical for the study's accuracy. Based on recommendations by Hair et al. (1998), a minimum sample size of 160 responses is required, given the study's 25 observed variables (25 observed variables x 5 = 125 items). To ensure the effectiveness of regression analysis, Tabachnick et al. (1996) propose that the sample size should satisfy the condition: $n \geq 8k + 50$, where n represents the sample size and k signifies the number of independent variables. Therefore, this study aims for a sample size of at least 250.

A convenient sampling technique is adopted for participant selection. In total, 342 questionnaires are distributed to residents in Vietnam via online channels. However, any questionnaires with unsatisfactory responses, such as identical answers for all questions or nonsensical entries, will be excluded from the analysis. This process results in a dataset comprising 307 valid questionnaires, forming the basis for data analysis. Data collection begins in July and August 2023.

4.3. Questionnaire Design

The questionnaire is structured into three sections. The initial section aims to gather demographic data from survey participants, encompassing gender, age, type of accommodation and average electricity bill. The second section is designed to collect information concerning respondents' current energy management habit, their interest and knowledge about AI-SHEMS, and their current electricity consumption habits. The third section comprises 25 questions aligned with the research model framework. Respondents will use a Likert five-point scale to express their agreement levels.

The scales utilised for factor analysis have been adapted from previous studies (but have been tailored for improved compatibility with the context of Vietnam and the specific focus on AI-SHEMS.

The results should be concisely presented. Results and discussion may be separate or combined based on the author’s requirement.

5. Data Analysis and Research Findings

5.1. Demographic analysis of respondents.

Table 5.1 presents information on demographic details of respondents who have participated in the survey questionnaire. Those characteristics hold an implication that the sample size is representative. Among 307 selected responses, 54% of which were males, with 45.3% for female counterparts. Regarding age distribution, the proportions were fairly equivalent for 3 groups of working ages, with those in 45-64 being the most prevalent. A majority of our participants were currently residing in apartment (43%) and having average electricity bill of around USD45-60/month.

Table 1: Demographic information

Characteristic		Frequency	%
Gender	Male	166	54.0
	Female	139	45.3
	Other	2	0.7
Age range	< 18	15	4.9
	18 - 24	87	28.3
	25 - 44	96	31.3
	45 - 54	78	25.4
	55 - 64	31	10.1
	> 65	0	0.0
Current type of accommodation	Single-family ground house	39	12.7
	Apartment/ Condo	132	43.0
	Townhouse	76	24.8
	Shared housing	42	13.7
	Other	18	5.9
Average monthly electricity bill (USD)	< 15	28	9.1
	15 - 30	36	11.7
	31 - 45	81	26.4

Characteristic		Frequency	%
	45 - 60	123	40.1
	60	39	12.7

Source: Research results, 2023

Table 2 presents information on current energy management habit, their interest and knowledge about AI-SHEMS. A striking observation is that only a small minority (10.1%) had prior experiences with AI-SHEMS, while the vast majority (89.9%) had no previous exposure to these systems. This distribution indicates a potential market for AI-SHEMS.

Table 2: Current energy management habits

Content		Frequency	%
Interest in smart home technologies and energy management system	Nointerest at all	56	18.2
	Slightlyinterested	87	28.3
	Moderately interested	101	32.9
	Very interested	63	20.5
Familiarity with AI-SHEMS	Not familiar at all	79	25.7
	Somewhat familiar	106	34.5
	Moderately familiar	64	20.8
	Very familiar	58	18.9
Past experiences with AI-SHEMS	Yes	31	10.1
	No	276	89.9

Source: Research results, 2023

5.2. Verification of the proposed model and hypotheses

In this study, the author used structural equation modelling (SEM) to validate the proposed model and hypotheses, employing AMOS 20.0 as the main analytical tool. Initially, we examined the dimensions of the components in the research model. Subsequently, the research model underwent thorough analysis and verification. The maximum likelihood method was employed for parameter estimation. To assess model fitness, we conducted both a measurement model test and a structural model test.

5.2.1. Testing of the measurement model

In the analysis of Cronbach's alpha, two observed variables (PU4 and PEU2) were excluded. Additionally, during the Exploratory Factor Analysis (EFA) step, one observed variable (PU2) was excluded. The summarized results of this analysis can be found in Table 3.

Table 3: The results of Cronbach's alpha and EFA analysis with SPSS 20.0

Factors	Observed variables	C_{α}	KMO, Extraction Sums (%)
Social Influence (SI)	3	0.833	0.837, 61.333 %
PerceivedCompatibility (PC)	4	0.846	
Perceived Usefulness (PU)	4	0.859	
Perceived Ease of Use (PEU)	4	0.860	
Emotions (EM)	4	0.852	
Intention to Use (BI)	3	0.772	

Source: Research results, 2023

Confirmatory factor analysis (CFA) was performed to assess the quality and appropriateness of the measurement model (Anderson and Gerbing, 1988), aiming to establish the reliability, convergent validity, and discriminant validity of the constructs under study.

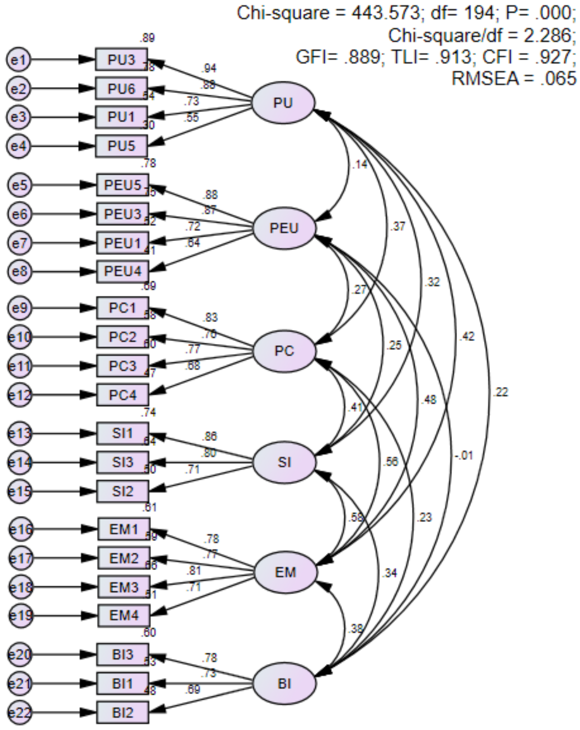

Fig2: Confirmatory factor analysis

Source: Research results, 2023

The outcomes of the CFA demonstrated the goodness-of-fit indices for the measurement model, which are outlined as follows: the chi-square value for this measurement model was 443.573 with 194 degrees of freedom. The chi-square/dfequaled 2.286 and achieved Marsh and Hocevar's (1985) standard that the ratio of chi-square to the degree of freedom ratios should be between 2 and 5; besides, GFI = 0.889, TLI = 0.913, CFI = 0.927, RMSEA= 0.065. According to Marcoulides and Schumacker (1996), the goodness-offit model and the overall statistics both achieved the standards of model fitting.

Table 4 presents the composite reliability (CR) values for the constructs, with the minimum value being 0.776 and the maximum value being 0.866, all exceeding the 0.7 threshold. Additionally, Table 4 also presents the average variance extracted (AVE) values, with the lowest value being 0.537 and the highest value being 0.627, all meeting the condition of being greater than 0.5.

Table 4: Composite reliability (CR) and Average Variance Extracted (AVE)

	CR	**AVE**
EM	0.853	0.593
PU	0.866	0.627
PEU	0.862	0.613
PC	0.848	0.584
SI	0.834	0.627
BI	0.776	0.537

Source: Research results, 2023

Next, we'll assess discriminant validity by testing H0: The correlation coefficient between the concepts is 1. In Table 5.5, all p-values are below 0.05, rejecting H0 and confirming H1: the correlation coefficient for each concept significantly differs from 1 with 95% confidence. Thus, the concepts exhibit discriminant validity.

Table 5: Test for discriminant validity

			Estimate	r2	SE=SQRT((1-r2)/(n-2))	CR=(1-r)/SE	P_value = TDIST(|CR|,n-2,2)
PU	<-->	PEU	0.14	0.0196	0.05669591	15.16864263	0.00000
PU	<-->	PC	0.373	0.139129	0.053127468	11.80180464	0.00000
PU	<-->	SI	0.321	0.103041	0.054229597	12.52083804	0.00000
PU	<-->	EM	0.419	0.175561	0.05199114	11.17498086	0.00000
PU	<-->	BI	0.216	0.046656	0.055908121	14.02300741	0.00000
PEU	<-->	PC	0.27	0.0729	0.055133222	13.2406556	0.00000
PEU	<-->	SI	0.25	0.0625	0.055441595	13.52774926	0.00000
PEU	<-->	EM	0.478	0.228484	0.050294738	10.37881938	0.00000
PEU	<-->	BI	-0.006	0.000036	0.057258803	17.56935094	0.00000
PC	<-->	SI	0.405	0.164025	0.052353621	11.36502094	0.00000
PC	<-->	EM	0.56	0.3136	0.047439349	9.275000864	0.00000
PC	<-->	BI	0.231	0.053361	0.05571117	13.80333611	0.00000
SI	<-->	EM	0.58	0.3364	0.046644804	9.004218421	0.00000
SI	<-->	BI	0.342	0.116964	0.053807063	12.22887789	0.00000
EM	<-->	BI	0.379	0.143641	0.052988059	11.71962152	0.00000

5.2.2. Testing of the structural model

Path analysis using AMOS 20.0 was employed to estimate the path coefficients representing relationships between constructs in the research model. The overall goodness-of-fit indices of the structural model are as follows: the chi-square value was 533.501 with 201 degrees of freedom, chi-square/df equalled 2.654, GFI = 0.865, TLI = 0.889, CFI = 0.903, RMSEA= 0.074. The data shows a good fit with the hypothesized structural model.

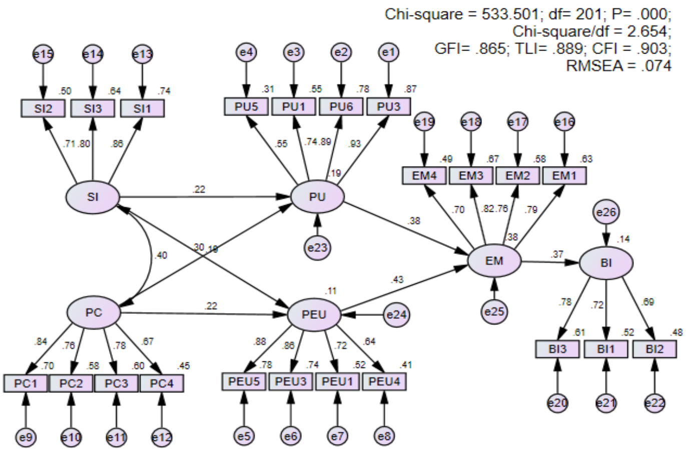

Fig 3: Structural equation modelling

Source: Research results, 2023

Table 6: Regression Weights

			Est.	S.E.	C.R.	P
PU	<---	SI	.253	.078	3.253	.001
PEU	<---	SI	.228	.087	2.637	.008
PU	<---	PC	.351	.079	4.428	***
PEU	<---	PC	.267	.088	3.038	.002
EM	<---	PU	.318	.048	6.660	***
EM	<---	PEU	.336	.047	7.156	***
BI	<---	EM	.327	.063	5.220	***

Source: Research results, 2023

Table 7 provides a more detailed description of the relationships within the model.

Table 7: Standardized Regression Weights

			Estimate
PU	<---	SI	.219
PEU	<---	SI	.187
PU	<---	PC	.299
PEU	<---	PC	.215
EM	<---	PU	.383
EM	<---	PEU	.428
BI	<---	EM	.368

Source: Research results, 2023

The results in Table 5.7 indicate that: The variable PC has stronger impacts on both PU and PEU compared to the SI variable. Similarly, the PEU variable has a stronger impact on EM compared to the PU variable. All relationships within the model are positive relationships (beta > 0).

Based on the results of Path analysis, the results of hypothesis testing are presented in the Table 8 below:

Table 8: Research Hypotheses Conclusion

Hypothesis	Content	Beta	P_value	Result
H_1	Social Influence has a positive impact on Perceived Usefulness	0.219	0.001	Accept
H_2	Social Influencehas a positive impact on Perceived Ease of Use	0.187	0.008	Accept
H_3	Perceived Compatibility has a positive impact on Perceived Usefulness	0.299	0.000	Accept
H_4	Perceived Compatibility has a positive impact on Perceived Ease of Use	0.215	0.002	Accept
H_5	Perceived Usefulness has a positive impact on Emotions	0.383	0.000	Accept
H_6	Perceived Ease of Use has a positive impact on Emotions	0.428	0.000	Accept
H_7	Emotions has a positive impact on Intention to Use	0.368	0.000	Accept

6. Discussion and Implications

The findings of this case study on customer acceptance of AI-Based Smart Home Energy Management Systems in Vietnam have revealed several crucial insights, shedding light on the determinants of consumer behaviour in adopting this innovative technology.

First, the study identifies Perceived Compatibility as the most influential factor driving both Perceived Usefulness and Perceived Ease of Use in the context of AI-based smart home energy management systems in Vietnam. This finding corroborates the research by Rogers (1995), who introduced the concept of compatibility as a critical factor in the diffusion of innovations. Our results align with previous research, including one from Ellabban & Abu-Rub (2016) (which focuses on customer acceptance of smart grid systems) and Yang et al. (2017) (on IoT Smart home adoption), which demonstrates that the extent to which new technologies fit with users' existing practices significantly affects their acceptance, though the scope of this study focuses on customer acceptance of smart grid systems.

Second, the present study confirms that Perceived Usefulness and Perceived Ease of Use are antecedents to Emotions, which, in turn, influence the Customer's Intention to Use. These findings are consistent with the Technology Acceptance Model (TAM) developed by Davis (1989). According to TAM, perceived usefulness and perceived ease of use are primary determinants of users' intentions to adopt technology. The study extends this model in the context of AI-based smart home energy management systems and reinforces the significance of these factors in shaping user attitudes and intentions.

Third, while the direct impact of emotions on technology adoption has been explored in various contexts, our study specifically highlights the intermediary role of emotions between perceived usefulness and ease of use and the intention to use. This underscores the importance of addressing users' emotional responses in the design and marketing of these systems. Previous research, such as the work of Venkatesh et al. (2012), has shown that emotions play a pivotal role in technology acceptance, and our findings align with these insights, emphasising their relevance in the context of smart home energy management systems.

Considering these findings, this article outlines implications for policymakers, technology developers, and marketers in Vietnam to formulate effective strategies that promote widespread adoption of these systems, aligning with the goals of National Power Development Plan VIII and fostering a greener future for households in Vietnam.

Regarding the policymakers, it is important to establish clear regulatory guidelines and standards for AI-SHEMS to ensure safety, data privacy, and interoperability. More importantly, it is necessary to encourage the development of all start-ups in the field of AI and data technology by creating a favourable regulatory environment that promotes innovation while protecting consumers. Besides, to educate and raise customer awareness of using AI in their energy management system, the authorities should launch nationwide campaigns to educate consumers about the benefits of AI-based systems, emphasise their compatibility with existing technologies and the potential for energy savings. The popular channels that can be used are television, social media, and community events to disseminate information. Finally, it is crucial to foster collaboration between the government, utility companies, and technology providers to facilitate the integration of AI-based systems into the existing energy infrastructure to align with the goals of National Power Development Plan VIII.

Regarding Technology developer, it is notably important to develop user-friendly interfaces and focus on making the setup and daily use of these systems as simple as possible to enhance Perceived Ease of Use for the customers. Moreover, the energy system varies from types of houses to the usage of each family; therefore, it is essential to provide options for customization to address individual household needs and preferences. Then all the softwares and hardwares need to be updated regularly to ensure that customers perceive the system as useful and effective.

Finally, for the Marketers, it is clear that not many Vietnamese people have information of this AI-SHEMS; hence trial periods can be provided to introduce the benefits of this system. These trial periods may be in the form of limited-time promotions to allow potential customers to experience the system first-hand, and then encourage word-of-mouth referrals from satisfied users. Moreover, since this system is quite new to many users, excellent customer support is significantly important to assist users during installation and address any issues promptly. Positive post-purchase experiences can significantly impact customer emotions and intention to use.

In conclusion, the case study findings emphasised Perceived Compatibility, Perceived Usefulness, and Perceived Ease of Use as critical factors in customer acceptance of AI-SHEMSs in Vietnam offer actionable insights for policymakers, technology developers, and marketers. By aligning strategies with the objectives of National Power Development Plan VIII and prioritising user satisfaction, these stakeholders can play a pivotal role in fostering sustainable energy consumption for households in Vietnam.

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References

[1] Acheampong RA and Cugurullo F, Capturing the behavioural determinants behind the adoption of autonomous vehicles: Conceptual frameworks and measurement models to predict public transport, sharing and ownership trends of self-driving cars. Transportation Research Part F: Traffic Psychology and Behaviour, Vol 62: 349–375, (2019).

[2] Al-Rahmi WM et al.,*Integrating Technology Acceptance Model With Innovation Diffusion Theory: An Empirical Investigation on Students' Intention to Use E-Learning Systems.*IEEE, Vol 7, (2019).

[3] Alt MA, Vizeli I and Săplăcan Z, *Banking with a Chatbot – A Study on Technology Acceptance.* Studia Universitatis Babeș-Bolyai Oeconomica, Sciendo, Vol 66 (Issue 1): 13–35, (2021).

[4] Anderson JC and Gerbing DW, *Structural equation modeling in practice: A review and recommended two-step approach.*Psychological Bulletin, Vol 103 (Issue 3): 411–423, (1988).

[5] Bagozzi RP, Dholakia UM and Pearo LK, *Antecedents and consequences of user perceptions in social commerce: Why do users trust and recommend particular online sellers?.* Journal of the Academy of Marketing Science, Vol 41 (Issue 3): 315–339, (2018).

[6] Bansai P and Kockelman K, *Forecasting Americans' long-term adoption of connected and autonomous vehicle technologies.*Transportation Research Part A: Policy and Practice, Vol 95: 49–63, (2017).

[7] Boonsiritomachai W and Pitchayadejanant K, *Determinants affecting mobile banking adoption by generation Y based on the Unified Theory of Acceptance and Use of Technology Model modified by the*

Technology Acceptance Model concept. Kasetsart Journal of Social Sciences, Vol 40 (Issue 2): 349–358, (2017).

[8] Chen X and Li T, *Understanding Smart Home Adoption: A Comprehensive Literature Review.* Sustainability, Vol 13 (Issue 5): 2725, (2021).

[9] Davis FD, *Perceived usefulness, perceived ease of use, and user acceptance of information technology.* MIS Quarterly, Vol 13 (Issue 3): 319–340, (1989).

[10] Davis FD, Bagozzi RP and Warshaw PR, *User Acceptance of Computer Technology: A Comparison of Two Theoretical Models.*Management Science, Vol 35 (Issue 8): 982–1003, (1989).

[11] Du H, Zong S, Liu J and Wang Q,*An Energy Management Strategy of Smart Home Considering User Behavior and Energy Price Uncertainty.* IEEE Transactions on Industrial Informatics, Vol 16 (Issue 12): 7840–7848, (2020).

[12] Ellabban O and Abu-Rub H, *Smart grid customers' acceptance and engagement: An overview.* Renewable and Sustainable Energy Reviews, Vol 65: 1285–1298, (2016).

[13] Fishbein M and Ajzen I, *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research.*
Addison-Wesley, (1975).

[14] Gursoy D, Chi OH, Lu L and Nunkoo R, *Consumers acceptance of artificially intelligent (AI) device use in service delivery.*International Journal of Information Management, Vol 49: 157–169, (2019).

[15] Gursoy D, Chi CGQ and Lu L, *Antecedents and outcomes of travelers' information privacy concerns in the context of AI-powered recommendation systems.*Tourism Management, Vol 78: 104065, (2020).

[16] Hameed MA, Counsell S and Swift S, *A conceptual model for the process of IT innovation adoption in organisations.* Journal of Engineering and Technology Management, Vol 29 (Issue 3): 358–390, (2012).

[17] Hair J, Anderson R, Tatham R and Black W, *Multivariate data analysis (7th edition).* Prentice Hall, (1998).

[18] Kapser M and Abdelrahman M, *Acceptance of autonomous delivery vehicles for last-mile delivery in Germany – Extending UTAUT2 with risk perceptions.* Transportation Research Part C: EmergingTechnologies, Vol 111: 210–225, (2020).

[19] Kim H-Y, McGill AL, Morwitz V and Sengupta J, *Minions for the Rich? Financial Status Changes How Consumers See Products with Anthropomorphic Features.*Journal of Consumer Research, Vol 45 (Issue 2): 429–450, (2018).

[20] Islam AKMN, *E-learning system use and its outcomes: Moderating role of perceived compatibility.*Telematics and Informatics, Vol 33: 48–55, (2016).

[21] Jones MC and Beatty RC, *Towards the development of measures of perceived benefits and compatibility of EDI: A comparative assessment of competing first order factor models.*European Journal of Information Systems, Vol 7: 210–220, (1998).

[22] Lazarus RS, *Progress on a Cognitive-Motivational-Relational Theory of Emotion.*American Psychologist, Vol 46 (Issue 8), (1991b).

[23] Lazarus RS, *Cognition and Motivation in Emotion.* American Psychologist, Vol 46 (Issue 4), (1991a).

[24] Le Anh Tuan KMND, Le Minh Ha DHT and Le Quynh Anh, *Energy Consumption and Energy Efficiency Improvement in the Vietnamese Residential Sector.* Sustainability, Vol 11 (Issue 7): 2140, (2019).

[25] Liang X, Liu D and Wei KK, *An investigation of users' continuance intention towards mobile healthcare apps.*Industrial Management & Data Systems, Vol 119 (Issue 6): 1323–1341, (2019).

[26] Lin H, Chi OH and Gursoy D, *Antecedents of Customers' Acceptance of Artificially Intelligent Robotic Device Use in Hospitality Services.* Journal of Hospitality Marketing & Management, Vol 29 (Issue 5): 530–549, (2020).

[27] Maruping LM, Bala H and Venkatesh V, *Going beyond intention: Integrating behavioral expectation into the unified theory of acceptance and use of technology.*Journal of the Association for Information Science and Technology, Vol 68 (Issue 3), (2016).

[28] Marcoulides GA and Schumacker RE, *Advanced structural equation modeling: Issues and techniques.*Lawrence Erlbaum Associates, (1996).

[29] Marsh HW and Hocevar D, *Application of confirmatory factor analysis to the study of self-concept: First- and higher order factor models and their invariance across groups.*Psychological Bulletin, Vol 97 (Issue 3): 562–582, (1985).

[30] Moore GC and Benbasat I, *Development of an instrument to measure the perceptions of adopting an information,* (1991).

[31] Moti DB and Walla N, *The effects of Compatibility, Social Influence, and Perceived Ease of Use on Perceived Usefulness of Mobile Payment Services.* International Journal of Scientific & Technology Research, Vol 9 (Issue 2): 1865–1873, (2020).
[32] Puklavec B, Oliveira T and Popovic A, Unpacking business intelligence systems adoption determinants: An exploratory study of small and medium enterprises. Economic Business Review, Vol 16 (Issue 2): 185–213, (2014).
[33] Qiu H, Li M, Shu B and Bai B, Enhancing Hospitality Experience with Service Robots: The Mediating Role of Rapport Building. Journal of Hospitality Marketing & Management, (2019).
[34] Raue M, D'Ambrosio LA, Ward C, Lee C, Jacquillat C and Coughlin JF, The Influence of Feelings While Driving Regular Cars on the Perception and Acceptance of Self-Driving Cars. Risk Analysis, Vol 39 (Issue 2): 358–374, (2019).
[35] Ribeiro MA, Gursoy D and Chi OH, Customer Acceptance of Autonomous Vehicles in Travel and Tourism. Journal of Travel Research, Vol -- (Issue --): 1–17, (2021).
[36] Rogers EM, Diffusion of Innovations. New York: Free Press, (1995).
[37] Rogers EM, Diffusion of Innovations. New York: Free Press, (2003).
[38] Roy P, Ramaprasad BS, Chakraborty M and Prabhu N, Customer Acceptance of Use of Artificial Intelligence in Hospitality Services: An Indian Hospitality Sector Perspective. Global Business Review, Vol -- (Issue --): --, (2020).
[39] Singh N, Sinha N and Francisco JL-H, Determining factors in the adoption and recommendation of mobile wallet services in India: Analysis of the effect of innovativeness, stress to use and social influence. International Journal of Information Management, Vol 50: 191–205, (2020).
[40] Smith M and Jeffery RCH, Addressing the challenges of artificial intelligence in medicine. Internal Medicine Journal, Vol 50 (Issue 10): 1278–1281, (2020).
[41] Segars AH and Grover V, Re-Examining Perceived Ease of Use and Usefulness: A Confirmatory Factor Analysis. MIS Quarterly, Vol 17 (Issue 4): 517–525, (1993).
[42] Pal D and Vanijja V, Perceived Usability Evaluation of Microsoft Teams as an Online Learning Platform during COVID-19 using System Usability Scale and Technology Acceptance Model in India. Children and Youth Services Review, (2020).
[43] Tabachnick BG and Fidell LS, Using Multivariate Statistics (3rd edition). New York: Harper Collins, (1996).
[44] Venkatesh V and Davis FD, A theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. Management Science, Vol 46 (Issue 2): 186–204, (2000).
[45] Venkatesh V and Morris MG, Why Don't Men Ever Stop to Ask for Directions? Gender, Social Influence, and Their Role in Technology Acceptance and Usage Behaviour. MIS Quarterly, Vol 24 (Issue 1): 115–139, (2000).
[46] Venkatesh V, Morris MG, Davis GB and Davis FD, User Acceptance of Information Technology: Toward a Unified View. MIS Quarterly, Vol 27 (Issue 3): 425–478, (2003).
[47] Venkatesh V, Thong JY and Xu X, Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. MIS Quarterly, Vol 36 (Issue 1): 157–178, (2012).
[48] Venkatesh V, Sykes TA, Aljafari R and Poole MS, The future is now: calling for a focus on temporal issues in information system research. Industrial Management & Data Systems, Vol 121 (Issue 1): 30–47, (2021).
[49] Vietnam Energy Efficiency Outlook Report 2019, Vietnam Energy Efficiency Outlook Report 2019. Retrieved from http://gizenergy.org.vn/en/article/vietnam-energy-outlook-report-2019-released, (2019).
[50] Wang SM, Huang YK and Wang CC, A Model of Consumer Perception and Behavioral Intention for AI Service, (2020).
[51] Yang H, Lee W and Lee H, IoT Smart Home Adoption: The Importance of Proper Level Automation. Journal of Sensors, (2017).