LUND UNIVERSITY

Department of Psychology

Applying the Theory of Planned Behavior to Predict Electricity Consumption: A Longitudinal Study

Alfred Pålsson Höök

Master´s Thesis
2024

Supervisor: Marlis Wullenkord

Abstract

The Theory of Planned Behavior (TPB) is a widely applied theory to assess the impact of attitudes, subjective norms, perceived behavioral control and intention on behavior. The aim of this study is to analyze the impact of intention on actual electricity consumption as well as the relative impact of the underlying factors on intention to save electricity. This separates the study from most previous studies as these tend to use self-assessment measurements of electricity consumption. The study consists of a five week, longitudinal, quantitative data collection. This data was then analyzed using both longitudinal and non-longitudinal structural equation modeling. Analysis found practically nonexistent relationships between intentions to save electricity and actual electricity consumed across the five weeks in the longitudinal model. Perceived behavioral control was found to be the most influential predictor of intention. The relative impact of attitudes started out non-significantly in week one but increased over time, and the relative impact of subjective norm decreased over time to end up as non-significant. This is compared with previous findings that generally has found attitudes to be the strongest predictor of intention to save electricity, followed by perceived behavioral control and subjective norms.

Keywords: Theory of planned behavior, Electricity consumption, Intention-behavior gap, Structural equation modeling, Longitudinal.

Thank you

Thank you to Marlis Wullenkord and Christian Klöckner for both pedagogical guidance and immense patience, their help has been absolutely instrumental in the writing of this thesis.

Applying the Theory of Planned Behavior to Predict Electricity Consumption: A Longitudinal Study

Psychological factors play a crucial role in understanding how and why people act in relation to the climate. Knowledge regarding the psychology of climate change is necessary in the design of policies and interventions that can make human interactions with the environment more sustainable. Such psychological knowledge can inform policymakers, marketers, and organizations on the effectiveness of strategies to encourage pro-environmental behavior (PEB). By leveraging psychological insights, decision-makers can tailor interventions and campaigns that resonate with the values and beliefs of different people, thereby increasing acceptance and adoption of sustainable practices (Kumar & Nayak, 2023, Klöckner, 2013).

A considerable amount of the CO_2 emitted by humans stems from electricity consumption (Gordic et. al., 2023). In Europe, households alone made up 27% of primary energy usage in 2020 (Gordic et. al. 2023), emphasizing the importance of understanding what psychological factors predict household energy consumption. A high level of commitment to energy efficiency among citizens has been shown to be critical in Europe's efforts to implement the 'European Green Deal' (Hainsch et. al., 2022). Behavioral analysis and psychological interventions to change the patterns of consumption of citizens are becoming more prevalent in the scientific discourse (Abramhamse et. al., 2005). Technological solutions are increasingly presented in tandem with behavioral ones (Abrahamse et. al., 2005), and multimethod research shows that, when designed correctly, and used in combination with the right non-behavioral interventions, behavioral interventions have the potential to reduce the emissions of households significantly (Stern, 2020). Psychological models of behavior have thus become an important aspect of designing interventions to decrease household electricity consumption (Stern, 2020). The theory of planned behavior (TPB), being one of the most applied frameworks for understanding the underlying factors of intention and behavior (Bosnjak, Ajzen & Schmidt, 2020), can therefore play an important part in deepening our understanding of the psychology of electricity consumption. This knowledge can in turn be used to improve the design of interventions to decrease household electricity consumption and thus help stem the significant CO_2-emission that originates from household electricity consumption (Gordic et. al., 2023).

The aim of this study is to analyze the relative impact of attitudes, subjective norms, perceived behavioral control and intention on electricity consumption behavior. Unlike most previous studies of these factors on electricity consumption, this one will utilize an objective measurement of electricity consumption rather than a self-assessed one. It will also be longitudinal, adding further depth to the analysis and thus expanding the knowledge on how these factors predict actual electricity consumption. The general research questions are; what is the relationship between intention to save electricity and actual electricity consumption? As well as, what is the relationship between attitudes, subjective norms, perceived behavioral control and intention to save electricity? And finally, are there any changes over time in these relationships?

Theoretical Background

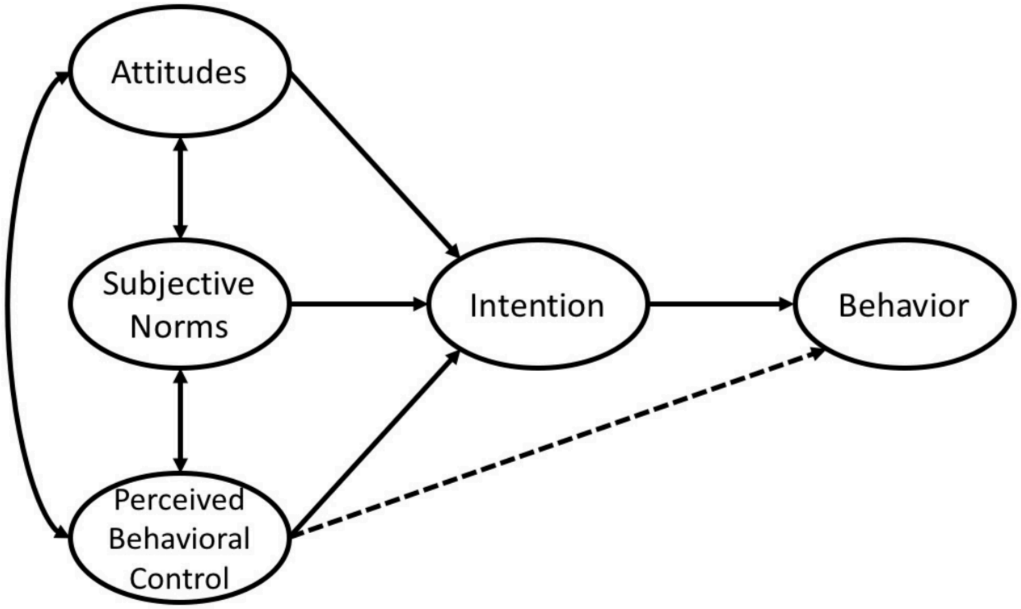
This literature review will begin with a conceptual explanation of the theory of planned behavior (TPB). Then, I will discuss the theory in a more applied fashion focusing on PEB, and then specifically focusing on electricity consumption. Following this, I will present the methodologies of previous TPB-studies of both PEB generally and electricity consumption behavior specifically, in order to explain the methodological relevance of this study. Finally, I will synthesize the findings of previous studies relating to electricity consumption measurements and integrate them in their practical context, in order to show the applied relevance of this study. Lastly, I will outline the hypotheses guiding this work.

The Theory of Planned Behavior

TPB (Ajzen, 1991) is a well-established theory used to explain human behavior and the factors that predict it. In fact, it is one of the most applied theories in behavioral science (Bosnjak, Ajzen & Schmidt, 2020). Figure 1 provides a graphical presentation of the structure of the original theory of planned behavior. The fundamental idea is that intention is the primary determinant of behavior, stemming from three main intention-predicting factors (Ajzen, 1991, Ajzen & Schmitt, 2020), namely: attitudes, subjective norms, and perceived behavioral control (PBC). Attitudes describe an individual’s mental outlook towards a behavior. To what extent does the individual have a favorable/unfavorable evaluation or appraisal of the behavior? Subjective norms signify the perceived social pressure to perform or not perform a behavior. Does the performer feel pressured/supported by their social group to perform/not perform the behavior?

Figure 1

The original model of the Theory of Planned Behavior



Perceived behavioral control means the subjective ease with which one can perform the behavior. Does the performer feel the behavior is possible to perform? Perceived behavioral control not only predicts intention but has a direct effect on behavior as well. A person who perceives low behavioral control will think they are unable to perform a behavior, even if they have an intention to do so.

Application of Theory of Planned Behavior for Studying Pro-Environmental Behavior

Pro-environmental behaviors are human actions that result in net positive environmental outcomes when compared to alternative behaviors (Lange, 2023). They include actions such as conservation of resources, waste reduction, use of environmentally friendly vehicles (Shanmugavel, 2023), and support for environmental causes (Farrukh, 2023). PEB as a construct is defined by the environmental benefits it produces relative to any associated personal costs or sacrifices, such as time, effort, or financial investment. In recent psychological research, PEB has been the most common construct used to measure the actions of the individual in relation to climate change (Lange, 2023). The relative role and impact of the different factors that make up TPB has been studied extensively with regards to PEB (Alzubaidi, 2021, Gansser & Reich, 2023). These factors, in a PEB-context, will be presented in depth one at a time in the following sections.

Attitudes

Attitudes, in the case of PEB, signifies one's attitudes towards acting pro-environmentally. If one has positive attitudes towards PEB this should positively predict one's intention to engage in it. The more positive the attitudes the larger the intention to act pro-environmentally. The strong impact of attitudes on intention has been shown in a number of different areas of PEB such as choice of environmental food and green modes of transportation (Gansser & Reich, 2023). Attitudes have also been shown to significantly impact intention to engage in the specific subfield of PEB called pro-environmental consumption (Nguyen et. al., 2019, Screen et. al., 2018, Qin & Song, 2022). Compared to subjective norms and PBC, attitudes were found to be the strongest predictor of intention to buy environmentally sustainable food (Canova et. al., 2020, Weber et. al., 2020). With regards to transportation, attitudes were found to predict people’s intentions to use public transport as well as to engage in green transportation behavior in general (Donald et. al., 2014, Qin & Song, 2022).

Subjective Norms

Subjective norms, in the case of PEB, refers to the extent to which a person experiences that their social surroundings values pro-environmental actions. It does not mean the actual norms of that person's social environment per se but rather what they themselves experience to be those norms. The more pro-environmental the subjective norms of a person the higher their intention to act pro-environmentally. Subjective norms have been found to predict pro-environmental consumption (Nguyen et. al., 2019, Screen et. al., 2018), in one case more so than attitudes (Mohd Suki, 2016). However, when studying millennials' purchasing intentions of sustainable products, subjective norms did not significantly predict intention (Lavuri, 2022). With regards to sustainable food, subjective norms have been found to be both the least influential predictor of intention (Asif et. al., 2018) and the predictor with an impact in between that of attitudes and perceived behavioral control (Fleșeriu et. al., 2020), depending on study. Subjective norms have also been found to significantly predict the intention of people to switch to an electric vehicle (Moons & De Pelsmacker, 2012).

Perceived Behavioral Control

PBC, in a pro-environmental context, describes the extent to which a person feels that engaging in a pro-environmental behavior would come with difficulty. A person might have a positive attitude towards a PEB but feel insufficient behavioral control in order for that attitude to lead to action. PBC has been shown to have a significant relationship to green purchase intention (Sreen et. al., 2018) but in other studies it has been found to have no significant impact on PEB (Lavuri, 2022). PBC has been shown to have a significant impact on the intention to buy organic food, although it was the weakest predictor compared to attitudes and subjective norms (Bamberg et. al., 2003). The impact of PBC on the willingness to switch to an electric vehicle was non-significant (Moons & De Pelsmacker, 2012), but it consistently predicted willingness to use public transport (Bamberg et. al., 2003).

Overall, attitudes, subjective norms and PBC have consistently been shown to predict intention to some extent in PEB studies (Gansser & Reich, 2023). The relative impact of attitudes, subjective norms and PBC varies from study to study and depending on the behavior measured as an outcome. Attitudes is, however, very often the most predictive factor while subjective norms and PBC tend to vary in their positioning on the 'hierarchy of impact' (Gansser & Reich, 2023). However, the ability of pro-environmental intention to predict pro-environmental behavior in PEB generally has been found to be affected by external factors such as monetary incentives, lack of information as well as internal factors such as competing intentions (Bamberg & Möser, 2007, Zhang et. al., 2020). Intention-behavior gaps have been reported in studies of PEB as well as other areas of research which use TPB (Conner & Norman, 2022).

Application of Theory of Planned Behavior for Studying Electricity Consumption Behavior

Electricity consumption is one specific expression of PEB among many. TPB has previously been applied to study electricity consumption behavior and findings have been somewhat varied. The relationship between attitudes, subjective norms, PBC and intention as well as the relationship between intention and electricity consumption varied from study to study. In some studies, both attitudes, subjective norms and PBC have been found to positively impact the intention to save electricity (Nguyen & Hoang, 2022). However, in others, PBC and attitudes have been the only ones to consistently impact intention, and by extent behavior, with subjective norms having little to no impact on intention to save electricity (Abrahamse & Steg, 2011, Wang et al., 2011 & Alam & Rashid, 2012). Table 1 shows an overview of studies conducted regarding TPB and electricity consumption behavior (Gansser & Reich, 2023).

Table 1

Overview over studies using TPB to predict intentions related to energy.

	Predictors			
	Attitudes	Subj. norms	PBC	Content of Intention
Author (Year)				
Ali et. al. (2019)	* (.519)	n.s.	* (.199)	Purchasing energy-saving household products
Bamberg et. al. (2003)	* (.460)	* (.300)	* (.240)	Using an offered brochure about green electricity products
Bhutto et. al. (2020)	* (.480)	* (.081)	* (.324)	Purchasing energy-efficient appliances
Daiyabu et. al. (2023)	* (.263)	* (.260)	n.s.	Investing in renewable energy
Hossain et. al. (2022)	* (.204)	-	-	Purchasing energy-efficient appliances
Li et. al. (2018)	* (.181)	n.s.	* (.474)	Willingness to pay for green housing
Liao et. al. (2020)	* (.179 & .171)	-	-	Energy-saving
Ong et. al. (2022)	* (.161)	* (.169)	* (.666)	Switching to nuclear power
Tan et. al. (2017)	* (.153)	n.s.	* (.356)	Purchasing energy-efficient household appliances
Nguyen, Hoang & Mai (2022)	* (.177)	* (.182)	* (.169)	Engaging in household energy-saving

Note. * = statistically significant impact of attitude, subjective norms or perceived behavioral control on intention. n.s. = non-significant impact. - = not studied. Parentheses contain the standardized coefficients. This table is based on a table from Gansser and Reich (2023). Findings by Nguyen, Hoang & Mai (2022) were not included in the original table.

Despite different measures of electricity consumption behavior being utilized, attitudes have consistently been shown to predict intention (Gansser & Reich, 2023). In several studies, it has been shown to be the most impactful compared to subjective norms and PBC (Bamberg et. al., 2003). In another study, subjective norms have been shown to be the most impactful factor in household electricity-saving intention (Nguyen, Hoang & Mai, 2022). However, at the same time, there are studies that do not find that subjective norms predict intentions to buy energy-saving household products (Ali et. al., 2019, Tan et. al., 2017). Thus, the relative impact of subjective norms varies across studies and across types of electricity saving behavior. PBC has also consistently been found to have a significant impact on electricity consumption behavior (Gansser & Reich, 2023), and when studying participants' intention to buy energy-efficient appliances it has been found to be the strongest (Tan et. al. 2017).

An interesting finding with regards to PBC is that it has shown the lowest relative impact on intention, when studying people with low environmental concern specifically but the highest relative impact for people with high environmental concern (Bamberg et. al., 2003). All in all, as previously mentioned, attitudes seem to repeatedly show the strongest impact, both in the case of electricity consumption behavior and in other areas of PEB (Gansser & Reich, 2023, Bamberg et. al., 2003, Fleșeriu et al., 2020).

The relative impact of subjective norms and perceived behavioral control varies more depending on the study and their position in the 'hierarchy of impact' is thus not as given as that of attitudes. Knowledge of the relative impact of the three underlying factors have real world implications as more focus can then be committed to the more impactful factors in future research as well as real-life interventions. Of the eight studies included in Table 1 that studied TPB and electricity consumption behavior, three (Bamberg et. al., 2003, Daiyabu et. al., 2023, Nguyen, Hoang & Mai, 2022) report a bigger impact of subjective norms while six report a bigger impact of perceived behavioral control on intention (Ali et. al., 2019, Hussain et. al., 2022, Bhutto et. al. 2020, Li et. al., 2018, Ong et. al., 2022, Tan et. al., 2017).

There are several potential explanations for the discrepancy in these findings. First, not all studies model only the factors of TPB, but some integrate it with other frameworks for explaining behavior. Most common is the value-belief-norm theory, which was explicitly developed to explain behavior relating to the climate and compared to TPB puts more focus on the impact of personal values and beliefs on one's sense of obligation (norms) to act (Abrahamse

& Steg, 2011). Others construct a more complex model out of a merger of several psychological frameworks, such as habit and awareness of consequences, with TPB and the norm-activation model, another model that posits that personal norms, influenced by awareness of consequences and ascription of responsibility, motivate individuals to engage in PEB (Klöckner, 2013). Naturally, aspects such as complexity of relationships and potential interaction effects might lead to changed impact of variables. Thus, using the original TPB might yield a different result than one of the alternatives. This study will stick to using the original model as this provides the broadest base of comparison with previous studies.

Second, different studies use different expressions of intention as well as different outcome measures. There is a difference between the intention to buy an appliance and abstaining from electricity consumption for example. And while some studies measure electricity consumption through self-assessment (Alam & Rashid, 2012, Wang et. al., 2011) others use a more objective measure such as ‘smart’ electricity meters (Abrahamse & Steg, 2011, Klöckner et. al., 2024). This difference is important when considering previous findings regarding TPB and PEB generally. In self-assessment studies of PEB, participants are asked to rate their pro-environmental behavior themselves (Gansser & Reich, 2023). Recent studies, however, found low correlations between self-assessed PEB and more indirect measures (Koller, Pankowska & Brick, 2023, Lange & Dewitt, 2021, 2022). This indicates an intention-behavior gap. Several external factors, such as environmental involvement and shopping context, that might hinder the link between intention and behavior have been identified, both regarding PEB in particular and TPB applied in other contexts (Grimmer, Martin & Morgan, 2017). In fact, recent experimental studies found weak relationships between intention, attitudes, subjective norms, PBC and objective PEB (Koller, Pankowska & Brick, 2023, Lange & Dewitt, 2021, 2022). This indicates that self-assessed PEB might better predict pro-environmental *intention* than pro-environmental *behavior*.

In summary, most studies indicate that attitudes, subjective norms, and PBC all impact intention when studying PEB. Although all three factors appear to be impactful, the relative impact of them on the intention to save electricity seem to vary from study to study. The most common ‘hierarchy of impact’ seems to be attitude followed by PBC followed by subjective norms.

Assessing Electricity Consumption

The aforementioned findings regarding a lacking relationship between intention and behavior in PEB-studies (Bamberg & Möser, 2007, Zhang et. al., 2020), can call the accuracy of self-assessment measures of electricity consumption behavior into question as electricity consumption behavior is one specific subcategory of PEB. In studies of PEB the discrepancy between self-assessed and objective measures took the form of a gap between intention to act pro-environmentally and actual pro-environmental behaviors in studies using self-assessment measures. Most previous studies applying TPB to electricity consumption behavior specifically have used self-assessment measurements. This study will therefore fill a research gap left behind by these studies as this study will use an objective measurement of electricity consumption behavior shedding further light on the actual impact of the factors of TPB on electricity saving behavior. Furthermore, this study is also longitudinal where previous findings were cross-sectional, meaning that this study will contribute with added depth and nuance. Any changes in the impact of the factors over the five weeks that the data collection ran will be analyzed. In the future, the findings of this study might prove useful in comparison with other self-assessment studies of electricity consumption behavior in order to identify any potential intention-behavior gap similar to the one found in general TPB-studies of PEB.

The Present Study

As previously stated, as self-assessed measurements of TPB and electricity consumption behavior have shown such varying results, and considering the discrepancy between self-assessed and objective TPB-findings in PEB more generally, there is a need for further research regarding the impact of the factors of TPB on objectively measured electricity consumption. The findings of this study will be useful in assessing potential intention-behavior gaps similar to the one found in the aforementioned TPB-studies regarding PEB.

H1 relates intention to actual electricity consumption. H2-4 looks at the impact of each of the underlying factors, attitudes, subjective norms and PBC on intention to save electricity. The hypotheses being that each of the three factors has a positive relationship to the intention to save electricity. The more positive the attitudes, the subjective norms and the higher the perceived behavioral control, the lower the consumption of electricity per participant.

Finally, H5 focuses on the relationship between intention to save electricity and the three factors relative to each other. The fifth hypothesis is based on the ‘hierarchy of impact’ of the factors previously found through self-assessment of electricity consumption. Should this model, using objective measures, result in a 'hierarchy of impact' similar to the one established by self-assessment studies, then the self-assessed findings can be considered to be strengthened further and H5 supported.

Based on the theoretical background I propose the following five hypotheses:

H1

Intention to save electricity has a negative relationship to electricity consumption.

H2

Attitudes towards saving electricity have a positive relationship over time to intention to save electricity.

H3

Subjective norms towards saving electricity have a positive relationship over time to intention to save electricity.

H4

Perceived behavioral control of saving electricity has a positive relationship over time to intention to save electricity.

H5

The relationship between attitudes towards saving electricity and intention to save electricity is the strongest, followed by perceived behavioral control of saving electricity and finally subjective norms towards saving electricity.[1]

There are both theoretical and practical implications of this study. If the relative impact of attitudes, subjective norms and PBC differ to a large degree from previous findings using self-assessed measurement this will contribute with further evidence of a intention-behavior gap similar to the one found in TPB-studies of general PEB. This could also call into question the internal validity of studies of electricity consumption behavior using self-assessment methods. There are also practical implications of this research. If there is a intention-behavior gap in self-assessed electricity consumption studies any policy or real-life intervention based on self-assessment findings might not have been constructed in the most efficient way or perhaps

[1] Hypothesis 5 is not the same as the one presented in the pre-registration. This is due to the fact that the original five hypotheses were formulated as part of a study proposal for a previous course. This previous course did not allow for as thorough a literature review as the current study and thus came to other conclusions regarding the relative impact of attitudes, subjective norms and perceived behavioral control on intention to save electricity. The original fifth hypothesis can be found in the pre-registration.

even in a non-effective way. This could constitute a waste of resources if the policy/intervention caused people to think they consume less electricity without them actually doing so. In a worst-case scenario, people who think they decreased their consumption might be affected by the rebound effect, causing them to consume more electricity as a consequence, either consciously or subconsciously (Labandeira et. al., 2020). In such a case, the policy or intervention would have the opposite effect of the one it was designed for. In order to avoid such a situation and bridge any potential intention-behavior gap in TPB-studies of electricity consumption, studies using objective electricity measures, such as this one, are essential.

Method

This study was pre-registered on AsPredicted under the title *THEORY OF PLANNED BEHAVIOR & OBJECTIVE ELECTRICITY CONSUMPTION* and number 166181 on March 14, 2024. https://aspredicted.org/Y1B_DNK

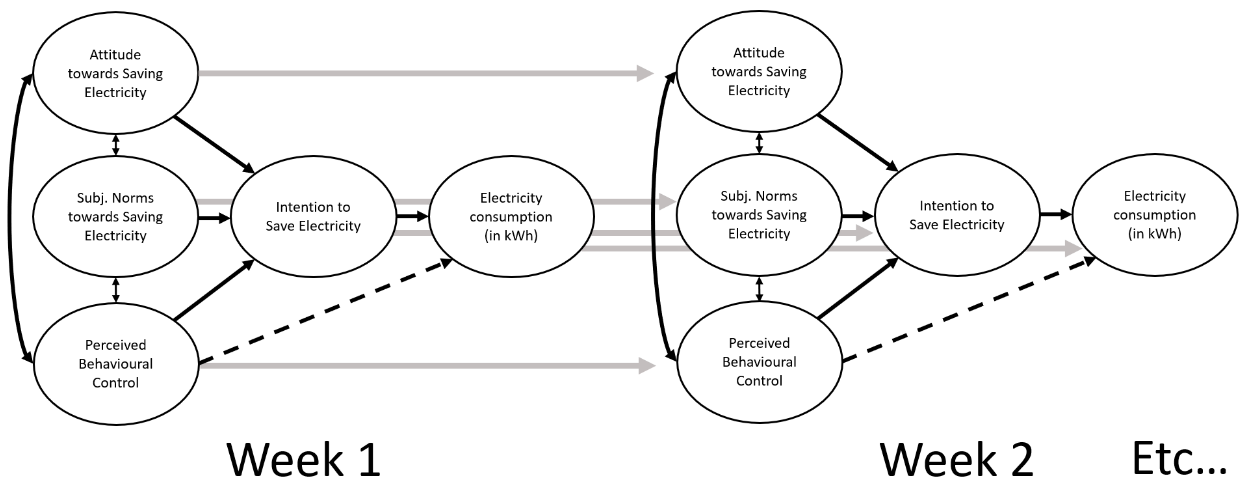
Design and Procedure

The study consists of a 5-week long, longitudinal, quantitative analysis of the relative impact of attitudes, subjective norms, and PBC on intention to save electricity, as well as the impact of intention to save electricity on actual electricity consumption (in kWh). See Figure 2 for a conceptual model of the analysis. The current study uses actual electricity consumption, measured in kilowatt-hours, as the dependent variable. Attitudes towards saving electricity, subjective norms towards saving electricity, perceived behavioral control of saving electricity and intention to save electricity are all independent variables proposed to impact the dependent variable, directly or indirectly in accordance with TPB.

The data is provided by the project *Energy Efficiency Through Behavior Change Transition* (ENCHANT). The project is based in the Norwegian University of Science and Technology (NTNU). It is funded by the European Union's Horizon 2020 research and innovation program [project number 957115]. The overall aim of ENCHANT is to assess the effectiveness of behavioral intervention strategies—either single or in combination—on electricity saving, and to study psychological factors impacting the effectiveness of interventions in European households. The ethical feasibility of ENCHANT has been approved by the Norwegian Agency for Shared Services in Education and Research (SIKT, formerly NSD; case number 120694) and by the data protection officer of the Norwegian University of Science and Technology (Habibi Asgarabad et. al., 2024).

Figure 2

Conceptual model of the impact of attitudes, subjective norms and perceived behavioral control on intention and the impact of intention on electricity consumption over time.



Note. The light gray arrows indicate stability over time. Shown in the conceptual model are only the two first weeks but weeks three, four and five will follow consecutively after week 2, hence the 'etc…' in the model.

The study procedures were approved by the Institutional Review Board at NTNU, and the participants provided their informed consent prior to participation (Habibi Asgarabad et. al., 2024). Participants were assured of the confidentiality of their data, and they had the right to withdraw from the study at any time without consequences. Participants from households in Norway and Germany were recruited through voluntary sampling methods. Participants from Romania were recruited using a local survey company.

The ENCHANT-surveys includes a wide array of items regarding things like electricity saving behaviors and demography for example. The items relevant to this study are the ones regarding psychological factors of electricity consumption behavior and the ones regarding the actual electricity consumption measurement. After consent and registration, the participants were provided with an initial survey regarding demography, access to electricity consuming devices (e.g., tumble dryers, charging of electric vehicles at home, and heating or cooling with electricity) and psychological factors (e.g., perceived difficulty of saving electricity, electricity saving habit strength, personal norms regarding electricity consumption). Thereafter, the participants were asked to answer surveys at the beginning of each of the five weeks about their attitudes, subjective norms, perceived behavioral control and intention regarding the saving of electricity. Electricity consumption for that week was then measured at the end of the week. Electricity consumption was also divided per person living in the household and normalized to 7 days every week. This so that the electricity reading only signifies the consumption of the participant and not the consumption of their household in its entirety. Participants were prompted weekly via email to provide meter reading data and answer the surveys. The data was collected from January 3rd, 2023 until November 6th, 2023. Further details regarding the project can be found in Klöckner et. al. (2024).

Participants

Initially, the ambition of ENCHANT was to include participants from a total of six countries in the study, those being Austria, Germany, Italy, Norway, Romania, and Turkey. The aim was to recruit 1500 participants per country, to be studied over a span of five weeks. Due to an insufficient number of participants, Austria, Italy, and Turkey had to be excluded from the project, leaving a total of $N = 2434$ participants from Germany, Norway, and Romania. Because of difficulty recruiting a sufficient number of households through voluntary sampling methods alone, the project hired a survey company to recruit Romanian participants. The reason for not using survey companies in the other countries with insufficient participating households was financial limitations. To get in contact with potential participants, the study collaborated with energy suppliers/manufacturers, local governments/governmental energy agencies, and energy-focused NGOs. In order to be eligible for the study the participant had to; be aged 18 or above, reside in Norway, Austria, Germany, Romania, Italy or Turkey and finally, have access to an electricity meter for their household's consumption and pay for electricity based on actual consumption. The data was also anonymized prior to me getting access to it. As this study uses the data in its anonymized state, no further ethical precautions were necessary.

Of the $N = 2434$ participants, $n = 1330$ (54.4%) identified as male and $n = 1094$ (44.7%) identified as female, with $n = 10$ identifying as other, and $n = 12$ answers missing. The mean age was 49 years ($SD = 13.0$, Max = 102, Min = 19). The country in which the participants lived, the number of people living in the household, the highest level of education obtained, job situation and self-assessed social status can be found in Table 5A in the appendix.

There are two additional demographic questions that relate more directly to electricity consumption and energy poverty. As energy poverty was made up of two items a mean result for these two items was computed for each participant and said mean was used in the model. A majority of participants (56.1%) never struggle to pay their electricity bill, 17.5% responded 'Sometimes' and only 0.5% always struggled. Similarly, 37.5% of the respondents spend 5-10% of their income on energy during the last 12 months. 86.2% of the respondents paid 15% or less of their income on energy. See Table 6B in the appendix for the energy related demographics.

Materials

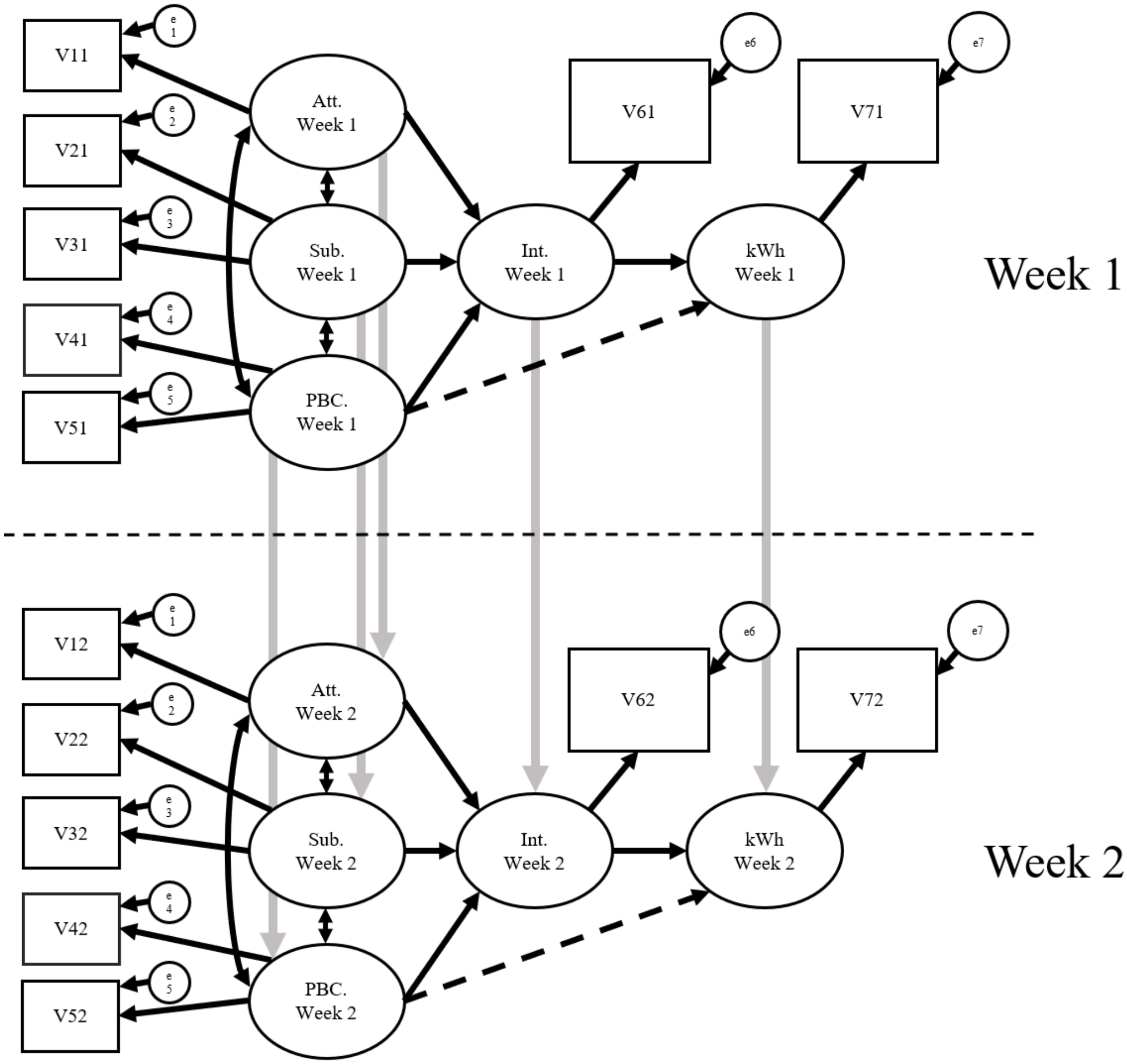
Four instruments based on TPB were used in this study, see Figure 3 for a conceptual model. The instruments 'Intention to Save Electricity', 'Attitude towards Saving Electricity', 'Social Norms towards Saving Electricity' and 'Perceived Behavioral Control of Saving Electricity' are all developed and validated from TPB in previous meta-analysis $X^2(20) = 490.95$, $p < .001$; CFI = .965; TLI = 922; SRMR = .023; RMSEA = .071 [.066 .077]) specifically to study electricity consumption (Klöckner, 2013). All instruments use a 5-grade Likert-scale.

Intention was measured by the item 'I intend to save electricity during next week', represented by V6 in Figure 3, and goes from 'Strongly agree' to 'Strongly disagree'. Attitudes was measured by the item 'Saving electricity next week would be…', represented by V1 in Figure 3, and goes from 'Very unpleasant' to 'Very pleasant'. Subjective norms was measured by the items 'Most people who are important to me approve of me saving electricity next week', represented by V2 in Figure 3 and 'Most people like me save electricity next week', represented by V3 in Figure 3 that goes from 'Strongly disagree' to 'Strongly agree'. PBC was measured by the items 'I am confident that I am able to save electricity next week', represented by V4 and 'Saving electricity next week is up to me', represented by V5 in Figure 3, that goes from 'Totally false' to 'Totally true' and 'Strongly disagree' to 'Strongly agree', respectively.

At the end of each week, the per capita electricity consumption of the households of the respondents were also measured through readings of the household's electricity meters and divided per person in the household and normalized to 7 days in order to obtain consumption per person. Electricity consumption is represented by V7 in Figure 3. These reports were given in Kilowatt-hours.

Figure 3

Structural model



Note. Att. = Attitudes towards saving electricity, Sub. = Subjective norms towards saving electricity, PBC. = Perceived behavioral control towards saving electricity, Int. = Intention to save electricity, kWh = Actual electricity consumption. The light gray arrows indicate stability over time in the items. The conceptual model only shows the first two weeks but week two then relates to week three in the same way as week one does to week two. This structure is repeated until week five.

Data Preparation and Statistical Analysis

Outliers were removed by the original ENCHANT-team prior to me getting access to the data. Decisions regarding the removal of outliers were based on comparisons of means and 5% trimmed means. Original data and robust estimation methods both contributed to the outlier analysis (Klöckner et. al., 2024).

Prior to running the analysis some alterations had to be performed in order to prepare the data for analysis. I found that a handful of observations from 'Actual electricity consumption' had become negative when they were imputed by the original ENCHANT-team. It is unclear whether observations other than the negative ones were also impacted by the imputation as this was implemented by the original ENCHANT-team. In total the negative values were $N = 218$, with the division among the items being $n = 56$ for V71, $n = 43$ for V72, $n = 43$ for V73, $n = 30$ for V74 and $n = 46$ for V75. The number of negative values can be seen in Table 7C in the appendix. Using the documentation of the R-package Amelia II, I deemed it sufficient to remove the observations containing negative values of these imputed variables prior to analysis (Honaker et. al., 2011).

Finally, because of the large difference between the TPB-items, which were measured using Likert-scales, and the dependent variable, which was measured in kWh per person, z-score standardization was implemented. The reason for this was to bring all variables to a common scale, allowing for model fit and easier analysis of the coefficients.

Longitudinal structural equation modeling (LSEM) was used to test the five hypotheses using the statistical software R (R Core Team, 2022) and the package laavan (Rosseel, 2012). This method was chosen due to its ability to examine variability and change over time at the level of latent variables, while correcting for random measurement error (Geiser et. al., 2021). LSEM is especially appropriate for analyzing the complex relationships between latent variables in hypothesis five. In this study, the impact of attitudes, subjective norms, PBC and intention on electricity consumption across time was considered using auto-regressive variables, allowing the factors of one week to impact the corresponding factors the following week. Auto-regressive modeling allows one to analyze how attitudes, subjective norms and BPC influence changes in intention to save electricity over time and how the impact of intention on electricity consumption changes over time. This provided an understanding of the pathways through which attitudes, subjective norms and PBC relate to consumption over time (Little, 2013).

The LSEM-model included seven measured variables, one for each item included in the survey plus the electricity meter reading (V1-V7). These related to five latent constructs (Att., Sub., PBC., Int., kWh), one for each construct in the TPB adapted to electricity consumption and one, kWh, for electricity consumption. See Table 4 for an overview of the relationships between measured variables and latent constructs and Figure 3 for a conceptual model of the relations.

Taking into consideration the number of participants of the study being $N = 2434$ and $N = 1000$ is considered large for a LSEM, based on the literature (Lee & Whittaker, 2023), I deemed the sample in the ENCHANT-data large enough to perform the analysis. Concerning power rates and type I error rates, power rates over 0.8 were preferred as is norm (Lee & Whittaker, 2023) and the nominal type I error was set to 0.05 (Lee & Whittaker, 2023).

Table 4

Measured variable-Latent construct relations.

Variable code	Survey item	Construct code	Construct
V1	Saving electricity next week would be	Att.	Attitude towards saving electricity
V2	Most people who are important to me approve…	Sub.	Subj. norms towards saving electricity
V3	Most people like me save electricity next week	Sub.	Subj. norms towards saving electricity
V4	I am confident that I am able to save electricity next week	PBC.	Perceived behavioral control to save electricity
V5	Saving electricity next week is up to me	PBC.	Perceived behavioral control to save electricity
V6	I intend to save electricity next week	Int.	Intention to save electricity
V7	Electricity meter reading (kWh)	kWh	Electricity consumed

Note. This table does not include specifications for time of measurement.

The analytical quality of the model was assessed using comparative fit index (CFI) (Bentler, 1990) and the Tucker-Lewis index (TLI) (Tucker & Lewis, 1973) with values > .95 representing a good fit, as well as the root mean square error of approximation (RMSEA), with cutoff < .05 indicating close fit and < .08 indicating reasonable fit, and standardized root mean square residual (SRMR), with cutoff < .08 indicating good fit and < .1 indicating reasonable fit (Hu & Bentler, 1998).

Results

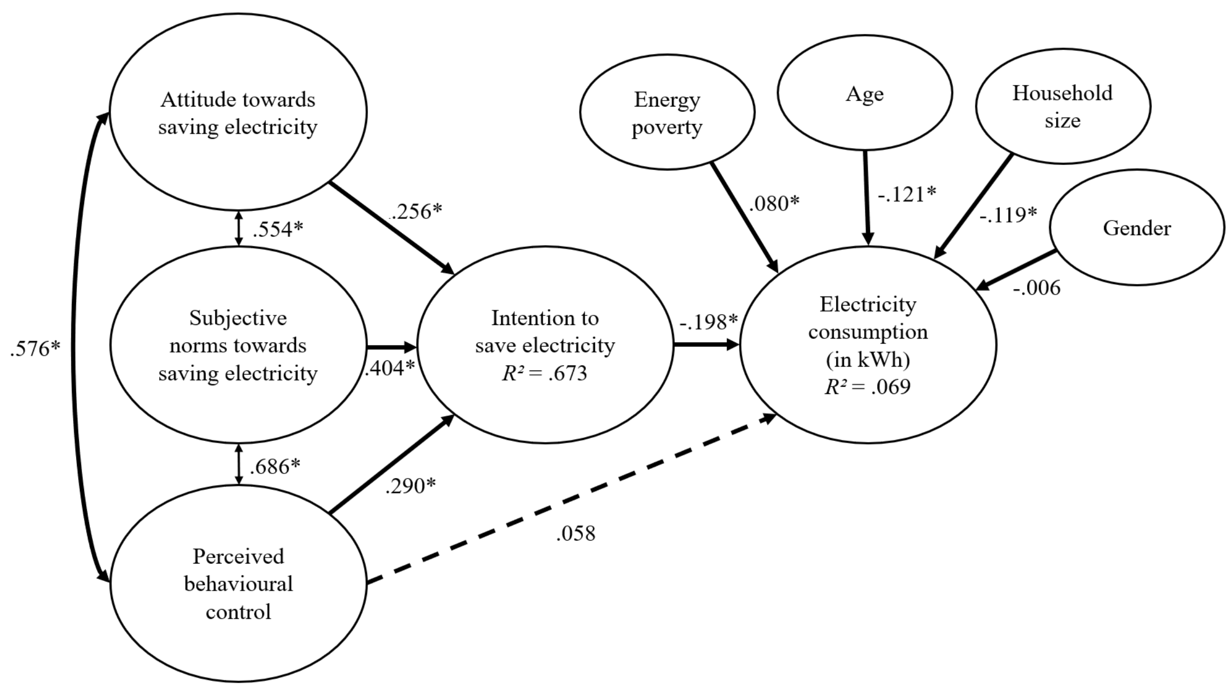
I initially ran a SEM that was not longitudinal in nature. Following this, I ran and analyzed the first longitudinal model. Finally, I revised and updated this model, and this is the model I used in analysis of the hypotheses. The complete R-syntax and detailed results of all analyses can be found in the knitted html in the appendix.

Non-Longitudinal Model

I used an initial SEM without autoregressive effects to study relationships across all five weeks in a non-longitudinal manner. As there was no longitudinal aspect of the initial model, the measurements of all weeks informed the same latent factors, such that, all the items measuring attitudes across all weeks informed the latent attitudes factor, all the items measuring subjective norms across all weeks informed the latent subjective norms factor, and all the items measuring PBC across all weeks informed the latent perceived behavioral control factor. The items measuring intention to save electricity across all weeks informed the latent intention factor, and the items measuring actual electricity consumption across all weeks informed the latent electricity consumption factor. Figure 4 shows a diagram of the initial SEM, with attitudes, subjective norms and PBC predicting intention, and intention and perceived behavioral control predicting actual electricity consumption. Furthermore, I added demographic variables (i.e., age, household size, gender, and energy poverty) as predictors of actual electricity consumption in week one as these might help to explain differences in actual electricity consumed. This SEM did not fit the data well (X^2[688, N = 2352] = 12483.550, p = < .001, Comparative Fit Index [CFI] = .821, Tucker-Lewis Index [TLI] = .809, Root Mean Square Error of Approximation [RMSEA] = .085, Standardized Root Mean Square Residual [SMRM] = .082). Table 4 displays the regression and covariance coefficients of the initial SEM. Attitudes, subjective norms and PBC explained a large amount of the variance in intention (R^2 = .682). Attitudes (β = .235, p = < .001), subjective norms (β = .372, *p* = < .001) and PBC (β = .343, *p* = < .001) all predicted intention. Intention to save electricity predicted actual electricity consumption (β = -.182, *p* = < .001) and the relationship that it described was negative, meaning that it did indicate that higher intention to save electricity was negatively associated with actual electricity consumption. Perceived behavioral control showed no relationship to actual electricity consumption (β = .037, *p* = .319). The demographic variables energy poverty (β = .079, *p* = < .001), age (β = -.122, *p* = < .001) and household size (β = -.124, *p* = < .001) all predicted actual electricity consumption, gender however, did not (β = -.005, *p* = .803). The model practically explained no variance in actual electricity consumption (R^2 = .067).

Figure 4

Diagram of the initial structural equation model



Note. * indicates a statistically significant coefficient, $p \leq .05$.

Table 4

Results of the initial non-longitudinal structural equation model.

	B	*SE*	*p*	β
Regressions				
Int ~ Att	.184	.019	< .001	.235
Int ~ Sub	.294	.024	< .001	.372
Int ~ PBC	.341	.032	< .001	.343
kWh ~ Int	-.341	.072	< .001	-.182
kWh ~ PBC	.069	.069	.319	.037
kWh ~ Energy poverty	.083	.021	< .001	.079
kWh ~ Age	-.009	.002	< .001	-.122
kWh ~ Household size	-.095	.016	< .001	-.124
kWh ~ Gender	-.010	.039	.803	-.005
Covariances				
Att. ~~ Sub.	.235	.014	< .001	.554
Sub. ~~ Pbc.	.234	.014	< .001	.700
Att. ~~ Pbc.	.202	.012	< .001	.597

Note. Att = attitudes, Sub = subjective norms, PBC = perceived behavioral control, Int = intention, kWh = actual electricity consumption.

The unsatisfactory model fit indices indicate that not all information is captured by a model that does not take longitudinal relationships into account. Rather, the initial non-longitudinal SEM provides an interesting comparison to a longitudinal model as improved model fit indices for the longitudinal model would indicate the relevance of a longitudinal perspective. An inspection of modification indices revealed that seven of the ten most influential modification indices were correlations between the same items at different times, items measuring perceived behavioral control (V4), subjective norms (V5) and actual electricity consumption (V7). This further indicates that a longitudinal model might be appropriate. The ten largest modification indices can be found in Table 8D in the appendix.

Initial Longitudinal SEM

I constructed and ran two iterations of the longitudinal SEM. In the initial version, the direct relationships proposed in the TPB were modeled, namely attitudes, subjective norms and PBC with intention, and intention and perceived behavioral control with actual electricity consumption. The longitudinal effects were modeled through auto-regressive effects from each factor on itself the following week. For example there was an autoregressive effect from attitudes in week one to attitudes in week two and so on. The covariance between attitudes, subjective norms and PBC for each week was modeled. The relationship between the first week of actual electricity consumption and the demographic variables, energy poverty, household size, age and gender were also included. For a complete overview of the different models and the output that they generated see the knitted html in the attached document 'Complete analysis in R'.

The initial longitudinal model fit the data worse than the initial non-longitudinal SEM ($X^2(651, N = 2352) = 7963.642$, $p = < .001$, CFI = .817, TLI = .793, RMSEA = .088, SMRM = .101). This constitutes the following change in fit indices compared to the non-longitudinal model, CFI = -.004, TLI = -.016, RMSEA = +.003, SMRM = +.019. Furthermore, the second item of the factor for PBC (i.e., "Saving electricity next week is up to me") consistently had the lowest factor loadings compared to all other items. See Table 9E in the appendix. The idea that said item, codified as V5, was the item causing problems in the model was further strengthened when inspecting explained variances R^2. V5 consistently has the least variance explained of the items in all five weeks, with $R^2 = .263$ in week 1, $R^2 = .315$ in week 2, $R^2 = .340$ in week 3, $R^2 =$ 329 in week 4 and $R^2 = .317$ in week 5. For all R^2 of the initial longitudinal model see Table 10F in the appendix (the relevant variables are highlighted). Given that V5 did not load highly on its latent factor and that the latent factor therefore likely could not capture all variation in V5 over time, it was allowed to covary with itself in the updated longitudinal model. Furthermore, the top ten most influential modification indices in the initial longitudinal model were all different combinations of V5 for different weeks. See Table 11G in the appendix for the modification indices of the initial longitudinal model. The amount of variance explained in actual electricity consumption in the first week is similar to the amount explained by the non-longitudinal model at $R^2 = .089$ (compared to $R^2 = .067$ in the non-longitudinal model).

Updated Longitudinal SEM

As previously mentioned I allowed V5 to covary with itself across all weeks in the updated model. The updated longitudinal SEM fit the data better than the previous models ($X^2(641, N = 2352) = 5089.184$, $p = < .001$, CFI = .889, TLI = .872, RMSEA = .054, SMRM = .098). This constitutes the following change in fit indices compared to the initial longitudinal model, CFI = +.072, TLI = +.079, RMSEA = -.034, SMRM = -.003. See Figure 5 and Tables 12H-15K in the appendix for further information regarding the regressions, R^2 and modification indices of the updated longitudinal model. The updated model explained 10.7 % of the variance in electricity consumption during week 1, compared to 8.9 % in the previous model. It also explained 37.7 % of the variance in intention to save electricity during week 1, as compared to 36.6 % in the previous model.

With regards to the demographic covariates, both age and household size showed statistically significant negative relationships to actual electricity consumption, $\beta = -.115$, $p = < .001$ and $\beta = -.129$, $p = < .001$ respectively, while energy poverty showed a small but positive relationship ($\beta = .065$, $p = .001$) and gender showed no relationship at $\beta = -.006$, $p = .786$. This indicates that younger participants living in smaller households generally consumed more electricity. This finding is in line with previous research regarding household size as it has generally been found that bigger households consume less electricity per capita (Huebner et. al., 2016). This also makes intuitive sense as more people share the same appliances. With regards to age, previous findings show that the consumption patterns over a 24 hour period differ between age groups, rather than there being a big difference in total consumption (Andersen et. al., 2021). The modification indices for the updated model also look more varied and did not suggest modifications only containing V5 to the same extent, see Table 15K in the appendix.

Figure 5

Diagram of the updated longitudinal model.

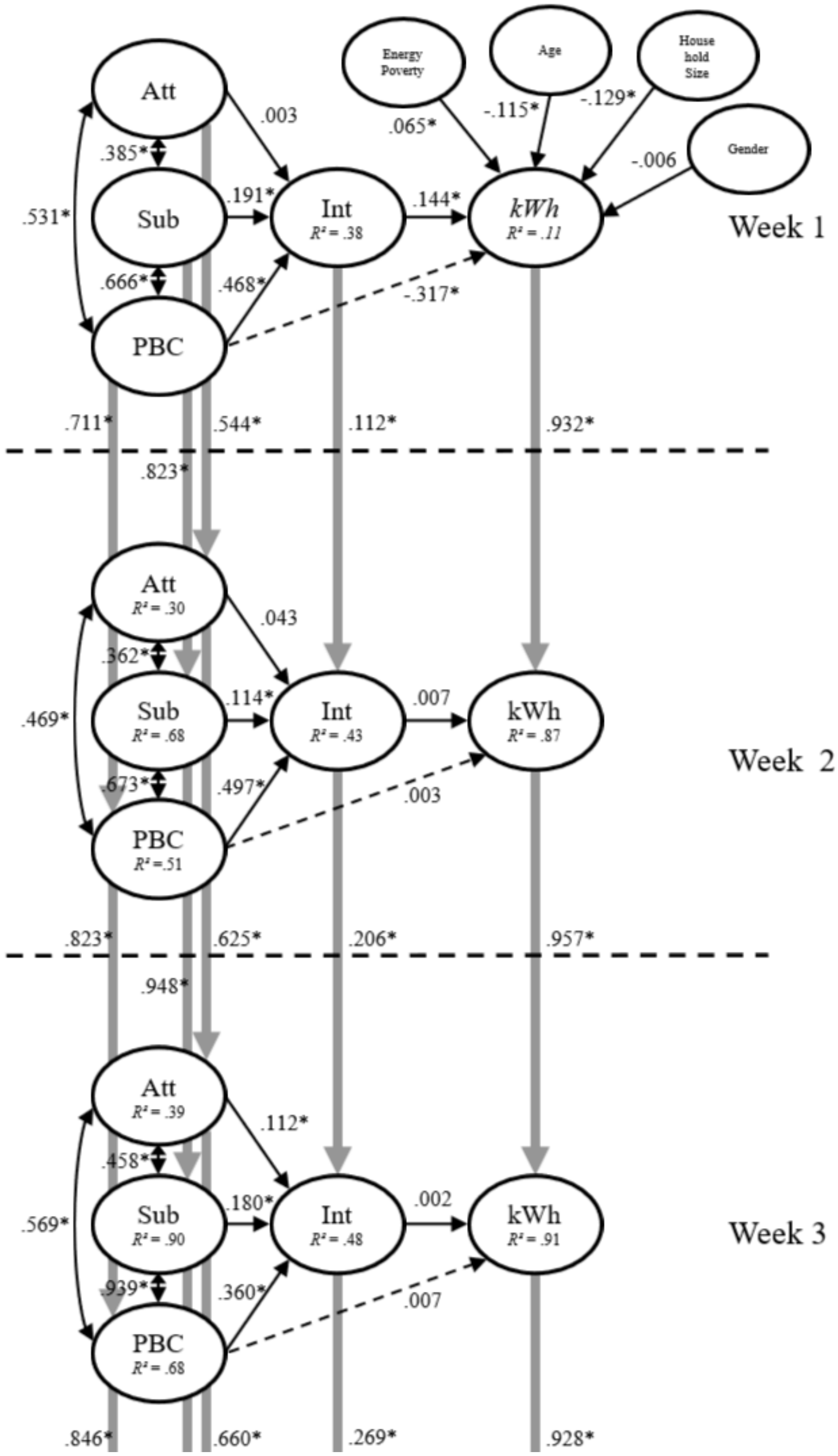
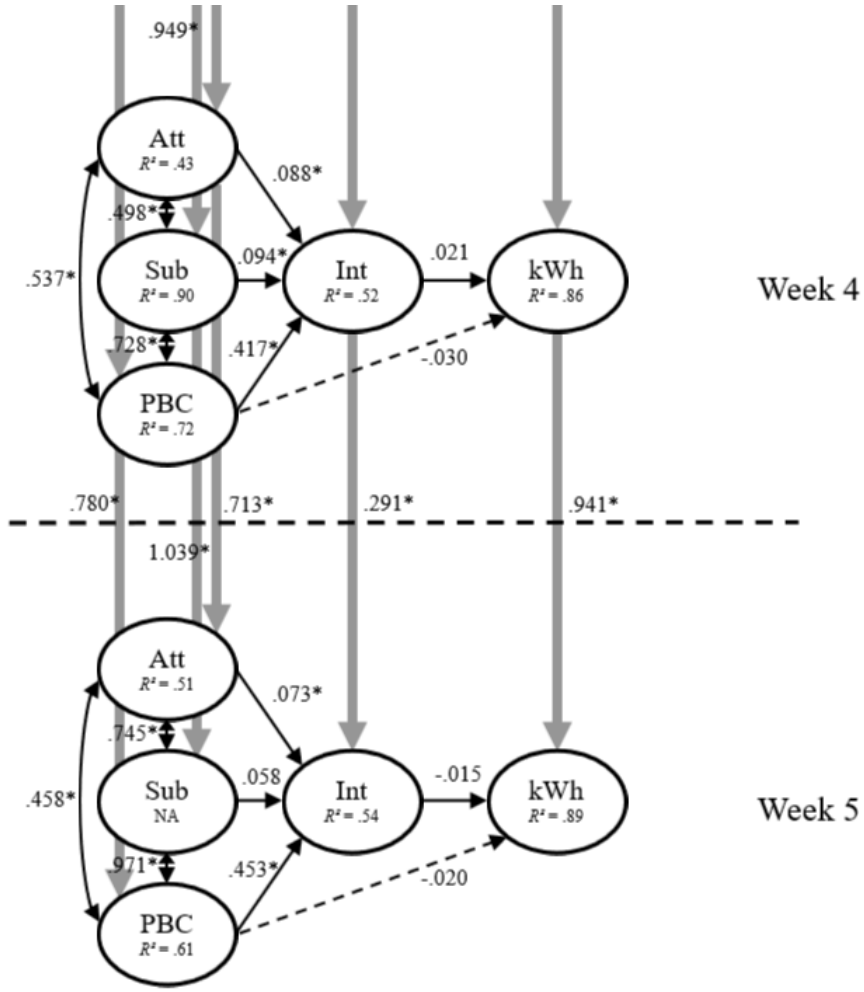


Figure 5 Continuation



Note. * indicates a statistically significant coefficient, $p \leq .05$.

Concerning the hypotheses. Regarding H1, intention to save electricity has a negative relationship to electricity consumption, the first week of the updated longitudinal model shows a significant regression from intention to actual electricity consumed ($\beta = .144$, $p = < .001$). The coefficient of this regression was however positive, linking an increase in intention to save electricity to more electricity consumed in the first week. Interestingly, in week one, PBC had a significant negative relationship to actual electricity consumption ($\beta = -.317$, $p = < .001$). This links an increase in perceived behavioral control to a decrease in electricity consumption. In the following weeks, the autoregressive effects from previous weeks had a very strong impact (for example week two at [β = .932, p = < .001]). As the autoregressive effect was introduced in weeks two to five the coefficients of intention to save electricity and PBC became non-significant. The fact that the relationships are significant in the first week but not in any of the following shows that these relationships do not change enough over time to explain variance in the outcome over time. Over time, intention thus seems unable to explain variance in electricity consumption beyond the autoregressive effect of electricity consumption in previous weeks. For the non-longitudinal model intention had a significant negative relationship to actual electricity consumption and PBC showed a positive trend, albeit non-significant. The initial non-longitudinal model thus supports H1 while the updated longitudinal model does not. H1 therefore needs to be rejected.

Regarding H2, attitudes towards saving electricity have a positive relationship over time to intention to save electricity. In the first week the coefficient between attitudes and intention was very small as well as non-significant (β = .003, p = .916) indicating no relationship between intention to save electricity and attitudes towards saving electricity. There was however a gradual increase in significance through week two (β = .043, p = < .154), and for week three (β = .112, p = < .001), week four (β = .088, p = .002) and week five (β = .073, p = .003) attitudes had a significant positive relationship with intention. There thus seem to be an increase over time in the strength of the relationship between attitudes towards saving electricity and intention to save electricity. The findings provide some support for H2.

Regarding H3, subjective norms towards saving electricity have a positive relationship over time to intention to save electricity, the relationship between subjective norms and intention was statistically significant for the first four weeks but not for the final week. It also seemed to lose relative impact over time compared to the other factors. From week one (β = .191, p = < .001), through week four (β = .094, p = .003) to the smaller and also non-significant week five (β = .058, p = .062), it should be mentioned that even though it is non-significant in week five, it is still very close to .05 and thus constitute a trend. The change over time in subjective norms towards saving electricity seem to show the opposite trend compared to that of attitudes towards saving electricity. A decreasing but positive relationship to intention to save electricity instead of an increasing one over time. Much like with attitudes towards saving electricity the findings can therefore be said to provide some support for H3.

Regarding H4, perceived behavioral control of saving electricity has a positive relationship over time to intention to save electricity, the findings show the strongest relationship between PBC and intention to save electricity out of the three underlying factors. The model shows statistically significant regressions for all five weeks and the highest coefficient for each week as well. The strongest relationship is in week two ($\beta = .497$, $p = < .001$) and the weakest in week three ($\beta = .360$, $p = < .001$). Week three was the only week with a coefficient below .400. There is also no trend in change over time. The impact remains stable over time. The findings support H4.

Finally H5, the relationship between attitudes towards saving electricity and intention to save electricity is the strongest, followed by perceived behavioral control of saving electricity and finally subjective norms towards saving electricity. As previously mentioned, the relationship between perceived behavioral control to save electricity and intention to save electricity is the strongest across all five weeks consistently showing the strongest relationship by far. In week four for example, attitudes and subjective norms showed relationships of $\beta = .088$, $p = .002$ and $\beta = .094$, $p = .003$ respectively, while PBC showed $\beta = .417$, $p = < .001$. In week five attitudes towards saving electricity ($\beta = .073$, $p = .003$) also surpassed subjective norms ($\beta = .058$, $p = .062$) in impact after the two had consistently trended in opposite directions during the previous four weeks. Noteworthy also is the relative stability of the autoregressive effects over time, there is an increase over time, but the change is not drastic. H5 is not supported by the findings.

Discussion

The purpose of this study was to gain further insight into the relative impacts of attitudes, subjective norms, PBC and intentions on actual electricity consumption over time. The longitudinal nature of the study and the objective measure of electricity consumption provided nuance and complexity to the analysis that had previously been somewhat lacking with regards to electricity consumption. Most previous studies of this area have been cross-sectional and the inclusion of a longitudinal element adds nuance and complexity.

Regarding the link between intention to save electricity and actual electricity consumed, a positive relationship was found in the first week. This indicates that an increase in intention to save electricity correlates with an increase in actual electricity consumed. There is however no relationship in the following four weeks, indicating that there is no relationship over time as this factor does not change enough across the weeks to explain variance in the outcome over time. The amount of variance explained in the dependent variable, actual electricity consumption, is very low both for the non-longitudinal model and for the first week of the updated longitudinal model. In the following four weeks the autoregression explains most of the variance in actual electricity consumption and the other predictors have very little impact. Intention and PBC seem unable to explain variance in actual electricity consumed. This inability is in line with previous studies that have found a gap between intention and behavior (e.g., Mack et. al. 2019). Seeing as the current study, with its objective measure of electricity consumed, found practically non-existent relationships between intentions to save electricity and actual electricity consumed across the five weeks, this lends further support to the idea that intention to save electricity does not predict actual electricity consumed well over time. The findings of this study therefore further indicate the existence of an intention-behavior gap in TPB-based electricity consumption studies, similar to that found in PEB-studies more broadly (Koller, Pankowska & Brick, 2023, Lange & Dewitt, 2021, 2022). The findings of this study are thus fairly consistent with previous findings regarding the relationship between intention and behavior in PEB. This advances the notion that the theory of planned behavior insufficiently predicts the outcome behavior. The limited predictive validity of the model has been the main focus of criticism against TPB not related to PEB as well (Conner & Norman, 2022, Sniehotta et. al., 2014). Extensive research has found that other psychological factors such as habit strength (Gardner et. al., 2011) and planning (Carraro & Gaudreau, 2013) predict behavior over and above the ability of intention, and PTB, to do so. There might therefore be other psychological factors upon which interventions should be based in order to achieve the largest increase in household electricity saving. This is a serious limitation of the theory´s usability. Practically speaking, the notion that TPB-based instruments of electricity consumption may be ineffective tools for measuring actual electricity consumption is strengthened.

Concerning the underlying factors, attitudes, subjective norms and PBC, it was found that PBC had the strongest relationship to intention to save electricity. The relative impact of attitudes and subjective norms seemed to switch over time, with the impact of attitudes increasing over time and the impact of subjective norms decreasing over time. The findings of this study were not in line with the majority of previous studies regarding the relative impact of these three factors. The most common 'hierarchy of impact' from previous studies were attitudes as the most powerful, followed by PBC and finally subjective norms. However, this hierarchy between the factors has not been universally found in previous studies (see Table 1 for an overview of previous findings) as some studies report stronger impact of subjective norms than PBC (Bamberg et. al., 2003, Daiyabu et. al., 2023, Nguyen, Hoang & Mai, 2022). Nevertheless, in previous studies attitudes have consistently been ranked as the most powerful factor. A reason for this discrepancy between the current and previous studies, might be found in the longitudinal nature of the final model. In the initial non-longitudinal model attitudes had a significant relationship with intention that was on par with that of the other two underlying factors. When the data was divided up over the five weeks the relationship between attitudes and intention became very small initially and then grew over time as the same time as the relationship between intention and subjective norms decreased, as previously mentioned.

Perhaps this is an expression of how the importance of subjective norms in intention to save electricity decreases as the study carries on and becomes an integrated part of the participants' everyday life. Perhaps the participants felt more acutely aware of the fact that they participated in a large project and that many others also attempted to save electricity early on in the study. This collective frame might have translated to a comparatively large portion of influence for subjective norms in the early days of the study, but as everyday life carried on, this collective framing decreased as the participants felt more and more removed from the start-up phase of the study. As a consequence, attitudes may have become more important over time. With regards to the demographic covariates, both age and household size showed significant, negative relationships with actual electricity consumption. The finding regarding household size is both in line with previous research and makes intuitive sense. The finding regarding age is more interesting. Perhaps the relatively increase in consumption among younger people is a result of younger people using electric appliances to a larger degree and also using electricity for heating/cooling to a larger extent? Furthermore, as the study only used electricity consumption as a dependent variable and not energy use overall, perhaps older participants had a stronger tendency to use other sources of energy such as gas, thus decreasing their relative electricity consumption while maintaining the same energy consumption.

Another interesting finding was the very low explanatory power of V5, ‘Saving electricity next week is up to me’, as it consistently had the lowest correlation coefficient. Throughout the updated longitudinal model, subjective norms and perceived behavioral control covaried to a very high degree. V5 was the second item of two in the subjective norms-factor. The high level of covariance and the two items in subjective norms might explain the low explanatory power. This might be the result of the two items of subjective norms and the prior item of perceived behavioral control explaining the variance in the model to such a degree that there was little variance to be explained by V5. Alternatively, the item itself may have a good predictive power overall but not for the subjective norms-factors specifically.

Limitations & Directions for Future Research

A few study limitations need to be considered. While the initial aim of the ENCHANT-project was to gather data from six countries, only data from Germany, Norway and Romania were included in the final dataset due to issues with data collection (Klöckner et. al., 2024). The Romanian data was collected using an external third-party, this could cause some structural difference between the Romanian participants and the participants from the other two countries. Furthermore, as participants volunteered to participate in the study, there is a risk of self-selection bias. This is not a phenomenon that is exclusive to the study of electricity consumption or TPB, but it might have impacted who chose to participate in the study (Kaźmierczak et. al., 2023). As people tend to participate in studies consistent with their needs and individual characteristics, this study might have attracted a disproportionate number of participants who already have strong opinions about, or insight into, their electricity consumption. People with no interest in environmental questions or their own electricity consumption might have been less inclined and thus have been represented in the study to a lesser extent. Future studies might perform similar studies but attempt to gather data from participants that have not volunteered but rather have been selected at random from a population.

Another aspect of the model that should be addressed is the missing R^2-value of subjective norms in the fifth week for both the initial and the updated longitudinal model, see Tables 10F and 14J in the appendix. In spite of both visual and statistical inspection, no logical reason for this NA could be identified. This NA does introduce some limitations to the study as it prevents a complete understanding of the model performance, the limited scope of the NA does however mean that some conclusions can still be drawn. An interesting direction for future research would be to see if the pattern of change in attitudes and subjective norms would have continued if the study had been allowed to run for longer. If the study would have been ten weeks rather than five, would the relationship between attitudes and intention continue to grow stronger and stronger and the relationship between subjective norms and intention continue to grow weaker and weaker? A longitudinal study spanning a longer period of time might have resulted in a situation in which attitudes eventually became the strongest factor in this study, like in many previous non-longitudinal ones (Gansser & Reich, 2023).

Also, regarding the participants being from Romania, Germany and Norway, while these are in many ways culturally different populations, they do also share some geographical and cultural similarities, they are all countries in Europe and the northern hemisphere. They are all located quite far from the equator, albeit some farther than others, and experience warm summers and cold winters. This naturally has an immense impact on the electricity consumption-habits of the participants. Cultural factors particular to the countries might also impact the patterns of consumption, wealthy countries might have adapted electric vehicles and electronic heating/cooling systems to a larger degree than other areas of the world, also having large effects on patterns of consumption. For future research it would be of great interest to perform similar studies on populations that live in parts of the world that are very geographically and/or culturally different from Europe. The instrument in itself can also perhaps be somewhat of a limitation in that the number of items used were relatively few, in some cases only one item was used per factor. Future studies might utilize more extensive measurements of TPB.

Another potential limitation is that the data was previously imputed by the original research-team of ENCHANT, resulting in some values of actual electricity consumption being negative. While the number of negative values was low, this might be a sign of a larger issue as it is unknown whether other values were also impacted by the imputation. The negative values thus raise concern regarding the validity of the rest of the data. The negative values were so few that their removal was not considered a problem with regards to the analysis but there might have been some consistent characteristic of these specific values that caused them to become negative due to imputation. Inspections of the other responses of these respondents did not indicate any unusual patterns of behavior but nevertheless it should be stated that there might have been some unknown underlying reason for their becoming negative during prior imputation.

Furthermore, the model of the study, even in its updated state, did not fit the data well. The findings of the study could have been presented as more definitive proof had the model fit the data in a more satisfactory manner. Allowing for the items of 'Saving electricity next week is up to me' to covary, and including the demographic items in the first week strengthened the model quite a bit. In future research, a similar longitudinal study to the current one could be carried out but utilizing a more complex model than the TPB. One of the amalgamations of TPB and other theories mentioned in the theoretical background section might be a good starting point for such a study (Klöckner, 2013, Abrahamse & Steg, 2011). Combining these more complex models of human intention and behavior with objective measures of electricity in a longitudinal setting could provide further insight and nuance. TPB, although being one of the most commonly applied theories in behavioral science, has been accused of being somewhat reductive (Bosnjak, Ajzen & Schmidt, 2020).

Finally, the participants were themselves prompted to read their smart meter every week which gave them insight into their electricity consumption. This could have an effect on their consumption as they were provided with a weekly number of whether or not their attempts (or lack thereof) to save electricity have any practical effect. Perhaps an alternative measurement of the electricity consumption that did not involve the participants would be an interesting route to take for further research. Furthermore, it would be interesting to see the current research on TPB and electricity consumption accompanied by studies performed in a more laboratory setting, allowing for greater control of potential third variables. Future experimental studies of the lacking relationship between intention to save electricity and actual electricity consumed specifically could be very interesting.

Implications

The aforementioned lacking relationship between intention to save electricity and actual electricity consumption has some serious implications for real-life applications of TPB in interventions, as mentioned in the previous section. If an electricity-saving intervention is based on TPB and findings regarding intention to save electricity, said intervention, even if it successfully increases a population's intention to save electricity, might not translate into an actual decrease in the amount of electricity consumed. The current study thus indicates that when testing interventions aimed at decreasing electricity consumption the change in actual electricity consumed should be measured using smart meters or another similarly objective instrument. Intention to save electricity cannot be considered a sufficient indication of change in electricity consumption. Furthermore, PBC seems to have a stronger relationship to the intention to save electricity than previously thought and has a significant relationship to actual electricity consumed. This has both theoretical implications for TPB in the study of electricity consumption and might also have more practical implications. Perhaps interventions aimed at influencing electricity consumption should focus on PBC to a larger degree? Seeing that PBC showed a stronger relationship to actual electricity consumed compared to intention to save electricity. Overall, these findings point to the importance of including a behavioral aspect in any attempt to change the electricity consumption pattern of a population. As mentioned in the introduction, behavioral analysis is an important aspect of any interventions which aim at changing a behavior. An intervention that solely increased the intention to save electricity might not have resulted in the decrease in household electricity consumption necessary to decrease CO_2-emission.

Conclusion

Despite aforementioned limitations, this research provides further evidence towards the lacking relationship between intention and behavior in TPB, specifically regarding electricity consumption. The present research contributes to problematizing interventions aimed at increasing only intentions to save electricity as these may not simply translate into behavior. The study also presents evidence of the relative impact of attitudes, subjective norms and perceived behavioral control that do not align with previous findings in the PEB-subfield of electricity consumption. Even though the generality of these findings must be further strengthened by future research, the present study has provided clear support that an increase in intention to save electricity does not necessarily translate to a decrease in electricity consumed and that perceived behavioral control is the most impactful factor influencing intention to save electricity. These findings hold practical relevance for the future construction of interventions aimed at reducing household electricity consumption. Future research could develop the model further or increase the temporal span of the data gathering.

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Appendix

The complete R-syntax of the study can be found in the attached document 'Complete analysis in R'.

Table 5A

Further demographics including country, number of people living in the household, highest level of education, job situation & self-assessed social status.

Country	*n*	%
Norway	1135	46.4
Germany	664	27.1
Romania	647	26.5
Number of people living in the household	*n*	%
1	288	11.8
2	822	33.6
3	527	21.5
4	576	23.5
5	165	6.7
6	46	1.9
7	18	0.7
8	3	0.1
10	1	0.0
Highest level of education	*n*	%
Still in education	15	0.6
Basic education	18	0.7
Vocational training	220	9
High-school degree	316	12.9

Table 5A

Highest level of education	*n*	%
University degree	1821	74.4
Other	54	2.2
Missing	2	0.1
Job situation	***n***	**%**
Working full time	1758	71.9
Working part time	196	8
In full time education	40	1.6
Without paid work/Looking for work	35	1.4
Retired	320	13.1
Not able to work	51	2.1
Other	45	1.8
Missing	1	0
Self-assessed social status	***n***	**%**
1 - Worst off	11	0.4
2	16	0.7
3	113	4.6
4	156	6.4
5	257	10.4
6	342	13.9
7	709	28.8
8	628	25.7
9	162	6.6
10 - Best off	52	2.1

Table 6B

Energy poverty related demographics

Do you struggle to pay for your electricity bill, because it takes too much of your monthly income?	*n*	%
Never	1372	56.1
Rarely	546	22.3
Sometimes	427	17.5
Often	89	3.6
Always	12	0.5
On average across the year, how much of your household's income did you use to pay for energy during the last 12 months?	***n***	**%**
Below 5%	602	23.6
5-10%	957	37.5
10-15%	550	21.5
15-20%	254	9.9
20-30%	129	5.1
Missing	3	0.1

Table 7C

Number of negative values as a result of prior imputation.

Item	*N*	%
Actual electricity consumption Week 1	56	2.3
Actual electricity consumption Week 2	43	1.8
Actual electricity consumption Week 3	43	1.8
Actual electricity consumption Week 4	30	1.2
Actual electricity consumption Week 5	46	1.9

Table 8D

Top ten modification indices for the non-longitudinal model.

lhs	*op*	*rhs*	*mi*	*epc*	*sepc.lv*	*sepc.all*	*sepc.nox*
v54	~~	v55	464.568	.254	.254	.508	.508
v45	~~	v65	388.455	.231	.231	.460	.460
v72	~~	v73	373.140	.036	.036	.619	.619
v52	~~	v55	334.487	.224	.224	.424	.424
v53	~~	v54	333.250	.213	.213	.433	.433
Att	~	kWh	303.329	-.228	-.334	-.334	-.334
v52	~~	v53	299.460	.209	.209	.404	.404
Int	=~	v44	286.552	.988	.507	.506	.506
Att	~~	kWh	285.949	-.195	-.321	-.321	-.321
v53	~~	v55	275.746	.195	.195	.393	.393

Table 9E

Latent variables of the initial longitudinal SEM.

	B	*SE*	*p*	β
f2_w1 =~ v21	1.000			.735
=~ v31	.854	.043	< .001	.629
f3_w1 =~ v41	1.000			.748
=~ v51	.686	.050	< .001	.513
f2_w2 =~ v22	1.000			.744
=~ v32	.885	.035	< .001	.657

Table 9E

	B	*SE*	*p*	β
f3_w2 =~ v42	1.000			.791
=~ v52	.714	.046	< .001	.561
f2_w3 =~ v23	1.000			.747
=~ v33	.936	.039	< .001	.698
f3_w3 =~ v43	1.000			.770
=~ v53	.766	.044	< .001	.583
f2_w4 =~ v24	1.000			.760
=~ v34	.930	.033	< .001	.703
f3_w4 =~ v44	1.000			.794
=~ v54	.734	.043	< .001	.574
f2_w5 =~ v25	1.000			.677
=~ v35	.955	.036	< .001	.645
f3_w5 =~ v45	1.000			.815
=~ v55	.706	.057	< .001	.563

Note. f2 = Subjective norms, f3. = perceived behavioral control, w = week, all items starting with v represent the respective items in figure 2. All v5s are highlighted and the latent factors with only one observed variable have been excluded due to these always having a coefficient of 1.000.

Table 10F

R-squared of the initial longitudinal SEM.

Variable	R^2
v11	1.000
v21	.540
v31	.395
v41	.559
v51	.263
v61	1.000
v71	1.000
v12	1.000
v22	.554
v32	.432
v42	.626
v52	.315
v62	1.000
v72	1.000
v13	1.000
v23	.558
v33	.487
v43	.593
v53	.340
v63	1.000
v73	1.000
v14	1.000

Table 10F

Variable	R^2
v24	.577
v34	.494
v44	.630
v54	.329
v64	1.000
v74	1.000
v15	1.000
v25	.459
v35	.416
v45	.664
v55	.317
v65	1.000
v75	1.000
f4_w1	.366
f5_w1	.089
f1_w2	.303
f2_w2	.698
f3_w2	.560
f4_w2	.406
f5_w2	.866
f1_w3	.406
f2_w3	.902
f3_w3	.775

Table 10F

Variable	R^2
f4_w3	.468
f5_w3	.915
f1_w4	.450
f2_w4	.911
f3_w4	.801
f4_w4	.502
f5_w4	.864
f1_w5	.520
f2_w5	NA
f3_w5	.719
f4_w5	.522
f5_w5	.891

Note. The data in f2_w5 was visually inspected in order to find some reason for the NA, but the data appeared normal.

Table 11G

Top ten modification indices for the initial longitudinal model.

lhs	*op*	*rhs*	*mi*	*epc*	*sepc.lv*	*sepc.all*	*sepc.nox*
v54	~~	v55	883.003	.435	.435	.666	.666
v53	~	v54	708.106	.382	.382	.593	.593
v52	~~	v55	706.124	.396	.396	.592	.592
v53	~~	v55	690.958	.381	.381	.587	.587
v52	~~	v53	641.690	.374	.374	.566	.566
v15	~~	v15	638.855	-.759	.000	.000	.000
v52	~~	v54	630.056	.369	.369	.556	.556
v51	~~	v53	586.494	.370	.370	.538	.538
v51	~~	v52	559.556	.370	.373	.528	.528
v51	~~	v54	533.185	.353	.353	.511	.511

Table 12H

Latent variables of the updated longitudinal SEM.

	B	*SE*	*p*	β
f2_w1 =~ v21	1.000			.736
=~ v31	.857	.044	< .001	.631
f3_w1 =~ v41	1.000			.781
=~ v51	.549	.031	< .001	.430
f2_w2 =~ v22	1.000			.743
=~ v32	.887	.036	< .001	.657

Table 12H

	B	*SE*	*p*	β
f3_w2 =~ v42	1.000			.836
=~ v52	.510	.028	< .001	.430
f2_w3 =~ v23	1.000			.745
=~ v33	.939	.039	< .001	.698
f3_w3 =~ v43	1.000			.812
=~ v53	.577	.027	< .001	.466
f2_w4 =~ v24	1.000			.755
=~ v34	.936	.033	< .001	.703
f3_w4 =~ v44	1.000			.841
=~ v54	.546	.026	< .001	.457
f2_w5 =~ v25	1.000			.671
=~ v35	.963	.036	< .001	.644
f3_w5 =~ v45	1.000			.892
=~ v55	.526	.030	< .001	.463

Note. f2 = Subjective norms, f3. = perceived behavioral control, w = week, all items starting with v represent the respective items in figure 2.

Table 13I

Regressions of the updated longitudinal model.

	B	*SE*	*p*	β
f1_w2 ~ f1_w1	.449	.018	< .001	.544
f1_w3 ~ f1_w2	.641	.021	< .001	.625
f1_w4 ~ f1_w3	.671	.019	< .001	.660

Table 13I

	B	*SE*	*p*	β
f1_w5 ~ f1_w4	.699	.018	< .001	.713
f2_w2 ~ f2_w1	.818	.034	< .001	.823
f2_w3 ~ f2_w2	.940	.028	< .001	.948
f2_w4 ~ f2_w3	.953	.026	< .001	.949
f2_w5 ~ f2_w4	.916	.025	< .001	1.039
f3_w2 ~ f3_w1	.753	.033	< .001	.711
f3_w3 ~ f3_w2	.785	.029	< .001	.823
f3_w4 ~ f3_w3	.875	.027	< .001	.846
f3_w5 ~ f3_w4	.824	.028	< .001	.780
f4_w1 ~ f1_w1	.003	.031	.916	.003
f2_w1	.260	.052	< .001	.191
f3_w1	.600	.063	< .001	.468
f4_w2 ~ f1_w2	.052	.036	.154	.043
f2_w2	.155	.049	.002	.114
f3_w2	.596	.052	< .001	.497
f4_w1	.111	.025	< .001	.112
f4_w3 ~ f1_w3	.128	.032	< .001	.112
f2_w3	.241	.044	< .001	.180
f3_w3	.443	.055	< .001	.360
f4_w2	.202	.029	< .001	.206
f4_w4 ~ f1_w4	.099	.032	.002	.088
f2_w4	.124	.042	.003	.094
f3_w4	.496	.054	< .001	.417

Table 13I

	B	*SE*	*p*	β
f4_w3	.269	.029	< .001	.269
f4_w5 ~ f1_w5	.084	.029	.003	.073
f2_w5	.087	.047	.062	.058
f3_w5	.509	.050	< .001	.453
f4_w4	.290	.031	< .001	.291
f5_w1 ~ f4_w1	.144	.032	< .001	.144
Energy poverty	.070	.021	< .001	.065
Age	-.009	.002	< .001	-.115
Household size	-.102	.016	< .001	-.129
Gender	-.011	.040	.786	-.006
f3_w1	-.406	.048	< .001	-.317
f5_w2 ~ f4_w2	.007	.012	.563	.007
f5_w1	.931	.036	< .001	.932
f3_w2	.004	.019	.848	.003
f5_w3 ~ f4_w3	.002	.012	.892	.002
f5_w2	.958	.018	< .001	.957
f3_w3	.008	.015	.573	.007
f5_w4 ~ f4_w4	.021	.011	.061	.021
f5_w3	.927	.036	< .001	.928
f3_w4	-.036	.020	.064	-.030
f5_w5 ~ f4_w5	-.016	.012	.177	-.015
f5_w4	.938	.026	< .001	.941
f3_w5	-.023	.016	.153	-.020

Note. f1 = Attitudes, f2 = Subjective norms, f3. = Perceived behavioral control, f4 = Intention, f5 = Actual electricity consumption, w = week.

Table 14J

R-squared of the updated longitudinal SEM.

Variable	R^2
v11	1.000
v21	.542
v31	.399
v41	.609
v51	.185
v61	1.000
v71	1.000
v12	1.000
v22	.552
v32	.431
v42	.699
v52	.185
v62	1.000
v72	1.000
v13	1.000
v23	.556
v33	.488
v43	.659

Table 14J

Variable	R^2
v53	.217
v63	1.000
v73	1.000
v14	1.000
v24	.571
v34	.494
v44	.707
v54	.209
v64	1.000
v74	1.000
v15	1.000
v25	.451
v35	.415
v45	.795
v55	.214
v65	1.000
v75	1.000
f4_w1	.377
f5_w1	.107
f1_w2	.296
f2_w2	.677
f3_w2	.506
f4_w2	.433

Table 14J

Variable	R^2
f5_w2	.866
f1_w3	.391
f2_w3	.898
f3_w3	.678
f4_w3	.483
f5_w3	.914
f1_w4	.436
f2_w4	.900
f3_w4	.716
f4_w4	.520
f5_w4	.864
f1_w5	.508
f2_w5	NA
f3_w5	.609
f4_w5	.541
f5_w5	.891

Note. The data in f2_w5 was visually inspected in order to find some reason for the NA, but the data appeared normal.

Table 15K

Top ten modification indices for the initial longitudinal model.

lhs	*op*	*rhs*	*mi*	*epc*	*sepc.lv*	*sepc.all*	*sepc.nox*
v15	~~	v15	639.569	-.759	.000	.000	.000
f1_w5	=~	v15	528.516	-.331	-.280	-.331	-.331
f5_w1	~	f5_w5	500.068	1.453	1.447	1.447	1.447
v12	~~	v13	457.764	-.171	-.171	NA	NA
v72	~~	v73	339.639	-.028	-.028	NA	NA
f5_w3	~	f5_w4	339.639	-.315	-.315	-.315	-.315
f5_w3	~~	f5_w4	338.729	-.043	-.397	-.397	-.397
v73	~~	v73	338.578	.046	.000	.000	.000
f5_w4	=~	v73	338.138	-.314	-.314	-.314	-.314
f5_w4	~	f5_w2	337.400	.479	.479	.479	.479