An Integrated Theoretical Model to Predict the Intention to Use Energy Monitoring Applications. Evidence from Germany

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Abstract

Energy consumption monitoring systems are becoming increasingly sophisticated, yet their adoption to support environmentally friendly decision-making remains low. In this paper, we develop an integrated theoretical model based on Reasoned Action Approach, Unified Theory of Acceptance and Use of Technology 2, and the Self-Efficacy Theory to analyze energy monitoring adoption in a smart home context. We apply the model to empirically test the intention of German consumers to adopt an application for monitoring their energy consumption. Our results show that our model explains the intention to use energy monitoring applications, with common constructs, but highlight the important role of governmental support as a major novelty. We provide practical implications for development processes of energy monitoring applications and theoretical implications by proposing a new integrated model.

Keywords: Green IS, Energy Consumption, Smart Homes, IS Adoption, Integrated Model.

1. Introduction

The shift from fossil fuels to renewable energy is a critical challenge for society to reduce carbon emissions and slow down global warming and climate change (Caragliu & Graziano, 2022; Ketter et al., 2016). Recognizing this urgency, many national governments have prioritized energy transition in their policies (Stringer & Joanis, 2022). However, the understanding of how governmental support actually benefits to pro-environmental intentions and enhances the self-efficacy of pro-environmental behavior is not well understood. Hence, as renewable electricity represents 30% of total electricity generation and 146 countries have announced to raise their renewable energy share (REN21, 2023), saving energy is crucial (Watson et al., 2022). Various studies have been performed that investigate either the intention to use or reasons to purchase energy monitoring applications (e.g., Hua & Wang, 2019; Prete et al., 2017). However, prior research remains short on the explanation of factors that lead to an individual's perceived behavioral control. Further, there is not much evidence on how governmental support influences the intention to use energy monitoring applications. Our research is driven by the following research question:

RQ: What factors influence the adoption of energy monitoring applications?

To answer this question and thus close the identified research gaps, we investigate the adoption of applications for consumers to monitor their energy consumption. For this, we develop an integrated theoretical model, specifically, we investigate energy adoption using the Reasoned Action Approach (RAA), the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), and the Self-Efficacy Theory (SET).

To test our integrated model in an energy adoption context, we design an energy monitoring app (EMA) and conduct a survey with 214 participants in Germany. Germany was chosen as in 2022, 21% of German households used smart power outlets that enable them to monitor their energy consumption (BitkomResearch, 2022). Hence, there is a vast number of households in Germany not using smart power outlets yet. However, at the same time, consumer prices for energy in Germany are very high by international standards and the recent and ongoing energy crisis has had a profound impact on many households, exacerbating an already challenging situation (Schiffer & Ulreich, 2023). This may have changed Germans' perceptions about the adoption of an EMA. Our EMA, termed PowerPilot,

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was presented to participants to establish a real-world scenario and allow them to understand the context of our study. We used structural equation modelling to analyze hypothesized relationships.

Our paper is structured as follows. After this introduction, we provide a conceptual and theoretical background with a focus on related work, integrated theoretical model for green IS adoption, and hypotheses development. After presenting materials and methods, we show our results of descriptive statistics and hypothesis testing. We then discuss our findings, taking related work into account. Finally, our conclusion provides theoretical and practical implications, explain limitations and opportunities for future work.

2. Conceptual and theoretical background

2.1 Related Work

Several studies have examined the intention to use products or services that enhance sustainability. For instance, Ahmad et al. (2022) determined the purchase behavior of individuals, taking trust and self-efficacy theory into account. Jayaprakash and Pillai (2016) used a similar approach, using self-efficacy theory to evaluate the green IT self-efficacy of individuals. Further concerning self-efficacy theory, Ding (2022) and Ding and Jiang (2023) investigated the intention to reduce food waste reduction in restaurants by Generation Z individuals. Additionally, to reduce food waste, Sestino et al. (2023) conducted a study investigating waste fighting mobile applications taking communication focusses and status consumption orientation into account. Concerning servant leaderships, Mughal et al. (2022) used self-efficacy theory to predict employees' pro-environmental behavior dependent on employees' green self-efficacy. To determine energy saving intentions in Vietnam, Le-Anh et al. (2023) utilized behavioral-reasoning theory. For gathering determinants of Southern Italian households' intention to adopt energy-monitoring measures in residential buildings, Prete et al. (2017) used the reasoned action approach. To elaborate intention-behavior gaps, He et al. (2023) ascertained the appliance of energy-saving refrigeration in Southwest China. Through the lens of the theory of planned behavior, Lou et al. (2021) examined tea farmers' intentions to adopt a pesticide control technology. In contrast to the former studies, they found that perceived behavior control had a negative impact on behavior.

Further, integrated models exist that incorporate self-efficacy theory. Yadav et al. (2023) combined value-belief-norms and self-efficacy theory to predict climate-friendly behavior, while Gadenne et al. (2011) combined variables from theory of reasoned action, theory of planned behavior as well as technology adoption model to determine various environmental behaviors. Akroush et al. (2019) and Hua and Wang (2019) took a similar approach as Gadenne et al. (2011) did, as they estimated the purchasing intention of sustainable products. In terms of behavioral intentions to purchase energy-saving appliances in China, Liao et al. (2019) used environmental attitudes, concerns, and perceived psychological benefits as variables for their study.

However, while these integrated theoretical models predict intentions to engage in energy-saving behavior, they all fall short in explaining the root causes of the perceived control over such behaviors. Hence, we take related work into account and propose an integrated theoretical model that not only explains the intention to use an energy monitoring application but also sheds light on the root causes of the perceived behavioral control regarding its adoption.

2.2 Integrated theoretical model for green IS adoption

To report on green IS adoption, we designed an integrated theoretical model that combines reasoned action approach (RAA) (Fishbein & Ajzen, 2010), unified theory of acceptance and use of technology 2 (UTAUT2) (Venkatesh et al., 2012), and self-efficacy theory (SET) (Bandura, 1986). These theories are suitable to explain the intention to use technology and share conceptually similar variables. As such, we follow recommendations of Fishbein and Ajzen (2010) and integrate the variables attitude, perceived norms, and perceived behavioral control in our model. Using RAA, which is the combination of theory of reasoned action and theory of planned behavior, is reasonable, as it is one of the most important theories for predicting behavioral intentions in psychology (Bosnjak et al., 2020).

Further concerning the explanation of intention to use from an information-systems-related viewpoint, we use UTAUT2 according to Venkatesh et al. (2012). Combining those theories is reasonable, as related work shows (Akroush et al., 2019; Gadenne et al., 2011; Hua & Wang, 2019). Further, both theories share common elements that are used slightly differently. First, Fishbein and Ajzen (2010) recommend using abilities to determine intention to use to as control variables for theoretical models. As such, perceived ease of use and habit are such abilities and proposed as important variables in UTAUT2 (Venkatesh et al., 2012). Second, both theories point out that perceived norms as social influence are important for theoretical models, which is why we combine them in our model.

Additionally, we incorporate SET based on Bandura (1986) into our model, as it also shares variables with our previous theories. For instance, studies point out that perceived behavioral control and perceived self-efficacy are conceptually similar, which is why we add the theory to our integrated model. According to Bandura (1986) (and further developments of SET (Redmond, 2010)), emotional states, vicarious experiences, performance outcomes, and verbal persuasion should be considered as variables to explain SET (for environmental contexts, see Jayaprakash and Pillai (2016)). Again, some of those variables are linked to existing variables in our model. Hence, concerning performance outcomes, i.e., how easily individuals are able to use monitoring applications, we refer to perceived ease of use. Further concerning vicarious experiences in using mobile applications, we point out to the variable "habit" in our model. For emotional states and verbal persuasion, we derive variables from related work. As such and concerning emotional states, we take fear towards hazards into account, as this is an important variable to predict intention to use, according to Jayaprakash and Pillai (2016) and Gimpel et al. (2020). For verbal persuasion, we follow recommendations of Prete et al. (2017) and Liao et al. (2019) for environmental concern as well as Gadenne et al. (2011) and Akroush et al. (2019) for governmental regulations being important predictors for intention to use.

To better understand similarities between the variables in our model, Table 1 summarizes all variables used and defines synonyms for them.

Table 1. Overview on variables in relevant theories.

Variables of integrated theoretical model (reference(s)) (/synonym(s)(theory)(reference(s))) Definition in the integrated model *Studies concerning related work*	**RAA**	**UTAUT2**	**SET**
Attitude (Fishbein & Ajzen, 2010) reflects the stance an individual has towards the EMA. *(Ahmad et al., 2022; Akroush et al., 2019; Gadenne et al., 2011; Gimpel et al., 2020; Hua & Wang, 2019; Le-Anh et al., 2023; Prete et al., 2017; Webb et al., 2014; Yadav et al., 2023)*	X		
Perceived norms (Fishbein & Ajzen, 2010) (/social influence (UTAUT2)(Venkatesh et al., 2012) explain the opinion of others towards the EMA. *(Gadenne et al., 2011; Gimpel et al., 2020; Große-Kreul, 2022; Hua & Wang, 2019; Le-Anh et al., 2023; Prete et al., 2017; Webb et al., 2014; Yadav et al., 2023)*	X	X	
Perceived usefulness (Venkatesh et al., 2012) refers to the effectiveness of the EMA and the benefits provided to the individual. *(Hua & Wang, 2019)*		X	X
Hedonic motivation (Venkatesh et al., 2012) represents the influence of an individual's pleasure and pain receptors concerning their willingness to move towards a goal or away from a threat. *(Große-Kreul, 2022)*		X	
Habit (Venkatesh et al., 2012) (/vicarious experiences (SET)(Bandura, 1986)) reports on the usage routines of individuals for the use of energy monitoring applications. *(Gimpel et al., 2020; Webb et al., 2014)*		X	X
Perceived ease of use (Venkatesh et al., 2012) (/abilities (RAA)(Fishbein & Ajzen, 2010)(/performance outcomes(SET)(Bandura, 1986)) determines a degree of which the individual thinks that it can handle the EMA easily. *(Hua & Wang, 2019)*	X	X	X
Governmental support (Akroush et al., 2019; Gadenne et al., 2011) (/verbal persuasion (SET)(Bandura, 1986)) estimates the efficiency an individual perceives with respect to governmental-related energy efficiency measures. *(Akroush et al., 2019; Gadenne et al., 2011)*			X
Environmental concern (Liao et al., 2019; Prete et al., 2017) (/verbal persuasion (SET)(Bandura, 1986)) reports on the degree of endangerment an individual perceives towards the environment. *(Liao et al., 2019; Prete et al., 2017)*			X
Fear towards hazards (Gimpel et al., 2020; Jayaprakash & Pillai, 2016) (/emotional state (SET)(Bandura, 1986)) measures the emotion "anxiety" an individual feels towards environmental hazards. *(Gimpel et al., 2020; Jayaprakash & Pillai, 2016)*			X
Perceived behavioral control (Fishbein & Ajzen, 2010) (/effort expectancy (UTATU2)(Venkatesh et al., 2012))(/self-efficacy (SET)(Bandura, 1986)) describes the degree of freedom an individual perceives while determining the use of an EMA. *(Ding, 2022; Ding & Jiang, 2023; Gimpel et al., 2020; Große-Kreul, 2022; He et al., 2023; Hua & Wang, 2019; Le-Anh et al., 2023; Prete et al., 2017)*	X	X	X
Intention to use (Fishbein & Ajzen, 2010; Venkatesh et al., 2012) refers to an individual's tendency about using the EMA. *(Akroush et al., 2019; Ding, 2022; Ding & Jiang, 2023; Gimpel et al., 2020; Große-Kreul, 2022; He et al., 2023; Le-Anh et al., 2023; Sestino et al., 2023; Webb et al., 2014)*	X	X	X

2.3 Hypotheses development

To develop hypotheses, we integrate theories that aim to predict intention to use, namely RAA, UTAUT2, and SET. As attitude is a major predictor for intention to use (Fishbein & Ajzen, 2010), we assume that it will be important in our study. Further, as Gadenne et al. (2011), Ahmad et al. (2022), and others point out, we assume that positive attitudes regarding an EMA will lead to higher intentions. Hence, our first hypothesis is as follows:

H1: Attitude positively relates to the intention to use an EMA.

Fishbein and Ajzen (2010) state that perceived norms are important for investigating intention to use, which is supported by Venkatesh et al. (2012) who refer to social influence. Additionally, Prete et al. (2017), Große-Kreul (2022), and others state that positive opinions towards the use of an EMA will lead to higher intentions. Thus, our second hypothesis is as follows:

H2: Perceived norms positively relate to the intention to use an EMA.

Venkatesh et al. (2012) refer to perceived usefulness of the information system being relevant to determine intention to use. Further, Hua and Wang (2019) assume that perceived usefulness has a positive impact on intention to use, as they also investigated energy monitoring applications. This leads to our third hypothesis:

H3: Perceived usefulness positively relates to the intention to use an EMA.

Venkatesh et al. (2012) propose that hedonic motivation of individuals is important for determining intention to use. Additionally, Große-Kreul (2022) suggests that hedonic motivation will have a positive influence on intention to adopt smart meters. Therefore, our fourth hypothesis is as follows:

H4: Hedonic motivation positively relates to the intention to use an EMA.

Venkatesh et al. (2012) state that habit is an important factor for estimating intention, as it is represented by performing similar behaviors compared to the one in question. Habit then represents knowledge and experience gained, who are helpful for performing the behavior in question. Bandura (1986) argued similar in that he states that prior knowledge and vicarious experiences are relevant to determine an individual's self-efficacy. Concerning environmental contexts, Webb et al. (2014) used habit as a variable to predict monitoring procedures of domestic electricity consumption. Further, Gimpel et al. (2020) determined that habit is important for ascertaining the acceptance of smart energy technology for saving purposes. Accordingly, our fifth hypothesis is as follows:

H5: Habit positively relates to (a) the intention to use an EMA and (b) perceived behavioral control.

Further, Venkatesh et al. (2012) point out to perceived ease of use influencing the intention to use. Fishbein and Ajzen (2010) made similar statements by discussing that skills and abilities are important for the estimation of intention to use, with perceived ease of use representing such skills and abilities (Venkatesh et al., 2012). Further, those skills and abilities also influence perceived behavioral control (Fishbein & Ajzen, 2010). SET takes a similar approach, as Bandura (1986) states that an individual's perception of her/his performance outcome towards the behavior in question is important for determining one's self-efficacy and intention. Relevant studies argue that perceived ease of use is important, as its lead to a more favorable attitude and ultimately to a higher intention to use (Hua & Wang, 2019). Hence, our sixth hypothesis is as follows:

H6: Perceived ease of use positively relates to (a) the intention to use an EMA and (b) perceived behavioral control.

Bandura (1986) argues that verbal persuasion and encouragement are relevant for estimating an individual's self-efficacy. As such, persuasion can either be perceived on an individual or general social level towards the behavior in question. Hence, Gadenne et al. (2011) and Akroush et al. (2019) state that on a general social level and for energy saving behavior, the individual perception of the effectiveness of governmental regulations to support energy saving behaviors is important. Additionally, Akroush et al. (2019) discuss that if governments provide benefits to individuals for purchasing energy-efficient products, they will have a higher intention to purchase. This leads to our seventh hypothesis:

H7: Governmental support positively relates to (a) the intention to use an EMA and (b) perceived behavioral control.

Redmond (2010) states that certain factors that lead to encouragement and discouragement have to be considered for verbal persuasion, in order to gain knowledge about one's perceived self-efficacy. In environmental contexts and next to governmental support, environmental concerns are important. As such, Prete et al. (2017) and Liao et al. (2019) show that if individuals are concerned about the well-being of the environment, their intention to adopt energy-efficiency measures and to purchase energy-saving appliances is higher. Hence, our eighth hypothesis is:

H8: Environmental concern positively relates to perceived behavioral control.

Bandura (1986) argues that the emotional status of individuals is important to understand their self-efficacy and should be investigated. For environmental contexts, Jayaprakash and Pillai (2016) and Gimpel et al. (2020) state the fear towards hazards is important for perceived self-efficacy. Further, Jayaprakash and Pillai (2016) discuss that if individuals feel fear towards hazards, they also feel a need to gain control over actions that reduce this fear, i.e. energy saving behavior. Accordingly, our ninth hypothesis is:

H9: Fear towards hazards positively relates to perceived behavioral control.

Bandura (1986) states that the development of self-efficacy is important for behavior and performance. This is supported by Fishbein and Ajzen (2010), who state that perceived behavioral control is important for determining the intention to use. Further, if someone is able to define her/his own effort expected for the behavior in question, they perceive behavioral control, according to Venkatesh et al. (2012). For environmental contexts, Gimpel et al. (2020), Große-Kreul (2022), and others point out that once individuals perceive control about the behavior in question, their intention to perform this behavior is higher. Thus, our final hypothesis is as follows:

H10: Perceived behavioral control positively relates to the intention to use an EMA.

Figure 1 provides an overview of our integrated theoretical model.

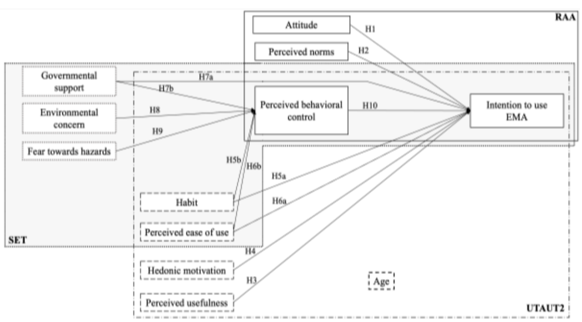

Figure 1. Research model.

3. Materials and methods

3.1 Research Design & Questionnaire

To determine which factors are important for the intention to use, we conducted a survey in October 2023 in Germany. We designed a hypothetical scenario (see Appendix) describing a situation where an app called "PowerPilot" allows to monitor energy consumption for home in real-time. Participants were informed about the app features, expected cost and energy saving potentials. We developed the scenario and provided information based on current data and research findings (Schleich et al., 2017). After scenario presentation, the survey participants were asked to answer an online questionnaire. We used our theories to design reflective variables for our study. As such and concerning RAA, we used the item template from Fishbein and Ajzen (2010) for intention to use (three items), attitude (four items), perceived norms (four items), and perceived behavioral control (four items). Further concerning UTAUT2, we used recommendations of Venkatesh et al. (2012) to define our items and took relevant studies in account. For perceived usefulness (four items), we derived the items from Hua and Wang (2019). For hedonic motivation (three items), we took the measures from Große-Kreul (2022) in account. Concerning habit (two items), we adopted our items from studies conducted by Webb et al. (2014) and Gimpel et al. (2020). For our items concerning perceived ease of use (three items), we considered research from Hua and Wang (2019). Concerning governmental support (four items), we took studies from Gadenne et al. (2011) and Akroush et al. (2019) into account. To report on environmental concern (3 items), we used the studies of Prete et al. (2017) and Liao et al. (2019) to design our items. For fear towards hazards (3 items), we derived the items from studies of Jayaprakash and Pillai (2016) and Gimpel et al. (2020). All items were measured on a seven-point Likert scale ranging from “1 – Do not agree at all” to “7 – Fully agree”. In addition, we collected basic demographic data (age, gender). As survey responses were collected simultaneously, there is the potential for common method bias (Campbell & Fiske, 1959). To proactively address this potential bias, we adhered to Kortmann’s (2015) guidelines regarding anonymity, confidentiality and the placement of dependent and independent variables. The questionnaire is shown in the appendix.

3.2 Sample

To gather our participants, we used the German crowdsourcing platform Clickworker. Compared to Amazon MTurk it provides higher quality of participants as minimum wages are followed. Moreover, Clickworker offers representative data for the German consumer market. Participants self-selected into the study. We included test questions at the beginning and end of the questionnaire to ensure that their self-reported status was correct. Further, as we paid individuals for participating in the survey, we followed recommendations of Goodman et al. (2012) and included attention checks in our survey to ensure the validity of the data. To rule out the risk that participants were responding to survey items randomly, we examined our dataset for suspicious response patterns, such as straight-lining or alternating extreme pole responses (Ringle et al., 2023). Finally, participants whose total time for answering the survey was less than 300 s were excluded from the further analysis, as it was assumed that their processing was inadequate. A total of 315 individuals participated in our survey, of whom 101 were excluded, as they did not pass our attention checks or insufficient processing. Of the 214 participants, 41.59 percent (n = 89) were female, 58.41 percent (n = 125) were male. The mean age was 38.59 years (SD = 11.67; min = 18, max = 65).

3.3 Data analysis

We used partial least squares, a method that is particularly suitable for processing structural equation models, to analyze our data using reflective and mediating constructs (Hair et al., 2019). Following recommendations of Hair (2021) concerning PLS-SEM, we conducted bootstrapping and PLS Predict procedures, and the PLS algorithm using SmartPLS 4.0.9.6 as software. For the bootstrap, we used 5,000 resamples, while we performed 10 folds and 10 repetitions for PLS Predict. Accordingly, we first investigated our reflective measurement models before evaluating the structural model in a second step. Concerning the reflective measurement models, all reflective variables met the indicator reliability criteria, as the loadings were higher than 0.7 (see Appendix) and the average variance extracted was above 0.5 (see appendix; Hair, 2021). To evaluate discriminant validity, we inspected the heterotrait–monotrait (HTMT) ratios of the correlations and their 95% one-sided bootstrap confidence intervals (Ringle et al., 2023). All HTMT-values were below 0.85 and the upper bound of the HTMT value's 95% one-sided bootstrap confidence interval was also below 0.85. Hence, discriminant validity was also given (Ringle et al., 2023). Having verified that our model met all the requirements of the measurement model, we evaluated the structural model. First, we tested for collinearity in the structural model. All VIF-values were below the threshold of three, indicating that the estimates were not affected by collinearity (Hult et al., 2018). Next, we investigated effect sizes using f^2 values, as proposed by Cohen (1988). While Cohen (1988) proposes values of 0.02, 0.15, and 0.35 for small, medium, and large effects, Kock and Hadaya (2018) state that effect sizes are dependent on the sample size. Thus, we conducted statistical power analyses using G*Power 3.1.9.7 (Mayr et al., 2007) and determined that our sample size is sufficient for using the effect sizes stated by Cohen (1988). For explanation power, Hair (2021) refer to R^2 values, with 0.25, 0.5, and 0.75 representing weak, moderate, and strong powers. Hence, with 58.0%, our explanation power is moderate. As the final step in our statistical analysis, we performed PLS predictions according to Shmueli et al. (2019) and CVPAT procedures by using recommendations of Liengaard et al. (2021). According to Hair et al. (2022) studies should report on both measures, as PLS predictions focus on the early antecedents, while CVPAT reports on the late antecedents of theoretical models. Concerning PLS predictions, we estimated that our PLS-SEM Q^2 prediction values were exclusively positive, and that our prediction errors were not highly symmetrically distributed. Hence, we investigated whether our PLS-SEM means absolute errors (MAEs) were lower than those of the linear regression model (LM). As the majority of the PLS MAEs were lower than the LM errors, we determined a medium predictive power for our model concerning our early antecedents. For CVPAT and our late antecedents, we tested indicator averages and average loss values of the linear model of the overall model. As our model has a significant average loss difference (ß: -0.051; p: 0.042) for our overall model vs. indicator average, we conclude that our model has predictive validity concerning our late antecedents (Liengaard et al., 2021).

4. Results

4.1 Descriptive statistics

The descriptive statistics and correlations among our variables are shown in Table 2.

Table 2. Descriptive statistics and correlations among variables.

	ATT	PN	PUSF	HM	HAB	PEOU	GS	ENC	FTH	PBC	BI	AGE	M	SD
ATT	1	.640**	.622**	.582**	.626**	.173*	.276**	.075	.123	.250**	.558**	-.136*	5.24	1.27
PN		1	.534**	.470**	.594**	.036	.321**	.174*	.198**	.017	.596**	-.227**	4.42	1.44
PUSF			1	.450**	.627**	.365**	.313**	-.015	.052	.214**	.594**	-.097	5.40	1.35
HM				1	.485**	.254**	.382**	.198**	.192**	.015	.485**	-.317**	4.50	1.42
HAB					1	.301**	.457**	.109	.152*	.152*	.632**	-.187**	4.62	1.43
PEOU						1	.029	-.091	-.051	.447**	.189**	.044	5.68	1.06
GS							1	.217**	.299**	-.075	.463**	.178**	3.81	1.60
ENC								1	-.032**	-.103	.181**	-.241**	3.37	1.76
FTH									1	-.089	.230**	-.221**	3.33	1.73
PBC										1	-.063	.108	5.98	1.17
BI											1	-.200**	3.87	1.60
AGE												1	38.59	11.67

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed)
ATT = attitude, PN = perceived norms, PUSF = perceived usefulness, HM = hedonic motivation, HAB = habit, PEOU = perceived ease of use, GS = governmental support, ENC = environmental concern, FTH = fear towards hazards, PBC = perceived behavioral control, BI = behavioral intention, SD = Standard Deviation, n = 214.

4.2 Hypothesis testing

Concerning our hypotheses, we support H1 (ß=.157; P<.05; f^2=.020), H2 (ß=.203; P<.01; f^2=.046), H3 (ß=.215; P<.01; f²=.051), H5a (ß=.187; P<.01; f²=.034), H6b (ß=.434; P<.001; f²=.218), H7a (ß=.174; P<.01; f²=.052), and H10 (ß=-.218; P<.001; f²=.078), while we do not support H4 (ß=.011; P>.05; f²=.000), H5b (ß=.101; P>.05; f²=.009), H6a (ß=.116; P>.05; f²=.019), H7b (ß=-.092; P>.05; f²=.008), H8 (ß=-.037; P>.05; f²=.002), and H9 (ß=-.045; P>.05; f²=.002). For the R²-values in our model and according to Hair et al. (2022), the explanatory power for perceived behavioral control is weak, while it is moderate for intention to use. Further, we used the age of our participants as a control variable and found several significances, that are: towards attitude (ß=-.143; P<.01; f²=.021), perceived norms (ß=-.226; P<.001; f²=.054), hedonic motivation (ß=-.317; P<.001; f²=.112), habit (ß=-.118; P<.01; f²=.037), governmental support (ß=-.178; P<.01; f²=.033), environmental concern (ß=-.242; P<.001; f²=.062), and fear towards hazards (ß=-.251; P<.001; f²=.067). The research model results are displayed in Figure 2.

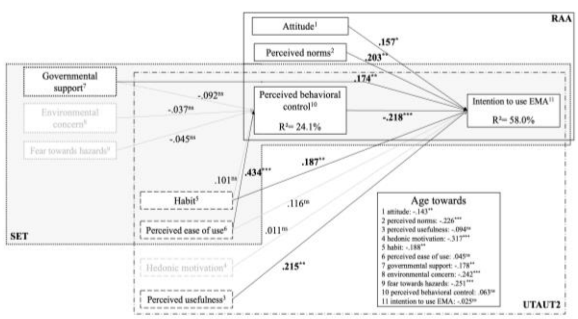

Figure 2. Research model results.

5. Discussion

This study investigates the intention to use energy-monitoring applications among German consumers using an integrated theoretical model approach. For this model, we combined RAA, UTAUT2, and SET and our results reveal that our model explains 58% of the variance of intention to use EMA, which is a moderate explanation power, according to Hair et al. (2019). Regarding our research question, the results show that attitude, perceived norms, governmental support, perceived behavioral control, habit, and perceived usefulness are relevant to determine the intention to use EMA. Thus and concerning attitude, our results support the propositions of Akroush et al. (2019) for Jordan, Liao et al. (2019) for China, and Prete et al. (2017) for southern Italy that attitude is important for purchase intentions of energy-monitoring products. For perceived norms, we state that recommendations of peers are important for the intention to use EMA, which is supported by various studies, such as Gimpel et al. (2020) and Große-Kreul (2022) for individuals' acceptance of smart energy technology in Germany, and Hua and Wang (2019) for the intention to purchase energy-efficient appliances in China. In contrast to Gadenne et al. (2011), who found no association between governmental support and environmental behavior, our results indicate that governmental support significantly influences the intention to use EMA. Hence, we propose that governments should motivate their citizens to use EMA and provide benefits, as we determined that once German individuals perceive that they are sufficiently supported, their intention is higher. Surprisingly, our results show that perceived behavioral control negatively influences intention to use, which is contrary to most prior research showing a positive influence (e.g., Ahmad et al., 2022; Gimpel et al., 2020; Le-Anh et al., 2023). As our results also reveal that perceived ease of use is the lone predictor for perceived behavioral control, we determined that individuals who do not perceive that they are able to control the EMA intend to use them. Thus, we assume that individuals would like to gain more control over the use of EMA, e.g., as others should help them setting up their EMA at home. Vice versa, individuals who perceive that they have a high control over the use of EMA do not intend to use them. Accordingly, and with respect to perceived usefulness having an influence, our participants do state that EMA have to be sufficient for energy-saving purposes in order to use them and that abilities are the root-causes for having control over the use, as perceived ease of use is relevant. Another explanation for perceived behavioral control having a negative influence could be that once our individuals perceive that they have control over using the EMA, they do not perceive the need to use EMA anymore, as they might perceive that they already act energy efficient. Prior studies seem to strengthen that assumption, as they also state that once individuals perceive a certain degree of control over green IS, they also are more selective in which green IS to use (Lou et al., 2021). Further, and contrary to Hua and Wang (2019) investigating energy-efficient appliances in China, our results reveal that perceived usefulness is important for the intention to use EMA. While Hua and Wang (2019) state that individuals might be hesitant in purchasing EMA due to their unknown benefits, our results reveal that once individuals perceive benefits due to their use, their intention is higher. Our model also reveals that habit positively influences intention to use. Hence, we support propositions of Webb et al. (2014) that habit is important for monitoring domestic electricity consumption in the UK and Gimpel et al. (2020) for smart technology acceptance in Germany. As control variable, we used the age of our participants. Age has a negative influence on attitude, perceived norms, hedonic motivation, habit, governmental support, environmental concern, and fear towards hazards. This means that younger individuals perceive and feel endangered in terms of environmental well-being. Further, as they use mobile applications more regularly, they seem to be more open-minded in the evaluation of EMA, as they take recommendations of peers and governmental support into account. Unlike Liao et al. (2019), who found that older individuals purchase more energy-saving appliances than younger ones, we found no significant influence of age on the intention to use EMA.

6. Conclusion

This study contributes to research on sustainable energy transition, focusing on energy consumption and the adoption of energy-monitoring applications. To analyze adoption intentions of energy-efficient applications in Germany, we developed an EMA and surveyed participants building on an integrated theoretical model. Using the Reasoned Action Approach, Unified Theory of Acceptance and Use of Technology 2, and the Self-Efficacy Theory, we empirically tested the factors influencing the intention to adopt our EMA. Our results indicate that constructs from RAA, UTAUT2 and SET are significant predictors of energy monitoring intentions in smart homes. Based on these new insights, we expect that integrated theoretical frameworks will provide a comprehensive understanding of the factors influencing the adoption of energy-monitoring applications, crucial for the energy transition's future.

6.1 Theoretical Implications

Our study shows that RAA constructs (attitude, perceived norms, perceived behavioral control) and UTAUT2 constructs (perceived usefulness, hedonic motivation, habit, perceived ease of use) are relevant from a connected home and energy services perspective. Regarding SET we found that governmental support significantly impacts behavioral intention. This finding is notable since few studies have examined governmental support as a factor in EMA use. These insights provide theoretical implications, where we recommend considering RAA, UTAUT2 and SET in an integrated perspective in future studies. For example, the three theories can be crucial for analyzing value co-creation between energy providers and consumers. Value co-creation can play an important role for the process of creating value through interactions (Alotaibi et al., 2023), which is particularly relevant in supply-demand scenarios such as energy supply and demand systems (Watson et al., 2010). Further, we demonstrate how RAA, UTAUT2, and SET determine the intention to use EMA. Our integrated model can guide future studies on sustainable energy adoption by identifying key factors for EMA use. Moreover, our integrated model offers new insights into the root causes of perceived behavioral control regarding an EMA. While we found no empirical support for the impact of governmental support, environmental concern, and fear towards hazards on perceived behavioral control, we encourage future studies to further explore these factors in the context of sustainable behavior through IS.

6.2 Practical Implications

We derive three main practical implications from our study. First, as perceived usefulness is the strongest predictor of behavioral intention, energy providers should clearly communicate potential energy savings and EMA benefits, e.g. through personalized messaging. This approach helps customers understand how apps can be tailored to their energy usage, enhancing engagement and supporting savings. Additionally, perceived norms and governmental support significantly influence intention, so promoting EMA use among peers can encourage adoption. Regarding governmental support, energy providers might seek partnerships with local government to provide incentives to consumers. Second, our findings show that younger consumers are more influenced by perceived norms and value governmental support. Thus, energy providers should target younger peer groups and emphasize incentives from government regulations. We recommend considering age as a key factor in driving EMA adoption. Third, surprisingly, perceived behavioral control negatively impacts behavioral intention. However, we view this result against the backdrop that perceived behavioral control describes individuals' beliefs about their ability to perform a behavior. To that extent, we can interpret the result as such that individuals who expose lower intentions might feel the need for an app to gain more control about their energy consumption. Therefore, practitioners should measure consumers' level of control over their energy consumption to develop appropriate strategies towards supporting them to ensure effective energy-monitoring.

6.3 Limitations and Future Work

Our study has the following limitations. First, in our study, we did not distinguish between residential and business energy consumers. While we assume adoption might be similar across these consumer segments, future research could analyze differences between residential and business energy consumers. Particularly, aspects like consumption levels, peak usage patterns, billing structure, and the regulatory environment will come with major differences. Second, we developed an EMA focusing on managing deferrable devices like TVs, refrigerators, and computers. While managing deferrable devices is one promising area to support a sustainable energy transition, there are other areas like managing rights markets, dynamic pricing, and energy storage (Watson et al., 2022). Future research could investigate consumer adoption based on EMA focusing on these areas. Third, our study does not divide between voluntary and mandatory residential installations to save energy. With rising support for voluntary and regulations to have mandatory installations by governments, future research should take those considerations into account. Fourth, our study was conducted with participants in Germany. Hence, caution is needed when transferring our findings to different countries. Thus, we recommend that future research considers differences in cultures and countries. Fifth, participant selection is another limitation. Recruiting individuals for a study on monitoring energy consumption may lead to self-selection bias. Participants who are more concerned about reducing energy consumption may be more likely to participate. Additionally, since we recruited participants through an online survey platform, they may be more familiar with using mobile applications compared to those surveyed using pen and paper.

Appendix

The data and questionnaire for our study are stored here: https://doi.org/10.17605/OSF.IO/GEBK9

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