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Prediction of Thai Consumers' Behavioral Intentions to Use Home Energy Management System

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ABSTRACT
This study aimed to investigate the factors influencing consumers' intention to use home energy management systems (HEMS) in residential homes. A questionnaire survey was conducted with 500 representative groups of homeowners and residents in Bangkok and the Metropolitan Area of Thailand. Descriptive analysis and inferential statistical analysis were used to analyze the data. The results revealed that attitude toward behavior, perceived behavioral control, facilitating conditions, social influence, and performance expectancy have a significant impact on consumers' intention to use HEMS, while effort expectancy had no significant impact. The study has contributed to provide practical guidelines for regulators, entrepreneurs, and policymakers to improve strategies for HEMS adoption and for marketers and stakeholders to plan distribution, consumer channels, and supply chain management.

Keywords: HEMS, UTAUT, TPB, consumers' behavioral intentions, Thailand

1.0 INTRODUCTION

In the era of globalization, energy is essential to human civilization and all human activities such as work, business, industry, and residence (Stout & Best, 2001). Energy is crucial to a country's development (Ahuja & Tatsutani, 2009). Electrical energy is widely used, easily transformed, and delivered over long distances. It is the most common energy source in daily life. However, global energy consumption increases annually due to population growth, requiring sufficient energy to meet demand.

Renewable energy sources such as wind, geothermal, biomass, and sunlight, are non-depletable and are being promoted by governments globally (Chel & Kaushik, 2011). The transition to renewable energy is reducing environmental and health risks and replacing fossil fuels in households and energy enterprises (Owusu & Asumadu-Sarkodie, 2016).

A Home Energy Management System (HEMS) integrates sensors into home appliances and enables communication via home networks (Han et al., 2014). HEMS can remotely control appliances through the Internet, smartphones, or tablets (Mahapatra & Nayyar, 2022). The benefits of HEMS include reducing power consumption, improving smart grid efficiency, optimizing demands, and enabling household devices (Mahapatra & Nayyar, 2022). By allowing consumers

to adjust their energy consumption behavior, HEMS contributes to electricity savings and lower electricity bills, leading to long-term energy savings for countries (Srikranjanapert et al., 2021).

Many countries, including the United States, and Europe, have adopted HEMS in households with government support to reduce emissions and support the development of smart cities (Billanes & Enevoldsen, 2021). Thailand is also promoting the use of HEMS through the Thailand Smart Grid Development Master Plan 2015-2036(EPPO, 2022). The HEMS market is expected to grow rapidly due to its numerous benefits (Chen, Xu, et al., 2020). However, consumer attitudes and perceptions towards HEMS technology are diverse. Although most households are interested in the benefits of HEMS, many are still not accepting its use (Chen, Xu, et al., 2020).

1.1 Problem Statement

Kotani and Nakano (2022) used the Unified Theory of Acceptance and Use of Technology (UTAUT) to model the purchase process and investigate influencing purchasers' intentions and behaviors in a study on zero-energy house purchases. However, few studies have utilized other theories such as UTAUT and the Theory of Planned Behavior (TPB). Moreover, few studies have combined more than one theory to investigate the technology acceptance. Therefore, this study aims to fill this gap by examining the factors that influence consumers' intention to use HEMS in Thailand using UTAUT and TPB. The findings can be used by regulators, policymakers, appliance manufacturers, smart home product developers, and marketers to improve strategies, plan distribution and marketing, and manage the supply chain for HEMS systems.

2.0 LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 The Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a technology acceptance model developed by Venkatesh et al. (2003). The UTAUT theory unifies various theories about technology acceptance by incorporating four determinants of intention to use and usage behavior: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC).

UTAUT was originally developed to model the adoption of information technology but has since been applied to a wide range of technologies. For instance, Kotani and Nakano (2022) used UTAUT to investigate the purchase decision process and information acquisition of zero-energy houses in Japan. The study aimed to model the purchase process and provide insights the development of more appropriate information dissemination strategies and supporting policies to promote the adoption of these houses.

The study by Venkatesh et al. (2003) found that the UTAUT model outperforms other theories in explaining user behavior, with 70% of the variance in behavioral intention (BI) and 50% of technology use explained by the UTAUT model. This result was confirmed by Dwivedi et al. (2019) through an empirical examination of the UTAUT model.

2.2 The Theory of Planned Behavior (TPB)

The Theory of Planned Behavior (TPB) is a development of the Theory of Reasoned Action (TRA) (Fishbein, 1967) that predicts and describes an individual's thought process when deciding on an action (Fishbein, 1967). According to TPB, a person's intention is the most important and immediate predictor of the action they will take (Ajzen, 2005). TPB, used to understand and predict behavior, posits that behavior is immediately influenced by behavioral intentions and, in some cases, perceived behavioral control. Ajzen (2005) noted that three factors impact behavioral intentions: attitudes toward the behavior, subjective norms, and perceived behavioral control.

Xu et al. (2018) studied homeowners' willingness to pay for home energy management systems (HEMS) in New York and Tokyo, examining the impact of demographic and socio-psychological factors. The findings showed that addressing societal norms and cost concerns is necessary to boost HEMS adoption. Yew et al. (2022) combined the TPB with pro-environmental behavior research to explore the drivers of residential energy management information systems use in smart homes. The study provided valuable insights into sustainable technology applications, residential energy consumption, and cleaner production that can aid in achieving the UN Sustainable Development Goals (SDGs).

2.3 Hypotheses Development

2.3.1 PE and BI

Previous studies have demonstrated that performance expectancy is a significant predictor of behavioral intention (Chatterjee et al., 2021; Zhang & Yu, 2022). Nurwidiana et al. (2021) also found, based on UTAUT, that performance expectancy had the most significant positive on the willingness to adopt rooftop photovoltaic solar systems in Indonesian homes. Therefore, it was hypothesized that:

H1: Performance expectancy (PE) has a significant impact on consumers' behavioral intention to use HEMS.

2.3.2 EE and BI

Previous research has found the positive correlation between effort expectancy and behavioral intention (Mansur et al., 2019; Wu & Lee, 2017). In a study by Aggarwal et al. (2019), the factors that impact Indian consumers' purchase intentions for rooftop solar systems were analyzed, and effort expectancy emerged as a crucial factor. Popova and Zagulova (2022) applied the UTAUT model in the context of smart city development and found that residents' intention to use smart city applications in their daily lives is positively influenced by their effort expectancy. As a result, it was hypothesized that:

H2: Effort expectancy (EE) has a significant impact on consumers' behavioral intention to use HEMS.

2.3.3 SI and BI

Prior research has established that social influence plays a significant role in shaping an individual's behavioral intentions (S. Kim et al., 2015; Wu & Lee, 2017). Kotani and Nakano (2022) used UTAUT's purchase process model to examine the information gathering and decision-making process behind the purchase of zero-energy houses in Japan and found that social influence can effectively drive intention, resulting in a purchase. Warkentin et al. (2017) found that social influence has a positive influence on the intention to adopt smart meter technology. Thus, it was hypothesized that:

H3: Social influence (SI) has a significant influence on consumers' behavioral intention to use HEMS.

2.3.4 FC and BI

Previous research has indicated that facilitating conditions play a role in determining behavioral intention (Amin & Zaman, 2021; MANSUR et al., 2019; Wu & Lee, 2017). Kotani and Nakano (2022) studied the factors impacting the purchase decision of zero-energy houses (ZEHs) and found that facilitating conditions significantly enhance behavioral intention, leading to the adoption of ZEHs. This finding was supported by a similar study by L.-S. Lau et al. (2020), which

found that facilitating conditions positively influence the behavioral intention to adopt solar energy. Thus, it was hypothesized that:

H4: Facilitating conditions (FC) have a significant impact on consumers' behavioral intention to use HEMS.

2.3.5 ATB and BI

Several studies have found a significant effect of attitude on behavioral intention to adopt new technology (Choi & Park, 2018; Shiferaw & Mehari, 2019; Yuen et al., 2020). Bekti et al. (2021) found a positive relationship between attitude and customer intention to use rooftop PV, using a combination of UTAUT and TPB theories. Dwivedi et al. (2019) studies the adoption and usage of information system and information technology innovation based on UTAUT and found that attitude has a direct effect on behavioral intention. Therefore, the following hypothesis was proposed:

H5: Attitude toward behavior (ATB) has a significant impact on consumers' behavioral intention to use HEMS.

2.3.6 PBC and BI

A number of studies have found a significant relationship between perceived behavioral control and behavioral intention(Choi & Park, 2018; Masa'deh et al., 2022; Yang, 2019). Santosa et al. (2022) found that consumers' perceptions of their own behavioral control have a positive association with their behavioral intentions regarding the adoption of digital signatures. Gunawan et al. (2022) conducted research on factors affecting the adoption of electric vehicles and found that one's perception of their own behavioral control can impact their interest in driving an electric vehicle. Based on these findings, the following hypothesis was proposed:

H6: Perceived behavioral control (PBC) has a significant impact on consumers' behavioral intention to use HEMS.

In this study, we presented a conceptual framework as shown in Figure 1 that outlines the relationships between key variables affecting Thai consumers' behavioral intention to use HEMS.

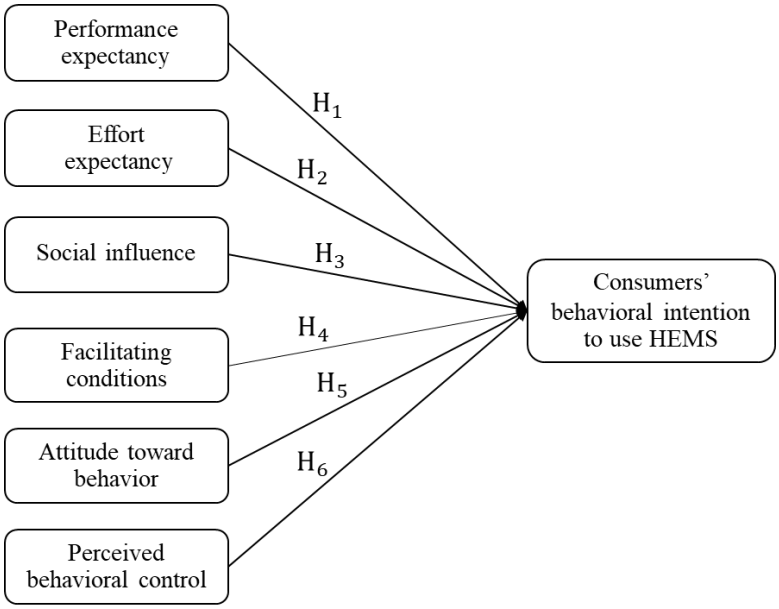

Figure 1. Conceptual framework.

3.0 RESEARCH METHODOLOGY

3.1 Sampling Design

The sample is a representative group of homeowners and residents in Bangkok and the Metropolitan area of Thailand. This study focuses on six provinces in the region – Bangkok, Nonthaburi, Pathum Thani, Samut Prakan, Nakhon Pathom, and Samut Sakhon – which have large populations and high numbers of homes.

This research employed non-probability sampling. Convenience sampling is a method in which samples are chosen for the researcher's convenience (Zikmund et al., 2013). This technique is useful when the population is so large that randomization is impractical (Etikan et al., 2016). Convenience sampling has several benefits, including the ability to collect a large number of respondents quickly (Zikmund et al., 2013). Screening questions were set to only include homeowners and residents who met the criteria for the study.

In accordance with Roscoe, 1975, a sample size of 30 to 500 is deemed appropriate for most behavioral studies, and a sample size larger than 500 may increase the risk of a Type II error (Sekaran & Bougie, 2016). The minimum sample-to-variable ratio is 5:1, with 15 – 50 cases per observed variable being the ideal number (Hair et al., 2018). This means that, with 27 observed variables in this study, a minimum sample size of 405 was required, and a total of respondents' data were collected and screened for analysis after data collection.

3.2 Instrument Design and Data Collection

In this study, a questionnaire survey method was employed to gather data. An online questionnaire survey was utilized as the primary means of data collection and was designed using Google Forms. Responses were collected through the link provided in Google Forms, where the data was securely stored in a password-protected electronic format. The survey was distributed via email and various social media platforms, including Facebook, WhatsApp, and LINE, along with a clear explanation of the study's objective.

The methodology used existing scales developed by other scholars in this study. The use of existing scales is more reliable and efficient than developing new measurements (Hyman et al., 2006). The questionnaire items for each variable were adopted from prior research in the field. Some items were modified to fit the technology acceptance of the home energy management system (HEMS).

The questionnaire was divided into three parts:

Part 1: The questionnaire contained two screening questions aimed at identifying eligible respondents with regards to their intention to use HEMS. The questions were designed to determine whether the respondents lived in Bangkok Metropolitan area and owned a residence, as well as whether they had already installed or used a HEMS in their residence.

Part 2: The questionnaire was designed to gather demographic information from each respondent, such as gender, age, education level, occupation, monthly income, and marital status.

Part 3: This study used a questionnaire with 6 independent variables and one dependent variable, each measured on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). The questionnaire was based on the conceptual framework of the study. There are seven constructs as follows: The scale measured performance expectancy (PE) based on Gunawan et al. (2022); Bekti et al. (2021); The scale measured effort expectancy (EE) based on Bekti et al. (2021); The scale measured social influence (SI) based Bekti et al. (2021); Lau et al. (2020); The scale measured facilitating condition (FC) based on Lau et al. (2020); Gunawan et al. (2022); The scale measured attitude toward the behavior (ATB) based on Yuen et al. (2020); Gunawan et al. (2022);

The scale measured perceived behavioral control (PBC) based on Bekti et al. (2021); Gunawan et al. (2022); and The scale measured consumer's behavioral intention to use HEMS (BI) based on Bekti et al. (2021); Gunawan et al. (2022).

The reliability of the questionnaire was tested using the Cronbach's alpha coefficient. The test was performed for each variable, including PE, EE, SI, FC, ATB, PBC, and BI. A value of 0.6 or higher for the Cronbach's alpha indicates that the variables are reliable and consistent (Bizarrias et al., 2019). As per Sekaran & Bougie. (2016), a reliable questionnaire is considered as an appropriate tool for data collection The results of the Cronbach's alpha test are shown in Table 1.

Table 1. Summary of Reliability Statistics

Variables	No. of Items	Cronbach's Alpha Coefficient
Performance expectancy (PE)	4	0.703
Effort expectancy (EE)	4	0.633
Social influence (SI)	4	0.716
Facilitating conditions (FC)	3	0.621
Attitude toward the behavior (ATB)	4	0.730
Perceived behavioral control (PBC)	4	0.751
Consumers' behavioral intention to use HEMS (BI)	4	0.801

The results of the Cronbach's alpha test indicate that the reliability of all questionnaire items and variables were greater than 0.6, which means the questions are reliable(Hulin et al., 2001). The highest score was for the consumers' behavioral intention to use HEMS (0.801), followed by perceived behavioral control (0.751), attitude toward the behavior (0.730), social influence (0.716), performance expectancy (0.703), effort expectancy (0.633), and facilitating conditions (0.621).

3.3 Data Analysis

An inferential analysis was conducted using SPSS to investigate the relationships between variables, test, and interpret the hypotheses in this study. The means and standard deviations (SD) were computed and summarized for each variable. Pearson's correlation coefficient and multiple linear regression (MLR) were then analyzed.

The Pearson's correlation coefficient was used to measure the strength of the relationship between the variables in the study. The coefficient, denoted by "*r*," ranges from -1 to 1, and indicates a positive relationship between the variables if the dependent variable increases as the independent variable increases (Schober et al., 2018). Conversely, a negative relationship between the variables is concluded if the dependent variable increases as the independent variable decreases (Hauke & Kossowski, 2011).

Multiple linear regression (MLR) was used to determine the relationship between several independent variables and one dependent variable. The MLR equation is expressed as $\hat{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_i X_i$, where $\hat{Y}$ is the dependent variable, β_0 is the intercept, β_i is the regression coefficient, and X_i is the independent variable (Jobson, 1991).

4.0 RESULTS

4.1 Demographic Profiles of Respondents

According to the demographic information, the results indicate that the majority of respondents were female (n = 269, 53.8%) with the highest age average between 31 and 40 years old (n = 298,

59.6%). Most respondents resided in Pathum Thani province (n = 208, 41.6%) and lived in detached houses (n = 137, 27.4%). The majority of respondents held a bachelor's degree (n = 326, 65.2%) and were employed in private companies (n = 221, 44.2%). They reported earning between 30,001 and 50,000 THB (n = 224, 44.8%) and were single (n = 327, 65.4%), the largest group among the respondents.

4.2 Descriptive Statistics

In the descriptive analysis, the mean scores and standard deviations (SDs) were calculated for each variable. The interpretation of mean scores was classified according to Moidunny (2009) and is shown in Table 2. The summary of the analysis was shown in Table 3.

Table 2. Interpretation of Mean Score

Mean Score	Interpretation	Meaning
1.00 – 1.80	Very Low	Strongly Disagree
1.81 – 2.60	Low	Disagree
2.61 – 3.20	Medium	Neutral
3.21 – 4.20	High	Agree
4.21 – 5.00	Very High	Strongly Agree

Table 3. Level of Mean Score and Standard Deviation of the Study Variables

Variables	Mean Score ($\bar{x}$)	Standard Deviation (*SD*)	Level
Performance expectancy (PE)	4.41	0.47	Very High
Effort expectancy (EE)	4.35	0.49	Very High
Social influence (SI)	4.11	0.60	High
Facilitating conditions (FC)	4.10	0.68	High
Attitude toward the behavior (ATB)	4.40	0.51	Very High
Perceived behavioral control (PBC)	4.13	0.67	High
Consumers' behavioral intention to use HEMS (BI)	4.17	0.63	High

As shown in Table 3, the descriptive results show the overall mean scores, standard deviations, and perception levels of variables. The highest mean score was for performance expectancy (PE) ($\bar{x}$ = 4.41, *SD* = 0.47), indicating a very high level. This was followed by attitude toward the behavior (ATB) ($\bar{x}$ = 4.40, *SD* = 0.51) at a very high level, effort expectancy (EE) ($\bar{x}$ = 4.35, *SD* = 0.49), at a very high level, consumers' behavioral intention to use HEMS (BI) ($\bar{x}$ = 4.17, *SD* = 0.63), at a high level, perceived behavioral control (PBC) ($\bar{x}$ = 4.13, *SD* = 0.67), at a high level, social influence (SI) ($\bar{x}$ = 4.11, *SD* = 0.60), at a high level, and facilitating conditions (FC) ($\bar{x}$ = 4.10, *SD* = 0.68), at a high level.

4.3. Correlation Analysis

Table 4 shows the results of the correlation analysis, used to analyze the relationships of each variable in Thai consumers' behavioral intention to use a home energy management system. The results of the correlation analysis, which included seven variables, are presented. There was statistically significant correlation at the 0.01 level for performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), attitude toward the behavior (ATB), perceived behavioral control (PBC), and consumers' behavioral intention to use HEMS (BI), with correlation coefficients (*r*) ranging from 0.489 to 0.740.

Table 4. The Pearson Correlation Matrix

Variables	PE	EE	SI	FC	ATB	PBC	BI
PE	1.000	0.653**	0.547**	0.499**	0.489**	0.532**	0.582**
EE		1.000	0.531**	0.572**	0.490**	0.588**	0.588**
SI			1.000	0.623**	0.519**	0.652**	0.668**
FC				1.000	0.565**	0.740**	0.706**
ATB					1.000	0.610**	0.662**
PBC						1.000	0.726**
BI							1.000

**Correlation is significant at the 0.01 level (2-tailed).

As shown in Table 5, the summary of the hypothesis testing demonstrates the correlation coefficient and interpretation of the strength of the relationship between the two variables (the independent variable and the dependent variable). The results showed that the relationship between FC, EE, SI, and ATB had a moderate to strong positive impact on BI. Meanwhile, the relationship between FC and PBC had a strong positive impact on BI. All *p*-values were less than 0.0001, which is below the significance level of 0.01, indicating a significant relationship between the independent variables (PE, EE, SI, FC, ATB, PBC) and the dependent variable (BI) at the 0.01 level of significance. Thus, all null hypotheses were rejected, indicating that PE, SI, SI, FC, ATB, and PBC can positively influence of Thai consumers' behavioral intentions to use HEMS.

Table 5. A Summary of Correlation Coefficient.

Hypothesis	Correlation (*r*)	*p*-value	Statistical Result	Explanation
H_{10}: r = 0 H_{1a}: r ≠ 0	0.582	< .0001	Rejected H_{10}	There is a moderate and positive relationship between PE and BI
H_{20}: r = 0 H_{2a}: r ≠ 0	0.588	< .0001	Rejected H_{20}	There is a moderate and positive relationship between EE and BI
H_{30}: r = 0 H_{3a}: r ≠ 0	0.668	< .0001	Rejected H_{30}	There is a moderate and positive relationship between SI and BI
H_{40}: r = 0 H_{4a}: r ≠ 0	0.706	< .0001	Rejected H_{40}	There is a strong and positive relationship between FC and BI
H_{50}: r = 0 H_{5a}: r ≠ 0	0.662	< .0001	Rejected H_{50}	There is a moderate and positive relationship between ATB and BI
H_{60}: r = 0 H_{6a}: r ≠ 0	0.726	< .0001	Rejected H_{60}	There is a strong and positive relationship between PBC and BI

4.4 Multiple Linear Regression

4.4.1 Model Analysis

To test the hypotheses, multiple linear regression (MLR) was used. MLR is a statistical method where multiple variables are analyzed to determine the strongest predictor. Key factors to consider are the variance inflation (VIF), tolerance, and eigenvalue, according to O'brien (2007) and Kim (2019). Multi-collinearity analysis checks for strong correlations between predictors, with goal of identifying if one can be predicted from other linearly (Daoud, 2017; Farrar & Glauber, 1967).

Table 6 shows the multiple correlation (R) to be 0.825 and the coefficient of determination (R^2) to be 0.681. According to Hair et al. (2013), R^2 value of 0.25 indicate weak accuracy, 0.5 indicate moderate accuracy, and 0.75 indicate substantial accuracy. Results suggest that predictor variables (PE, EE, SI, FC, ATB, and PBC) can predict 68.10% of consumers' behavioral intention to use HEMS (BI) with a standard error of 0.36. The Durbin-Watson statistic of 1.837, between 1.5 and 2.5, shows that the data is not autocorrelated (Tabachnick & Fidell, 2007). Furthermore, to

assess multi-collinearity in our multiple linear regression (MLR) analysis, we evaluated the correlation coefficients among the independent variables, excluding BI. The results showed that these coefficients ranged from 0.489 to 0.740, which is below the threshold of 0.80. Thus, no multi-collinearity was observed (Berry et al., 1985; Shrestha, 2020). As a result, multiple regression analysis is valid for predicting BI in this study.

Table 6. Results of Multiple Linear Regression Analysis (Model Summary)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.825[(a)]	0.681	0.677	0.360	1.837

Note: [(a)] Predictors: (Constant), PBC, PE, ATB, SI, EE, FC., Dependent Variable: BI

Table 7 presents the analysis of variance to test the significance of the multiple correlation coefficients. Statistically significant results were found at the 0.01 level, indicating that at least one of the six independent variables had a significant effect on the dependent variable. Therefore, the relationship between the independent variable (PE, EE, SI, FC, ATB, and PBC) was found to be significant through linear correlation. Further equation development was performed based on this correlation.

Table 7. Results of Multiple Linear Regression Analysis (ANOVA)

Model		Sum of Squares	df	Mean Square	F	Sig. (*p*)
1	Regression	136.211	6	22.702	175.504	0.000[(b)]***
	Residual	63.771	493	0.129		
	Total	199.981	499			

Note: Dependent Variable: BI., [(b)] Predictors: (Constant), PBC, PE, ATB, SI, EE, FC., ** $p < 0.01$

Table 8 displays the results of the independent variables and their unstandardized coefficients (B). Five variables, performance expectancy (PE) (B=0.146, p<0.01), social influence (SI) (B=0.197, p<0.01), facilitating conditions (FC) (B=0.197, p<0.01), attitude toward behavior (ATB) (B=0.289, p<0.01), and perceived behavioral control (PBC) (B=0.203, p<0.01), were found to have a significant influence on consumers' behavioral intention to us HEMS (BI). For example, the p-value of PE is .003 which is smaller than the significance level of 0.05. This means that the null hypothesis that the coefficient of PE is zero in the population is rejected, and it is assumed that the coefficient of PE is different from zero. Thus, all independent variables, except effort expectancy (EE) (B=0.073, p>0.05), have a significant impact on consumers' behavioral intention to use HEMS. In other words, the higher the PE, SI, FC, ATB, and PBC, the greater the likelihood of consumers' behavioral intention to use HEMS. However, EE has no significant influence on consumers' behavioral intention to use HEMS, as its p-value is greater than 0.05.

Table 8. Results of Multiple Linear Regression Analysis (Coefficients)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig. (*p*)
		B	Std. Error	Beta (*β*)		
1	(Constant)	-0.518	0.177		-2.932	0.004**
	PE	0.146	0.048	0.109	3.033	0.003**
	EE	0.073	0.048	0.056	1.521	0.129^{ns}
	SI	0.197	0.039	0.185	5.063	0.000**
	FC	0.197	0.038	0.212	5.230	0.000**
	ATB	0.289	0.042	0.235	6.929	0.000**
	PBC	0.203	0.041	0.215	4.990	0.000**

Note: Dependent Variable: BI., ** $p < 0.01$, ^{ns} not significant at $p = 0.05$

The results of the hypothesis testing are presented in Table 9. Five hypotheses were supported, namely PE, SI, FC ATB, and PBC. One hypothesis, EE, was not supported. Based on these results, the five supported hypotheses can be used to predict Thai consumers' behavioral intention to use HEMS. A mathematical equation for this prediction can be developed as follows:

The raw score of predicting equation

$\hat{Y} = - 0.518 + 0.146PE + 0.073EE + 0.197SI + 0.197FC + 0.289ATB + 0.203PBC$

where Y = consumers' behavioral intention to use HEMS

The multiple linear regression results can be interpreted as follows: When all independent variables are equal to zero, the value of the dependent variable BI is -0.518. For the other independent variables, a change of one unit in their value will result in a change of the value of BI. For instance, if the value of the independent variable PE changes by one unit, the value of BI will change by 0.146.

The standardized score of predicting coefficient.

$\hat{Z} = 0.109PE + 0.056EE + 0.185SI + 0.212FC + 0.235ATB + 0.215PBC$

The standardized coefficients beta (β) indicates the relative strength and direction of the relationship between the independent and dependent variables and range from -1 to 1. A large beta value indicates a greater contribution of the respective independent variable to the explanation of the dependent variable (BI). In this model, the independent variable with the greatest influence on BI is attitude toward behavior (ATB).

Table 9. Results of hypothesis testing

Hypotheses	Statement	Result
H_1	Performance expectancy has a significant influence on Thai consumers' behavioral intention to use HEMS	Supported
H_2	Effort expectancy has a significant influence on Thai consumers' behavioral intention to use HEMS	Not Supported
H_3	Social influence has a significant influence on Thai consumers' behavioral intention to use HEMS	Supported
H_4	Facilitating conditions have a significant influence on Thai consumers' behavioral intention to use HEMS	Supported
H_5	Attitude toward behavior has a significant influence on Thai consumers' behavioral intention to use HEMS	Supported

H_6	Perceived behavioral control has a significant influence on Thai consumers' behavioral intention to use HEMS	Supported

The overall conceptual model of the prediction of Thai consumers' behavioral intentions to use home energy management system is illustrated in Figure 2

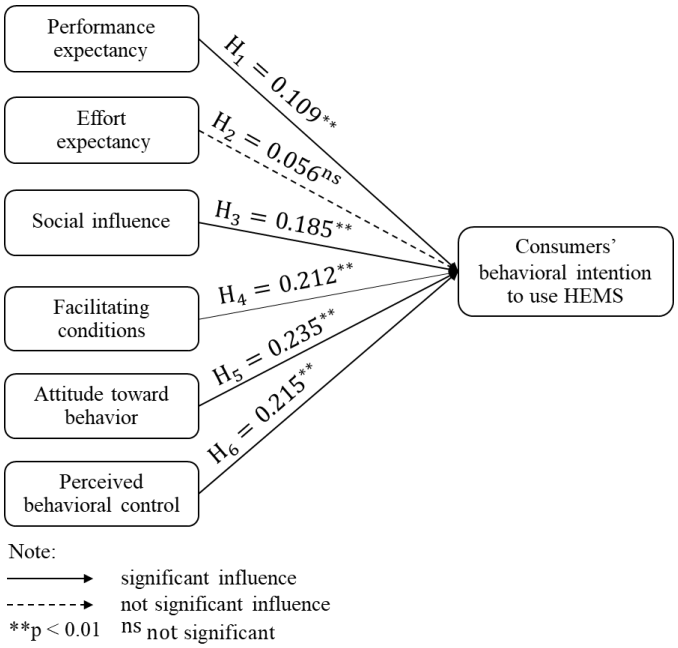

Figure 2. Conceptual model of Prediction of Thai consumers' behavioral intentions to use HEMS.

4.4.2 Multi-collinearity Testing

Table 10 shows the tolerance levels for performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), attitude toward the behavior (ATB), and perceived behavioral control (PBC) greater than 0.1 with values of 0.502, 0.472, 0.393, 0.564, and 0.349, respectively. The VIF values for these variables, 1.990, 2.118, 2.066, 2.544, 1.772, and 2.863, are lower than 5.0, indicating no multi-collinearity effect in the data (Hopkins & Ferguson, 2014; Jang & Topal, 2013). Furthermore, no eigenvalues or condition index relationship in the study suggest multi-collinearity, as eigenvalues close to zero and large corresponding condition numbers (Montgomery et al., 2021).

Table 10. Summary of Multi-collinearity Testing

Model		Collinearity Statistics	
		Tolerance	VIF
1	PE	0.502	1.990
	EE	0.472	2.118
	SI	0.484	2.066
	FC	0.393	2.544
	ATB	0.564	1.772
	PBC	0.349	2.863

Note: Dependent Variable: BI

4.4.3 Normality of Errors Testing

Figure 3 displays a normal the distribution of residuals as shown in the histogram. The Kolmogorov-Smirnov (K-S) was applied to verify the normal distribution due to the sample size being larger than 50 (Sager, 2010). The test result showed a statistical value of 0.05 with the p-value of 0.129 (greater than 0.05), failing to reject the null hypothesis. This confirms the standardized residuals are normally distributed, making MLR a suitable method for predicting the behavioral intention to use HEMS.

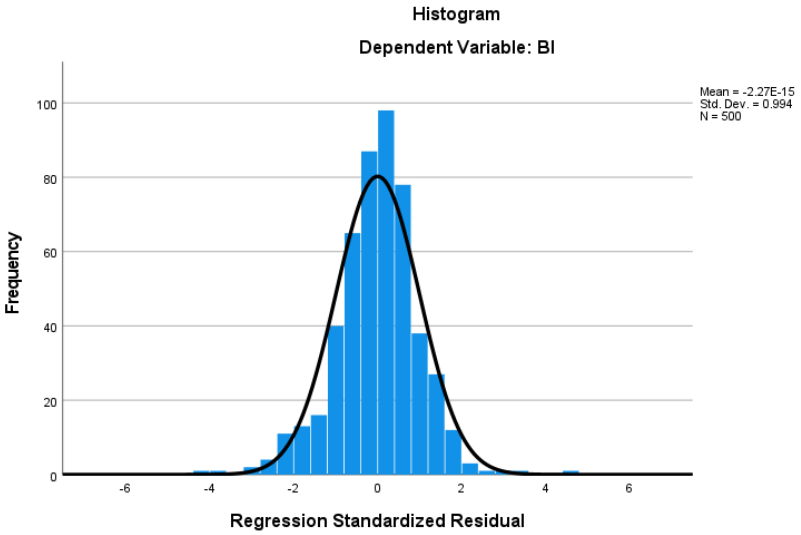

Figure 3. The histogram of Standardized Residual.

4.4.4 Heteroskedasticity Testing

For the residuals to have constant variance, the data must not exhibit heteroskedasticity. Figure 4 shows that the residual variance is consistent over the predicted values, indicating no heteroskedasticity (Godfrey, 1978). This allows the MLR formulated in the previous section to have practical applications.

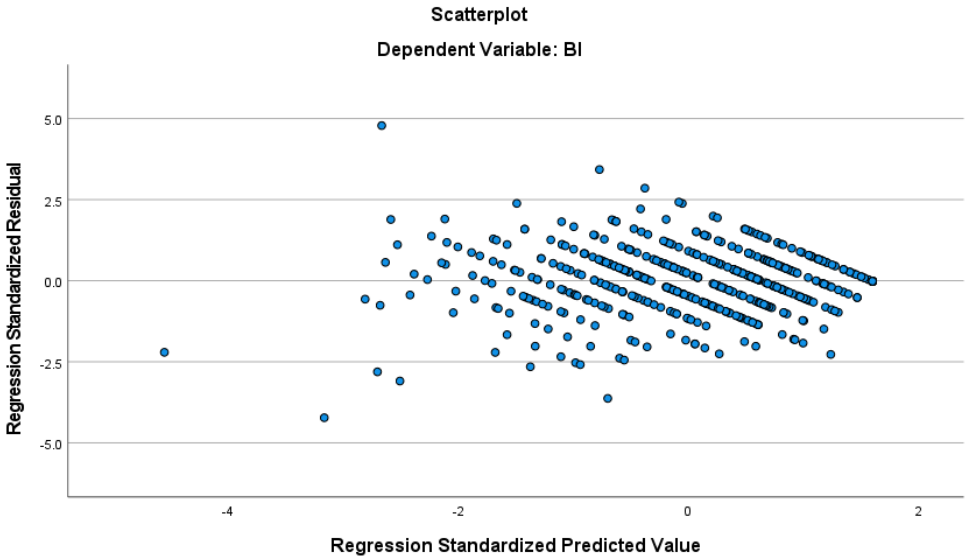

Figure 4. Scatter Plot.

5.0 DISCUSSIONS

The ATB had the greatest impact on Thai consumers' behavioral intention to use HEMS. Other studies also found that consumers' attitudes play a significant role in adopting new technologies (Bekti et al., 2021; Yuen et al., 2020). This study found that consumers have a positive attitude toward HEMS and believe that advancements in technology will be important.

Consumer perceptions of HEMS' benefits, such as lower electricity bills, reduced environmental impact, and ease of control and monitoring, support their decision to use HEMS (Balakrishnan & Geetha, 2021). Thus, greater consumer awareness of HEMS benefits could lead to greater incentive to use it in the future. Government policies play an important role in stimulating HEMS usage in Thailand. This study confirms the findings of Chen et al. (2020), who found attitudes are the strongest predictors of willingness to pay for HEMS.

The study found that the association between PBC and intention to use HEMS is significant and positive. This result aligns with previous research, including studies on shared autonomous vehicles (Yuen et al., (2020) and technology use (Choi & Park, 2018; Gunawan et al., 2022; Santosa et al., 2022).

The study found that the intention to use HEMS is positively impacted by FC (e.g., availability of resources for using the technology). This is consistent with previous research (Amin and Zaman (2021); Kotani and Nakano (2022); MANSUR et al. (2019). Adequate facilities such as money, usable space, and customer service, increase confidence in using new technology (Chatterjee et al., 2021; Dwivedi et al., 2019; Lau et al., 2020).

SI positively impacts the intention to use HEMS. This result aligns with previous literatures (Kotani & Nakano, 2022;). Consumers with high levels of SI are more likely to use HEMS frequently. Social pressure from environment, such as family, colleagues, workplace, and advertising, has a psychological impact on the adoption of HEMS (Gunawan et al., 2022; Kotani & Nakano, 2022). In a study by Kotani and Nakano (2022), SI had the biggest impact on the decision to use zero-energy homes in Japan.

The intention to use HEMS is impacted by PE, which is seen to have a positive effect on usage intentions. The study found that consumers' understanding of HEMS operation, perceived

benefits, and confidence in its ability to improve energy efficiency and reduce costs, lead to a favorable perception of HEMS and a greater tendency to intend to use it. This aligns with prior research by Chatterjee et al. (2021), Nurwidiana et al. (2021), and Zhang and Yu. (2022).

Despite the five significant hypotheses, this study revealed one non-significant factor in the relationship between EE and consumers' intentions to use HEMS (BI). EE had a positive but insignificant effect on BI (p-value > 0.05). This contradicts the findings of previous studies by Aggarwal et al. (2019), and Popova and Zagulova (2022).

The reason for this discrepancy may be due to the majority of the consumer group in this study viewing HEMS as a relatively new technology. Many consumers are not familiar with HEMS and have concerns about its installation, maintenance, and compatibility with household appliances. In addition, they may be worried about the availability of after-sales service and support.

6.0 IMPLICATIONS

This study provides recommendations for distributor companies or other HEMS stakeholders to focus on developing consumers' perception of benefits, including comfort, reduced electricity bills, reduced environmental impact, and simple control and monitoring. Recommendations include educating consumers on compatibility and benefits, serving as a guideline for regulators and policymakers to promote HEMS adoption, guiding entrepreneurs and suppliers in business model development, and informing appliance manufacturers, smart home product developers, and marketers on distribution management and reaching consumers.

7.0 CONCLUSIONS AND LIMITATIONS

The aim of this study was to identify the crucial factors affecting Thai consumers' intention to adopt home energy management system (HEMS). A quantitative approach was taken in Bangkok and the Metropolitan area of Thailand through an online questionnaire survey. The multiple linear regression analysis was used to analyze the impact of different factors on consumers' intention to use HEMS.

This study found that five factors, including attitude toward behavior, perceived behavioral control, facilitating conditions, social influence, and performance expectancy, have a significant impact on consumers' intention to use HEMS. The study combined the theories of UTAUT and TPB to provide an understanding of consumer behavior and decision-making process towards HEMS adoption.

The findings of this study can assist policymakers, regulators, appliance manufacturers, smart home product developers, and marketers in their efforts to promote the adoption and use of HEMS. They can use the information to better understand consumer attitudes and preferences, plan distribution, and tailor their marketing strategies accordingly.

Despite the contributions, there are a few limitations that still need to be acknowledged. Firstly, the non-probability sample is limited to Bangkok and Metropolitan Area residents. Further research with a more extensive sample across Thailand is recommended. Lastly, the study's reliance on quantitative surveys limits depth of understanding. Mixed methods research is suggested for a deeper understanding of consumer behavior.

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