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Residential Electricity Consumption: The Role of Psychological Factors

An Empirical Analysis of the Effect of Energy-Saving Attitudes and Intentions on Residential Electricity Consumption

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Executive Summary

Given the more frequent occurrence of weather extremes, growing awareness and responsibility of the climate crisis and its consequences can be observed within the population. It seems as if growing climate change concerns ultimately lead to more and more people switching to an ecological lifestyle. However, from time to time, one does observe a divergence of what individuals claim to do in order to limit the effects of climate change and what they actually do. This so-called *green gap* was verified in several domains of human behavior, among others, in residential energy-conserving behavior. As energy consumption is one of the main contributors to a household's carbon footprint, improving one's understanding of the determinants of residential energy consumption behavior is fundamental to promoting energy-conserving behavior effectively, thereby limiting climate change.

Therefore, this thesis used an explanatory research approach to investigate the relationship between the psychological variables energy-saving attitudes and intentions and electricity consumption. The study is based on the Theory of Planned Behavior. The IDEAL Household Energy Dataset, published by the University of Edinburgh, served as the primary data source. This master's thesis focused on 30 Scottish single-households. The households' responses to survey questions measuring energy-saving attitudes and intentions were matched with electricity consumption estimates based on sensor data measuring instantaneous power usage over a period of more than five weeks.

The results indicate that energy-saving attitudes have a negative effect on electricity consumption, whereas energy-saving intentions do not impact actual electricity consumption to a statistically significant degree. Moreover, a mediating effect of energy-saving intentions on the relationship between energy-saving attitudes and electricity consumption, which is based on the Theory of Planned Behavior, could not be detected. This study contributes to the residential energy-conserving literature focusing on psychological factors by (1) using actual energy consumption data, (2) focusing on single households, and (3) providing evidence for the importance of controlling for the time an individual spends at home.

Keywords: Green Gap – Residential Electricity Consumption – Attitude – Intention – Theory of Planned Behavior – Energy-Saving Behavior

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List of Abbreviations

BIGSMALL	Data-Driven Methods for a New National Household Energy Survey
h	hour
HESO	Household Energy-Saving Options
IDEAL	Intelligent Domestic Energy Advice Loop
IEEE	Institute of Electrical and Electronics Engineers
IPCC	Intergovernmental Panel on Climate Change
ITC	International Trade Center
kW	kilowatt
kWh	kilowatt-hour
min	minute
NILM	Non-Intrusive Load Monitoring
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
s	second
SEM	Structural Equation Modeling
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
W	watt

1. Introduction

"You are what you do, not what you say you'll do."

- Carl Gustav Jung (n.d.), Swiss psychiatrist and psychoanalyst -

With this statement, Jung addresses an issue of universal importance, one that becomes increasingly important these days, particularly in the context of climate change. The planet and society have changed extremely over the last decades. Based on the IPCC report from 2021, it is scientifically proven that human life influences and changes the earth's climate. Humans are increasingly confronted with weather extremes such as heatwaves, agricultural and ecological droughts as well as heavy precipitation leading to devasting floods.[1] According to the European Union (2021), *"Europeans consider climate change to be the single most serious problem facing the world"* (p. 7). The increased awareness of climate change and its consequences leads many individuals to realize their responsibility in the climate crisis.[2] As a result, the demand for ecological (so-called 'green' products) increases tremendously (International Trade Centre, 2019). Among others, people indicate to buy more organic food, eat less meat, reduce disposable products and waste in general, increase recycling, use more public transportation, purchase energy-efficient appliances and switch to renewable electricity contracts (European Union, 2021).

It seems as if growing concerns related to climate change are ultimately leading to increased demand for environmentally-friendly products and a more sustainable lifestyle (Prothero et al., 2011). Still, what individuals claim to do may not necessarily be in line with what they actually do. For example, research in several areas of human behavior[3] has proven an attitude-behavior gap (Denton et al., 2020; Juvan & Dolnicar, 2014; H. J. Park & Lin, 2020; Schäufele & Hamm, 2018; So et al., 2021; Yamoah & Acquaye, 2019) or an intention-behavior gap (Birch & Memery, 2020; Diddi et al., 2019; Echegaray & Hansstein, 2017; Gonçalves et al., 2021; Rausch & Kopplin, 2021; Sultan et al., 2020). Often, people have positive attitudes

[1] For example, the flood in Germany and Belgium killed 222 people in July 2021 (D. Carrington, 2021).

[2] More than 50 % of respondents in the 'Eurobarometer Special 513' stated that they had changed their lifestyle to reduce climate change in the past six months (European Union, 2021).

[3] Including, among others, sustainable food & drink purchase behavior, recycling, sustainable fashion & tourism, and carbon offsets.

and/or intentions towards behaving in a socially desirable way. However, these attitudes and intentions do not necessarily lead to actual behavior or behavioral changes. The discrepancy between individuals’ environmental concerns and what they actually do to limit climate change and solve ecological problems is defined as the green gap (Antimova et al., 2012; Devinney et al., 2010; ElHaffar et al., 2020; Fahy, 2005; Gruber & Schlegelmilch, 2014). The green gap is verified in the commercial and non-commercial segments (ElHaffar et al., 2020). In the commercial segment, the green gap is related to purchase behavior inconsistent with consumers’ attitudes and intentions towards sustainable consumption (Gruber & Schlegelmilch, 2014). The green gap in the non-commercial segment is linked to, for example, recycling and energy-saving behavior (ElHaffar et al., 2020), the latter of which provides the focus of this study.

As, with 35 %, the energy supply sector (including electricity, heat, and other energy) is the largest contributor to global GHG emissions (IPCC, 2014), and electricity consumption accounts for one-fourth of EU final energy consumption in households (Eurostat, 2021), reducing residential electricity consumption is pivotal in order to limit climate change (Belaïd & Joumni, 2020; Bruderer Enzler et al., 2019; E. Park & Kwon, 2017). Thus, this master’s thesis analyzes residential electricity consumption behavior. Current research related to the effect of attitudes and intentions on residential electricity consumption only allows for ambiguous conclusions. On the one hand, several research papers find significant relationships between attitudes, intentions, and residential electricity usage behavior, whereas, on the other hand, some studies confirm the green gap.

Hence, the motivation for this master’s thesis is to investigate and gain a more profound understanding of the relationship between the psychological variables energy-saving attitudes and intentions and actual electricity consumption. By applying a deductive research approach, this study attempts to find an answer to the following research question:

What effect do energy-saving attitudes and energy-saving intentions have on residential electricity consumption?

This master’s thesis utilizes an explanatory research approach by empirically investigating whether the existence of a green gap in the context of residential electricity consumption behavior exists.

The remainder of this thesis is structured as follows: Academic literature related to the attitude-behavior and intention-behavior gap focusing on residential energy consumption is reviewed in chapter 2. In addition, the Theory of Planned Behavior is delineated in that chapter. Based on the second chapter, a theoretical framework for hypothesis generation is developed, and derived hypotheses are presented in chapter 3. Next, the methodology applied is explained, and the primary data source of this master's thesis is described in chapter 4. Subsequently, sections 5 and 6 focus on data analysis and discussions as well as implications of the obtained results, respectively. Then, in chapter 7, limitations are discussed, and potential directions for future research are elaborated in chapter 8. Finally, an overall conclusion is drawn in chapter 9.

2. Literature Review

The subsequent chapter first defines attitudes, the attitude-behavior gap, intentions, and the intention-behavior gap. It then reviews the existing literature focusing on the effect of attitudes and intentions on residential energy consumption and presents an overview of identified limitations. Finally, this chapter concludes with an introduction to the Theory of Planned Behavior, which constitutes the theoretical framework of this master's thesis.

The researcher consulted ScienceDirect, Scopus, Springer, JSTOR, and EBSCO for relevant literature. The following search keywords were utilized: *Green Gap; Attitude-Behavior Gap; Intention-Behavior Gap; Attitudes; Intentions; Energy-Saving Behavior; Energy-Conservation; Residential Electricity Consumption*.

2.1 Definitions

2.1.1 Attitudes and the Attitude-Behavior Gap

There are several definitions of attitudes in social psychology, which all agree that attitudes are related to positive/negative, (un)favorable, or (un)pleasant evaluations (Bem, 1970; Eagly & Chaiken, 1993; Hill, 1990; Oskamp, 1990). For example, Eagly and Chaiken (1993) characterize attitudes as *"a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor"* (p. 1). In a more recent study, Hai et al. (2017) define attitudes as *"a state of human mind that is expressed either in positive (favourable) or negative (unfavourable) manner towards an individual, group, object or event"* (p. 320). In this study, attitudes towards a specific behavior, so-called 'behavioral attitudes,' play an important role. They are defined as *"the individual's positive or negative evaluation of performing the particular behavior of interest"* (Ajzen, 2005, p. 118). Measuring behavioral attitudes is key when analyzing consumer behavior, as they are closely related (Ajzen, 2005; Peter & Olson, 2010; Shabnam et al., 2021). Nevertheless, an inconsistency between households' attitudes towards performing a specific behavior and their actual behavior is observed (Gifford & Sussman, 2012). This phenomenon has been termed as the attitude-behavior gap, or in some research articles, referred to as the attitude-action gap. The attitude-behavior gap is verified if no statistically significant relationship between behavioral attitudes and the particular behavior is identifiable.

2.1.2 Intentions and the Intention-Behavior Gap

As pointed out by Devinney et al. (2010),*"[i]ntentions are the stated willingness to act in a specific manner"* (p. 51). Intentions are a person's prediction about their future behavior. Individuals' knowledge and external factors such as social pressure, time, money, etc., can influence and/or change their intentions (Ajzen, 2005). According to Ajzen (1991), *"[i]ntentions are assumed to capture the motivational factors that influence a behavior; they are indications of how hard people are willing to try, of how much of an effort they are planning to exert, in order to perform the behavior"* (p. 181). Based on the findings of Armitage and Conner (2010) as well as of T. L. Webb and Sheeran (2006), behavioral intentions are good predictors of actual behavior in various situations. However, several researchers express concerns about whether intentions are reliable predictors for actual behavior. In doing so, they refer to the so-called 'intention-behavior gap,' which describes a phenomenon in which people's intentions to perform a specific behavior do not match their actual behavior (M. J. Carrington et al., 2010; Devinney et al., 2010; Frederiks et al., 2015; Sheeran, 2002; T. L. Webb & Sheeran, 2006). Corresponding to the attitude-behavior gap, the intention-behavior gap is verified if no statistically significant relationship between intentions and the particular behavior is identifiable.

2.2 The Effect of Attitudes

This section reviews recent literature focusing on the effect of attitudes on residential energy consumption. First, it discusses studies revealing evidence for the attitude-behavior gap. Second, it introduces research detecting no proof for the gap, and finally, it presents four papers finding no clear evidence.

2.2.1 Evidence for the Attitude-Behavior Gap

In one of the first studies related to green gap research, Ritchie et al. (1981) have focused on the effect of dwelling and socio-demographic characteristics, utilized electric appliances, energy-saving attitudes, knowledge, preferences, and self-reported behavior on in-home energy consumption. Their study was based on survey and actual energy consumption[4] data

[4] Including energy for heat, electricity consumption, and car fuel.

from 743 Canadian households. The authors found no significant relation between energy-saving attitudes and actual energy consumption. However, the dwelling type, housing size, family income and size, as well as the participants' age, significantly increased energy consumption.

In a more recent article, Huebner et al. (2016) investigated the effect of building and socio-demographic characteristics, electrical appliance ownership and usage, and attitudes towards climate change on residential electricity consumption. The study detected a marginal impact of attitudes towards climate change on actual electricity consumption as long as no other predictors were included in the regression. However, the effect became insignificant once additional variables were added to the regression. The main predictors for electricity consumption were household and home size as well as appliance ownership and usage.

A similar research focus was adopted by Jakučionytė-Skodienė et al. (2020), who investigated the link between dwelling and socio-demographic characteristics, environmental knowledge, pro-environmental behavior, attitudes towards energy consumption, actual energy consumption,[5] and related CO_2 emissions in Lithuania. The authors found no statistically significant relationship between attitudes towards energy consumption and electricity consumption of the 230 participating households. Yet, the analysis revealed that residential electricity consumption depends on pro-environmental behavior, gender, dwelling type, the number of residents, and on whether children under the age of six live in the family.

In contrast to the studies mentioned above, the study carried out by Viklund (2004) is based entirely on survey data. The researcher asked 797 Swedish citizens about their attitudes towards the environment and energy production technologies,[6] their risk perceptions, and self-reported electricity-saving behavior. The author found that a large majority of the respondents (94.7 %) had pro-environmental attitudes, and around 60 % of the sample reported an extremely high or high attitude towards saving electricity. However, Viklund inferred that environmental attitudes do not necessarily translate into electricity-saving actions as only a

[5] Including electricity, central heating, natural gas, and wood. Consumption data was calculated based on a household's monthly spendings for electricity, central heating, natural gas, and wood.

[6] Including renewables, fossil fuels and nuclear.

marginal, although statistically significant, effect of environmental attitudes on self-reported electricity-saving behavior was detected.

Botetzagias et al. (2014) have chosen a comparable research approach by focusing on the effect of socio-demographic characteristics, as well as of psychological and moral determinants, on self-reported electricity curtailment behavior in Greece. The scientists surveyed 285 households and did not find a significant relationship between energy-saving attitudes and self-reported electricity curtailment behavior. Instead, the findings pointed out that perceived behavioral control,[7] age, and gender are the main predictors for electricity curtailment behavior.

Compared to the previous papers, Brandon and Lewis (1999) went one step further by testing whether feedback, including energy-saving tips and information about financial and environmental costs, has a significant negative effect on real gas and electricity consumption of 120 households in the UK. In addition, the authors conducted a survey measuring, among others, environmental attitudes and socio-demographic characteristics. The researchers' analysis revealed that household size and income, age, and whether participants are in a tenancy agreement significantly affected energy consumption before the study intervention. In contrast, no statistically significant relationship between environmental attitudes and past energy consumption was detected.
For the intervention period, all the socio-demographic characteristics became insignificant. Feedback and environmental attitudes had a marginal statistically significant negative impact on energy consumption. Still, the authors concluded that pro-environmental attitudes do not necessarily translate into lower consumption.

2.2.2 No Evidence for the Attitude-Behavior Gap

One of the first studies which identified a significant relationship between attitudes and electricity usage behavior was conducted by Seligman et al. in 1979. The researchers measured attitudes towards energy usage of 56 US-American couples. Furthermore, the researchers

[7] Perceived behavioral control deals with the individual's perceived ability to control their behavior and depends on their available resources like ability, skills, time, money, and/or collaboration with other people (Ajzen, 1991).

collected actual electricity consumption data for the summertime. The analysis revealed that energy attitudes explained nearly 55 % of the variance in electricity usage behavior.

In a more recent study, Abrahamse and Steg (2011) investigated the effect of socio-demographic characteristics, basic human values,[8] energy-saving attitudes, perceived behavioral control, and subjective norms[9] on energy-saving intentions as well as on actual residential gas and electricity usage behavior in the Netherlands. The two scientists identified that energy-saving attitudes significantly impacted actual energy consumption behavior next to household size, income, age, and self-transcendence values.[10]

A similar methodology was utilized by Sapci and Considine (2014). The researchers examined the effect of socio-demographic characteristics and energy-saving attitudes on residential electricity consumption in the US. The authors matched survey responses from 612 households with actual electricity consumption data and found a statistically significant negative relationship between environmental attitudes and electricity consumption behavior. In addition, dwelling size, income, and electric heating had statistically significant positive effects on electricity consumption.

In contrast to the previously presented studies, the following three research papers utilized a mono-method data collection technique (Saunders et al., 2020) by conducting only surveys. For instance, Martinsson et al. (2011) investigated the relationship between general environmental attitudes, socio-demographic characteristics, and energy consumption on the basis of self-reported heat and hot water consumption. The research study, in which more than 3300 Swedish citizens participated, detected that socio-demographic characteristics such as housing type, income, and age, are strong predictors for self-reported energy consumption behavior. Furthermore, general environmental attitudes significantly influence energy consumption, although their effect was weaker when compared to socio-demographic characteristics. Additionally, the scientists showed that the impact of general environmental

[8] Including universalism, self-direction, power, achievement, tradition, security, and stimulation values. See Table B1-1 in Appendix B 1 for definitions.

[9] Subjective norms are related to the individual's perceived social pressure to behave in a certain manner in a specific context (Ajzen, 2020).

[10] According to Abrahamse (2019, p. 19): *"Self-transcendence values are characterised by a concern for the welfare of other people or altruistic goals, and this end of the dimension includes values such as social justice, equality and care for nature."*

attitudes on energy consumption was higher for individuals that lived in an apartment and had a higher income.

Another study, focusing on 800 Portuguese students, examined the relationship between pro-environmental knowledge, attitudes towards energy, and energy-saving behavior (Paço & Lavrador, 2017). The authors discovered a weak but statistically significant relationship between attitudes towards energy and self-reported energy-saving behavior, while they did not discover a significant link between pro-environmental knowledge and energy-saving behavior.

Compared to the other studies, Hong et al. (2019) analyzed not only the effect of psychological variables, including energy-saving attitudes, environmental responsibility,[11] and materialistic consumer values,[12] on residential energy-saving behavior but also the effect of a government policy subsidizing energy-saving products. Based on a survey with 497 Chinese citizens, the study indicated that energy-saving attitudes and environmental responsibility positively influenced self-reported energy-saving behavior. Furthermore, the government subsidy policy positively affected self-reported energy-saving behavior.

2.2.3 No clear Evidence

In the course of the literature review, the researcher identified four research papers providing ambiguous evidence for the attitude-behavior gap. They are to be presented in the following section.

First, Barr et al. (2005) assessed the link between pro-environmental attitudes and purchase behavior (buying energy-efficient electrical appliances), habits (willingness to change energy consumption behavior), and self-reported energy-saving behavior in the UK. Based on several questions measuring pro-environmental attitudes, the researchers categorized the 1265 participants into four environmentalist groups: Committed, Mainstream, Occasional, and Non-environmentalists. The authors found a link between pro-environmental attitudes and self-

[11] According to Hong et al. (2019, p. 156), environmental responsibility *"is an individual's sense of responsibility to take measures actively to solve environmental problems based on a full understanding of environmental benefits."*

[12] According to Hong et al. (2019, p. 156): *"Materialism is the value of possessing money and property to pursue happiness and demonstrate the promotion of social status."* Individuals with high materialistic consumer values are expected to have lower energy-saving intentions.

reported energy-saving behavior, purchase behavior, and habits for the conscious energy savers, whereas no link was detected with regard to the Non-environmentalists.

Second, in a more recent study, Boomsma et al. (2019) analyzed the relationship between socio-demographic and dwelling characteristics, psychological factors (including attitudes), and energy-saving behavior among 536 social housing residents in the UK. The analysis revealed that condensation, dampness, and mold significantly decreased energy-saving behavior related to heating. Besides, the relationship between energy-saving attitudes and energy-saving behavior related to heating was insignificant. However, a statistically significant negative link between energy-saving attitudes and energy-saving behavior regarding electrical appliances was detected. These findings align with a recently published study from China. In their survey, Zhang et al. (2021) asked whether respondents would be willing to change their habits regarding lighting, thermal conform, and unused electrical appliances in order to save energy. The researchers detected evidence for an attitude-behavior gap for self-reported practices related to lighting as well as heating and cooling, whereas they did not identify a gap with regard to unused electric appliances.

Finally, Bruderer Enzler et al. (2019) linked 723 questionnaire answers from Swiss households, measuring, among others, environmental attitudes with actual electricity consumption. Their analysis disclosed that stronger environmental attitudes lead to a statistically significant reduction in electricity use when analyzing consumption data from multi-person and single-households. However, the effect became statistically insignificant when considering only single-households.

Finally, based on the findings of the research papers addressed in this literature review, it may reasonably be concluded that the results regarding the influence of attitudes on residential energy consumption have so far been rather ambiguous.

2.3 The Effect of Intentions

In the following three sections, research papers are presented that (1) confirm the intention-behavior gap, (2) find a significant relationship between energy-saving intentions and energy consumption behavior, and (3) reveal no clear evidence.

2.3.1 Evidence for the Intention-Behavior Gap

In a study from 2013, D. Webb et al. examined the influence of autonomous and controlled motivation,[13] energy-saving intentions, and past behavior on residential energy-saving behavior. The analysis detected a significant relationship between the energy-saving intentions and the self-reported energy-saving behavior of 200 Australian study participants when not including autonomous and controlled motivation factors. However, the significance of the relationship disappeared when adding both motivation factors as independent variables. Only autonomous motivation had a significant positive effect on energy-saving behavior.

In a recent study, van den Broek et al. (2019) investigated the effect of energy-saving intentions, energy consumption habits, and situational processes (including perceived behavioral control and objective control[14]) on the self-reported energy-saving behavior of 247 citizens from Western European countries. The results showed that situational processes and energy consumption habits had a significantly positive impact on energy-saving behavior. In contrast, no statistically significant relation was found between energy-saving intentions and self-reported energy consumption behavior.

Going one step beyond the previously presented studies, Lee et al. (2020) developed a model for explaining the occurrence of the intention-behavior gap in residential electricity consumption. According to the authors, there exists an inconsistency between perceived and actual electricity consumption. Therefore, by providing households with information about their actual electricity consumption, households' misperceptions about their electricity usage are prevented, which in turn reduces electricity overconsumption and minimizes the occurrence of the intention-behavior gap. The scientists tested their model in a field experiment with 704 participants from South Korea, including a survey and the measurement of household electricity consumption. The study results indicated a mismatch between

[13] *"Autonomous motivation comprises both intrinsic motivation and the types of extrinsic motivation in which people have identified with an activity's value and ideally will have integrated it into their sense of self. When people are autonomously motivated, they experience volition, or a self-endorsement of their actions. Controlled motivation, in contrast, consists of both external regulation, in which one's behavior is a function of external contingencies of reward or punishment, and introjected regulation, in which the regulation of action has been partially internalized and is energized by factors such as an approval motive, avoidance of shame, contingent self-esteem, and ego-involvements. When people are controlled, they experience pressure to think, feel, or behave in particular ways. Both autonomous and controlled motivation energize and direct behavior […]"* (Deci & Ryan, 2008, p. 182).

[14] Objective control is defined as the individual's ability to control the thermostat, lights, radiator, washing machine, etc. (van den Broek et al., 2019).

perceived and actual electricity consumption, implying an intention-behavior gap. However, the analysis also showed that providing electricity usage information significantly decreased electricity consumption, which means that the intention-behavior gap can be reduced.

Related to the studies of Brandon and Lewis (1999) as well as Lee et al. (2020), Xu et al. (2021) also developed an intervention with the aim of reducing residential energy consumption. The authors examined the effect of a newly developed intervention, called Household Energy-Saving Options (HESO),[15] on residential energy-conserving behavior. The study is based on a survey of 101 Singaporean participants. Besides testing the HESO, the researchers investigated factors influencing energy-saving intentions and self-reported energy-conserving behavior. Next to finding a significant reduction in self-reported energy consumption due to the HESO, the study results revealed no statistically significant effect of energy-saving intentions on self-reported energy-saving behavior, indicating the existence of the intention-behavior gap.

2.3.2 No Evidence for the Intention-Behavior Gap

In an article from 1983, Seligman et al. focused on the determinants of residential electricity conserving behavior. Among others, the relationships between energy-saving attitudes and intentions on the one hand and actual electricity consumption, on the other hand, were investigated. The study is based on a survey and actual electricity consumption data of 96 US-American households. The researchers found a statistically significant negative relationship between energy-saving intentions and actual electricity consumption.

In a more recent study, S. Wang et al. (2018) examined the effect of electricity-saving habits, positive anticipated emotions[16] towards saving electricity, and intentions to save electricity on electricity-saving behavior in China. Based on 320 survey responses, the analysis showed that intentions to save electricity and electricity-saving habits significantly increased self-reported

[15] "*HESO was derived from the binary option in the financial industry, a contract between buyers and issuers. Binary options allow buyers to execute their right if the exercise condition is met at the expiration date. Sharing similar functional characteristics with the binary option, HESO is designed to be traded between households (buyers) and issuers in an open market. Households pay the HESO premium to issuers to obtain the contract. With HESO, households can earn the monetary reward (higher than the premium) if they achieve their prearranged electricity-saving goal within a fixed period. Otherwise, they receive nothing […]*" (Xu et al., 2021, para. 3).

[16] According to S. Wang et al. (2018, p. 174): *"[P]ositive anticipated emotion refers to the positive psychological states when performing a certain behavior (e.g., household electricity saving behavior). Positive anticipated emotion consists of expected feelings of pride, exciting and confidence."*

electricity-saving behavior. However, the scientists discovered a statistically significant negative effect of positive anticipated emotion on electricity-saving behavior, meaning that individuals with strong positive anticipated emotions towards saving electricity reported less electricity-saving behavior, which clearly weakens the link between electricity-saving intentions and self-reported electricity-saving behavior.

In a study from 2021, J. Du and Pan investigated the relationship between psychological factors and energy-saving intentions. Furthermore, the authors tested whether there is a link between energy-saving intentions and self-reported energy-saving behavior. Two hundred ninety post-graduates living in dormitories in Hong Kong participated in the survey. The study revealed a statistically significant negative relationship between energy-saving intentions and self-reported energy usage behavior.

The research focus of the following article is comparable to the studies conducted by Brandon and Lewis (1999), Lee et al. (2020), and Xu et al. (2021). Mack et al. (2019) designed an intervention to overcome the intention-behavior gap: The researchers installed a smart meter web portal in 86 German households and examined the effect of energy-saving information, commitment, and self-monitoring on residential electricity consumption. The research findings are based on survey and smart meter data and showed that study participants who undertook to a saving tip had higher saving goal intentions. Furthermore, in combination with self-monitoring, their electricity consumption was significantly lower.

2.3.3 No clear Evidence

The researcher identified one study with ambiguous findings providing evidence for the intention-behavior gap as well as no evidence for the gap. It is to be discussed in the following paragraph.

Thøgersen and Grønhøj (2010) developed a framework in order to explain the relationships between socio-demographic and psychological characteristics, self-reported energy-saving behavior, and actual electricity consumption. The scientists tested the framework empirically by matching survey responses to electricity consumption data from 320 Danish citizens. The study detected a positive relationship between home size and actual electricity consumption. Furthermore, a statistically significant negative link was found between self-reported energy-saving behavior, household size, and electricity consumption. Additionally, the scientists detected a significant positive relationship between energy-saving intentions and self-reported energy-conserving behavior for men only, which implies that the existence of an intention-behavior gap may be limited to women and, accordingly, gender-related.

Finally, based on the presented studies, it may reasonably be concluded that current research finds ambiguous results related to the effect of intentions on residential energy consumption.

2.4 Identified Limitations

While reviewing the literature on the effect of attitudes and intentions on residential energy consumption, the researcher noticed several limitations of current research studies, which are to be discussed in more detail in the following section.

2.4.1 Theory-Based Research Approach

First, some of the examined academic papers[17] based their research on a theoretical framework. However, most studies did not base their research on a theory. Accordingly, while various studies have aimed to answer the question of whether a gap between attitudes, intentions, and behavior exists, only a few of them[18] were able to provide possible explanations and solutions (ElHaffar et al., 2020).

2.4.2 Self-Reported Energy-Saving Behavior vs. Actual Energy Consumption

Second, while some researchers utilized actual energy consumption data,[19] more than half of all reviewed studies[20] conducted surveys and used self-reported behavior as an approximation for real energy usage behavior, which does not necessarily reflect actual energy consumption

[17] Abrahamse and Steg (2011); Botetzagias et al. (2014); Claudy et al. (2013); Gadenne et al. (2011); Paço and Lavrador (2017); Seligman et al. (1983); D. Webb et al. (2013); Xu et al. (2021).

[18] Brandon and Lewis (1999); Lee et al. (2020); Mack et al. (2019); Xu et al. (2021).

[19] Abrahamse and Steg (2011); Brandon and Lewis (1999); Bruderer Enzler et al. (2019); Huebner et al. (2016); Jakučionytė-Skodienė et al. (2020); Lee et al. (2020); Mack et al. (2019); Ritchie et al. (1981); Sapci and Considine (2014); Seligman et al. (1979); Seligman et al. (1983); Thøgersen and Grønhøj (2010).

[20] Barr et al. (2005); Boomsma et al. (2019); Botetzagias et al. (2014); Claudy et al. (2013); J. Du and Pan (2021); Gadenne et al. (2011); Hong et al. (2019); van den Broek et al. (2019); Paço and Lavrador (2017); Martinsson et al. (2011); Viklund (2004); Valkila and Saari (2013); S. Wang et al. (2018); Xu et al. (2021); Zhang et al. (2021).

behavior (M. J. Carrington et al., 2010; Carrus et al., 2021; Gatersleben et al., 2002; Olsen, 1981; Saboya de Aragão & Alfinito, 2021).

Olsen (1981) lists four reasons why self-reported behavior might be an unreliable proxy for actual behavior. First, it could be subjected to response and/or social desirability bias, which is also acknowledged by Gifford and Sussman (2012). Second, environmental awareness does not automatically translate into knowledge about the ecological consequences of particular energy usage behavior: Respondents might perceive their behavior as environmentally friendly but behave quite contrarily due to a lack of knowledge. The third factor is related to the measurement of energy-saving behavior. In several surveys,[21] the questionnaire includes various questions related to the household's energy-saving behavior like switching off the light after leaving a room, etc. These are aggregated to one energy-saving behavior index. In general, the impact of these measured behaviors on energy savings is relatively small. Hence, it could be the case that a household with a high energy-saving index might, in reality, have a high energy consumption. The fourth reason is also related to the measurement of energy-saving behavior. The energy-saving behavior index is often calculated without ranking measured behaviors according to their energy-saving potential, decreasing the studies' conclusiveness.

2.4.3 Time Horizon

Third, as most of the reviewed studies were based on surveys, they used a cross-sectional study design, meaning that attitudes and/or intentions and self-reported energy-saving behavior were measured at a particular point in time. However, this is a limitation as the obtained results were only snapshots. In contrast, studies measuring actual energy consumption behavior utilized a longitudinal study design as energy consumption was observed over a longer period of time. This is already an improvement compared to the studies completely based on self-reported behavior. Still, there are significant differences in the observation periods ranging

[21] Barr et al. (2005); Botetzagias et al. (2014); Gadenne et al. (2011); Paço and Lavrador (2017); Thøgersen and Grønhøj (2010); Viklund (2004); S. Wang et al. (2018); Zhang et al. (2021).

from one month to three months[22], more than six months,[23] to a whole year.[24] As energy consumption varies throughout a year, the findings of the studies using annual data are more reliable as these studies completely cover seasonal consumption patterns. However, all these studies have one limitation in common: Attitudes and/or intentions were only measured once, usually before the energy consumption measurement. Still, attitudes and intentions may change over time (Kollmuss & Agyeman, 2002), a fact which has not been considered so far.

2.4.4 Measurement of Attitudes and Intentions

Fourth, the lack of a standardized method for measuring an individual's attitudes and intentions is another limitation. The questionnaire utilized to measure attitudes and/or intentions is usually based on other research studies but never the same. Therefore, it is almost impossible to compare research results in detail, as studies investigate attitudes and/or intentions differently and with different foci. Additionally, attitudes and/or intentions are often measured in a too general and not behavior-specific manner,[25] reducing the studies' validity.

Fifth, in studies that collected data on actual household energy consumption,[26] attitudes and/or intentions are usually measured for only one resident. It is assumed that all residents in one household share the same attitudes and/or intentions. As this is not necessarily the case, the results of these studies should be scrutinized.

2.4.5 Missing Control Variable

Sixth, the researcher noticed a major limitation of studies utilizing actual energy consumption data. People who spend more time at home will automatically consume more energy, regardless of their energy-saving attitudes/intentions. None of the previously discussed papers controlled for this factor. It is, accordingly, questionable whether these research studies

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[22] Jakučionytė-Skodienė et al. (2020); Seligman et al. (1979); Seligman et al. (1983).

[23] Brandon and Lewis (1999).

[24] Abrahamse and Steg (2011); Bruderer Enzler et al. (2019); Huebner et al. (2016); Lee et al. (2020); Mack et al. (2019); Ritchie et al. (1981); Sapci and Considine (2014); Thøgersen and Grønhøj (2010).

[25] Brandon and Lewis (1999); Huebner et al. (2016); Mack et al. (2019); Ritchie et al. (1981); Viklund (2004).

[26] Abrahamse and Steg (2011); Ritchie et al. (1981); Sapci and Considine (2014); Vringer et al. (2007); Xu et al. (2021).

correctly captured the effect of energy-saving attitudes and intentions on actual electricity consumption.

2.4.6 Sample Bias

Seventh, the findings of the research studies cannot be generalized, as studies were based on non-randomized samples representing only a small fraction of the population (Frederiks et al., 2015). Few studies focus on students[27] or socially disadvantaged families.[28] In general, highly-educated and high-income households are overrepresented.[29] In addition, most participants are often either young[30] or old.[31] Furthermore, there seems to be a gender imbalance as most respondents are either males[32] or females.[33] Besides, the sample has often a bias towards households with high environmental awareness[34] or strong views on energy-saving behavior.[35]

Overall, the relationship between attitudes, intentions, and residential energy consumption seems to be very complex. So far, researchers fail to agree on the influence of these psychological variables on the energy usage behavior of private households. The topic is analyzed from social, psychological, and economic perspectives, and this interdisciplinary research context makes it even more difficult to compare research findings. Nevertheless, some models and theories were developed and applied in order to investigate the influence of attitudes and intentions on residential energy consumption. They are to be discussed in more

[27] J. Du and Pan (2021); Paço and Lavrador (2017).

[28] Boomsma et al. (2019).

[29] Abrahamse and Steg (2011); Brandon and Lewis (1999); Gadenne et al. (2011); Hansla et al. (2008); Jakučionytė-Skodienė et al. (2020); Mack et al. (2019); Ritchie et al. (1981); Sapci and Considine (2014); Viklund (2004); S. Wang et al. (2018); Xu et al. (2021); Zhang et al. (2021).

[30] J. Du and Pan (2021); Paço and Lavrador (2017); van den Broek et al. (2019); Zhang et al. (2021).

[31] Boomsma et al. (2019); Bruderer Enzler et al. (2019); Faiers and Neame (2006); Gadenne et al. (2011); Viklund (2004).

[32] Abrahamse and Steg (2011); Bruderer Enzler et al. (2019); Gadenne et al. (2011); Huebner et al. (2016); Mack et al. (2019).

[33] J. Du and Pan (2021); Hong et al. (2019); Jakučionytė-Skodienė et al. (2020); Paço and Lavrador (2017); van den Broek et al. (2019).

[34] Abrahamse and Steg (2011); Bruderer Enzler et al. (2019); Gadenne et al. (2011); Ozaki (2011); Salmela and Varho (2006).

[35] Thøgersen and Grønhøj (2010); Valkila and Saari (2013); D. Webb et al. (2013).

detail in the following section. Still, the findings vary from study to study, implying that further research is necessary.

2.5 Theory

Several theories are related to the green gap research. According to ElHaffar et al. (2020), they can be categorized into the rational economic and behavioral paradigm. The rational economic paradigm assumes rational, utility-maximizing consumer behavior (Henry, 2012). In contrast, the behavioral paradigm considers consumer behavior to be more complex and affected by emotions and cognitive biases meaning that rational behavior is not always observed in reality (Kahneman, 2003b, 2003a). Green gap research, based on the Value-Belief-Norm Theory (Stern et al., 1999), the Attitude-Behavior-Context Theory (Guagnano et al., 1995; Stern, 2000), the Theory of Reasoned Action (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975), the Theory of Planned Behavior (Ajzen, 2005), and the Behavioral Reasoning Theory (Westaby, 2005), can be assigned to the rational economic paradigm. The Prospect Theory (Kahneman & Tversky, 1979) and the Construal Theory (Trope et al., 2008; Trope & Liberman, 2003) are predominant theories belonging to the behavioral paradigm in the green gap literature.

The Theory of Planned Behavior (TPB) is prevalent from all these presented theories. According to Kollmuss and Agyeman (2002), Claudy et al. (2013), and ElHaffar et al. (2020), the TPB is applied in many social psychology research studies, focusing on the relationship between attitudes and intentions, and behavior. Rivis et al. (2009) and Abrahamse (2019) point out that the TPB is the most important theoretical framework for explaining pro-environmental behavior as enablers and barriers of ecological behavior are illuminated. Furthermore, Kaiser et al. (2005) find a high explanatory power of the TPB for predicting conservation behavior. For example, C. Chen and Knight (2014) and Gao et al. (2017) utilize the TPB to analyze energy-conserving behavior at work. Additionally, based on Klöckner (2013) and S. Wang et al. (2016), the TPB is a common theoretical framework for analyzing residential energy-saving behavior. For instance, Abrahamse and Steg (2011), Ajzen et al. (2011), C. Chen et al. (2017), J. Du and Pan (2021), Ru et al. (2018), and S. Wang et al. (2018) utilized the TPB to analyze residential energy usage behavior. Therefore, the theory is particularly relevant for this master’s thesis and is examined in more detail in the following section. The TPB forms the basis of the conceptual model and hypothesis discussed in chapter 3.

2.5.1 The Theory of Planned Behavior

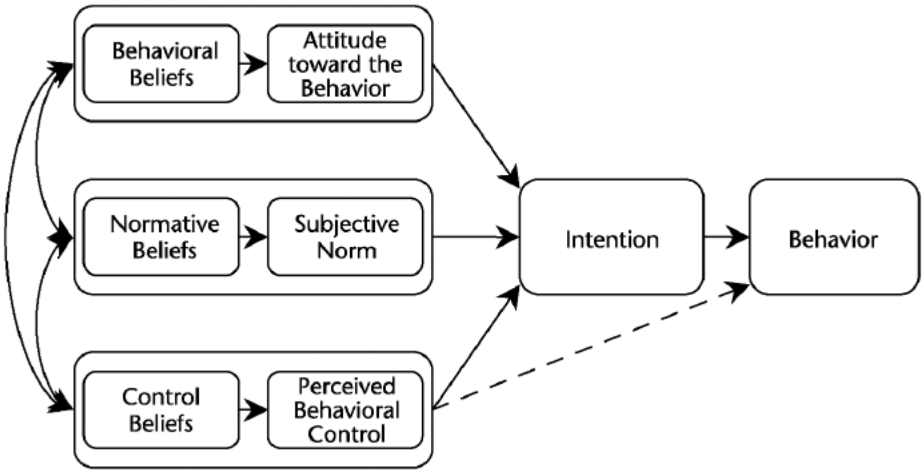

Figure 2-1: Illustration of the Theory of Planned Behavior (Ajzen, 2005, p. 126)

The TPB's purpose is to predict and provide an explanation for context-specific human behavior (Ajzen, 1991). Figure 2-1 illustrates the TPB and reveals that the theory's central element is that an individual's actual behavior can be predicted through the individual's intentions to perform a specific behavior.

Behavioral intentions[36] are a function of attitudes towards the behavior, subjective norms, and perceived behavioral control. The relative influence of these three factors differs and depends on the behavior and context (Abrahamse, 2019).

Attitudes towards a specific behavior[37] are determined through an individual's behavioral beliefs. Ajzen (2020) defines behavioral belief as *"the person's subjective probability that performing a behavior of interest will lead to a certain outcome or provide a certain experience"* (p. 315).

As stated in Ajzen (2005, p. 124):

$$A_B \propto \sum b_i e_i$$

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[36] See section 2.1.2 for the definition of intentions.

[37] See section 2.1.1 for the definition of attitudes.

Individual's attitudes (A) towards a behavior (B) are directly proportional to the sum of beliefs (b) that behavior (B) results in outcome i times the evaluation (e) of outcome i. Thus, an individual who believes that a certain behavior leads to positive outcomes likely has positive attitudes towards the behavior. In contrast, an individual with mainly negative outcome beliefs is expected to hold rather negative behavioral attitudes.

Subjective norms are related to the individual's perceived social pressure to behave in a certain manner in a specific context and are influenced by normative beliefs. Normative beliefs can be divided into descriptive and injunctive. Injunctive normative beliefs are an individual's expectations about whether a referent group or person[38] supports or condemns the specific behavior, whereas descriptive normative beliefs are related to an individual's anticipation of whether this referent group or individual would perform the behavior or not (Ajzen, 2020).

In line with Ajzen (2005, p. 125):

$$SN \propto \sum n_i m_i$$

Subjective norms (SN) are directly proportional to the sum of normative beliefs (n) regarding referent group or individual i times the individual's importance (m) to obey the referent group or individual i.

Finally, perceived behavioral control deals with the individual's perceived ability to control their behavior and depends on the individual's available resources like ability, skills, time, money, and/or collaboration with other people (Ajzen, 1991). Control beliefs influence perceived behavior control and are defined as an individual's judgment about the existence of determinants that simplify or complicate performing the behavior. Control beliefs are grounded in past experiences, social referent's experiences, and other secondary information. The more resources an individual believes they have, needed to perform the behavior, and the fewer impediments in an individual's perception exist, the higher an individual's perceived behavioral control (Ajzen, 1991, 2005, 2020).

[38] Potential social referents are parents, spouses, friends, colleagues, or the individual's doctor.

As described by Ajzen (2005, p. 125):

$$PBC \propto \sum p_i c_i$$

Perceived behavioral control (PBC) is directly proportional to the sum of control beliefs (c) about whether determinant i is given times the power (p) of determinant i on simplifying or complicating the behavior performance.

The TPB is an extension of the Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975), which does not consider that humans do not always have complete control over their behavior. Therefore, the TPB includes perceived behavioral control next to intentions as a predictor for actual behavior. After all, if a person does not think that they have the resources needed to perform the behavior, behavioral intentions will be a poor predictor for actual behavior.

Ajzen (2005) indicates that the TPB assumes that an individual's intentions to perform a behavior are grounded in their beliefs, which he denotes as a 'reasoned approach,' and which is why the TPB belongs to the rational economic paradigm. However, it is worth noting that individuals' beliefs are not assumed to be rational; they can be biased or erroneous. Moreover, socio-demographic characteristics, personality traits, and values are background factors that influence individuals' beliefs but have no direct effect on behavioral intentions or actual behavior (Ajzen, 2020).

Based on Ajzen (2020), the assumption of sufficiency holds for the TPB, meaning that no additional variables are necessary to accurately predict actual behavior, if behavioral intentions and perceived behavior control are measured. Furthermore, measuring behavioral attitudes, subjective norms, and perceived behavioral control are sufficient to predict behavioral intentions. However, the theory is still open for extensions, although there are several criteria to be fulfilled by additional variables. First, it must be possible to measure the predictors context- and behavior-specific. Second, there should be a causal link between the new variable and behavioral intentions or actual behavior. Third, the additional variable must be independent of the already included predictors in the TPB. Fourth, it should be possible to apply the additional predictors to various relevant behaviors in social science (Ajzen, 2020).

3. Hypotheses

The following chapter presents the conceptual model and introduces the three hypotheses to be tested in this study.

3.1 Conceptual Model

Figure 3-1 illustrates the conceptual model that serves as the basis for this master's thesis. This study aims to gain a better understanding of the relationship between energy-saving attitudes, intentions, and actual electricity consumption behavior. As testing the complete TPB sequence is beyond the scope of this master's thesis, a reduced TPB model was utilized. More precisely, this study focused on the link between attitudes, intentions, and actual behavior in the TPB sequence. In addition, the researcher included a control variable for 'occupied days,' which is based on the fact that people who spend more time at home will automatically consume more electricity, regardless of their energy-saving attitudes/intentions. To the best of the researcher's knowledge, no previous research study has included this variable.

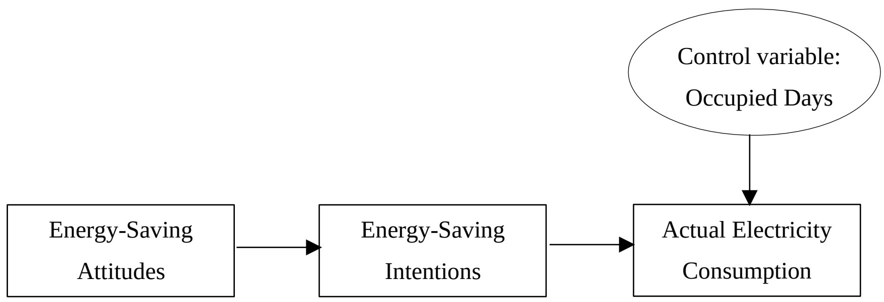

Figure 3-1: Conceptual Model

3.2 Energy-Saving Attitudes

According to the TPB, the more positive an individual's behavioral attitudes are, the stronger their intention to perform the behavior (Ajzen, 2005). Abrahamse and Steg (2011), Ajzen et al. (2011), Ru et al. (2018), C. Chen et al. (2017), J. Du and Pan (2021), S. Wang et al. (2018), and Q.-C. Wang et al. (2021), who base their research studies on the TPB, find a significant positive relationship between energy-saving attitudes and intentions. Moreover, Seligman et al. (1983), who base their paper on the TRA, show that energy-saving attitudes are the main predictor for energy-saving intentions. Furthermore, Guerin et al. (2000) find that attitudes are adequate predictors for energy-saving intentions. Therefore, it can be assumed that households with strong energy-saving attitudes are likely to have strong energy-saving intentions, which leads to the first hypothesis:

H1: *Energy-saving attitudes positively influence energy-saving intentions.*

3.3 Energy-Saving Intentions

Based on the TPB, actual behavior can mainly be predicted through intentions to perform the particular behavior (Ajzen, 2005). Thus, households with strong energy-saving intentions are expected to consume less electricity than households with lower energy-saving intentions. Ajzen et al. (2011), S. Wang et al. (2018), D. Webb et al. (2013) , and J. Du and Pan (2021), who ground their research paper in the TPB, find a positive relationship between energy-saving intentions and self-reported energy-saving behavior. Additionally, Seligman et al. (1983), whose study is closely related to this master's thesis, confirm a negative relationship between energy-saving intentions and actual electricity consumption behavior. Therefore, the second hypothesis of this master's thesis is that:

H2: *Energy-saving intentions negatively influence a household's electricity consumption.*

In addition, the mediating effect[39] of intentions on attitudes' impact on actual behavior is formulated in the TPB. However, to the researcher's best knowledge, no study has so far investigated this effect in the context of electricity consumption behavior. Therefore, this master's thesis is the first study that analyzes the mediator role of intentions by formulating the following hypothesis:

H3: *The effect of energy-saving attitudes on actual electricity consumption is mediated by energy-saving intentions.*

[39] According to MacKinnon et al. (2007), a mediating variable (sometimes termed indirect effect) is defined as a variable between the explanatory and explained variable that explains the relationship between the explanatory and the explained variable. The explanatory variable influences the mediating variable, which in turn affects the explained variable.

4. Methodology

Saunders et al. (2020) is used as the primary reference to identify an appropriate methodological approach. The purpose of this chapter is to elaborate on how the research question is answered. In the initial step, the research design and strategy are specified. Then, as the researcher has not collected data herself, the following step constitutes a detailed description of the dataset utilized to investigate the effect of energy-saving attitudes and intentions on residential electricity consumption. Furthermore, the study design and the construction of the variables are elucidated in detail.

4.1 Research Design and Strategy

The overall purpose of this thesis is to investigate the potential existence of a causal link between energy-saving attitudes as well as intentions and actual electricity consumption. The choice of an explanatory research design is based on this thesis's aim to explain the relationship between the aforementioned variables, thereby contributing to a yet small number of research papers utilizing actual electricity consumption data rather than self-reported behavior only. This master's thesis has followed a deductive research approach as it tests the occurrence of the green gap in residential electricity consumption. According to Saunders et al. (2020), a quantitative research approach is suitable for deductive research, which is why it was chosen for this thesis. To answer the research question, a longitudinal study design measuring actual whole-home electricity consumption of private households and conducting a survey measuring energy-saving attitudes and intentions is necessary. Due to time constraints, this research strategy would have been beyond the scope of this master's thesis, which, accordingly, utilized the IDEAL Household Energy Dataset (Goddard et al., 2021; Pullinger et al., 2016; Pullinger et al., 2021) as a primary data source. Pullinger et al. (2016) collected data using a longitudinal experimental research strategy. The research project is to be described in more detail in the following section.

4.2 Dataset Description

The IDEAL Household Energy Dataset was published by the University of Edinburgh in April 2021 and is based on the first project phase (August 2016 – June 2018) of two research projects, Intelligent Domestic Energy Advice Loop (IDEAL) and Data-Driven Methods for a

New National Household Energy Survey (BIGSMALL), financed by the UK Engineering and Physical Sciences Research Council. The research goal of BIGSMALL was to enhance Non-Intrusive Load Monitoring (NILM) approaches, whereas IDEAL focused on residential energy-saving feedback (Pullinger et al., 2021).

The IDEAL Household Energy Dataset is based on a randomized control trial in Scotland.[40] Pullinger et al. (2021) targeted households interested in smart technology and saving energy for environmental and/or cost reasons. The eligibility criteria for participating in the IDEAL home energy advice project are summarized in Table 4-1. Among others, sensors measuring power and gas usage were installed in 255 private households with one to five residents. Households were assigned to one of three study classes, distinguishable from each other on the basis of the installed sensors as well as app features (see Table 4-2 for details). Data was measured over a period of 23 months. However, the start and end of the measurement period varied between homes. Measurement data[41] for participating households were available for a minimum of 55 and maximum of 673 days. 286 days was the average and 267 days the median. Besides the installment of sensors, five surveys were conducted, collecting, among other things, socio-demographic attributes, participants' values, energy-saving attitudes, intentions, and energy awareness, detailed dwelling characteristics, electric appliance ownership, and energy tariffs of participating households. It should be noted that the IDEAL Energy Household Dataset contains only anonymized data (Pullinger et al., 2021).

Table 4-1: Eligible Criteria for Participating in the IDEAL Study (Pullinger & Kilgour, 2021, p. 5)

1. Located in Edinburgh, Lothians or south Fife areas of Scotland, and living in a non-moveable home not shared with other households.
2. Willing to participate until June 2018, and unlikely to have any change of occupants during that time; and home usually occupied by same occupants at least nine months of the year. (Initially this was proxied by disallowing private rented accommodation and paying guests, but this restriction was removed in February 2017 to increase recruitment rates).

[40] The research project focused on Edinburgh, the Lothian region, and South Fife. Appendix A 1 includes a map of Scotland and shows the focus regions.

[41] Refers to measurement days for apparent power. The following statistics exist for real power measurements: Measurement data for participating households were available for a minimum of 25 and a maximum of 627 days. Two hundred forty days was the average and 219 days the median.

Table 4-1 (continued)

3. Home heated with gas central heating in majority of rooms, with a gas combi boiler.
4. Sensor-readable model of gas meter (we could read a range of pulse-enabled gas meters), and non-smart electricity meter (to help avoid confounding effects of another In-Home Display system); willing to keep these until June 2018 unless needing changed for safety reasons.
5. Home has broadband and occupant is willing to leave router on at all times, and let project use the connection, until June 2018. (Potential participants were advised of a chance of increased broadband monthly costs in the rare cases they still had capped data allowances).
6. No electricity or gas prepayment (to reduce risk of system downtime arising from gaps in energy supply).
7. None of the following (and no plans to acquire before June 2018): microgeneration; hot water heating other than via combi boiler; storage heaters, air conditioning or heat pumps, Mechanical Ventilation with Heat Recovery, solid fuel fires unless used infrequently; Agas; electric vehicle charging.
8. No plans for major changes to property before June 2018 (e.g. removing walls, building extensions, fitting double glazing).
9. Adequate access to combi boiler pipes, electricity and gas meters and (for enhanced installations) most of the appliances to be monitored and willing to allow the required electricity rewiring.
10. Good signal propagation for the sensor system: For standard installs, this was managed by evaluating based on home's WiFi propagation and placing a recruitment constraint that outdoor gas meters had to be close to the property and sheltered from rain; for enhanced installs, this was evaluated based on the propagation rates from IDEAL standard sensors over the first few weeks after the standard installation visit.
11. Willing for anonymised data to be lodged in a data archive after project end.
12. Moderate or higher level of self-reported digital literacy for at least one occupant in the home (to increase chances that the IDEAL app could be used by the occupants).
13. No children under 7 or pets (enhanced homes); all potential participants made aware of need to keep system components out of reach of any children under 3.

Table 4-2: Summary of the Differences between Study Classes (Energy Feedback, n.d.; Pullinger et al., 2021, p. 7)

	Control study class ($n = 107$)	**Treatment study class** ($n = 109$)	**Enhanced study class** ($n = 39$)
Standard sensors			
Whole-home electricity use: 1-second apparent power (converted to W)	✓	✓	✓
Whole-home gas use: Per fixed-volume pulse (converted to kW)	✓	✓	✓
Temperature, humidity, light-level per room: 12-second frequency	✓	✓	✓
Boiler pipe temperatures for central heating and hot water pipes: 12-second frequency	✓	✓	✓
Enhanced sensors			
Whole-home electricity use: 5-second real power (measured in W)	✗	✗	✓
Laundry: Washing machines, tumble dryers, combined washing machine-tumble dryers	✗	✗	✓ *
Personal washing: Inlet pipes for hot water taps for baths, showers, and bathroom sinks, or wastewater outlet pipes or underside of the unit	✗	✗	✓ *
Space heating and cooling: Radiator pipes (inflow and outflow) in all rooms, fixed gas fires, electric heaters, dehumidifiers	✗	✗	✓ *
Hot food and drink preparation: Cookers, ovens, hobs, microwaves, kettles, kitchen sinks	✗	✗	✓ *
Washing up: Dishwashers, inlet pipes for hot water taps for kitchen sinks, or wastewater outlet pipes or underside of the unit	✗	✗	✓ *
Other cleanings: Vacuum cleaners	✗	✗	✓ *
Appliances running in the background: Fridges, freezers, fridge-freezers, aquariums	✗	✗	✓ *
Leisure appliances: Hot tubs, wine coolers	✗	✗	✓ *

Table 4-2 (continued)

	Control study class ($n = 107$)	**Treatment study class ($n = 109$)**	**Enhanced study class ($n = 39$)**
IDEAL app features			
Current outside temperature and weather	✓	✓	✓
Prognosis of outside temperature for the next day	✗	✓	✓
Current average in-home temperature	✓	✓	✓
Temperature and humidity data of each room	✗	✓	✓
Current and historical electricity and gas usage data	✓	✓	✓
Visualization of appliance electricity/gas consumption[**]	✓	✓	✓
Charts matching different sensor data	✗	✓	✓
Data comparison of different periods is possible	✗	✓	✓
Chart explanations	✗	✓	✓
Provision of common energy-saving tips	✓	✓	✓
Heat challenges (turn down radiators in unused rooms)	✗	✓	✓

[*] Not all appliances were monitored because of physical/technical barriers or households' preferences.
[**] For the 'treatment' and 'control' study class, machine learning techniques were utilized to detect appliance-level electricity/gas consumption.

4.3 Study Design

This master's thesis merged survey responses with sensor data from the IDEAL Household Energy Dataset to determine whether energy-saving attitudes and intentions are reflected in homes' electricity consumption. Thus, it can be classified as a multi-method quantitative study (Tashakkori & Teddlie, 2010).

The study focused on three variable types: Psychological variables, household characteristics, and actual electricity consumption. The first two variable types were obtained from the survey, whereas the latter was calculated on the basis of sensor data. As all households were assigned a unique Home ID, matching survey responses with power measurements was possible. In section 4.4, all variables relevant to the conceptual model presented in section 3.1 are described in detail.

Based on the findings in section 2.4.4, this master's thesis has focused on single-households. Therefore, in the first step, 49 out of the 255 households in the original IDEAL Household Energy Dataset were selected as a relevant sample. However, the sample was then reduced to 35 homes in a second step, because the survey responses of fourteen single-households were either unavailable or incomplete.

In a third step, the researcher compared the data measurement period of the remaining 35 households. Figure 4-1 illustrates the start and end date of power measurements, sorted by start date in the first place and by Home ID in the second place. The figure shows that, for several households, data is available for a period of almost two years. However, the time overlap of the power measurements is limited. To determine the relationship between energy-saving attitudes and intentions and actual electricity consumption correctly, it is necessary to compare electricity consumption of the participating households during the same period, because otherwise there could be many external factors influencing electricity consumption (e.g., change in electricity tariff, public holidays, or seasonal weather conditions). Therefore, the researcher decided to focus on the measurement period between 30th of April 2018, 11:44:20, and 7th of June 2018, 10:29:05, representing the biggest time overlap[42] of the households in the sample.

[42] The focus period is equal to 37 days, 22 hours, 44 minutes, and 45 seconds.

Based on this decision, the household with the Home ID 88 was removed from the sample as no power measurements were available for the period mentioned above. Thus, the sample decreased to 34 households. The power measurements during the focus period for the remaining 34 households were cleaned in a fourth step. Another four homes were excluded due to significant time gaps[43] in sensor readings. Accordingly, the study finally focused on 30 households.

According to Public Holidays Global (2017), there were two public holidays in Scotland during the focus period, namely on 7th and 28th May 2018. Thus, it is not unlikely that participants in the sample might not have been at home, which may have resulted in significantly lower electricity consumption measurements during the focus period. By visually inspecting power measurements of the 30 households, the researcher searched for longer periods of low power readings but could not detect any significant differences to their 'normal' consumption profiles. Therefore, it was assumed that all households were 'at home' during the focus period.

[43] Time gaps greater than two hours range from fourteen to twenty-five days for these households. See Appendix A 2 for details.

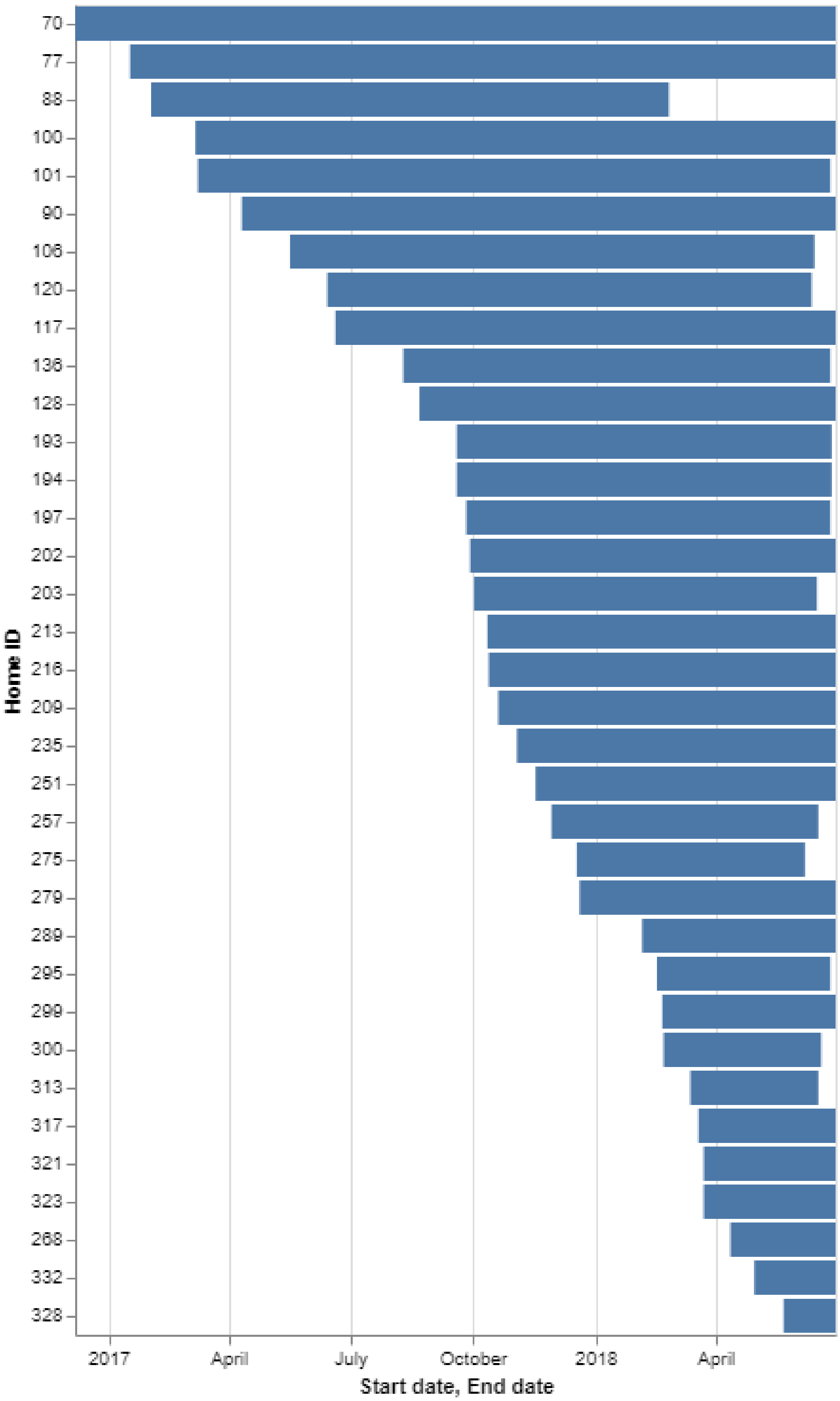

Figure 4-1: Overview of the Start and End Date of Electricity Consumption Measurement, sorted by Start Date

4.4 Description of Variables

4.4.1 Construction of Psychological Variables

Five surveys were conducted during the 20 months project phase of the IDEAL research project.[44] The researcher classified survey questions into questions measuring energy-saving attitudes and intentions. The classification was based on extensive review and analysis of the survey questionnaires in the research studies presented in the literature review. Furthermore, the attitude and intention definitions, introduced in section 2.1, and the sample TPB questionnaire developed by Fishbein and Ajzen (2010), presented in Appendix A 4, as well as a TPB manual written by Francis et al. (2004) were utilized to ensure that the measured variables align with the TPB, which is the basis of the research model and the derived hypothesis. The following sections describe the construction of both variables in detail.

4.4.1.1 Energy-Saving Attitudes

The master's thesis applied the definition of Ajzen (2005), presented in section 2.1.1, to define energy-saving attitudes, which correspondingly are 'the individual's positive or negative evaluations of conserving energy.' As behavioral attitudes are a hypothetical concept, it is impossible to measure them directly (Ajzen, 2005). Therefore the measurement of energy-saving attitudes was broken down into several sub-questions that measure the individual's evaluation of energy-saving behavior. This method is commonly utilized in research studies[45] focusing on the effect of psychological variables on residential energy consumption. Therefore, the variable *energy_saving_attitudes* was constructed using three survey questions from the All-occupant survey 1.

Table 4-3 gives an overview of the questions utilized to measure energy-saving attitudes. A 7-point Likert scale ('1: Not important at all' to '7: Very important') was used for all three questions, which is in line with the scale utilized in the TPB manual (Francis et al., 2004) and

[44] In Appendix A 3, more details about the conducted surveys can be found.

[45] See for example: Boomsma et al. (2019); Brandon and Lewis (1999); Bruderer Enzler et al. (2019); Claudy et al. (2013); J. Du and Pan (2021); Gadenne et al. (2011); Hansla et al. (2008); Hong et al. (2019); Jakučionytė-Skodienė et al. (2020); Ozaki (2011); Ru et al. (2018); S. Wang et al. (2016); S. Wang et al. (2018); Q.-C. Wang et al. (2021); M. C. Wang et al. (2021); D. Webb et al. (2013); Wei et al. (2016); Yang et al. (2016).

the sample questionnaire (Fishbein & Ajzen, 2010). Low scores reveal weak energy-saving attitudes, whereas high scores indicate strong energy-saving attitudes.

Table 4-3: Overview of Utilized Questions to Measure Energy-Saving Attitudes

Labeling	**Question**	**Rating scale**
save_energy	*Thinking in general, how important is it to you in your day-to-day life at home to use as little energy as possible?*	*7: Very important 6 5 4: Somewhat important 3 2 1: Not important at all*
buy_appliances_energy_efficiency	*When you buy a new electrical appliance, like a TV, fridge, or computer, how important are each of the following things when you decide which model to buy? Energy efficiency*	*7: Very important 6 5 4: Somewhat important 3 2 1: Not important at all*
importance_environment	*The next questions will help give us an idea about what is important for you when you do day-to-day things at home that use energy. How important are each of these in your day-to-day life at home? Reducing my impact on the environment.*	*7: Very important 6 5 4: Somewhat important 3 2 1: Not important at all*

The first question directly measured energy-saving attitudes as participants were asked to evaluate the importance of energy-saving behavior in their day-to-day life. It was assumed that, if a household considered energy-saving behavior an important part of everyday life, the participant positively evaluated energy-saving behavior. However, it is acknowledged that the question did not specify why households rate the use of as little energy as possible as important. Next to environmental concerns, saving money might have also been a valid reason.

The second question also focused on energy-saving attitudes in a direct manner, as households that assessed energy efficiency as important when buying a new electrical appliance for their home were expected to evaluate energy-saving behavior positively. For example, Zhang et al. (2021) used a similar question to measure energy-saving attitudes. However, as already discussed for question one, the question did not focus on the underlying reasons why a household placed high importance on buying electric appliances with high energy efficiency ratings. Once again, financial savings rather than environmental concerns might have been the vital argument.

The third question measured energy-saving attitudes, because households that expressed high importance towards reducing their environmental impact when using electrical appliances were considered to evaluate energy-saving behavior positively. Furthermore, a household reduces its impact on the environment every time it conserves energy.[46] The third question focused on the households' ecological concerns when using energy. The question was included in order to compensate for the fact that the first and second question did not specify why participants valued saving energy and buying energy-efficient appliances as important. After all, in order to reliably investigate the existence of the green gap, energy-saving attitudes must be based on ecological concerns. If, for example, the third question was not included, and a statistically significant negative effect of energy-saving attitudes on electricity consumption was found, this could just as well be due to financial reasons, rather than a household's high ecological consciousness. By including the third question, the researcher assured that energy-saving attitudes were measured from the correct angle.

Although the first and the third question were asked in the three All-occupant surveys, the researcher decided to focus on the survey responses of the initial questionnaire to assure that there was no time lag between the measurement of attitudes and intentions as the question utilized to measure energy-saving intentions was only measured in the initial face-to-face survey.[47]

[46] Following the motto: *The best energy is the one you do not consume*.

[47] The answers measuring the importance of saving energy and the importance of reducing the household's impact on the environment for each participating home from the conducted survey at the middle and the end of the study period were still utilized to assess the consistency of the responses. See Appendix A 5 for details.

Ajzen (2020) indicates that confirmatory factor analysis should be applied to validate the developed construct of questions measuring the TPB's latent variables.[48] Additionally, several reviewed studies[49] utilized factor analysis to test the construction of the psychological variables in their research. According to Hair et al. (2014), factor analysis identifies underlying relationships of highly correlated observed variables, allowing for the construction of a latent variable (in this case, *energy_saving_attitudes*). However, based on Hair et al. (2014), the minimum required sample size for conducting a factor analysis is 50 observations. Accordingly, the method proved inapplicable to this master's thesis, with its study's sample size comprising below 50 observations.[50]

Therefore the variable *energy_saving_attitudes* was constructed following an approach utilized by several research papers related to this master's thesis.[51] For each household, the sum of the three Likert scale responses was calculated and divided by three in the next step:

$$energy\_saving\_attitudes = \frac{save\_energy + buy\_appliances\_energy\_efficiency + importance\_environment}{3}$$

In doing so, the researcher calculated Cronbach's Alpha, a commonly utilized statistical test to assess the reliability of the latent variable *energy_saving_attitudes*. It tests the internal consistency of responses (Saunders et al., 2020). A Cronbach's Alpha value greater than 0.7 suggests a sufficient internal consistency of responses (Nunnally & Bernstein, 1994). Table 4-4 reveals the result of the consistency test.[52] The scale reliability coefficient of the variable *energy_saving_attitudes* was above 0.7, indicating that the measurement of energy-saving attitudes based on the three survey questions may be considered adequate.

[48] Latent variables are variables that are difficult to measure directly. Therefore, they are inferred from several variables that can be observed ("Latent Variable," 2010).

[49] See for example: Barr et al. (2005); Brandon and Lewis (1999); Claudy et al. (2013); J. Du and Pan (2021); Gadenne et al. (2011); Perri et al. (2020); Ru et al. (2018); Thøgersen and Grønhøj (2010); S. Wang et al. (2016); S. Wang et al. (2018); Q.-C. Wang et al. (2021); M. C. Wang et al. (2021); D. Webb et al. (2013); Wei et al. (2016); Yang et al. (2016).

[50] For the sake of interest, the researcher tried to conduct a factor analysis in Stata, but Stata did not find a solution during the iteration process for confirmatory factor analysis, which tests the hypothesis that a relationship between the observed variables (in this case, survey questions) *save_energy*, *buy_appliances_energy_efficiency*, and *importance_environment* and the underlying latent variable *energy_saving_attitudes* exists.

[51] See for example: Boomsma et al. (2019); Bruderer Enzler et al. (2019); Martinsson et al. (2011); Thøgersen and Grønhøj (2010); Xu et al. (2021).

[52] A more detailed analysis can be found in Appendix A 6.

Table 4-4: Reliability of the Variable energy_saving_attitudes

Variable	Cronbach's Alpha	Number of Items
energy_saving_attitudes	0.7515	3

4.4.1.2 Energy-Saving Intentions

Based on the intention definition by Ajzen (1991), presented in section 2.1.2, energy-saving intentions are considered to 'capture the motivational factors that influence energy conservation; they are indications of how hard people are willing to try, of how much of an effort they are planning to exert, in order to save energy.' In this study, the variable *energy_saving_intentions* was measured using one question of the primary face-to-face survey. Households were asked about their motivations for participating in the IDEAL research project. Respondents could choose between a 7-point Likert scale, with 1 implying 'Not a motivation at all' and 7 indicating 'A very strong motivation.' Among gaining increased knowledge about energy usage, keeping the home comfortable, technology curiosity, helping research, and obtaining a tablet, the following motivation factors were listed:

"I would like help to find ways to reduce energy use to save money" and

"I would like help to find ways to reduce energy use to reduce my impact on the environment."

As the study aims to test the existence of the green gap in residential electricity consumption behavior, the study considered only the latter statement for measuring energy-saving intentions as only these energy-saving intentions were based on environmental concerns.

This statement can be utilized to measure energy-saving intentions: If households indicated that they were strongly motivated to participate in the research study, because they wanted to decrease their energy consumption for environmental reasons, it implied that they had strong energy-saving intentions.

4.4.2 Electricity Consumption

The variable *electricity_consumption* is based on whole-home sensor data measuring real power for households in the 'enhanced' study class ($n = 6$) and apparent power for homes in the 'control' ($n = 12$) and 'treatment' ($n = 12$) study class. In a first step, apparent power measurements of the 'treatment' and 'control' study class were converted into estimates for real power measurements using a power factor of 0.73074. The utilized method of converting apparent power measurements into estimates for real power measurements for the households in the ‘control’ and ‘treatment’ study class is described in detail in the following section 4.4.2.1. Then, based on the (estimated) real power measurements, electricity consumption, measured in kWh, was estimated for the focus period using the Trapezoidal rule, which is explained in detail in section 4.4.2.2.

4.4.2.1 Conversion Method: From Apparent Power To Real Power

The definitions of real and apparent power are the following:

“Real power [P] is the part of power converted into non-electric form (e.g., heat, light, mechanical power) and registered by the meter” (Lindner et al., 1985, p. 121).

“Apparent power [S] is the product of terminal voltage and current obtained without taking any phase shift into account” (Lindner et al., 1985, p. 123).

Based on these definitions, real power measurements were of interest for this master’s thesis, because they measure a household’s actual electricity consumption. Therefore, the researcher searched for a method to convert apparent power measurements into estimates for real power measurements.

According to Lindner et al. (1985, p. 123):

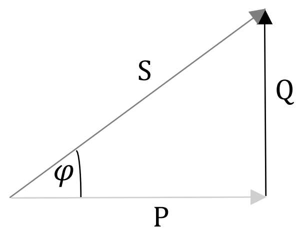

Figure 4-2: The Power Triangle (Lindner et al., 1985, p. 123)

$S = \sqrt{P^2 + Q^2}$

S: $apparent\ power$; P: $real\ power$; Q: $reactive\ power$

The power factor is defined as:

$\lambda = \cos\varphi = \frac{P}{S} = \frac{real\ power}{apparent\ power}$

If the power factor is given, it is possible to convert apparent to real power:

$\lambda = \frac{P}{S} <-> \lambda S = P$

As the power factor was not listed in the IDEAL Household Energy Dataset and reliable information on average power factor for private homes in Scotland/the UK/Europe was unavailable, the researcher developed a method to approximate the power factor for households in the 'control' and 'treatment' study class. For households in the study class 'enhanced' ($n = 39$), it was possible to calculate the average power factor as apparent and real power were measured. As erroneous values had already been removed from the apparent and real power raw datasets presented in the IDEAL Household Energy Dataset,[53] the researcher utilized the raw dataset of the households in the 'enhanced' study class to calculate the mean power factor for each household.[54]

First, apparent and real power measurements were matched using the statistical software Stata (StataCorp, 2019), version 16.0. The key variable for matching apparent and real power was the timestamp: DDMMYYYY HH:MM:SS. Second, the power factor for each matched timestamp was calculated using the power factor formula from above. In total, six households were excluded from the power factor calculations.[55] Thus, the average power factors of 33 homes were calculated (see Table A7-1 in Appendix A 7). The average power factors ranged from a minimum of 0.46108 to a maximum of 0.919749. The mean and the median of the average power factors were 0.730724 and 0.760687, respectively. In the final step, the mean of the average power factors (0.730724) was used to convert apparent power measurements into estimates for real power measurements for homes in the 'control' ($n = 12$) and 'treatment' ($n = 12$) study class using the following equation:

$\lambda = \frac{P}{S} <-> \lambda S = P <-> 0.730724S = P$

[53] See Appendix A 2 for details.

[54] This means that time gaps were not filled, and not all real and apparent power measurements could be matched, which reduces the accuracy of the calculated mean power factors. However, it should be noted that filling time gaps could also reduce the accuracy of the mean power factors as missing data would be filled with estimated data such that the researcher believed that using the raw dataset was more appropriate than using a cleaned dataset.

[55] For three homes, real power measurements on appliance level were only included in the IDEAL Household Energy Dataset and not for the whole home. Two households were excluded because of unlabelled real power measurements. It was unclear whether the sensor measured real power for the entire household or on appliance level. According to Pullinger et al. (2021), the home with ID 231 is categorized as a household participating in the study class 'enhanced'; however, no real power measurements for this household were found in the sensor dataset.

$\lambda = 0.73074 = mean\ power\ factor$

$S = apparent\ power, given\ for\ all\ homes\ in\ the\ control\ and\ treatment\ study\ class$

Each apparent power data point was multiplied by 0.730724 to get an approximation for real power.

4.4.2.2 Conversion Method: From Real Power To Energy

According to Alexander and Sadiku (2013), electrical energy E is the integral with respect to time x of power P (see Figure 4-3 for an illustration):

$$E = \int_{x_{Start}}^{x_{End}} P(x)dx$$

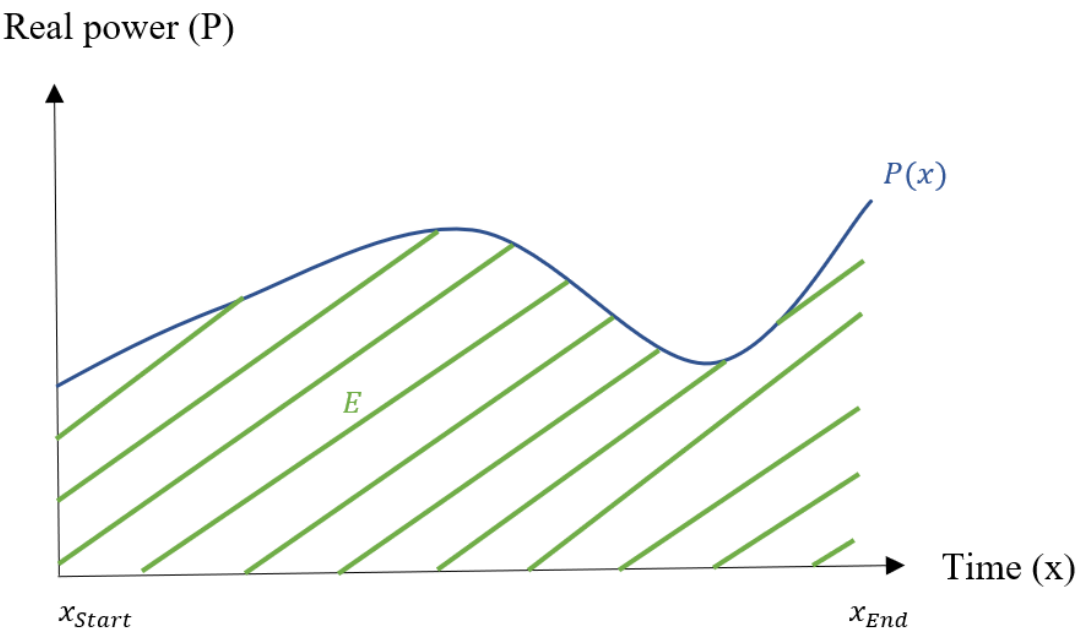

Figure 4-3: Illustration of the Relationship between Real Power and Energy

As real power was measured in one/five-second intervals,[56] a household's consumed electrical energy can be approximated through the Riemann sum, which is an approximation of an integral by a finite sum (Oberbroeckling, 2020). Through visual inspection of the real power measurements, the researcher noticed that the real power measurements varied significantly.

[56] The frequency depends on the installed sensor in the participating household. In the 'treatment' and 'control' study class, measurements in one-second intervals were available. In homes, part of the 'enhanced' study class, power measurements were available in five-second intervals.

On the basis of this observation, the Trapezoidal rule, a method of Riemann summation, was chosen due to its advantage, in comparison to more common Riemann summation methods such as the left endpoint, the right endpoint, or the midpoint rule (Newton, 1997), of obtaining more accurate results for irregular functions.

In this study, the following Trapezoidal rule was utilized to approximate consumed electrical energy based on real power measurements P_t at time x_t:

$$\tilde{E} = \sum_{t=1}^{n} \frac{1}{2}(x_t - x_{t-1})(P_{t-1} + P_t) = \sum_{t=1}^{n} \frac{1}{2}\Delta x(P_{t-1} + P_t)$$

$\tilde{E}$ is the approximated consumed electrical energy. As $(x_t - x_{t-1})$ is always either one or five seconds, this expression can be written as Δx. n is equal to either 3278685 or 655737 observations, depending on whether sensors measured power every one or five seconds.[57]

Figure 4-4[58] shows that the Trapezoidal rule uses the area of a trapezoid ($\tilde{E}_t$) to approximate the area below the graph of $P(x)$.

The researcher utilized Stata (StataCorp, 2019), version 16.0, to estimate each household's electrical energy consumption. Input variables were real power measurements (in W) obtained during the focus period and time (in s).[59] The estimated consumed electrical energy $\tilde{E}$ for the focus period had Ws as a unit and was converted into kWh using the following equation: $\frac{\tilde{E}}{1000\frac{W}{kW}*3600\frac{s}{h}}$

[57] 3278685 is the difference in seconds between the start '30.04.2018 11:44:20' and the end '07.06.2018 10:29:05' of the focus period. 655737 is obtained by dividing 3278685 by 5. In total, there are 3278685 power measurements for homes in the 'treatment' and 'control' study class as the sensor measured power every second and 655737 power measurements for households in the study class 'enhanced' since the installed sensor measured power in a frequency of five seconds.

[58] Please notice that Figure 4-4 shows the integration process of the Trapezoidal rule for only one interval and not for the whole series. This is because the figure has an illustrative purpose.

[59] The researcher generated a new variable, called 'total seconds,' that summed up seconds in one or five-second intervals, depending on the installed sensor in the participating household, throughout the whole focus period, as Stata is unable to subtract timestamps in the DDMMYYYY HH:MM:SS format. Therefore, the start date of the focus period, 30.04.2018 11:44:20, was converted into second zero, and the end date, 07.06.2018 10:29:05, was converted into second 3278685. For illustrative purposes, the timestamp conversion process is outlined in Table A8-1 in Appendix A 8.

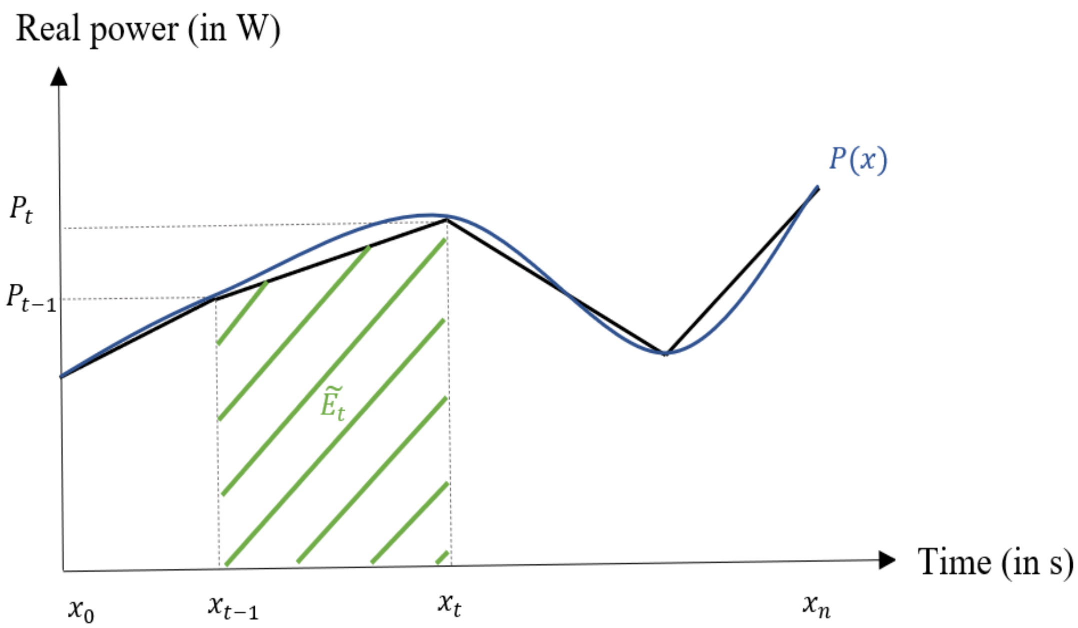

Figure 4-4: Illustration of the Trapezoidal Rule

4.4.3 Control Variables

Control variables were utilized in this study to guarantee that the causal effect of energy-saving attitudes and intentions on residential electricity consumption was measured. A lack of such control variables might have led to a systematic difference between study participants, causing an over-or underestimation of the relationship between energy-saving attitudes and intentions and residential electricity consumption (Wooldridge, 2013).

4.4.3.1 Occupied Days

Based on the discussion in 2.4.5, it was necessary to control for the average number of days a study participant is at home. Electricity consumption would automatically be higher if study participants spent more time at home, irrespective of their energy-saving attitudes and intentions. Therefore, this study controlled for this variable.

The variable *'occupied_days'* was based on one question asked in the primary participant survey 1, namely participants were asked the following question:

In a typical week, how many days would you say your home is occupied during the day; that is, with at least one person in it for most of the day?

Each participant could choose between 0, 1, 2, 3, 4, 5, 6, and 7 days. The household's answer to this question was utilized in this study.

4.4.3.2 Treatment: Energy-Saving Feedback

It was necessary to control for the treatment effect related to energy-saving feedback as households in the 'control' study class were exposed to a reduced set of features in the IDEAL app (see Table 4-2 for details), compared to households in the 'enhanced' and 'treatment' study class, who received the same energy-saving feedback. It was reasonable to control for this difference between the 'control' study class and the 'treatment' and 'enhanced' study class, because it was likely that electricity consumption of households in the 'treatment' and 'enhanced' study class was systematically lower due to the more in-depth energy-saving feedback they received.

Since the only difference between the 'treatment' and the 'enhanced' study class was that different sensors were installed,[60] it was assumed that the sensor type measuring power did not influence electricity consumption behavior. Thus, households in the 'treatment' and 'enhanced' study class both belonged to the energy-saving feedback treatment group. Therefore, the following dummy variable was utilized in this master's thesis to control for the treatment effect related to energy-saving feedback:

x: Control for treatment (energy-saving feedback)

$x = 1$: 'Enhanced' and 'Treatment' study class

$x = 0$: 'Control' study class

[60] Next to a sensor measuring apparent power, a sensor directly measuring real power was installed in households, part of the 'enhanced' study class.

5. Data Analysis and Results

This chapter focuses on data analysis and hypothesis testing. It is structured as follows: The first section gives an overview of the socio-demographic and dwelling characteristics as well as the electricity consumption of the participating households during the focus period. The section concludes with a table containing summary statistics of all variables. The second section discusses necessary assumptions for the data analysis, and finally, the three hypotheses presented in section 3 are tested in the third section. For the data analysis, the researcher has utilized Stata (StataCorp, 2019), version 16.0.

5.1 Descriptive Statistics

Figure 5-1 illustrates the socio-demographic characteristics of the 30 participating homes. Two third of the participants were female. This study has focused mainly on households in permanent employment, as more than 86 % of the study sample belonged to the working-age population,[61] and 22 out of 30 participants worked between 21 and 50 hours per week. In addition, 66 % of the sample had at least a university degree, and 20 out of 30 persons had an equivalized household income above the U.K. median individual gross income of £21.900.[62]

Figure 5-2 gives an overview of the dwelling and housing characteristics. Most homes (80 %) were located in Edinburgh, whereas one home was situated in Fife and East Lothian, respectively, and two persons came from Midlothian. Twenty-two respondents lived in a flat, and eight people indicated that they resided in a house or bungalow. It is worth mentioning that some participants have lived in very old buildings: 13 participants stated that they resided in a flat/house or bungalow built between 1850 and 1930, while only five people specified that their residence was built in 2002 or later. The floor area ranged from 37 to 125 square meters, and the average and median floor area were 68.12 and 67.75 square meters, respectively. A majority of participants ($n = 18$) spent two days per week at home, corresponding to the fact that most people in this sample worked. However, three participants spent only one day at

[61] According to OECD (n.d.), people between 15 and 64 belong to the working-age population.

[62] Goddard et al. (2021) compared a household's median income to the UK median individual gross income to determine if its median income was above or below it. The UK median individual gross income was taken from UK National Statistics (2012), which estimated the percentile points of the income distribution and was based on the annual Survey of Personal Incomes. Goddard et al. (2021) utilized the 50th percentile pre-tax income for 2013-14, equal to £21,900.

home, whereas four people indicated that they spent seven days at home. Of these four persons, three were retired, while one was self-employed.

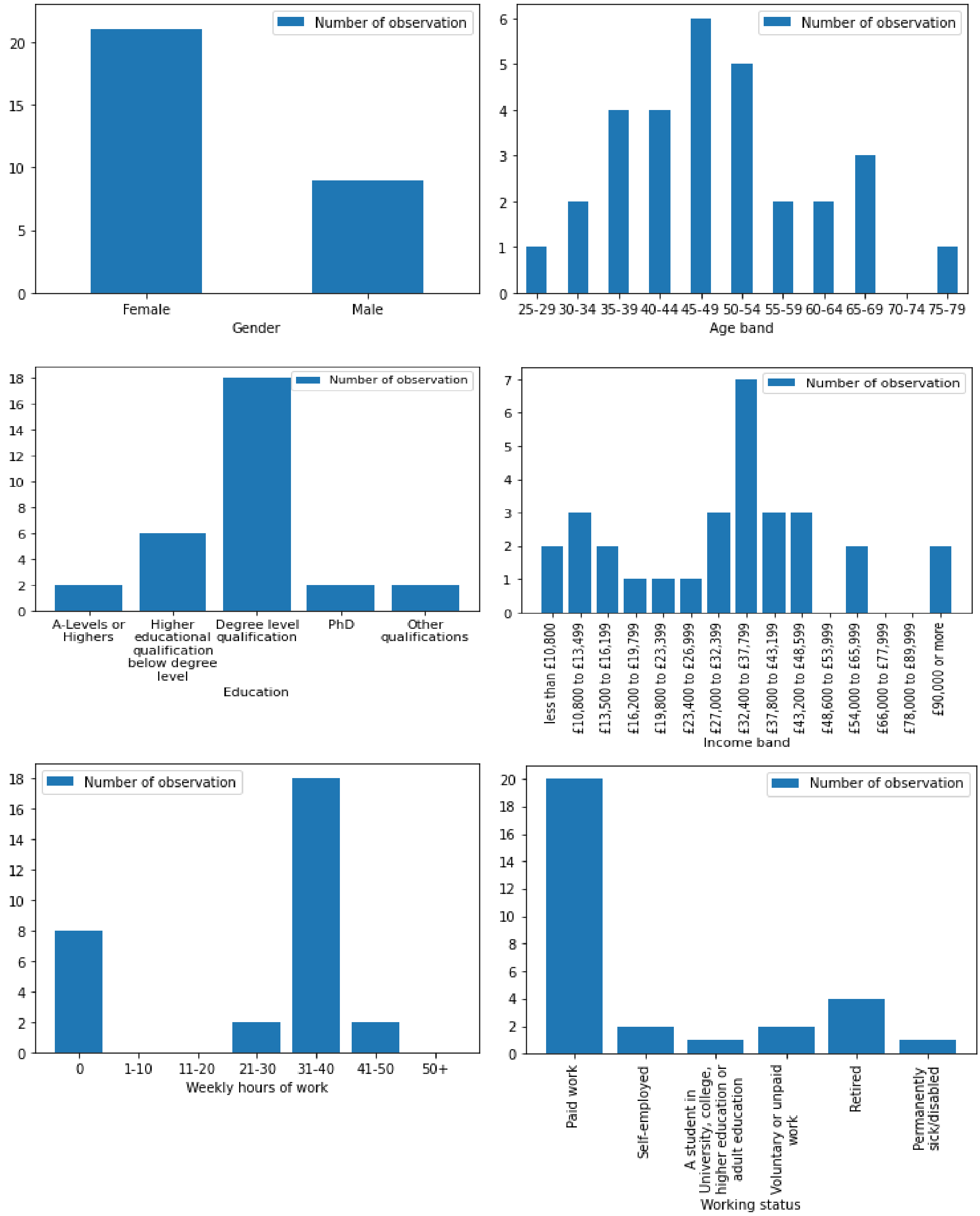

Figure 5-1: Overview of Socio-Demographic Characteristics in the Sample

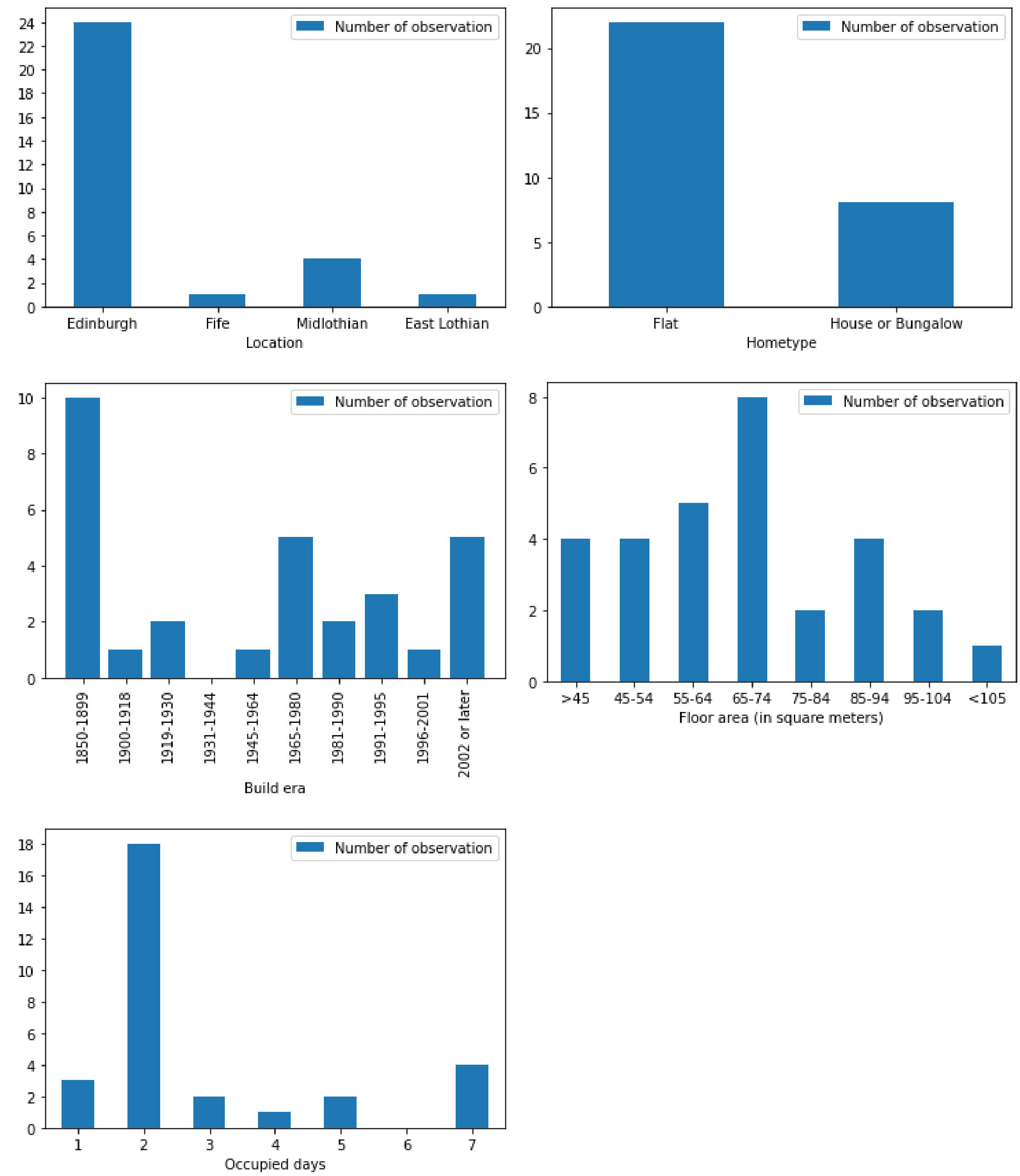

Figure 5-2: Overview of Dwelling Characteristics in the Sample

Figure 5-3 illustrates participants' electricity consumption (in kWh), sorted by their study class, between 30th of April and 7th of June 2018. Mean electricity consumption was 136.83 kWh. The 95 % Confidence Interval lies between 115.87 kWh and 157.79 kWh. With 61.17 kWh, household 216 consumed the least electricity, while household 202, with 296.69 kWh, had the highest electricity consumption during the focus period.

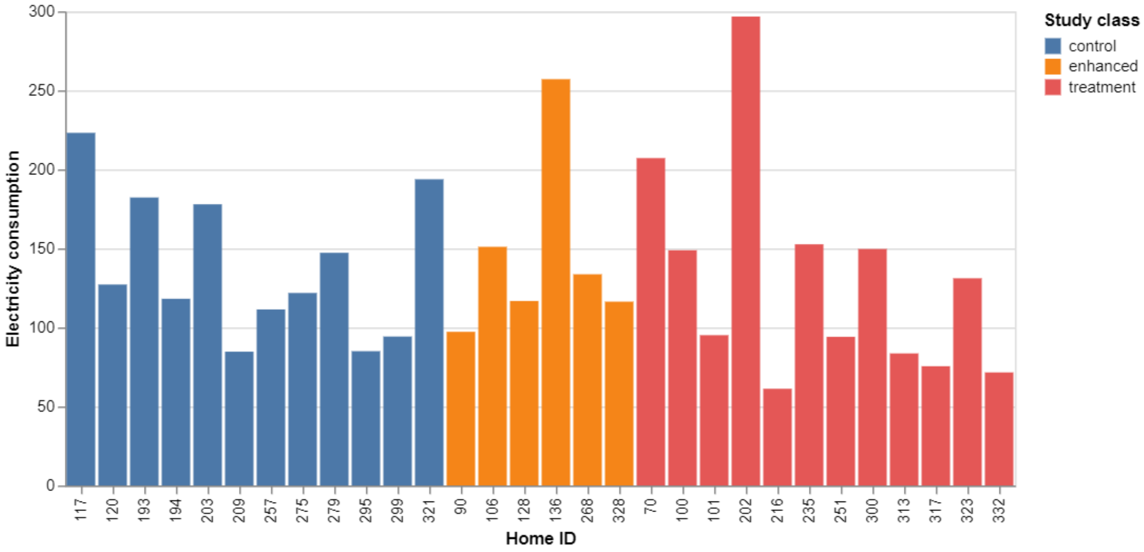

Figure 5-3: Overview of Households' Electricity Consumption during the Focus Period

According to Ofgem[63] (2020), the 25 % quantile and 50 % quantile for typical annual domestic electricity consumption values are 1800 kWh and 2900 kWh, respectively. Based on these numbers, typical electricity consumption for the focus period (38 days) should approximately range from 187 kWh to 302 kWh.[64] However, most of the households in the study sample consumed less electricity. There are several explanations for these deviations. First, the typical U.K. household[65] is not a single household, meaning that electricity consumption for single homes is typically lower than the values presented by Ofgem. Second, electricity consumption varies between seasons in the UK and is typically higher during winter.[66] As 187 kWh and 302 kWh are based on annual electricity consumption measurements, they are likely to overestimate electricity consumption during the focus period between April and June. Furthermore, the recruited households must not be compared to average electricity consumers. Based on Table 5-1, the study sample consisted largely of motived households with high energy-saving attitudes ($mean = 5.62$) and intentions ($mean = 6.167$). In addition to this, each household could monitor its electricity consumption and received energy-saving

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[63] Ofgem is the UK energy regulator.

[64] $1800\ kWh * \frac{38}{365} = 187.4\ kWh$ and $2900\ kWh * \frac{38}{365} = 301.9\ kWh$

[65] According to Sharfman and Cobb (2020), the average household size is 2.4 in the UK.

[66] According to Gavin (2014), the average daily electricity consumption in the UK is 36 % higher in winter compared to summer.

feedback through the IDEAL app, which was intended to facilitate the reduction of electricity consumption. Accordingly, it is not surprising that electricity consumption values are rather low.

Table 5-1 summarizes the number of observations, mean, standard deviation, minimum and maximum value for all variables utilized in this analysis.

Table 5-1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
electricity_consumption	30	136.8281	56.13885	61.17324	296.6889
energy_saving_attitudes	30	5.622222	.9043672	3.666667	7
energy_saving_intentions	30	6.166667	1.205829	3	7
occupied_days	30	2.9	1.881855	1	7

5.2 Assumptions of Analysis

Ordinary Least Squares (OLS) regression analyses, one of the most widely utilized statistical techniques in economics to analyze the relationship between a dependent and one or several independent variables, are conducted to test the hypotheses presented in chapter 3. This method is utilized in several research papers closely related to this study.[67] OLS minimizes the sum of squared residuals in order to obtain estimates for the population parameters. OLS regression analyses have the advantage that they have proven powerful even for small sample sizes[68] and are, accordingly, equally applicable to the one utilized in this study. However, testing the hypotheses using OLS regression analysis requires several assumptions to be satisfied. For simple linear regression, the following six classical linear model assumptions

[67] For instance, Gadenne et al. (2011), Ajzen et al. (2011), and Abrahamse and Steg (2011), who based their theoretical framework on the TPB and focused on energy-conserving behavior. Other examples are Fang et al. (2021) and Hansla et al. (2008), who based their theoretical framework on the TPB but focused on residential willingness to support renewable energy development and residential willingness to pay for green electricity, respectively. Sapci and Considine (2014), who tested the effect of energy-saving attitudes on electricity consumption but did not base their research model on the TPB, or Bruderer Enzler et al. (2019), who focused on the impact of environmental attitudes on residential electricity consumption. Furthermore, Viklund (2004) utilized OLS regression to test whether environmental attitudes significantly reduce a household's electricity consumption. Additionally, Hong et al. (2019) used OLS regression to examine the effect of energy-saving attitudes on self-reported energy-saving behavior.

[68] According to Hair et al. (2014), at least 20 observations are necessary for simple regressions, and according to Wooldridge (2013), a general rule of thumb of a sample size $n = 30$ is often utilized in econometrics.

must be met: Linearity in parameters, random sampling, variation in the independent variable, zero conditional mean, homoskedasticity, and normality. For multiple linear regressions, the third assumption of the classical linear model assumptions changes to no perfect collinearity between the independent variables, while all other assumptions stay the same. If the first five assumptions are satisfied, OLS estimators are the best, linear, unbiased estimators of the true population parameters, also known as the Gaus-Markov theorem (Hair et al., 2014; Wooldridge, 2013). These assumptions are to be discussed in more detail in the following section.[69]

5.2.1 Linearity in Parameters

Based on Wooldridge (2013), the assumption of linearity in parameters requires that each explanatory variable, every other explanatory variable held constant, is linearly related to the explained variable. This assumption defines the population model:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + u$$

The assumption entails that a one-unit increase in one of the independent variables, all else equal, will always have the same effect on the dependent variable.

5.2.2 Random Sampling

According to Wooldridge (2013), the utilized data must be based on a random sample of the population.

5.2.3 Variation in the Independent Variable / No Perfect Collinearity

As a third assumption, simple linear regression analysis requires that there must be some variation in the explanatory variable. For multiple linear regression analyses, the third assumption changes to the requirement that there is neither an independent variable that is constant nor perfect collinearity between the independent variables. Of course, the assumption of ‘no perfect collinearity’ allows for correlation between the explanatory variables. But still,

[69] It is noted that the actual testing and discussion of the assumptions can be found in Appendix B 1, Appendix B 2, and Appendix B 3 for each hypothesis separately.

it prohibits one explanatory variable from being constructed through a linear combination of another or several other explanatory variable(s) (Wooldridge, 2013).

5.2.4 Zero Conditional Mean

The zero conditional mean assumption: $E[u|x_1, \dots, x_k] = 0$ requires that all explanatory variables are exogenous. It is the most important assumption for evaluating whether the regression results can be interpreted causally. This assumption is often violated as a result of omitted variables, simultaneity (including reverse causality), and the occurrence of measurement errors (Wooldridge, 2013).

Omitted variables are defined as variables that correlate with an/several explanatory variable(s) and impact the explained variable, thereby causing the explanatory variable(s) to be endogenous and, accordingly, to correlate with unobserved determinants of the explained variable. Simultaneity describes a situation where the independent variable affects the dependent variable, but the dependent variable also has an effect on the independent variable. Reverse causality means that the dependent variable impacts the independent variable and not the other way around. The occurrence of measurement errors is especially relevant for violating the zero conditional mean assumption and leads to biased estimates (Wooldridge, 2013).

5.2.5 Homoskedasticity

Based on Wooldridge (2013), homoscedasticity requires the variance of the unobserved error term u to be the same for every value of the explanatory variable(s):

$$Var(u_i|x_1, \dots x_k) = \sigma^2$$

If the variance of the unobserved error term depends on the value of the explanatory variable(s), the model exhibits heteroskedasticity:

$$Var(u_i|x_1, \dots x_k) = {\sigma_i}^2$$

A consequence of heteroskedasticity is that standard estimates for the variance of the coefficient estimators are incorrect. Thus, statistical inference (e.g., t and F statistic, confidence intervals) is erroneous.[70] If the first four assumptions hold, and only the assumption of homoskedasticity fails, OLS estimators are only linear and unbiased estimators of the true population parameters, which means that heteroskedasticity does not threaten causal interpretation. Heteroskedasticity robust standard errors can be utilized in order to solve the problem of heteroskedasticity. The estimated coefficients will be the same, while only the standard errors will differ.

5.2.6 Normality

According to Wooldridge (2013), OLS estimators need to be normally distributed to test hypotheses. Therefore, the sixth assumption requires that the unobserved error term u does not depend on the independent variable(s), follows a normal distribution, and has a zero mean as well as the same variance σ^2:

$u \sim Normal(0|\sigma^2)$

5.3 Hypotheses Testing

After discussing necessary assumptions for OLS regressions, the following section outlines the testing of the three hypotheses derived in chapter 3. The regression results are presented at the end of this section, in Table 5-2.

5.3.1 Test of Hypothesis 1

The first hypothesis aims to investigate whether energy-saving attitudes positively influence energy-saving intentions.

To test H1, a simple linear regression, considering energy-saving attitudes as a predictor for energy-saving intentions, was conducted:

$y = \beta_0 + \beta_1 x + u$

y: *energy_saving_intentions*

[70] Usually standard errors are too small.

x: *energy_saving_attitudes*

u: *error term*

This approach is in line with the data analysis approach utilized by Abrahamse and Steg (2011), a research study closely related to this master's thesis.

In a preliminary step, it was ensured that the assumptions mentioned above were fulfilled.[71]

The first column in Table 5-2 indicates that a one-unit increase in energy-saving attitudes leads to a 0.754 unit increase in energy-saving intentions. The effect of energy-saving attitudes on energy-saving intentions reaches significance ($p < 0.01$) and supports H1. 32 % of the sample variation in energy-saving intentions is explained by energy-saving attitudes, which is considerable. The findings support the TPB, which states that the variable intentions to perform a specific behavior is a function of attitudes towards a behavior, subjective norms, and perceived behavior control. In sum, Hypothesis 1 is accepted.

5.3.2 Test of Hypothesis 2

The purpose of the second hypothesis is to examine whether energy-saving intentions negatively influence actual electricity consumption.

To test H2, the following multiple linear regression, considering energy-saving intentions as a predictor of actual electricity consumption and controlling for the average number of days per week a participant is at home as well as the treatment effect of the energy-saving feedback, was utilized:

$$\log(y) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + u$$

y: *electricity_consumption* (in kWh)

x_1: *energy_saving_intentions*

x_2: Control for *treatment* (energy-saving feedback) using a dummy variable

[71] See Appendix B 1 for details.

$x_2 = 1$: 'Enhanced' and 'Treatment' study class (received the same energy-saving feedback)

$x_2 = 0$: 'Control' study class

x_3: *occupied_days*

u: *error term*

Based on Bruderer Enzler et al. (2019), Huebner et al. (2016), Sapci and Considine (2014), as well as Thøgersen and Grønhøj (2010), the dependent variable, *electricity_consumption*, measured in kWh, appears in logarithmic form, because it is more realistic to assume that a one-unit increase in energy-saving intentions leads to a constant percentage decrease in electricity consumption, rather than a constant unit decrease in electricity consumption.

In a preparatory step for the analysis, it was confirmed that the assumptions mentioned in 5.2 were met.[72]

The second column in Table 5-2 reveals that a one-unit increase in energy-saving intentions is associated with an approximately 4.2 % decrease in electricity consumption, all else equal. However, the effect is not statistically significant, which is why this finding does not support H2 and the TPB.

On the other hand, the impact of 'occupied days,' measuring how many days on average a participant is at home during the week, on a household's electricity consumption, is statistically significant ($p < 0.1$). A one-day increase in average 'occupied days' per week is associated with an approximately 7.3 % increase in electricity consumption, all else equal. Finally, belonging to the treatment group and receiving additional energy-saving feedback is associated with an approximately 5.6 % decrease in electricity consumption, all else equal, though the effect is statistically insignificant.

The variables *energy_saving_intentions*, *occupied_days*, and *treatment* together explain about 13.6 % of the variation in electricity consumption, which is rather low, especially when taking

[72] See Appendix B 2 for details.

into consideration that the TPB assumes that intentions to perform a certain behavior are the main predictor of actual behavior.

It can, therefore, be concluded that the findings of H2 testing do not support the predicted negative effect of energy-saving intentions on electricity consumption. Nonetheless, the detected significant effect of the variable *occupied_days* underlines the importance of including it in analysis trying to explain electricity consumption behavior.

5.3.3 Test of Hypothesis 3

The third hypothesis investigates whether energy-saving intentions mediate the effect of energy-saving attitudes on actual electricity consumption.

The hypothesis is tested by means of a widely utilized approach in social science for testing mediation with regression analysis developed by Baron and Kenny (1986).[73] In their paper, they even refer to the TPB as a potential example for the application of their approach. The approach is described in more detail in the following section, while the path diagram in Figure 5-4 outlines the basis of their approach. Before conducting the regression analyses, it was once more confirmed that the assumptions mentioned in 5.2 were fulfilled.[74]

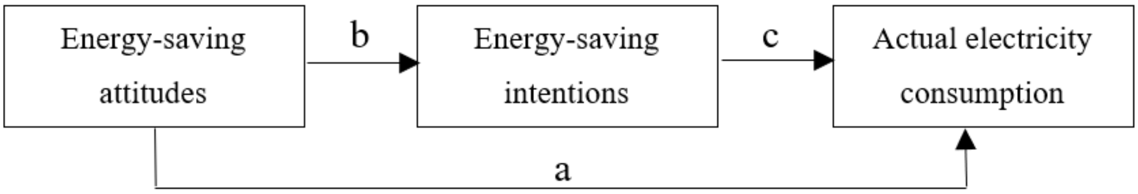

Figure 5-4: Path Diagram for the Mediation Effect of Intentions, based on Baron and Kenny (1986, p. 1176)

According to Baron and Kenny (1986), the variable *energy_saving_intentions* may be considered a mediator if three preconditions are fulfilled. They are to be described and tested in the following paragraphs.

[73] According to Research Gate (2021), the article was cited 44.770 times. In addition, MacKinnon et al. (2007) confirm that the approach developed by Baron and Kenny (1986) is widely applied in research studies testing the mediating effect of psychological variables. For example, Hansla et al. (2008) utilized the approach.

[74] See Appendix B 3 for details.

First, a statistically significant effect between energy-saving attitudes and actual electricity consumption must exist (represented in Figure 5-4 through path a). The following regression was used in order to test this effect:

$\log(y) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + u$

y: *electricity_consumption* (in kWh)

x_1: *energy_saving_attitudes*

x_2: Control for *treatment* (energy-saving feedback) using a dummy variable

> $x_2 = 1$: ‘Enhanced’ and ‘Treatment’ study class (received the same energy-saving feedback)
>
> $x_2 = 0$: ‘Control’ study class

x_3: *occupied_days*

u: *error term*

Although Baron and Kenny (1986) suggest utilizing a simple linear regression, it was necessary to control for the treatment effect and the average number of days the study’s participants were actually at home, as otherwise systematic differences between study participants were likely to occur, causing an over- or underestimation of the relationship between energy-saving attitudes and electricity consumption.[75]

The regression results presented in the third column of Table 5-2 indicate that a one-unit increase in energy-saving attitudes is associated with an approximately 14.7 % decrease in electricity consumption, all else equal. This effect is statistically significant ($p < 0.1$). Thus the first requirement is fulfilled.

It is worth mentioning that the effect of average occupied days per week on electricity consumption is statistically significant ($p < 0.05$). A one-day increase in average occupied days per week increased electricity consumption by approximately 9 %, all else equal.

[75] See 4.4.3 for a detailed explanation.

Conversely, being in the treatment group reduced electricity consumption by approximately 5 %, all else equal. However, the treatment effect is insignificant. The variables *energy_saving_attitudes*, *occupied_days*, and *treatment* together explain about 22.78 % of the variation in electricity consumption for this sample of single-households, which is considerably higher when compared to the obtained R^2 when testing H2.

The second prerequisite is that a statistically significant effect between energy-saving attitudes and energy-saving intentions must be present (represented in Figure 5-4 through path b). This effect was tested using the following linear regression:

$$y = \beta_0 + \beta_1 x + u$$

y: *energy_saving_intentions*

x: *energy_saving_attitudes*

u: *error term*

This linear regression is equal to the one utilized to test Hypothesis 1 in section 5.3.1. Therefore, based on the first column of Table 5-2, there is a statistically significant effect between energy-saving attitudes and intentions, which is why the second requirement is fulfilled.

The third condition necessitates a statistically significant effect between energy-saving intentions and actual electricity consumption (represented in Figure 5-4 through path c). The following regression was used to test this effect:

$$\log(y) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + u$$

y: *electricity_consumption* (in kWh)

x_1: *energy_saving_intentions*

x_2: Control for *treatment* (energy-saving feedback) using a dummy variable

> $x_2 = 1$: ‘Enhanced’ and ‘Treatment’ study class (received the same energy-saving feedback)
>
> $x_2 = 0$: ‘Control’ study class

x_3: *occupied_days*

u: *error term*

The regression equation is equal to the one used for testing Hypothesis 2 in section 5.3.2. It was controlled for the treatment effect and occupied days for the same reasons discussed with regard to the first requirement. The regression result in the second column of Table 5-2 reveals that there is no significant effect between energy-saving intentions and actual electricity. Accordingly, one necessary precondition for energy-saving intentions being a mediator is not fulfilled.

Therefore, it can be concluded that, unlike assumed by the TPB, energy-saving intentions do not mediate the effect of energy-saving attitudes on actual electricity consumption, and Hypothesis 3 is thereby rejected.

For the sake of completeness, the actual regression, which identifies whether energy-saving intentions mediate the effect of energy-saving attitudes on electricity consumption, is presented in the subsequent paragraph.[76]

The following regression was used to test the mediation effect:

$$\log(y) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + u$$

y: *electricity_consumption* (in kWh)

x_1: *energy_saving_intentions*

x_2: *energy_saving_attitudes*

x_3: Control for *treatment* (energy-saving feedback) using a dummy variable

[76] It is acknowledged that the fourth regression for detecting a mediator is criticized in recent literature as it does not calculate the indirect effect directly (MacKinnon et al., 2002). If the sample size was larger (minimum: $n = 180$ according to Wolf et al. (2013)), the researcher would have utilized Structural Equation Modeling (SEM) to test the mediation effect. According to Hair et al. (2014, p. 609), SEM is a *"[m]ultivariate technique combining aspects of factor analysis and multiple regression that enables the researcher to simultaneously examine a series of interrelated dependence relationships among the measured variables and latent constructs (variates) as well as between several latent constructs."* Several research papers related to this master's thesis (J. Du & Pan, 2021; Thøgersen & Grønhøj, 2010; van den Broek et al., 2019; S. Wang et al., 2018; Q.-C. Wang et al., 2021; D. Webb et al., 2013; Xu et al., 2021; Yang et al., 2016) utilized SEM. OLS regression analysis is not the best, but the most appropriate approach the researcher could utilize based on the small sample size.

$x_2 = 1$: ‘Enhanced’ and ‘Treatment’ study class (received the same energy-saving feedback)

$x_2 = 0$: ‘Control’ study class

x_4: *occupied_days*

u: *error term*

If, according to Baron and Kenny (1986), the effect of energy-saving attitudes on electricity consumption stays significant, this is evidence for a partial mediator. In contrast, they consider an insignificant effect to be evidencing the existence of a complete mediator.

Based on the regression results presented in the fourth column of Table 5-2, the effect of energy-saving attitudes is still significant, whereas the effect of energy-saving intentions on electricity consumption is not.

In summary, the results presented in Table 5-2 suggest a direct effect of energy-saving attitudes on energy-saving intentions and electricity consumption, while energy-saving intentions do not significantly affect electricity consumption. Furthermore, the variable occupied days has had a statistically significant positive effect on electricity consumption behavior in each regression conducted within the scope of this master’s thesis, which indicates its importance. In contrast to this, the treatment effect has proven statistically significant in none of the conducted regression analyses.[77]

[77] This is relevant for the IDEAL project because it reveals a rather weak effect of energy-saving feedback on electricity consumption. However, as the sample size of this study is rather small, leading to the fact that weak relationships are seldom statistically significant (Wooldridge, 2013) and analyzing the effect of providing energy-saving feedback was not the main focus of this master’s thesis, this result will not be discussed in more detail in the following discussion section.

Table 5-2: Regression Results

	(1) Energy-saving intentions	(2) Log(electricity consumption)	(3) Log(electricity consumption)	(4) Log(electricity consumption)
Energy-saving attitudes	0.754***		-0.147*	-0.167*
	(0.253)		(0.077)	(0.094)
Treatment		-0.056	-0.050	-0.044
		(0.143)	(0.134)	(0.138)
Occupied days		0.073*	0.090**	0.090**
		(0.038)	(0.037)	(0.038)
Energy-saving intentions		-0.042		0.025
		(0.059)		(0.069)
Constant	1.926	4.926***	5.442***	5.390***
	(1.572)	(0.394)	(0.431)	(0.461)
Observations	30	30	30	30
R^2	0.3200	0.1360	0.2278	0.2320

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6. Discussion

6.1 Main Insights

This thesis has aimed to analyze the relationship between psychological factors, including attitudes and intentions, and actual behavior through examining the link between energy-saving attitudes and intentions, and residential electricity usage behavior. The study was conducted on the basis of the following research question:

What effect do energy-saving attitudes and energy-saving intentions have on residential electricity consumption?

Data analysis revealed that energy-saving attitudes have a statistically significant effect on energy-saving intentions, providing support for H1. This result confirmed the role of energy-saving attitudes on energy-saving intentions as discussed by Abrahamse and Steg (2011), Ajzen et al. (2011), Ru et al. (2018), C. Chen et al. (2017), J. Du and Pan (2021), S. Wang et al. (2018), and Q.-C. Wang et al. (2021). However, the expected significant effect between energy-saving intentions and actual electricity consumption could not be detected, which is why H2 was rejected. This finding is in accordance with the results of van den Broek et al. (2019), Lee et al. (2020), D. Webb et al. (2013), and Xu et al. (2021). In addition, H3 was rejected as the assumed mediating effect of energy-saving intentions on the effect of energy-saving attitudes on electricity consumption could not be proven. Instead, there seems to be a direct link between energy-saving attitudes and electricity consumption, as a statistically significant effect was identified between both variables. These findings are in line with the obtained results of Seligman et al. (1979), Sapci and Considine (2014), and Abrahamse and Steg (2011), who detected a significant direct effect of attitudes on actual energy consumption behavior of private households. Accordingly, the study's results strengthened these researchers' findings. Consequently, this master's thesis has provided evidence for the intention-behavior gap, while not confirming the attitude-behavior gap.

6.2 Theoretical Implications

The TPB, which states that actual behavior can mainly be predicted based on behavioral intentions (Ajzen, 2005), formed the research basis of this thesis. However, in contrast to Seligman et al. (1983), who provided evidence for the usefulness of the TPB in order to explain residential energy consumption, this study's findings, at first glance, do not support an application of the TPB as a theoretical framework for explaining the relationship between energy-saving attitudes, energy-saving intentions, and electricity consumption behavior.

Ajzen (2020) lists several potential reasons explaining why behavioral intentions might be a weak predictor of actual behavior.

First, intentions may change over time. Since there was a time gap between the measurement of energy-saving attitudes and intentions on the one hand and the focus period, on the other hand, this could potentially explain the insignificant effect of energy-saving intentions on electricity consumption.[78]

Second, intentions are often biased towards the socially desirable outcome, which was one of the main reasons for analyzing actual electricity consumption behavior and, in doing so, potentially explaining the insignificant relationship.

Third, Ajzen (2020) reveals that individuals may forget about their behavioral intentions, which does not seem to be a convincing argument with regard to this study, as this thesis has analyzed electricity consumption data from a sample participating in a study about energy-saving feedback.

Finally, if individuals have low perceived behavioral control, behavioral intentions will be a poor predictor. As perceived behavioral control is related to the individual's perceived ability to control their behavior and depends on the individual's available resources such as ability and time (Ajzen, 1991), and routines and habits largely influence electricity consumption behavior (Darnton et al., 2011; Jakučionytė-Skodienė et al., 2020; van den Broek et al., 2019; Verplanken & Aarts, 1999; S. Wang et al., 2018); this might explain the weak relationship between energy-saving intentions and actual electricity consumption. For example, Xu et al. (2021) find no significant link between energy-saving intentions and self-reported energy-saving behavior but a strong relationship between perceived behavioral control and self-reported energy-saving behavior. Furthermore, Abrahamse (2019) underlines the relative importance of perceived behavior control for explaining energy-saving behavior. Therefore,

[78] See 7.2 for more details.

the TPB could potentially be utilized to give reasons for the insignificant effect between intentions and actual behavior.[79]

However, the abovementioned reasons do not explain the significant direct effect between energy-saving attitudes and electricity consumption. This suggests the conclusion that the reasoned approach of the TPB, which assumes only an indirect impact of behavioral attitudes on actual behavior, appears to be too narrow.

6.3 Contribution to the Literature

This master's thesis contributes to the green gap research focusing on residential energy consumption behavior. The literature review in chapter 2 revealed several limitations of current research studies. The study complements existing literature by (1) using actual electricity consumption data, (2) focusing on single households, and (3) controlling for the average time participants spent at home.

Even though there has already been extensive academic literature focusing on various determinants of self-reported energy-saving behavior of private households, research based on actual energy consumption data is limited. Unlike large parts of previous research, this master's thesis has examined real electricity consumption data, thus adding relevant insights to academic literature.

Furthermore, most reviewed studies focusing on actual energy consumption data assumed that energy-saving attitudes and/or intentions were the same for all household members. Measuring energy-saving attitudes and/or intentions for household residents separately or differentiating between the effect of attitudes and/or intentions on energy consumption in multi-person households and single-households has, so far, been scarcely addressed. Hence, this study contributes to the extent that it focused on one-person households in order to accurately capture the effect of energy-saving attitudes and intentions on residential electricity consumption.

[79] The researcher acknowledges that this thesis focused only on the variable 'energy-saving intentions' and could not measure perceived behavioral control, limiting this study's explanatory power and is discussed in more detail in chapter 7.

Finally, this master's thesis was the first study that controlled for the average number of days per week a participant is at home when investigating the effect of the psychological variables on electricity consumption. The analysis confirmed that a household's electricity consumption depends on participants' time spent at home, independent of their energy-saving attitudes and intentions. This finding suggests that future studies analyzing the effect of psychological determinants on electricity consumption should also control for this factor.

6.4 Policy Implications

Many governments around the globe have introduced different programs to increase energy-conserving behavior within private households (L. Du et al., 2017; Yue et al., 2013). A better understanding of residential electricity consumption behavior is fundamental for developing effective policy strategies to reduce private households' carbon footprints (Belaïd & Joumni, 2020). Therefore, besides theoretical implications and a contribution to the green gap literature, two energy policy implications can be deduced from this master's thesis.

First, energy policy intended to reduce residential electricity consumption, such as public information campaigns, should ideally focus on increasing households' energy-saving attitudes.

Second, the findings of this research project suggest that energy policy should especially focus on private households that spend a large amount of their time at home (e.g., retired people or people working from home) as total electricity saving potential is highest for these population groups. In times of the ongoing COVID-19 pandemic, the findings of this study are especially relevant, as the way of working has changed dramatically, and more and more companies are offering hybrid ways of working (Schilirò, 2021), which means that many people spend more time at home. Accordingly, when designing new energy-saving programs, these people should be targeted in particular.

7. Limitations

This chapter discusses the study's validity and reliability.

7.1 Validity

Based on Saunders et al. (2020), validity in quantitative research is associated with the question: 'What did the researcher measure?' Validity can be further split into internal and external validity, which are to be defined and addressed in the following paragraphs.

7.1.1 Internal Validity

Internal validity, sometimes termed measurement validity, is concerned with the accuracy of the research study's findings (Saunders et al., 2020). It is related to whether the IDEAL Household Energy Dataset includes measured information necessary to answer the research question. Jacob (1984) and Kervin (1992) acknowledge that using secondary data as the primary data source can lead to invalid research results if the utilized variables do not measure what the researcher intends to measure. Accordingly, the following section is critical for evaluating this master's thesis findings.

As this study utilized two different data types (power sensor readings and survey responses) from the IDEAL Household Energy Dataset, the subsequent section discusses, first of all, the internal validity of the power sensor readings as well as the derived estimates for electricity consumption and, in a second step, the accuracy of the utilized survey questions and responses to measure energy-saving attitudes and intentions. Finally, the accuracy of the hypotheses testing is to be reviewed.

7.1.1.1 Accuracy of the Power Sensor Readings

According to Pullinger et al. (2021), the installed sensor system was subjected to wide-ranging developments, prototyping, and testing in order to ensure a high degree of technical accuracy. The IDEAL home energy advice project researchers did several quality checks at the manufacturing plant of the sensor boxes, and only trained technicians were allowed to install the sensor systems. Furthermore, the scientists tested the precision of the measurements by analyzing the households' baseload as well as the load when turning on one electric appliance. They measured the power usage separately with an electric power consumption instrument, which confirmed that the installed sensor boxes obtained high measurement accuracy. In addition, the scientists accepted only households for which stable signal propagation for the sensor system could be guaranteed.[80] Based on this information, the power sensor readings in the IDEAL Household Energy Dataset can be assumed to be high-quality data.

7.1.1.2 Accuracy of the Estimates for Electricity Consumption

The provided sensor measurements of apparent and/or real power in the IDEAL Household Energy Dataset were not the ideal input data in order to answer the research question of this master's thesis, as they necessitated the development of an appropriate method for estimating electricity consumption. The researcher's approach of transforming apparent power measurements into estimates of real power measurements reveals itself as criticizable. Using the average power factor of the calculated mean power factors of the households in the 'enhanced' study class in order to transform apparent power measurements for the 'control' and 'treatment' study class into estimates for real power measurements was certainly not the best approach. After all, a household's power factor depends on the switched-on electric appliances and can, accordingly, fluctuate considerably. The mean power factors for the private homes in the 'enhanced' study class vary already a lot,[81] which is why it can be assumed that they would also differ for the households in the 'treatment' and 'control' study class. Given that the power factor could not be calculated for the households in the 'control' and 'treatment' study class and that no reliable reference for the power factor of a private home was found, the utilized approach for transforming apparent power measurements into estimates of real power measurements was the most appropriate approach the researcher could think of, given the time and resource constraints. However, the researcher concedes that this transformation process is a limitation that needs to be considered when interpreting the study's findings.

Although Pullinger et al. (2021) considered many potential issues with the sensor system and even tested different battery models, they could not entirely prevent the occurrence of missing data. As a result, the researcher needed to exclude four households from the sample due to too

[80] See Table 4-1 for details.

[81] See Appendix A 7 for details.

many missing data points to ensure a high degree of internal validity.[82] For the remaining 30 households, it was necessary to fill time gaps in order to receive comparable electricity consumption measurements for the focus period. The utilized methods for filling time gaps[83] can be criticized, especially the usage of historical data from the previous day to fill time gaps larger than two hours can be scrutinized. The researcher acknowledges that this method does not consider that electricity consumption differs between working days and weekends. However, as most time gaps greater than two hours occurred during the night (between 1 am and 5 am), the use of historical data was nonetheless considered an appropriate method to fill these time gaps.

Finally, the applied method for converting real power measurements[84] and estimates for real power measurements[85] into estimates for electricity consumption during the focus period is based on elementary electrical engineering and can therefore be considered appropriate.

7.1.1.3 Accuracy of the Survey Questions Measuring Energy-Saving Attitudes and Intentions

To assure a high level of internal validity in surveys, Cooper and Schindler (2014) underline the importance of construct and content validity, which are to be discussed in more detail in the following sections.

With regard to this master’s thesis, construct validity is associated with whether the survey questions actually measure the concepts of energy-saving attitudes and intentions. Therefore, by analyzing previously conducted research studies related to the research question and comparing utilized questions with the provided questions and responses in the IDEAL Household Energy Dataset, the researcher tried to ensure a high level of construct validity (Cooper & Schindler, 2014; Saunders et al., 2020).

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[82] The sum of time gaps greater than two hours for these four households ranged between 14 and 25 days. It would not be possible to obtain precise estimates for their electricity consumption during the focus period, which was approximately 38 days long. See Appendix A 2 for details.

[83] The nearest-neighbor approach was utilized for time gaps smaller than or equal to two minutes. Next, time gaps larger than two minutes but smaller than or equal to two hours were filled via linear interpolation. Finally, time gaps larger than two hours were filled with measurements of the previous day.

[84] The IDEAL Household Energy Dataset provided real power measurements for the households in the study class ‘enhanced.’

[85] The IDEAL Household Energy Dataset did not provide real power measurements for the households in the study class: ‘control’ and ‘treatment.’ Therefore, estimates for real power, based on apparent power measurements, were utilized.

According to Pullinger et al. (2021), the utilized questionnaires in the conducted surveys were, to a large extent, well-established survey questions from Scottish and international state or academic surveys. However, the questions used for measuring energy-saving attitudes and intentions were newly developed by the IDEAL researchers, which is a limitation.

Furthermore, the researcher cannot completely exclude the possibility that the selected question to measure energy-saving intentions was not accurate enough, which might potentially explain the rejection of Hypothesis 2.

Content validity of this master's thesis is concerned with whether the survey questions cover all facets of energy-saving attitudes and intentions. The researcher evaluated content validity based on a detailed literature review (Cooper & Schindler, 2014; Saunders et al., 2020) and has to acknowledge that the concept of energy-saving intentions is not completely covered, as only one question from the primary survey was utilized for measuring energy-saving intentions.[86] This is a limitation of the study, which could potentially explain the insignificant effect of energy-saving intentions on actual electricity consumption.

Furthermore, although the concept of energy-saving attitudes was measured by means of three survey questions, the researcher recognizes that the concept of energy-saving attitudes might not be covered completely. Additionally, the researcher was unable to validate the accuracy of the questions utilized to measure energy-saving attitudes via confirmatory factor analysis, as the sample size was too small.

In summary, it must be concluded that the utilized questions to measure energy-saving attitudes and intentions were not the perfect questions for measuring these concepts, which needs to be taken into account when interpreting the study's results.

7.1.1.4 Accuracy of the Hypotheses Testing

During hypotheses testing (H2 & H3), the researcher ensured a high degree of internal validity by controlling for occupied days and the treatment effect related to the systematic difference in energy-saving feedback.

[86] No other question in the conducted surveys has fitted the definition of energy-saving intentions.

As the sample size is small ($n = 30$), the researcher admits that the obtained OLS estimators might not be very precise,[87] leading to larger confidence intervals and less accurate hypothesis testing (Wooldridge, 2013).

Another threat to the accuracy of the hypotheses testing (H2 & H3) is that the IDEAL researchers did not ask study participants to register changes in their electricity tariff: Only once did they ask the households[88] to provide information about their electricity tariff. However, if changes in their electricity tariff did occur during the research period, these tariff changes might have motivated the households to change their consumption behavior. The researcher cannot exclude the possibility of an electricity tariff change during the focus period, which is a limitation of this study.

Furthermore, although the participating households are all located in the same region of Scotland, there could still be differences in weather, causing a systematic difference in electricity consumption between homes in Edinburgh, Fife, East Lothian, and Midlothian. This might have reduced the accuracy of the obtained OLS estimators.

Additionally, as explained in 2.5.1, the TPB states that behavioral intentions and perceived behavioral control are good predictors for actual behavior. However, this master's thesis has focused only on the link between behavioral intentions and actual behavior. It did not include a variable for perceived behavioral control, because the IDEAL Household Energy Dataset does not contain relevant questions that could be utilized to measure a household's perceived behavioral control. This is a limitation. By way of example: People may have very high energy-saving intentions but, nonetheless, assume that they think they lack the resources required for reducing their electricity consumption. In that case, they will likely have a high electricity consumption level, which aligns with the practicality barrier for pro-environmental action defined by Blake (1999) as well as the immediate selective motives related to personal needs outlined by Kollmuss and Agyeman (2002). Therefore, this missing variable, 'perceived

[87] The precision of OLS estimators is determined via their variance: $Var(\hat{\beta}_j) = \frac{\sigma^2}{SST_j(1-R_j^2)}$. See Appendix B 4 for a detailed discussion.

[88] Either during the primary participant survey (before the 9th of March 2017) or in the IDEAL app (after the 9th of March 2017) at the beginning of the measurement period.

behavioral control,' could be an explanation for the insignificant effect between energy-saving intentions and actual electricity consumption.

To sum it up, several limitations related to internal validity need to be considered when interpreting this master's thesis's findings.

7.1.2 External Validity

External validity focuses on whether it is possible to generalize the study's findings (Saunders et al., 2020). The first part of this section critically discusses the external validity of the IDEAL home energy advice project, which was the primary data source of this master's thesis. The second part focuses on the decisions during the research phase that might have potentially threatened external validity.

First of all, Pullinger et al. (2021) targeted households that have a certain interest in their energy usage behavior and smart technology during the recruitment process. Therefore, the occurrence of a selection bias is likely, which is underpinned by an upwards bias in education, income, and energy-saving attitudes and intentions in the sample and might have limited the generalizability of the study's findings. Furthermore, females were overrepresented in this study. However, it should be noted that these concerns are common problems in green gap research studies.[89]

Another constraint is that the IDEAL home energy advice project is geographically limited to Scotland and that, accordingly, this master's thesis's findings, if at all, apply to the Scottish population only. Since the IDEAL home energy advice project had several eligibility criteria[90] qualifying for participation in the research study, it is questionable whether the whole Scottish population is represented in the IDEAL Household Energy Dataset.

First, study participants had to live in Edinburgh, South Fife, or Lothians. Although these regions have high population densities (National Records of Scotland, 2019), they do not represent the whole Scottish population. Second, the eligibility criteria also excluded households with pre-payment methods, which make up 18 % of Scottish Electricity customers

[89] For details, see 2.4.6.

[90] See Table 4-1 for details.

(Matthews & Scherr, 2020). Third, participating households had to fulfill several technical requirements. They were, for example, required to have installed a gas water and space heating system. In addition to this, the households were not allowed to have either one of the following major electricity consumers: an electric vehicle, an air-conditioner, or a heat pump. Moreover, microgeneration and heat storage technologies were not permitted. All these technical requirements decrease the external validity of this study's findings. Fourth, at least one resident per household was required to have intermediate digital knowledge. This prerequisite leads to the exclusion of large parts of the elderly population, which is reflected in the fact that the majority of this study's sample belongs to the working-age population. All in all, the eligibility criteria reduce the generalizability of the study's findings.[91]

The researcher decided to focus on single households in the IDEAL home energy advice project during the research process because it cannot be assumed that all residents in multiperson households have the same energy-saving attitudes and intentions. However, the average Scottish household had 2,15 residents in 2018 (Scottish Government Statistics, 2018), which leads to yet another external validity sacrifice.

Furthermore, the researcher recognizes the trade-off between internal and external validity when reducing the sample from 34 to 30 due to large measurement gaps in the sensors measuring the households' power usage.

Lastly, this master's thesis has focused on residential electricity consumption at the end of spring/beginning of summer, obtaining results valid for these seasons only.

All in all, it is acknowledged that the results of this study are not likely to be generalizable.

7.2 Reliability

Reliability is related to the consistency and robustness of this master's thesis's results. It is associated with whether it is probable to obtain identical results if the study is replicated and whether other scientists would derive the same conclusions based on the raw data (Cooper &

[91] However, it should be noted that the eligibility criteria increase the internal validity of the study. There is often a conflict between internal and external validity in research (Saunders et al., 2020).

Schindler, 2014; Saunders et al., 2020). Therefore, the following section evaluates the utilized data collection and analysis techniques.

Robson and McCartan (2015) describe four threats to reliability, namely participant error or bias and observer error or bias. First, participant error is concerned with factors related to the research process that might influence participants' survey answers or electricity consumption behavior. Regarding the survey responses, the IDEAL researchers utilized an interviewer-administered questionnaire for the primary face-to-face interview and neutral wording for all conducted questionnaires. Concerning electricity consumption behavior, the IDEAL project used passive data collection methods, reducing the interaction between participants and researchers to a minimum. Therefore, the occurrence of a participant error is unlikely. Second, participant bias is related to participants not answering/acting truthfully for fear of negative consequences. As participants signed up voluntarily to take part in the study, the risk of participant bias seems negligible as well. Third, observer error focuses on how data is collected during the research process. Based on the discussion in section 7.1.1.1, the fact that the surveys in the IDEAL research project were pilot-tested, and an interviewer-administered questionnaire for conducting the face-to-face interview was utilized, a high degree of structure and standardization during the data collection process is evident. Therefore, the risk of observer errors is expected to be low. Fourth, observer bias is associated with interpretation problems. As this master's thesis has utilized OLS regression analysis to test the three hypotheses and derive its conclusions, the risk of observer bias is, once again, low. The study is based on a structured and well-explained methodology, which is why it should be possible to reproduce the results of this thesis without difficulties.

However, the researcher has noticed one threat to reliability. Since there is a time discrepancy between the measurement of energy-saving attitudes and intentions on the one hand and the focus period, where electricity consumption was measured, on the other hand, the households' energy-saving intentions might potentially have changed over time (Kollmuss & Agyeman, 2002). This might also explain the insignificant effect of energy-saving intentions on electricity consumption. The researcher could only check the response consistency of two questions utilized to measure energy-saving attitudes,[92] while the question employed to

[92] See section 4.4.1 and Appendix A 5 for details.

measure energy-saving intentions was asked only once, therefore not allowing a response consistency check.

8. Future Research

The first paragraph of this chapter focuses on potential future research based on the IDEAL Household Energy Dataset. The second part goes one step further by discussing future research topics beyond the IDEAL Household Energy Dataset.

First of all, one of the main limitations of this master's thesis is the utilized approach of transforming apparent power measurements into estimates for real power measurements. Future research could focus on this issue by finding a more appropriate process that considers that each household's power factor varies and depends on the switched-on electric appliances. Since the IDEAL Household Energy Dataset provides information about the ownership of electric devices, this information could be an ideal starting point for improving the process of transforming apparent into real power measurements.

Second, as the applied methods to fill time gaps in the power measurements can be criticized, future research could utilize, for example, machine learning techniques like k-nearest neighbor (M. C. Wang et al., 2021) to add missing data. It would be interesting to see if comparable estimates for households' electricity consumption are obtained.

Third, as pointed out in the previous limitation section, controlling for weather conditions (e.g., temperature and cloud coverage) in the different regions (Edingburgh, Fife, Lothian) could further increase the accuracy of the regression results and should be considered in potential future research studies related to this master's thesis.

Fourth, although this master's thesis indicated that, unlike energy-saving intentions, energy-saving attitudes directly affect electricity consumption, further research is necessary to verify the generalisability of these findings. For example, the study could be extended in terms of the sample size. Due to resource constraints as well as the assumption that energy-saving attitudes and intentions may vary within one and the same multiperson household, this study focused on single-households. However, there are several multiperson households in the dataset, for which it would be possible to construct energy-saving attitudes[93] for each individual household

[93] It is not possible to measure energy-saving intentions for all residents in a household as only the primary participant of each household answered the question utilized to measure energy-saving intentions.

member because the three questions utilized to construct energy-saving attitudes were part of the All-occupant surveys.

Next to increasing the sample size, future research could analyze the influence of energy-saving attitudes and intentions on gas consumption, as the IDEAL Household Energy Dataset also provides whole-home gas usage measurements. So far, this study has focused on electricity consumption. Still, it would be interesting to see whether comparable results are obtained when extending the study to residential gas consumption.

As this master's thesis has found evidence for scrutinizing the utilization of the TPB as a theoretical framework to explain the relationship between energy-saving attitudes and intentions and residential electricity consumption, future research could test other theories for explaining the relationship between psychological variables and actual behavior. For example, the Value-Attitude-Behavior Theory developed by Homer and Kahle (1988) could be applied to the IDEAL Household Energy Dataset. Since this master's thesis has already found a direct effect of energy-saving attitudes on electricity consumption, Homer and Kahle's theory might be more appropriate. In addition, the IDEAL Household Energy Dataset includes several survey questions about human values from the World Values Survey (Inglehart et al., 2018), which are grounded in the Theory of Basic Human Values (Schwartz, 1992, 1994). Thus, it would be possible to test the whole sequence of the Value-Attitude-Behavior Theory.

Going beyond the IDEAL Household Energy Dataset, the whole sequence of the TPB should be tested in the context of residential electricity consumption behavior, with a special focus on the variable 'perceived behavioral control.' After all, the explanatory power of this master's thesis is too limited to conclude whether the TPB is an appropriate theoretical framework for explaining residential electricity consumption behavior.

Additionally, based on the literature review findings, there is a clear need for standardization regarding the measurement of attitudes, intentions, and self-reported energy consumption behavior in order to increase the comparability of research results.

Besides, more researchers should utilize a longitudinal study design, as energy consumption varies significantly over seasons. Furthermore, scientists should measure attitudes and intentions several times over the research period, factoring in that attitudes and/or intentions may change over time (Kollmuss & Agyeman, 2002).

Moreover, based on the still rather small explanatory power of energy-saving attitudes,[94] future research should further explore additional factors influencing residential electricity consumption behavior such as, for example, socio-demographic and dwelling characteristics, ownership and usage of electrical appliances, and climate.

As mentioned in the limitation section, the dataset excluded households using prepayment methods to pay their energy bills. These households are often vulnerable and suffer from energy fuel poverty. Future research should pay special attention to this population group, as reducing their energy consumption would have a large impact on their energy bill and would increase their household income disproportionally (Matthews & Scherr, 2020).

Since this study has focused on four regions in Scotland, future research should include other geographic areas in Scotland and expand beyond Scotland to investigate whether the study's results can be generalized.

Finally, future research studies need to aim for a balanced sample in terms of gender, education, and income to increase the external validity of the findings. Moreover, ways must be found to recruit not only people who are interested in energy-saving but also people who are not at all concerned about their energy consumption. After all, insights into their energy consumption behavior have, so far, been just as scarce as they would be valuable to current research projects.

[94] $R^2 = 0.2278$, when controlling for *occupied_days* and *treatment* in addition.

9. Conclusion

This master's thesis sought to identify the links, if any, between energy-saving attitudes and intentions as well as the electricity consumption behavior of private households.

Three hypotheses based on the Theory of Planned Behavior were derived. These hypotheses were tested utilizing the IDEAL Household Energy Dataset as a primary data source. The study focused on 30 single-households participating in the IDEAL research project. These households' individual responses to survey questions measuring energy-saving attitudes and intentions were matched with electricity consumption estimates based on sensor data measuring instantaneous power usage between 30th April and 7th June 2018.

The results indicate that energy-saving attitudes have a negative effect on electricity consumption, whereas no statistically significant effect between energy-saving intentions and actual electricity consumption was found. Consequently, this master's thesis provides evidence for the intention-behavior gap, while it does not confirm the attitude-behavior gap.

Moreover, the presumed mediating effect of energy-saving intentions on the relationship between energy-saving attitudes and electricity consumption could not be confirmed. Thus, based on the study's findings, the reasoned approach of the Theory of Planned Behavior seems to be too narrow to explain the link between the psychological variables and residential electricity consumption behavior. However, there are several limitations related to this study. Therefore, further research is necessary in order to be able to conclude whether the theoretical framework of the Theory of Planned Behavior is applicable to explain the link between energy-saving attitudes and intentions and residential electricity consumption.

Finally, this study was the first study to analyze the effect of psychological factors on residential electricity consumption, while controlling for the time an individual spends at home. The results of this master's thesis underline the importance of this variable. Accordingly, future research studies investigating the link between psychological factors and household energy consumption should include this variable in their analysis.

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List of Appendices

Appendix A

Appendix B

Appendices

Appendix A – IDEAL Household Energy Dataset

Appendix A 1: Map of Edinburgh and the South-East City Region of Scotland

For the research project, households were recruited from all highlighted regions apart from the Scottish Borders region.

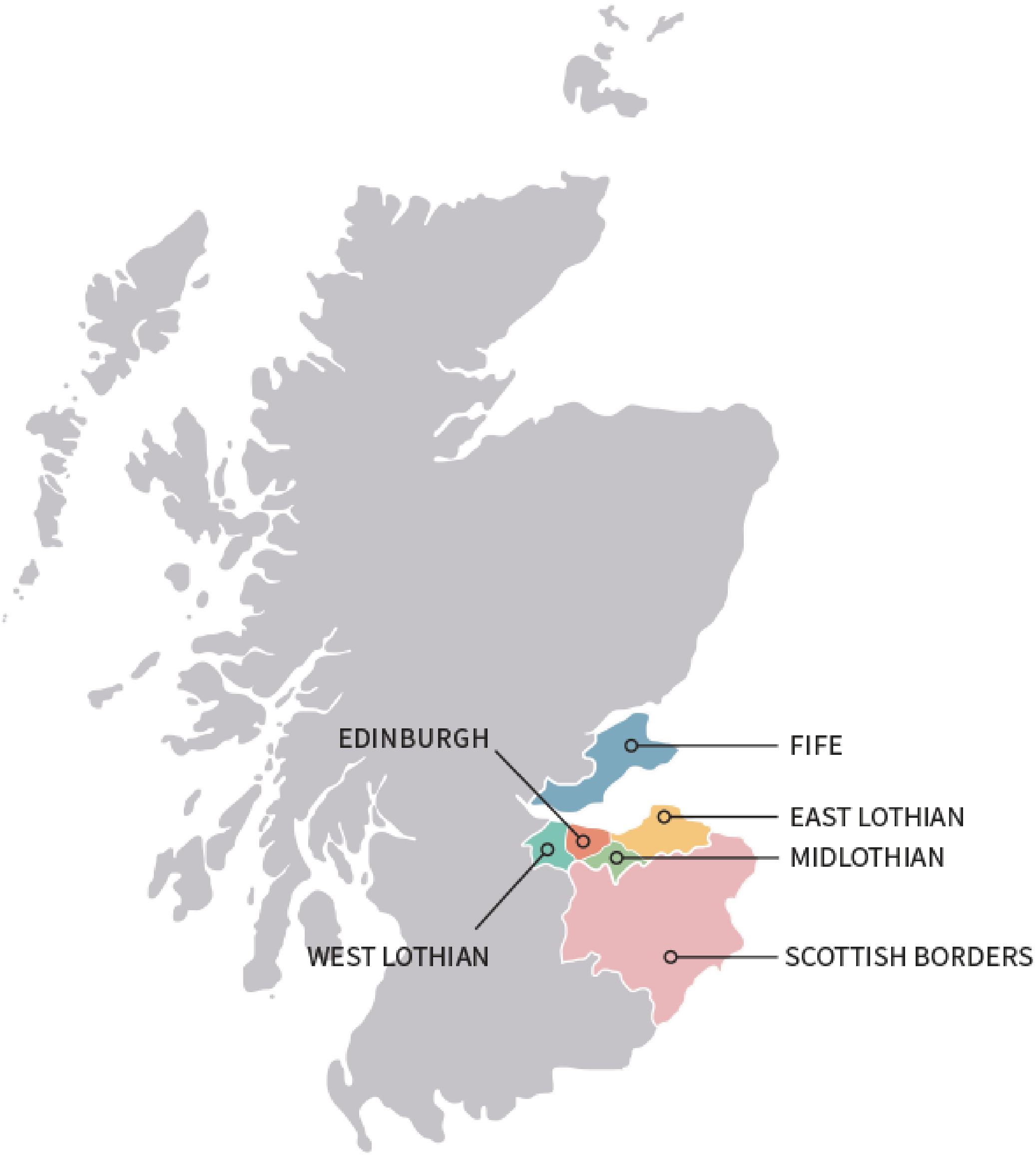

Figure A1-1: Map of the Study Location in Scotland (The Edinburgh and South East Region, 2015)

Appendix A 2: Data Cleaning

The collected whole-home electricity usage data in the IDEAL Household Energy Dataset could not be used directly. Instead, the dataset was cleaned following the data preprocessing steps described in Völker et al. (2021). The researcher utilized the programming language Python (Python Software Foundation, 2020), version 3.8.6, for all cleaning steps.

The first step concerned data validation and included eliminating anomalous readings; this was already done during the data collection process explained in Pullinger et al. (2021). According to Pullinger et al. (2021), erroneous values are electricity spikes above 20 kW/second; these values have already been removed from the raw dataset such that maximum measured apparent and real power data points ranged from 4770W to 16331W and 5820W to 12621W, respectively.

As Pullinger et al. (2021) point to sensor failures, time gaps were identified in a second step. Table A2-1 lists the sum of power measurement gaps for three different time gap categories for each of the 34 households in the sample. Time gaps were categorized into time gaps smaller or equal to 2 minutes, time gaps greater than 2 minutes, and smaller or equal to 120 minutes, and time gaps greater than 120 minutes.

Table A2-1: Sum of Power Measurement Gaps per Household

Study class	**HomeID**	**Gap ≤ 2min**	**2min < Gap ≤ 120min**	**Gap > 120min**
treatment	70	00:26:07	04:12:28	4 days, 5:22:25
treatment	77	00:28:57	03:55:53	21 days, 17:18:03
enhanced	90	00:25:47	1 day, 13:00:22	1 day, 16:38:08
treatment	100	00:32:15	06:57:20	3 days, 1:02:19
treatment	101	01:50:49	08:19:54	7 days, 1:55:58
enhanced	106	01:32:18	1 day, 5:31:32	5 days, 20:22:03
control	117	13:09:03	09:31:59	3 days, 1:10:19
control	120	00:30:08	05:30:21	3 days, 1:16:25
enhanced	128	00:07:32	1 day, 9:06:29	1 day, 16:50:49
enhanced	136	20:09:04	1 day, 9:42:23	1 day, 16:52:03
control	193	1 day, 5:14:19	3 days, 2:01:27	3 days, 9:17:10
control	194	00:31:32	03:38:53	3 days, 3:19:06
treatment	197	07:29:01	09:18:20	18 days, 2:09:29
treatment	202	21:07:49	2 days, 1:44:59	3 days, 1:13:48
control	203	00:17:04	05:20:31	3 days, 1:02:36
control	209	00:10:29	07:12:01	2 days, 23:07:17
treatment	213	17:24:58	1 day, 2:35:43	25 days, 20:32:09
treatment	216	03:57:21	7 days, 15:45:51	3 days, 2:46:03

Table A2-1 (continued)

Study class	**HomeID**	**Gap ≤ 2min**	**2min < Gap ≤ 120min**	**Gap > 120min**
treatment	235	13:11:54	1 day, 0:41:17	2 days, 23:14:30
treatment	251	00:20:02	07:06:27	2 days, 23:12:56
control	257	1 day, 18:05:22	3 days, 23:56:48	3 days, 3:46:21
enhanced	268	00:23:52	1 day, 9:31:15	1 day, 16:40:09
control	275	03:12:35	03:29:02	3 days, 3:02:36
control	279	00:25:50	04:02:36	3 days, 3:02:36
treatment	289	19:25:37	6 days, 18:10:17	14 days, 22:24:55
control	295	05:52:53	07:21:45	3 days, 8:13:23
control	299	00:36:28	03:30:03	3 days, 3:31:01
treatment	300	00:17:40	05:03:25	6 days, 23:39:05
treatment	313	04:43:56	21:52:46	3 days, 3:18:42
treatment	317	6 days, 19:46:55	2 days, 6:33:44	5 days, 10:30:57
control	321	00:33:47	06:04:47	3 days, 1:23:38
treatment	323	01:39:47	03:44:06	3 days, 3:18:34
enhanced	328	00:24:36	07:19:27	4 days, 2:33:04
treatment	332	09:26:16	14:49:07	6 days, 6:12:56

Figure A2-1 illustrates the information presented in the table. The researcher decided to exclude four households (77, 197, 213, and 289) from the study for internal validity reasons. The more time gaps greater than 120 minutes exist, the lower the accuracy of the final calculated value for the consumed electrical energy for the focus period and the lower the robustness of the research study's findings. Internal validity conflicts with external validity because excluding households from the analysis leads to a smaller sample such that the study's conclusions are less generalizable. However, with 34 homes, the sample is already small, such that generalization of the study's findings is already an issue and is addressed in section 7.1.2 in detail. Therefore the researcher decided to prioritize internal over external validity, and the sample was reduced to 30 homes.

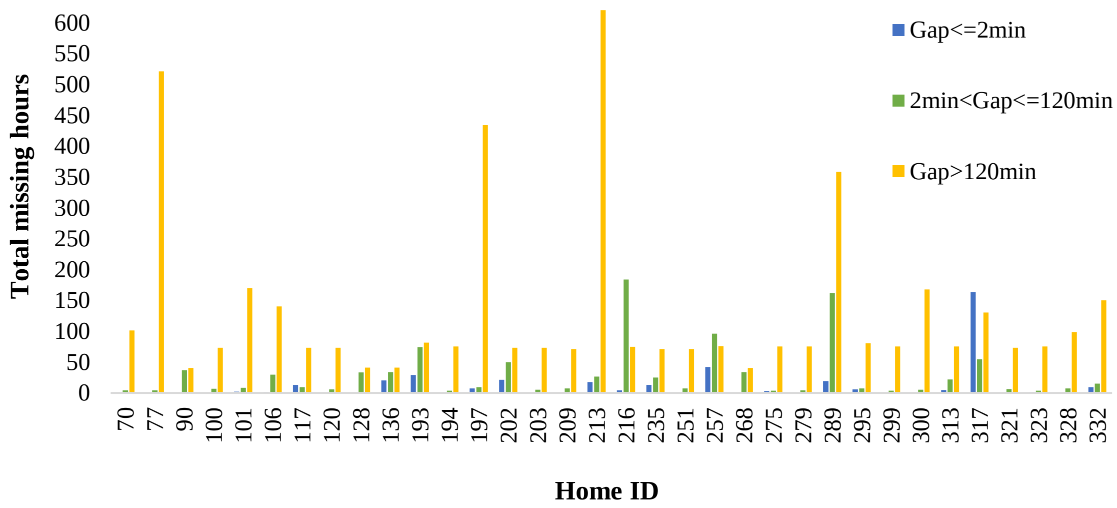

Figure A2-1: Sum of Power Measurement Gaps per Household, divided into Gaps smaller or equal to Two Minutes, Gaps greater than Two Minutes and smaller or equal to 120 Minutes, and Gaps greater than 120 Minutes

Figure A2-2 visualizes the identified gaps greater than 120 minutes. It shows that a majority of gaps occurred during the same time. For households, part of the ‘enhanced’ study class, whole-home electricity consumption was measured most accurately (6-20 measurement gaps), followed by homes in the ‘control’ (19-22 measurement gaps) and ‘treatment’ study class (19-26 measurement gaps). One significant measurement error, resulting in a gap ranging from 27 h 31 min 23 s to 124 h 34 min 38 s, occurred in all households between the 9th and 15th of May. Time gaps greater than two hours ranged from 2 h 0 min 1 s to 124 h 34 min 38 s. The average and the median were 4 h 33 min 52 s and 2 h 9 min 57 s, respectively.

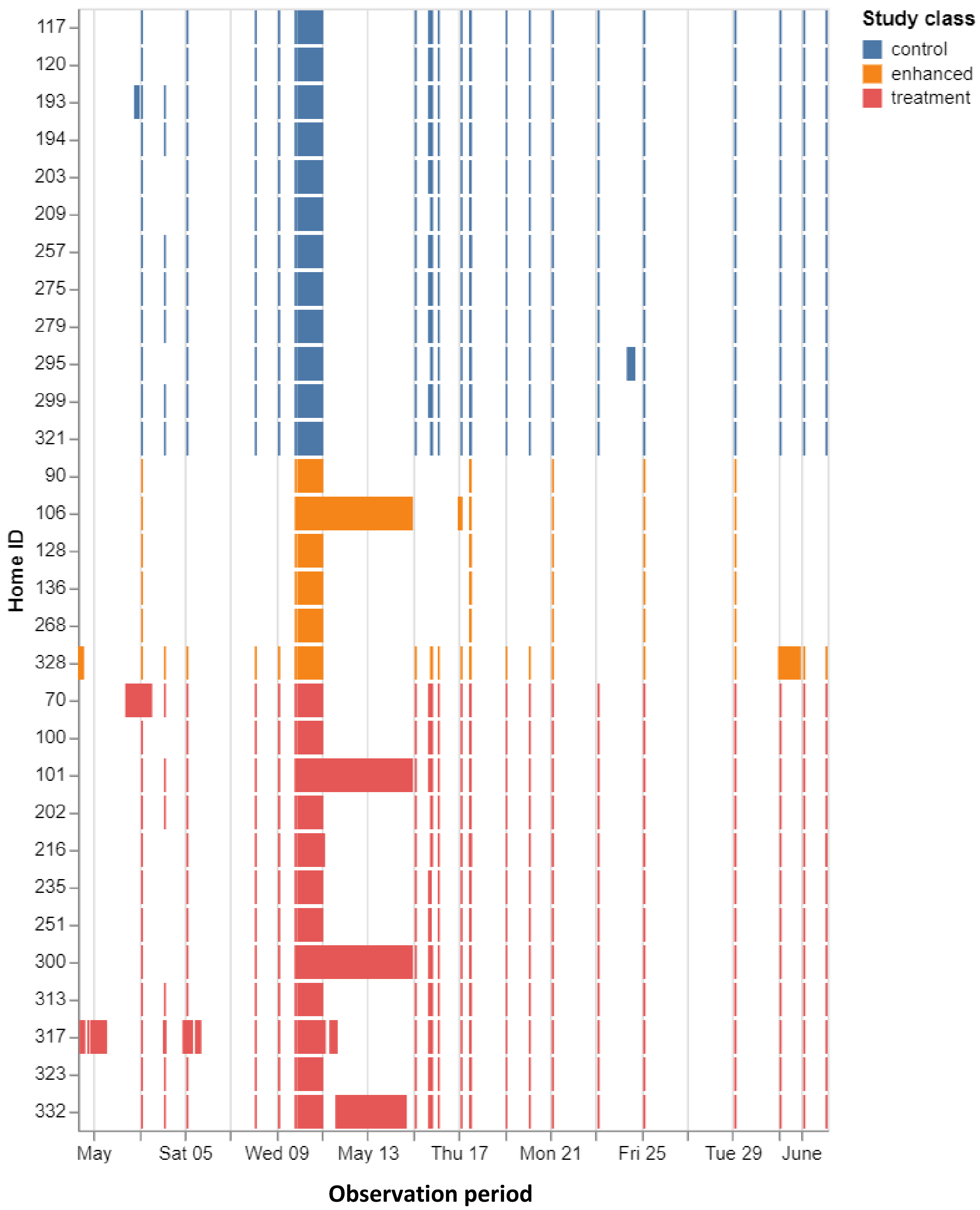

Figure A2-2: Overview of Measurement Gaps during the Observation Period, greater than 120 Minutes, per Household and grouped by Study Class.

As the IDEAL Household Energy Dataset contains real and apparent power measurements in irregular time intervals, the third step aimed to convert the raw dataset into a unified and interpretable format. Therefore, the raw dataset was resampled, meaning that missing timestamps were added such that real and apparent power measurements occur at a five/one-second frequency. In the next step, missing data were filled using different approaches depending on the length of the time gap. For time gaps smaller than or equal to two minutes, the nearest-neighbor approach (Sibson, 1981) was utilized such that gaps were filled with the closest available previously measured data point. This method has the advantage that it is easy to implement; however it could lead to worse results the longer the period is (Athawale & Entezari, 2013; Carrizosa et al., 2013). Time gaps larger than two minutes but smaller than or equal to two hours were filled through linear interpolation, a fast and straightforward method for estimating missing values (Z.-Y. Chen et al., 2012; M. C. Wang et al., 2021). However, as the accuracy of linear interpolation decreases the longer the missing data period is, time gaps larger than two hours were filled with measurements of the previous day.[95] According to Peppanen et al. (2016), using historical data from the previous day is a simple but efficient approach to fill missing readings. The researcher acknowledges that this method does not consider that electricity consumption differs between working days and weekends. However, as most time gaps greater than two hours occurred during the night (between 1 am and 5 am), it is assumed that the household's electricity consumption during this period does not significantly vary between working days and weekends. Accordingly, the use of historical data is still considered an appropriate method for filling time gaps.

[95] For households 317 and 328, there were several time gaps on the first day, such that measurements from the 29th of April were utilized to fill time gaps on this day.

Appendix A 3: Summary of Surveys in the IDEAL Household Energy Dataset

Table A3-1: Summary of Conducted Surveys (Pullinger et al., 2021, p. 10)

Survey	**Participants included**	**Data collection method**
Primary participant survey 1	*Primary participant*	*Computer-assisted personal interview*
All-occupant survey 1	*All home occupants aged 15+*	*Survey via IDEAL app*
Primary participant survey 2	*Primary participant*	*Web survey*
All-occupant survey 2	*All home occupants aged 15+*	*Survey via IDEAL app*
All-occupant survey 3	*All home occupants aged 15+*	*Web survey*

Appendix A 4: Measurement of Attitudes and Intentions according to the Sample TPB Questionnaire

The TPB sample questionnaire provided by Fishbein and Ajzen (2010) focuses on the behavior: Class attendance. Table A4-1 gives an overview of the utilized questions to measure attitudes and intentions towards class attendance. Fishbein and Ajzen (2010) notice that the questionnaire is only for illustrative purposes, and depending on the behavior, other question types could be useful. Nevertheless, it is included in this master's thesis to clarify the difference between attitudes and intentions and to make a comparison between the utilized questions measuring energy-saving attitudes and intentions possible.

Table A4-1: Measurement of Attitudes and Intentions according to the Sample TPB Questionnaire (Fishbein & Ajzen, 2010, pp. 457–464)

Sample TPB question	**Measurement of attitudes or intentions**
For me to attend the meeting of this class on a regular basis is: Extremely good: 1 2 3 4 5 6 Extremely bad: 7	*attitude*
For me to attend the meeting of this class on a regular basis is: Extremely valuable: 1 2 3 4 5 6 Extremely worthless:7	*attitude*
For me to attend the meetings of this class on a regular basis is: Extremely pleasant: 1 2 3 4 5 6 Extremely unpleasant: 7	*attitude*

Table A4-1 (continued)

Sample TPB question	Measurement of attitudes or intentions
For me to attend the meetings of this class on a regular basis is: *Interesting: 1* *2* *3* *4* *5* *6* *Boring: 7*	*attitude*
I plan to attend the meetings of this class on a regular basis: *Extremely likely: 1* *2* *3* *4* *5* *6* *Extremely unlikely: 7*	*intention*
I will make an effort to attend the meetings of this class on a regular basis: *I definitely will: 1* *2* *3* *4* *5* *6* *I definitely will not:7*	*intention*
I intend to attend the meetings of this class on a regular basis: *Strongly agree: 1* *2* *3* *4* *5* *6* *Strongly disagree: 7*	*intention*

Appendix A 5: Reliability of the Survey Responses

The questions *‘save_energy’* and *‘importance_environment’* were part of the three conducted All-occupant surveys at the beginning, the middle, and the end of the study period. To assess whether participants consistently answered the questions, Cronbach’s Alpha was calculated based on the three responses for each question. Table A5-1 reveals that households responded consistently as both Cronbach’s Alphas are above 0.7 (Nunnally & Bernstein, 1994).

Table A5-1: Reliability of the Survey Responses ‘save_energy’ and ‘importance_environment,’ utilized to Construct Energy-Saving Attitudes

Variable	**Cronbach’s Alpha**	**Number of Items**
save_energy	0.7509	3
importance_environment	0.8934	3

Appendix A 6: Analysis of Internal Consistency of the Variable energy_saving_attitudes

Though the index variable *'energy_saving_attitudes'* seems reasonable, the item option is included in Stata to determine if all three items (*'importance_environment,' 'save_energy,' 'buy_appliances_energy_efficiency'*) fit the index variable:

Table A6-1: Results of the Item Option in Stata

Item	Obs	Sign	Item-test correlation	Item-rest correlation	Average interitem covariance	alpha
importance_environment	30	+	0.8776	0.6999	0.3543	0.5232
save_energy	30	+	0.8239	0.5918	0.4859	0.6540
buy_appliances_energy_efficiency	30	+	0.7505	0.4603	0.6660	0.7995
Test scale						0.7515

The item-test correlations should be approximately equivalent for all items. Therefore, they might not be a good measurement to discover poorly fitting items as these items falsify the scale.[96] According to Nunnally and Bernstein (1994), the researcher should analyze the item-rest correlation, covering the correlation between the scale and an item. As the item-rest correlations are all relatively similar, the researcher concluded that the measured items fit well the index variable.

[96] The scale constitutes all other items.

Appendix A 7: Mean Power Factors for Households in the Study Class 'Enhanced'

Table A7-1: Mean Power Factors for Households in the Study Class 'Enhanced'

Home ID	Mean Power factor	Annotation
61	0.658194	
62	0.70545	
63	.	No real power measurement for the whole home.
65	0.599577	
73	0.46108	
90	0.799471	
96	0.884179	
105	0.795917	
106	0.652295	
128	0.786359	
136	0.858195	
139	0.797227	
140	0.820854	
145	0.744264	
146	.	Real power measurements are unlabelled.
162	0.658912	
168	.	No real power measurement for the whole home.
169	0.726696	
171	0.831144	
175	0.855275	
208	0.649008	
212	0.773515	
225	0.809504	
227	0.607421	
228	0.62175	
231	.	No real power measurements at all.
238	0.632309	
242	0.522672	
249	0.76549	
255	0.614551	
259	0.911564	
262	0.919749	
263	0.665749	
264	0.775168	
266	0.760687	
268	0.761248	
276	.	Real power measurements are unlabelled.
311	.	No real power measurement for the whole home.
328	0.688416	

Appendix A 8: Illustration of the Timestamp Conversion

Table A8-1: Illustration of the Timestamp Conversion

Timestamp	**Total seconds**
30.04.2018 11:44:20	0
30.04.2018 11:44:21	1
...	...
30.04.2018 11:44:25	5
...	...
30.04.2018 11:45:20	60
30.04.2018 11:45:21	61
...	...
07.06.2018 10:29:05	3278685

Appendix B – Data Analysis

Appendix B 1: Preliminary Tests of Necessary Assumptions for Testing Hypothesis 1

Hair et al. (2014) is the main reference for the following section.

1. Linearity in Parameters

Visual inspection via a scatterplot, where the explanatory variable energy-saving attitudes is plotted on the x-axis and the explained variable energy-saving intentions on the y-axis, is utilized to test if the linearity assumption is fulfilled.

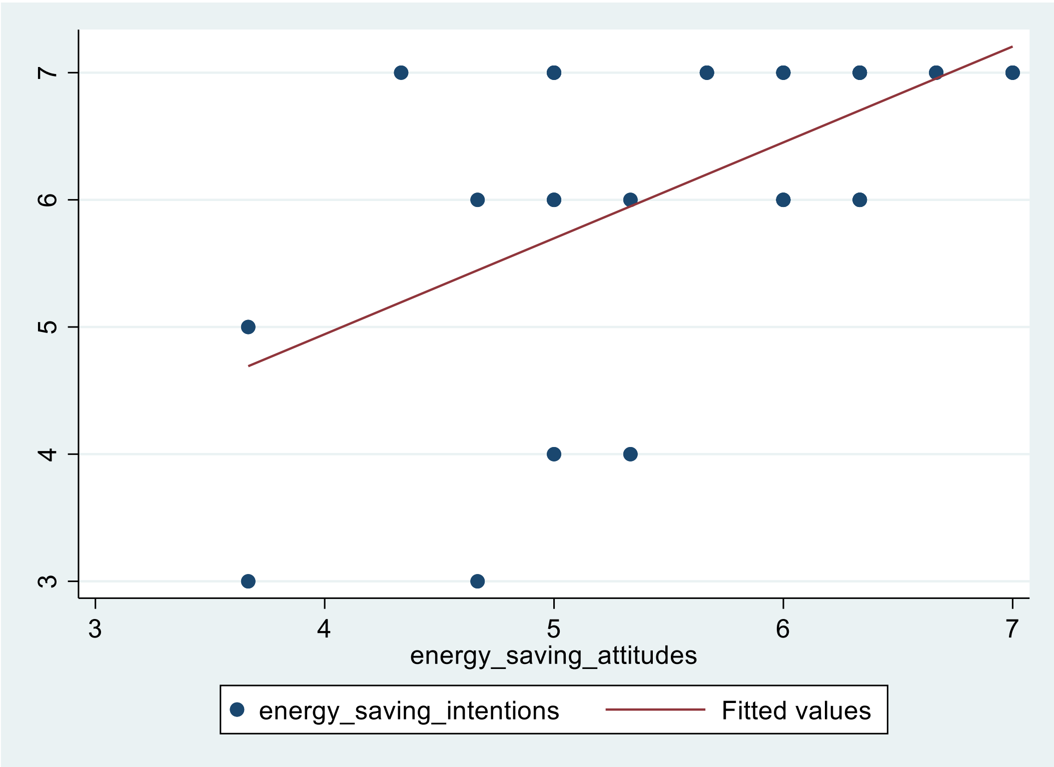

Figure B1-1: Scatterplot predicting Energy-Saving Intentions from Energy-Saving Attitudes

Based on Figure B1-1, it can be assumed that the linearity assumption is fulfilled for the relationship between energy-saving attitudes and intentions.

2. Random Sampling

This assumption is fulfilled because the provided data in the IDEAL Household Energy Dataset is based on a randomized control trial. Nevertheless, section 5.1 revealed a selection bias towards female, high-income, highly educated, employed households, which is a limitation of this study and is examined in more detail in the limitation section.

3. Variation in the Independent Variable

Simple linear regression analysis requires that there must be some variation in the explanatory variable, in this case, in energy-saving attitudes. Based on Table 5-1, this assumption is fulfilled.

4. Zero Conditional Mean Assumption

Several potential omitted variables could correlate with energy-saving attitudes and impact energy-saving intentions. Based on the literature review findings, examples of omitted variables could be socio-demographic characteristics like age, gender, income, or basic human values presented in Table B1-1.

Table B1-1: Overview of Basic Human Values (Schwartz, 2012, pp. 5–7)

Values	**Defining goal**
Self-direction	*Independent thought and action--choosing, creating, exploring*
Power	*Social status and prestige, control or dominance over people and resources*
Security	*Safety, harmony, and stability of society, of relationships, and of self*
Hedonism	*Pleasure or sensuous gratification for oneself*
Benevolence (social)	*Preserving and enhancing the welfare of society*
Benevolence (nearby)	*Preserving and enhancing the welfare of those with whom one is in frequent personal contact (the 'in-group')*
Achievement	*Personal success through demonstrating competence according to social standards.*
Stimulation	*Excitement, novelty, and challenge in life*
Conformity	*Restraint of actions, inclinations, and impulses likely to upset or harm others and violate social expectations or norms.*
Universalism	*Understanding, appreciation, tolerance, and protection for the welfare of all people and for nature*
Tradition	*Respect, commitment, and acceptance of the customs and ideas that one's culture or religion provides*

However, the TPB assumes that socio-demographic characteristics or human values are so-called ‘background factors’ that directly affect only behavioral, normative, and/or control beliefs (Ajzen, 2005, 2020). Therefore, as Hypothesis 1 was based on the TPB, it was assumed that the theory is true and there were no omitted variables.

Moreover, it was necessary to check whether simultaneity or reverse causality exists. As the first hypothesis was based on the TPB, neither reverse causality nor simultaneity were expected.

Furthermore, measurement errors could also result in the fact that it is impossible to interpret the estimated effect of energy-saving attitudes on energy-saving intentions as causal. This study was based on secondary data, and the variables energy-saving attitudes and intentions were constructed using three and one question(s) from the survey conducted in the IDEAL research project, respectively. The researcher used a sample questionnaire provided by Fishbein and Ajzen (2010) and the TPB manual developed by Francis et al. (2004) to ensure that the concept of attitudes and intentions was measured correctly. Nevertheless, the researcher acknowledges that the questions utilized to measure energy-saving attitudes and intentions might not be perfect. The researcher discusses these concerns in the limitation section 7.1.1.3.

5. Homoskedasticity

The Breusch-Pagan test was utilized to test whether the assumption of homoskedasticity is met (Wooldridge, 2013). The null hypothesis is that the error u has the same variance given any value of the explanatory variable:

$$Var(u|x) = \sigma^2$$

The Breusch-Pagan/Cook-Weisberg test for heteroskedasticity in Stata revealed the following result:

$$H_0: Constant\ variance$$

$$Variables: Fitted\ values\ of\ energy\_saving\_intentions$$

$$chi2(1) = 9.51$$

$$Prob > chi2 = 0.002$$

The null hypothesis was rejected such that the presence of heteroskedasticity can be assumed. Therefore, heteroskedasticity robust standard errors were utilized.

6. Normality of the error term distribution

A normal probability plot, which compares the standardized residuals to the normal distribution, was utilized to assess whether the normality assumption was fulfilled. The closer the plotted residuals follow the diagonal line, the more likely the error term is normally distributed. Based on Figure B1-2, normality can be assumed as all the points lie approximately along this diagonal line.

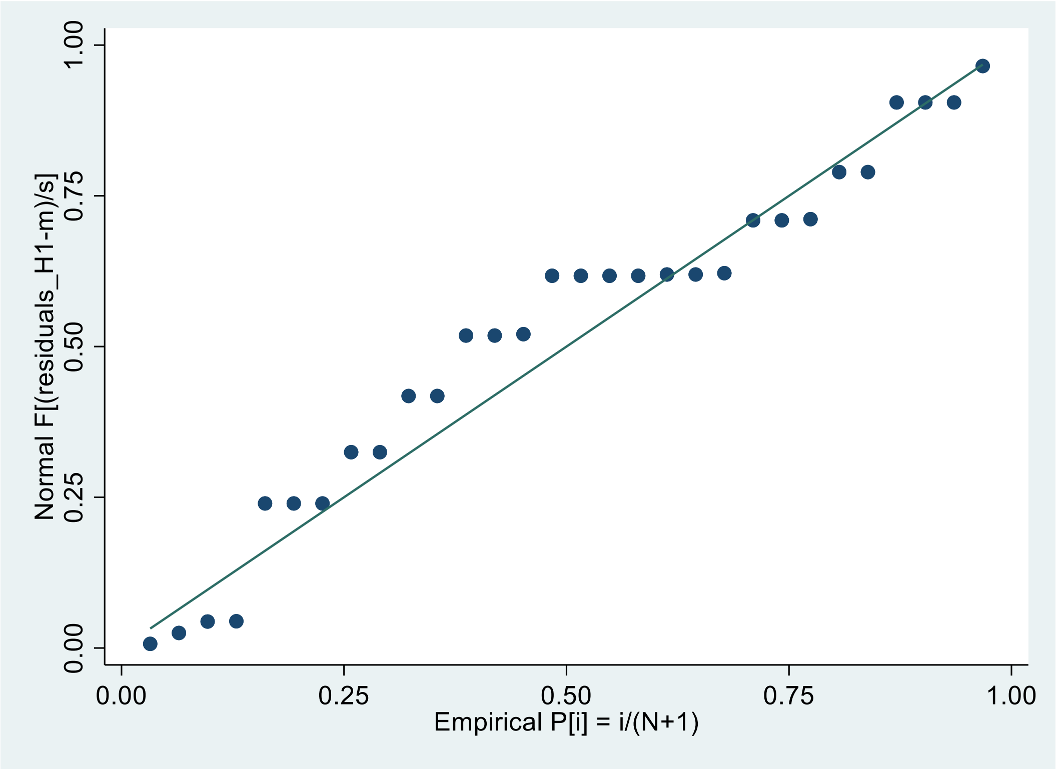

Figure B1-2: Normal Probability Plot of Residuals for Linear Regression

Appendix B 2: Preliminary Tests of Necessary Assumptions for Testing Hypothesis 2

Hair et al. (2014) is the main reference for the following section.

1. Linearity in Parameters

Graphical analysis of the residuals via plotting the predicted residuals on the y-axis and the fitted values on the x-axis was used to test if the linearity assumption was fulfilled. A reliable indicator for a linear relationship between the independent variables and the dependent variable is when the predicted residuals are randomly distributed around a horizontal line. Figure B2-1 reveals that the linearity assumption is met.

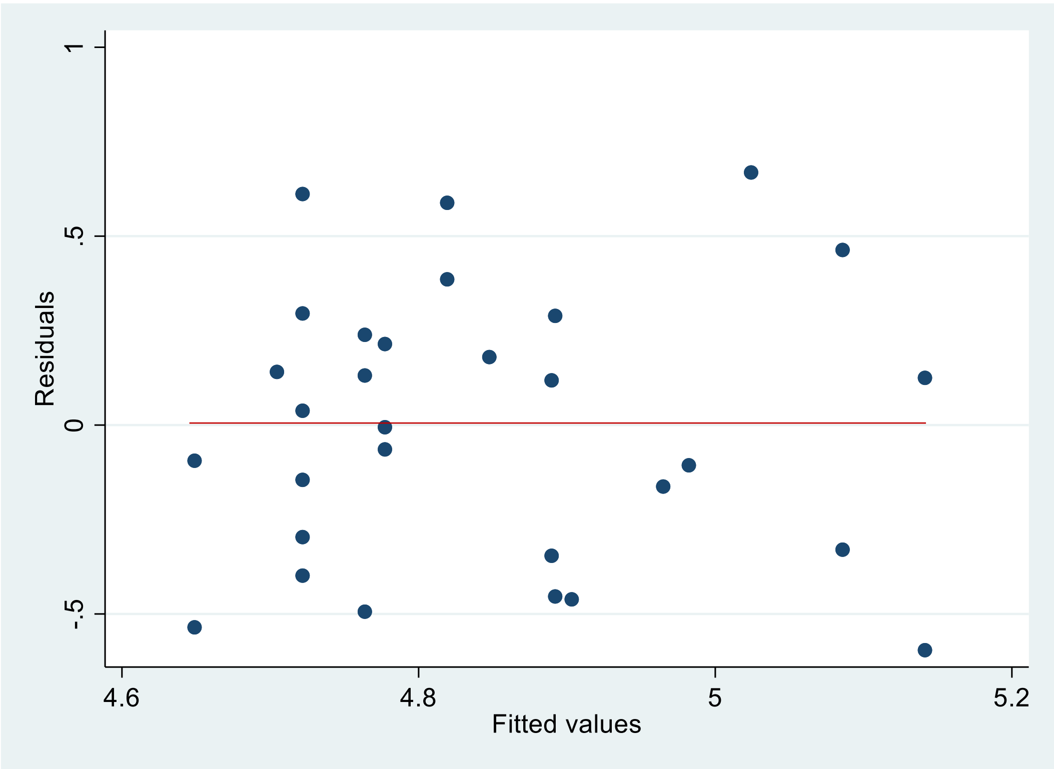

Figure B2-1: Residuals vs. Fitted Values Plot

2. Random Sampling

This assumption is fulfilled because the provided data in the IDEAL Household Energy Dataset is based on a randomized control trial. Nevertheless, section 5.1 revealed a selection bias towards female, high-income, highly educated, employed households, which is a limitation of this study and is examined in more detail in the limitation section.

3. No Perfect Collinearity

The presence of perfect collinearity was examined by analyzing the correlation matrix of the explanatory variables. Based on Table B2-1, it can be inferred that perfect collinearity was not an issue in this multiple linear regression as the independent variables were only weakly correlated.

Table B2-1: Correlation Matrix of the Explanatory Variables testing Hypothesis 2

	occupied_days	*treatment*	*energy_saving_intentions*
occupied_days	1.0000		
treatment	-0.0809	1.0000	
energy_saving_intentions	0.1444	-0.1148	1.0000

4. Zero Conditional Mean Assumption

Several potential omitted variables could correlate with energy-saving intentions and impact electricity consumption. Based on the literature review findings, examples of omitted variables could be socio-demographic characteristics like age, gender, income, or basic human values.[97]

However, the TPB assumes that socio-demographic characteristics or human values are so-called ‘background factors’ that directly affect only behavioral, normative, and/or control beliefs (Ajzen, 2005, 2020). Therefore, as Hypothesis 2 was based on the TPB, it was assumed that the theory is true and there were no omitted variables.

Moreover, it was necessary to check whether simultaneity or reverse causality exists. As the second hypothesis was based on the TPB, neither reverse causality nor simultaneity were expected.

Furthermore, measurement errors could also result in the fact that it is impossible to interpret the estimated effect of energy-saving intentions on electricity consumption as causal. This study was based on secondary data, and the variable energy-saving intentions was constructed using only one question from the survey conducted in the IDEAL research project. However,

[97] See Table B1-1 in Appendix B 1 for an overview of basic human values.

the researcher used a sample questionnaire provided by Fishbein and Ajzen (2010) and the TPB manual developed by Francis et al. (2004) to ensure that the concept of energy-saving intentions was measured correctly. Nevertheless, the researcher acknowledges that the question utilized to measure energy-saving intentions might not be perfect.

The process of transforming apparent power measurements into estimates for real power measurements, presented in section 4.4.2.1, and the utilized methods to fill time gaps, presented in Appendix A 2, can certainly be criticized such that the estimates for electricity consumption can be scrutinized as well.

The researcher discusses these concerns in detail in the limitation section 7.1.1.

5. Homoskedasticity

The Breusch-Pagan test was utilized to test whether the assumption of homoskedasticity was met (Wooldridge, 2013). The null hypothesis is that the error u has the same variance given any values of the explanatory variables:

$$Var(u_i|x_1, x_2, \dots, x_k) = \sigma^2$$

The Breusch-Pagan/Cook-Weisberg test for heteroskedasticity in Stata revealed the following result:

$$H_0: Constant\ variance$$

$$Variables: Fitted\ values\ of\ \log\ \_electricity\_consumption$$

$$chi2(1) = 0.70$$

$$Prob > chi2 = 0.4031$$

The null hypothesis was not rejected such that the presence of homoskedasticity can be assumed.

6. Normality of the Error Term Distribution

A normal probability plot, which compares the standardized residuals to the normal distribution, was utilized to assess whether the normality assumption was fulfilled. The closer the plotted residuals follow the diagonal line, the more likely the error term is normally distributed. Based on Figure B2-2, normality can be assumed as all the points lie approximately along this diagonal line.

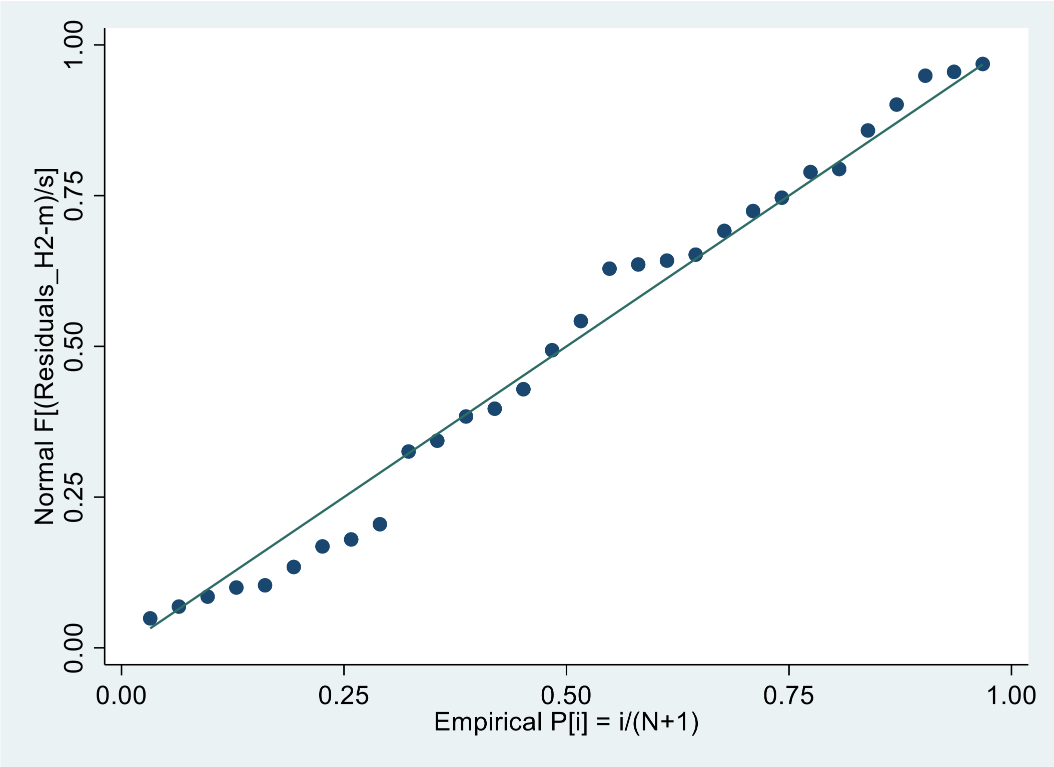

Figure B2-2: Normal Probability Plot of Residuals for Multiple Linear Regression

Appendix B 3: Preliminary Tests of Necessary Assumptions for Testing Hypothesis 3

The second and third regression analyses (path b and path c in Figure 5-4), utilized to test Hypothesis 3, are based on the regression analyses used for testing Hypotheses 1 and 2. Therefore, the preliminary tests described in Appendix B 1 and Appendix B 2 apply for these regressions. Thus, the following section focuses on (1) the regression analysis testing whether a direct link between energy-saving attitudes and electricity consumption exists (path a) and (2) the regression analysis testing whether the variable energy-saving intentions is a mediator.

Hair et al. (2014) is the main reference for the following section.

1. Linearity in Parameters

Graphical analysis of the residuals via plotting the predicted residuals on the y-axis and the fitted values on the x-axis was used to test if the linearity assumption was fulfilled. A reliable indicator for a linear relationship between the independent variables and the dependent variable is when the predicted residuals are randomly distributed around a horizontal line. Figure B3-1 and Figure B3-2 reveal that the linearity assumption was met in both cases.

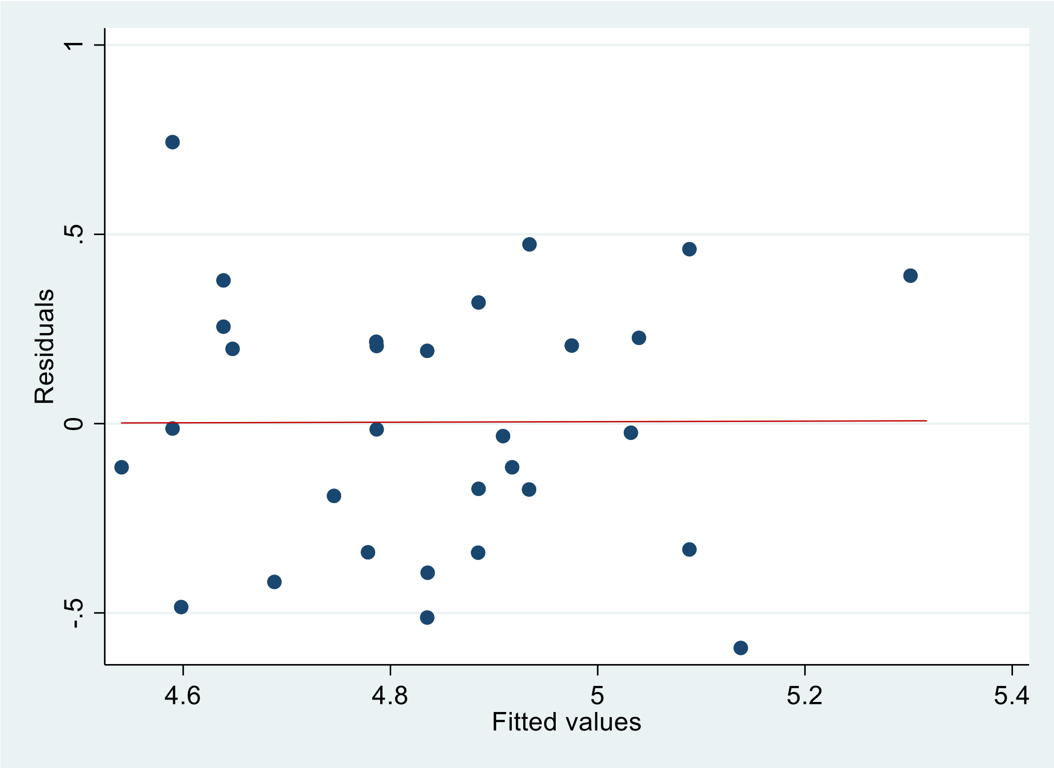

Figure B3-1: Residuals vs. Fitted Values Plot for the Multiple Linear Regression testing the Direct Link between Energy-Saving Attitudes and Electricity Consumption (Path a)

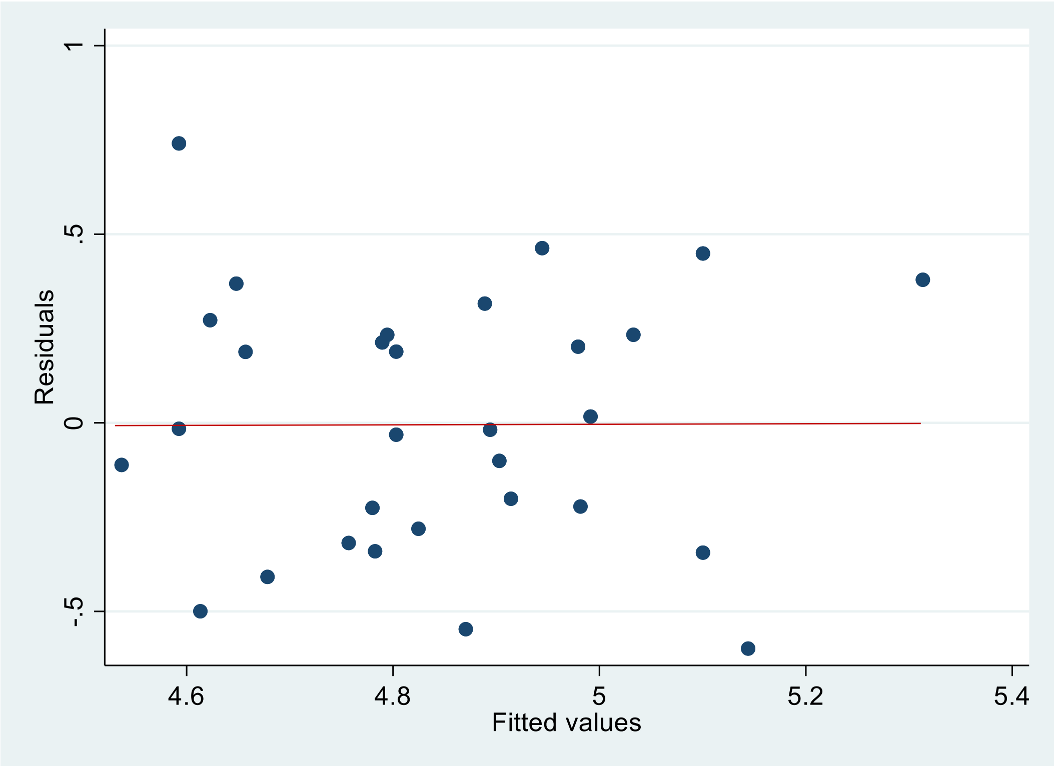

Figure B3-2: Residuals vs. Fitted Values Plot for the Multiple Linear Regression testing whether Energy-Saving Intentions is a Mediator

2. Random Sampling

This assumption is fulfilled because the provided data in the IDEAL Household Energy Dataset is based on a randomized control trial. Nevertheless, section 5.1 revealed a selection bias towards female, high-income, highly educated, employed households, which is a limitation of this study and is examined in more detail in the limitation section.

3. No Perfect Collinearity

The presence of perfect collinearity was examined by analyzing the correlation matrix of the explanatory variables. Based on Table B3-1, it can be inferred that perfect collinearity was not an issue in both multiple linear regressions as the independent variables were only weakly correlated.

Table B3-1: Correlation Matrix of the Explanatory Variables testing Hypothesis 3

	occupied_days	*treatment*	*energy_saving_attitudes*	*energy_saving_intentions*
occupied_days	1.0000			
treatment	-0.0809	1.0000		
energy_saving_attitudes	0.2945	-0.0408	1.0000	
energy_saving_intentions	0.1444	-0.1148	0.5657	1.0000

4. Zero Conditional Mean Assumption

Several potential omitted variables could correlate with energy-saving attitudes and intentions and impact electricity consumption. Based on the literature review findings, examples of omitted variables could be socio-demographic characteristics like age, gender, income, or basic human values.[98]

However, the TPB assumes that socio-demographic characteristics or human values are so-called ‘background factors’ that directly affect only behavioral, normative, and/or control

[98] See Table B1-1 in Appendix B 1 for an overview of human values.

beliefs (Ajzen, 2005, 2020). Therefore, as Hypothesis 3 was based on the TPB, it was assumed that the theory is true and there were no omitted variables.

Moreover, it was necessary to check whether simultaneity or reverse causality exists. As the third hypothesis was based on the TPB, neither reverse causality nor simultaneity were expected.

Furthermore, measurement errors could also result in the fact that it is impossible to interpret the estimated effect of energy-saving attitudes and intentions on electricity consumption as causal.

This study was based on secondary data, and the variables energy-saving attitudes and intentions were constructed using three and one question(s) from the survey conducted in the IDEAL research project, respectively. The researcher used a sample questionnaire provided by Fishbein and Ajzen (2010) and the TPB manual developed by Francis et al. (2004) to ensure that the concepts of energy-saving attitudes and intentions were measured correctly. Nevertheless, the researcher acknowledges that the question(s) utilized to measure energy-saving attitudes and intentions might not be perfect.

The process of transforming apparent power measurements into estimates for real power measurements, presented in section 4.4.2.1, and the utilized methods to fill time gaps, presented in Appendix A 2, can certainly be criticized such that the estimates for electricity consumption can be scrutinized as well.

The researcher discusses these concerns in detail in the limitation section 7.1.1.

5. Homoskedasticity

The Breusch-Pagan test was utilized to test whether the assumption of homoskedasticity was met (Wooldridge, 2013). The null hypothesis is that the error u has the same variance given any values of the explanatory variables:

$$Var(u_i|x_1, x_2, \dots, x_k) = \sigma^2$$

5.1 Multiple Linear Regression testing the Direct Link between Energy-Saving Attitudes and Electricity Consumption (Path a)

The Breusch-Pagan/Cook-Weisberg test for heteroskedasticity in Stata revealed the following result:

H_0: $Constant\ variance$

$Variables$: $Fitted\ values\ of\ \log\ \_electricity\_consumption$

$chi2(1) = 0.00$

$Prob > chi2 = 0.9994$

The null hypothesis was not rejected such that the presence of homoskedasticity can be assumed.

5.2 Multiple Linear Regression testing whether Energy-Saving Intentions is a Mediator

The Breusch-Pagan/Cook-Weisberg test for heteroskedasticity in Stata revealed the following result:

H_0: $Constant\ variance$

$Variables$: $Fitted\ values\ of\ \log\ \_electricity\_consumption$

$chi2(1) = 0.01$

$Prob > chi2 = 0.9429$

The null hypothesis was not rejected such that the presence of homoskedasticity can be assumed.

6. Normality of the Error Term Distribution

A normal probability plot, which compares the standardized residuals to the normal distribution, was utilized to assess whether the normality assumption was fulfilled. The closer the plotted residuals follow the diagonal line, the more likely the error term is normally distributed. Based on Figure B3-3 and Figure B3-4, normality can be assumed as all the points lie approximately along this diagonal line.

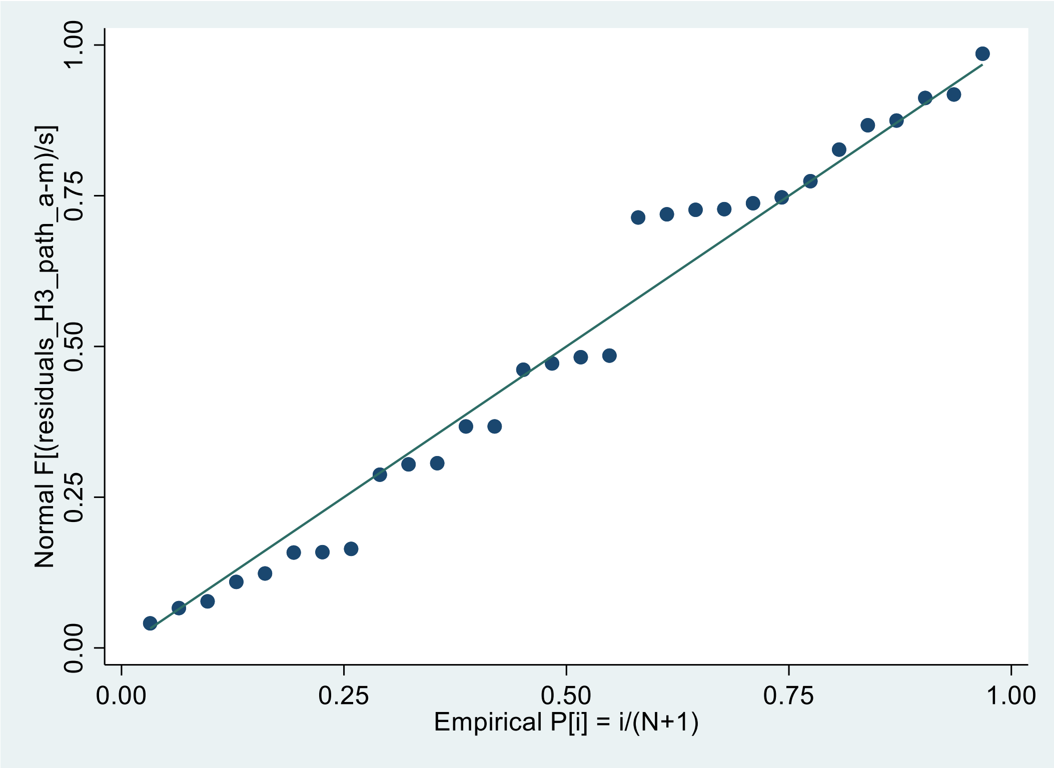

Figure B3-3: Normal Probability Plot of Residuals for the Multiple Linear Regression testing the Direct Link between Energy-Saving Attitudes and Electricity Consumption (Path a)

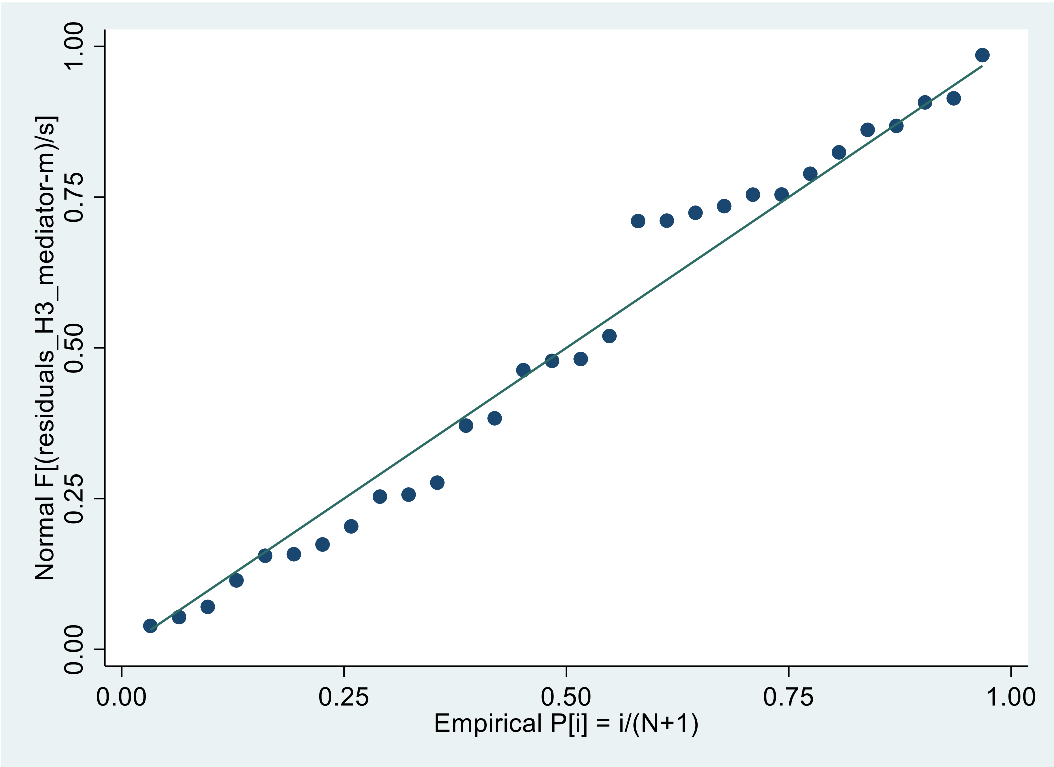

Figure B3-4: Normal Probability Plot of Residuals for the Multiple Linear Regression testing whether Energy-Saving Intentions is a Mediator

Appendix B 4: Precision of OLS Estimators

The subsequent summary is based on Wooldridge (2013).

The precision of OLS estimators is determined via their variance $Var(\hat{\beta}_j)$. The smaller $Var(\hat{\beta}_j)$, the more precise OLS estimators are, and the smaller confidence intervals are, and the more accurate hypothesis testing is.

If the Gauss-Markov assumptions hold, the following formula determines the variance of an OLS estimator $\hat{\beta}_j$:

$$Var(\hat{\beta}_j) = \frac{\sigma^2}{SST_j(1-R_j^2)}$$

σ^2: Error variance, which is a feature of the population and has nothing to do with the sample size. To reduce the error variance, more explanatory variables need to be added to the regression equation such that factors are taken out of the error term.

SST_j: Total sample variation in x_j. Everything else equal, it is preferred to have as much sample variation in x_j as possible. An increase in sample variation in each independent variable can be provided by increasing the sample size.

R_j^2: Proportion of total variation in x_j that can be explained by other independent variables appearing in the equation. This term should be as low as possible.