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Are Smart Meters Really Smart?

Understanding the effects of real-time feedback of electricity use in Sweden

Mats Tedenvall

Supervisors

Associate Prof. Luis Mundaca, IIIEE

Annika Widmark Sjöstedt, E.ON Sverige AB

Thomas Johansson, E.ON Sverige AB

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Tel: +46 – 46 222 02 00, Fax: +46 – 46 222 02 10, e-mail: iiiee@iiiee.lu.se.

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Abstract

Increased energy efficiency is a fundamental pillar to foster sustainable energy systems and a resource efficient economy. To that end, policies and measures to promote energy conservation and energy efficiency technologies are greatly needed in order to reduce or correct market and behavioural failures that prevent efficiency improvements, and resulting economic and environmental gains. To address information-related barriers, the roll out of Smart Meters (SMs) in the residential sector has gained considerable policy attention in the European Union. SMs enable real-time feedback to residents about their electricity use. A key tenet of SMs is that the provision of information encourages residential end-users to change their behaviour and make more rational choices about their electricity use and demand for energy services. This thesis empirically investigates the effectiveness of real-time feedback technology on Swedish households. The thesis provides a better understanding of how psychological, moral and contextual variables affect electricity use and related behaviour. Electricity use data from more than 4 700 users over four years together with a survey and econometrics were used for the research. Results show that feedback without any complementary interventions only provides a marginal effect (1.4-1.5%) in electricity reduction, and that contextual variables seem to be better predictors of electricity use rather than psychological variables. Results indicate that perceived behavioural control and personal norms appeared to be significant determinants of the perceived effectiveness of the feedback service. It is concluded that the implementation of SMs *per se* is likely to be insufficient to foster increased efficient use of electricity if this is not combined with other policy instruments, such as electricity pricing, awareness raising and tailored education campaigns.

Keywords: Behavioural change, effectiveness, electricity saving, household sector, Smart Meters

Executive Summary

Background

Energy is fundamental for human development. Increasing use of energy has been key to support development of socio-economic and technical systems. However, unsustainable production and use of energy have triggered sustainability problems. The most remarkable example is climate change but also other negative consequences such as health issues, water pollution and radioactivity stem from the increasing need of more energy supply. To promote sustainable energy systems, increased energy efficiency is vital.

On the demand side, the residential sector has always offered great cost-effective potentials to reduce the energy use. However, there is a large number of market and behavioural barriers (e.g. lack of information) that have also hindered the optimum level of energy efficiency to be reached. The delta between the optimum level of energy efficiency and the actual level is often labelled as the 'Energy Efficiency Gap'. The European Union (EU) has introduced several policies to close this gap. Information deficit is one of many barriers causing the energy efficiency gap. An example of information deficit within the residential sector is residents' limited understanding of the amount and cost of the electricity use. Lately the roll out of Smart Meters (SM), allowing for increased feedback of electricity use to the residents, has gained momentum across EU countries.

There is a growing number (still limited) of studies about the effectiveness of SMs and increased feedback. These studies show reductions of electricity use in the range of 0 to 15%, stressing different sources of uncertainties and casting doubts about expected policy outcomes resulting from the implementation of SMs.

Problem definition and objective

Improved feedback from SMs aims to affect the behaviour of end-users so they change their behaviour and make more rational choices about their electricity use. However, initial scientific evidence is showing that information in itself may not lead to a behavioural change. Many other factors, such as values, norms, attitudes, perceived behavioural control and habits are also affecting the behaviour. Also contextual factors, such as electricity price, income, living area, and age, among others, influence the behaviour (indirectly or directly). Furthermore, the effectiveness of feedback differs between geographical, cultural and temporal contexts. In fact, extrapolations are difficult to make and outcomes and experiences are very context-specific. The results are also dependent on behavioural biases and how the feedback is presented. There is also a limited understanding of the underlying factors driving the effect of feedback and for whom they are effective.

For the particular case of Sweden, few studies based on real-time electricity feedback have been carried out. A critical review of these studies reveals, for example, marginal reductions in electricity use, low participation rates, lack of large-scale trials, and statistically insignificant outcomes. As a whole, there is still limited understanding about the potential effectiveness of SMs and underlying factors affecting their performance in the Swedish residential sector.

To address this knowledge gap, the purpose of the thesis at hand is to increase our knowledge of how and to what extent real-time feedback (via smart phones, tablets and computers) influences electricity use in Sweden. Using the '100Koll' service provided by the energy company E.ON, the thesis aims to understand how effective the service has been in terms of reducing the electricity use and also how psychological, moral and contextual characteristics determine electricity use and the perceived effect of the real-time feedback. Little research has been done on the service, offering a great opportunity to increase the scientific knowledge about such electricity feedback in Sweden.

Methods

A variety of quantitative and qualitative methods were deployed to address this research.

In terms of methods for data collection, a literature review was used to provide an understanding of the theories behind SMs and human behavior. Additionally an extensive review of previous feedback studies was made with a specific focus on Sweden and Scandinavia to understand how this study relates to and complements the existing literature. Monthly electricity use data was gathered from an E.ON database and included data from two groups of customers: the 100Koll customers and a control group that had not installed 100Koll. The sample size of the 100Koll group was 2 751 users and 2 048 households represented the control group. The data included electricity use from January 2011 to April 2015. A survey regarding electricity behavior and related determinants was submitted to 2 173 of the 100Koll users, and 543 responses were retrieved and used for the analysis.

In terms of methods for data analysis, three methods were used for the calculation of the feedback effectiveness. The first method used climatic correction and historical use data for the estimation. The second method used the period just before the implementation period to estimate the expected use for both the control group and the 100Koll group. The third method was similar to the second but used the whole baseline period from January 2011 to estimate the expected use of the whole intervention period. The basic idea behind the three methods was to estimate how much electricity the 100Koll users would have consumed if 100Koll was *not* introduced (the expected use) and compare that estimation with actual electricity use after the intervention.

For the analyses of determining characteristics of electricity use and the perceived effect of the feedback five econometric models with different dependent variables were selected: *electricity use*, *electricity change* (i.e., the percentage difference between expected and the actual electricity use), *electricity saving behaviour* and two variables that described how much that 100Koll helps to reduce electricity use. For each of the five dependent variables, a regression model was specified. Each regression model had one dependent variable and several independent predictor variables (determining factors). The *first model* that was specified to explain the *electricity use* included three independent variables from the Theory of Planned Behaviour (TPB) (Ajzen, 1991): attitudes, subjective norms and perceived behavioural control; three independent variables from the Value-Belief-Norm (VBN) theory (Stern, 2000): awareness of consequences, ascribed responsibility to act and personal norms; and five contextual variables: age, education, income, living area and household size. The two variables that described how well 100Koll helps to reduce electricity use were also added as independent variables into the model. The *second model* that was specified to explain the *electricity change* included the same independent variables as for the electricity use model and in addition electricity use was added as an independent variable. The *third model* that was specified to explain the *electricity saving behaviour* included the same independent variables as the second model for electricity change and the *fourth* and the *fifth models* that were specified to explain how well 100Koll helps to reduce electricity use included all the variables from the TPB and the VBN theories, all the five contextual factors and the electricity use as independent variables. The electricity use and the electricity change variables originated from the E.ON database while the other three dependent variables and all the independent variables were captured from the survey. Stepwise linear regressions explained which independent variables could predict the dependent variables with statistical significance and also the significance of the independent variables. Bivariate and partial correlations were also used to analyse the association between the variables.

Key Findings

Using these three methods used it was found that 100Koll has resulted in electricity savings in the range of 1.4-1.5% (and 1.9% during the first four months after the implementation period). This result was consistent with existing literature that found average savings of 1.6% from a study of 19 SM interventions, but much lower compared to other earlier feedback studies that suggested savings up to 15%. The result was also in line with two Swedish feedback studies. The first was an energy experiment done by E.ON between 2012 and 2013, which resulted in savings of 2.2% compared to the control group. The explanation for the slightly higher result than was found in this study may be that in addition to feedback on phone and tablet, also five other interventions were used to improve the electricity saving. The other Swedish feedback study found statistically insignificant savings of 0.04% from a web service that provided electricity consumption statistic. The lower result in that study may be explained by a limited access of the service, as it was only accessible via web and lack of real-time feedback.

From the *first model*, it was found that only the contextual factors living area, income and household size could predict, to some extent, the *electricity use* with statistical significance. The three variables could predict 17.6% of the variance in electricity use. The result shows that the contextual factors, and not the psychological and moral factors, determine energy use. This finding is consistent with the existing literature. Partial correlations indicated that households that believe that 100Koll helps them to reduce electricity have lower total use of electricity.

The *second model* showed that the *electricity change*, during the 100Koll use, could not be predicted by any other variable than household size (i.e., the number of persons in the household), which only explained 3.5% of the variation.

When it comes to the *third model*, it was found that the perceived behavioural control and the level of education of the respondent could predict 7.4% of the *electricity saving behaviour*. The result suggested that a higher education level would lead to an electricity saving behaviour. However, the variable electricity saving behaviour mainly included behaviours that involved energy efficiency investments. Since recent studies suggest that people with higher education tend to enact less energy conservation measures (i.e., activities that means reducing use without investing in efficiency), it was not possible to conclude that higher education correlates with more electricity saving behaviour.

The *fourth model* showed that perceived behavioural control and personal norms were statistically significant predictors for how well the users perceive that *100Koll can help* them to reduce electricity. 16.7% of the variation was explained by the two variables.

The *fifth model* showed that only the personal norm was statistically significant predictor for explaining if *100Koll had helped* the users to take electricity saving actions. 5.2% of the variation was explained by the personal norm.

Conclusions and recommendations

This thesis aimed to better understand how effective, in terms of reduced electricity use, real-time feedback is in Sweden. Additionally the it aimed to get a better understanding of what psychological, moral and contextual factors that determine the electricity use and the effect of the 100Koll real-time feedback service.

It is concluded that the real-time feedback service only decreases the electricity use marginally (1.4-1.5%), which is consistent with recent literature but considerably lower than what earlier studies has concluded.

One of the reasons for the relatively low result of effectiveness may be that the effort needed to monitor 100Koll on a PC or a smart phone is higher than the expected gain. Perhaps a dedicated device like an in-home display would provide a higher result since no specific app or web page needs to be accessed. Other reasons may be that the cost of electricity for the household has decreased during the last years or that the design of 100Koll was not optimal for achieving a larger electricity reduction.

Moreover it was found that contextual factors could predict the electricity use in the households rather than psychological and moral factors, which confirms the findings in existing literature. The findings also suggest that the energy efficiency behaviour, to a marginal degree, is dependent on the perceived behavioural control of the users, which means that this factor also should influence the electricity use. With due limitation, the results indicate that perceived behavioural control and personal norms may influence the effect of the feedback service.

Results suggest that policy makers and energy companies should be aware that offering a service like 100Koll in isolation only results in marginal savings. However, it is possible that increased feedback of electricity use in combination with other policy interventions, such as educational campaigns and/or tariff interventions can increase the effect.

Based on the conclusions above regarding the influence from personal norms and perceived behavioural control, potential information campaigns that are combined with enhanced feedback of electricity use, similar to 100Koll, should aim to increase these two factors of the users. This means that users should be educated in how easy it is to reduce electricity use and that anyone can do something to contribute to the reduction. Additionally, awareness campaigns that make electricity users feel that they contribute to something important when reducing on electricity use would according to the results have positive effect combined with the increased feedback. The cost-effectiveness of an information campaign must also be taken into consideration before it is launched.

The findings and conclusions from this thesis should also be of interest for academia as it complements the feedback literature with a comparably large study on the effectiveness of real-time feedback of electricity use from Sweden.

Several ideas for further research have developed during the course of this thesis. One suggestion is to investigate the effects of combining real-time feedback with other interventions, such as price changes and specific information campaigns in order to see if the effect becomes significantly higher. Another idea is to further review the user interface of 100Koll and make sure it is designed to maximise the effect of the service. Trials with different designs may yield useful insights in this respect. A third suggestion comes from the fact the variables studied in this thesis only explained a limited part of the total variation in electricity use and effect of the 100Koll service. Therefore, more research regarding the impact of predicting factors other than those studied in this thesis is recommended and further conceptualisation and specification of models are needed.

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Abbreviations

AC	Awareness of Consequences
AR	Ascribed Responsibility
BLP	Baseline Period
EC	European Commission
IEA	International Energy Agency
IG	Intervention Group
IHD	In-Home Display
IP	Intervention Period
IPCC	International Panel on Climate Change
JAP	Just After Period
JBP	Just Before Period
kWh	kilowatt hour
M	Mean
Mdn	Median
N	Number
NEP	New Environmental Paradigm
PBC	Perceived Behavioural Control
PN	Personal Norms
SD	Standard Deviation
SMS	Short Message Service
SN	Subjective Norms
SMHI	Swedish Meteorological and Hydrological Institute
TPB	Theory of Planned Behaviour
VBN	Value Belief Norm
WLAN	Wireless Local Area Network

1 Introduction

1.1 Background

Energy is fundamental for human development (WEHAB Working group, 2002). Increasing use of energy has been key to support development of socio-economic and technical systems (WEHAB Working group, 2002). However, unsustainable production and use of energy have triggered sustainability problems (IEA, 2014a). The most remarkable example is climate change but also other negative consequences such as health issues, water pollution and radioactivity stem from the increasing need of energy supply (Miller & Spoolman, 2012). To promote sustainable energy systems, increased energy efficiency is vital (IEA, 2014b).

The EU has defined energy efficiency in the 2012 Energy Efficiency Directive (2012/27/EU) as "the ratio of output of performance, service, goods or energy, to input of energy" (article 2, paragraph 4). This means that with increased energy efficiency, it is possible to get the same amount of output with less energy input. The directive also includes binding targets to improve the energy efficiency by 20% in 2020 compared to projections made in 2007.

Energy efficiency is however not enough to meet the needed reductions (Darby, 2007). Moreover, energy sufficiency is essential to limit the threats with climate change (Darby, 2007). Sufficiency has to do with the level of consumption that is enough (Darby, 2007), but a short and clear definition of the term seems hard to define. Daley (1993) recognised the complexity of the term but also the importance of it and argued that although it is hard to define sufficiency it would be more difficult to continue as if there is no such thing as enough.

On the demand side, the residential sector has great potential to reduce the energy consumption (BPIE, 2011). The technical potential for energy efficiency in the building sector in the EU has been estimated at 29% (European Commission, 2009b). That shall be seen, however, as an upper limit to what is theoretically possible with the best available technologies on the market. The market potential which is considerably lower than the technical potential reflects all the obstacles and market imperfections that hinders the technical potentials from being fully realised (Jaffe & Stavins, 1994a; Jochem et al., 2000). The social-optimum potential that is between the market potential and the technical potential is defined as a level that is cost-effective for the society and eliminates all negative externalities (Jaffe & Stavins, 1994a). The gap between the actual energy use and the social-optimum potential is referred to as the *energy efficiency gap* (Jaffe & Stavins, 1994b). This gap is the result of different kinds of barriers (IPCC, 2007; Jaffe & Stavins, 1994a, 1994b; Sutherland, 1991)

The EU has introduced several policies to close the energy efficiency gap (Braungardt et al., 2014). This gap is caused by many different barriers and one of these is lack of information, also called information deficit (IPCC, 2007; Jaffe & Stavins, 1994b). An example of information deficit within the residential sector is residents limited understanding of the amount and cost of the electricity use (Fischer, 2008). The utility meter reading has not been easily accessible for the customers that traditionally only have seen the accumulated electricity consumed (van Elburg, 2009). To overcome this issue Smart Meters[1] (SMs) are being rolled out in Europe, allowing for increased feedback of electricity use (Covrig et al., 2014) and thus

[1] The EC has defined a SM system as to "an electronic system that can measure energy consumption, adding more information than a conventional meter, and can transmit and receive data using a form of electronic communication" (paragraph 3b in 2012/148/EU) (European Commission, 2012). In this thesis, the focus is on the SM's possibilities to convey electricity use to the consumer.

achieve a decrease of the energy efficiency gap.

The rollout of SMs in Europe is prompted by the Energy End-use Efficiency and Energy Services (EEE&ES) Directive (2006/32/EC) which mandates that member states, as far as possible shall make sure that when existing meters are replaced an SM is always installed. In 2009, the EU electricity directive (2009/72/EC) was adopted including a target saying that member states shall ensure that 80% of all consumers have a SM installed by 2020[2] (European Commission, 2009a). Sweden is one of the countries in EU that has come the furthest with the rollout of SMs (Covrig et al., 2014). Already in 2003, Sweden enacted a law (2002/03:85) that mandated monthly meter readings and that the information from those should be conveyed to the electricity consumers. Although the proposition did not state how to achieve the goal, it lead to an implementation of 'smart' electricity meters in most Swedish households (Dromacque, 2013)[3].

Many studies of the effectiveness of SMs and increased feedback have been done with results showing reductions of electricity use with various results from no impact up to 15% (See e.g., Bager & Mundaca, 2015; Darby, 2006; Ehrhardt-Martinez, Donelly, & Laitner, 2010; McKerracher & Torriti, 2013). In these studies, the effectiveness of SMs and feedback means the percentage difference between the measured electricity use after the feedback was initiated and the expected electricity use without the feedback.

1.2 Problem definition

Improved feedback from SMs aims to affect the behaviour of end-users so they change their behaviour and make more rational choices about their electricity use. However, scientific evidence shows that information in itself may not lead to a behavioural change (Fischer, 2008; Owens & Driffill, 2008). Many other psychological and moral factors, such as cognitive limitations, values, norms, attitudes, perceived behavioural control and habits of the individuals are also affecting the behaviour (Ajzen, 1991; Ajzen & Fishbein, 1972; Jackson, 2005; Stern, 2000; Triandis, 1977; Tversky & Kahneman, 1974). It has also been found that for some behaviours, the context overrides all the cognitive factors (Stern, 2000). Examples of contextual factors influencing the behaviour, directly or indirectly, are electricity cost, income, living area and age (Wilson & Dowlatabadi, 2007).

The effectiveness from feedback differ between geographical, cultural and temporal contexts (Ehrhardt-Martinez et al., 2010). The results are also dependent on behavioural biases and how the feedback is presented (Bager & Mundaca, 2015; Fischer, 2008); this means that extrapolations or generalizations are difficult to make. Several feedback studies have been done in Europe, but few feedback studies with real-time information have been done in Sweden. E.ON made a large energy saving experiment on increased feedback in 2012-2013 that resulted in 2.24% reduced electricity use compared to the control group (Uggmark, 2013). The experiment used real-time feedback with In-Home Display (IHD), smartphone and web applications, but the feedback intervention was combined with five other interventions[4] that

[2] SMs are not only important for their possibility to provide feedback to end-users; they are also critical components of smart electricity grids that can use the real-time data from SMs to balance the supply and avoid unnecessary losses (Christensen, Gram-Hanssen, & Friis, 2013). Additionally, they allow for remotely switching on and off the electricity supply (Christensen et al., 2013), and they reduce the cost of manually reading of electricity meters (Darby, 2010).

[3] No ex-post evaluation of this intervention has been found but other examples of similar kind of policies from Northern Ireland and the US has shown electricity reductions of 1.1-2.7% (Dromacque, 2013). Sweden has so far not introduced any new policies that aim to increase the feedback further.

[4] The interventions included a mascot that was happy when the electricity was low, more salience that showed how much money people loosed, comparison with users in the neighbourhood, reminders and a rewards (Uggmark, 2013).

made the independent effect from each separate intervention difficult to understand. Two other studies have been made in Sweden that both lacked statistical significance. One of them was made between 2008 and 2009 and found a reduction of 0.04% of a service that presented electricity statistics (Jurek Pyrko, 2009) and the other that was done in 2014 studied the effect from an IHD (Nilsson et al., 2014).

There is also a lack of studies of the underlying factors of the effect from feedback interventions (Abrahamse, Steg, Vlek, & Rothengatter, 2005). It is not enough just to understand how effective interventions are, but also to understand why and for whom they are effective (Allcott & Greenstone, 2012). In order to shape cost-effective policies for energy conservation and energy efficiency, it is important to understand the determinant factors for success or failure (Steg & Vlek, 2009; Van der Linden, 2014).

The characteristics of Sweden make it an interesting country to study. Sweden has a unique energy situation with a large part of energy coming from water and nuclear power, extensive district heating use produced mainly by waste and biofuels and an aggressive energy roadmap (IEA, 2013). It has also among the highest average consumption of electricity in Europe (Dromacque, 2013). If the effects from increased real-time feedback in Sweden and the reasons behind the effects are unknown, opportunities for the society to reduce negative consequences from electricity use[5] may be lost.

A case in Sweden, not being studied earlier is the electricity feedback service called 100Koll, which was launched by the energy company E.ON in February 2014. 100Koll provides electricity feedback on computers, tablets and smartphones. Although the service may bring the attractive benefit of reduced electricity use, it has not been introduced to comply with Swedish or European policies but instead to attract customers that find the service useful and to gain increased understanding of the customer´s use of electricity. Little research has been done on the service, offering a great opportunity to increase the scientific knowledge about such electricity feedback in Sweden.

1.3 Objective and research questions

The purpose of this thesis is to increase the knowledge of how real-time feedback on smart phones, tablets and computers influences electricity use in Sweden. Using the 100Koll service, the thesis aims to contribute to the development and implementation of effective policies for electricity reduction, including what kinds of behavioural and contextual factors potentially lead to a decrease in electricity use. The result will also add to the existing literature on SMs and electricity feedback with a new context and a new geographical area of intervention (Sweden).

In order to achieve the research purpose, the following two research questions were formulated:

1. What effectiveness with regards to reduced electricity use has 100Koll had on Swedish households?
2. How do people's psychological, moral and contextual characteristics determine the electricity use and the effect of the 100Koll real-time feedback service?

[5] Negative consequences from electricity includes, for example, CO_2 emissions (although they are small in Sweden), radioactive waste and risk of nuclear meltdowns, developed rivers, as well as increased land use from bio mass cultivation, solar panels and wind turbines (Miller & Spoolman, 2012).

By answering these questions, important stakeholders on different levels in the society can gain a deeper understanding in determining whether real-time electricity services shall be further promoted. It may also be possible to better understand what kind of consumers are more likely to react positively to the feedback services and do more to reduce energy use. This will help to reduce the information deficit and decrease the energy efficiency gap, which will lead to a more sustainable society.

1.4 Scope and limitations

This thesis was carried out between June and September 2015 in partnership with E.ON Sweden. The data obtained is only collected from this company and its customers. The case study included only Swedish households, and a majority of those represented single-family houses, but apartments were also included.

This study focused on one particular feedback intervention. The result was compared to other similar studies in the world but it was not in the scope of this thesis to experiment with different types of feedback. Instead, the thesis focused on psychological, moral and contextual factors that impacted energy behaviour and electricity use. There are, of course, many other important factors that are impacting electricity use, such as habits, electricity price, technical solutions, number of teenagers in the household and number of appliances (to mention a few). Those were, however, out of scope for this research.

1.5 Target audience

This thesis aims to fill a research gap within the household electricity use area, and the overarching purpose is to contribute to a reduction of electricity use in the society, with all the benefits that this brings. The thesis should be of interest for *policy makers*, especially in Sweden, that are concerned about reduced household energy use. The results may be used as minor contributions to ex-ante evaluations and potential cost benefit analyses for new policies. Additionally, it may help to inform the official policy makers about whom to target with policies and what kind of information policies may be helpful in combination with feedback interventions like the one studied.

The research also intends to fill a gap in the energy feedback literature by adding more understanding of effects of a feedback service in Sweden. As such, it can hopefully help *researchers* within the field to get an even better understanding of if, how and why this kind of feedback works in Sweden.

Finally, the research also targets *energy companies* that are seriously working on finding energy efficient solutions for their customers. E.ON, which has been a critical partner for this research, may use the input to better understand their customers in relation to electricity use and 100koll effectiveness.

1.6 Thesis outline

Chapter 1 presented the background to this thesis and the need for more research regarding electricity feedback to consumers in Sweden. The research questions were outlined, the scope and limitations presented and the target audience described.

Chapter 2 describes the theoretical framework for this research. It gives an understanding of previous results related to the research questions and sets this thesis in perspective to other studies. The data collected is used in the results and analysis sections.

Chapter 3 describes the methodology of the research and includes the conceptual framework that guided both the data collection and the analysis that also are described. 100Koll, the case under study, is also presented in detail in this chapter.

Chapter 4 presents the collected data and the results from the analysis.

In chapter 5, the results are discussed and compared with other similar studies, the validity of the results is reviewed, the methods used are discussed and potential policy implications from the findings are presented.

Chapter 6 concludes the thesis, presents the main findings from the results and explains the implications for the target audience of this thesis. Suggestions for further research are provided.

2 Theoretical framework

This chapter introduces the theory behind SMs, enhanced feedback and the consumer behaviour. The literature of consumer behaviour and behavioural change is extensive with a significant amount of models and theories (See e.g., Jackson, 2005). After the literature review it was decided to focus on two of the behavioural theories, the Theory of Planned Behaviour (TPB) and Value-Belief-Norm (VBN) theory as they was found to complement each other, have been used extensively in energy behaviour studies (Abrahamse & Steg, 2009; Armitage & Conner, 2001; Botetzagias, Malesios, & Poulou, 2014; Jackson, 2005; Wilson & Dowlatabadi, 2007) and were sufficient to answer the second research question.

A review of feedback studies made globally, including a more extensive study of results from Scandinavia and Sweden, is also included in this chapter. It was important to focus on this area of the world to be able to set the results from this study into perspective and enable analysis of potential reasons for the outcome. Additionally the review provided an under standing of methodologies of earlier similar studies, which was used as guidance of the methodology design for this research.

The literature reviewed was academic literature as well as documentary reports. Academic search engines have been used to find peer reviewed academic journals and books. Documentary reports include governmental reports and other officially published material. Moreover, meta-reviews and overviews from both the feedback literature (e.g., Abrahamse et al., 2005; Bager & Mundaca, 2015; Darby, 2006; Ehrhardt-Martinez et al., 2010; McKerracher & Torriti, 2013) and the behavioural literature (e.g., Armitage & Conner, 2001; Jackson, 2005; Wilson & Dowlatabadi, 2007) have been used to gain an understanding of the research area.

2.1 Theory behind smart meters and enhanced feedback

Electricity is an abstract product that has become a commodity in developed societies (IEA, 2014c). For most electricity users, understanding of how much is consumed, what appliances consume the most and how consumption varies over time is vague (Darby, 2006). In many cases, users receive feedback only via a bill that is received one to three months after consumption and few users can and may use this input to understand what behaviour and what appliances consume the most electricity (Darby, 2006). The assumption behind many studies is that this information deficit leads to a behaviour entailing more electricity use (e.g., Brandon & Lewis, 1999; Darby, 2006; Schleich, Klobasa, Gölz, & Brunner, 2013)

The psychological research on energy (and electricity) differs between efficiency behaviours and curtailment behaviours (See e.g. Stern & Gardner, 1981). Efficiency behaviours includes infrequent actions that involve some kind of investment, such as buying efficient light bulbs and appliances, while curtailment behaviours are more frequent actions whereby the user decreases energy use by using less energy, such as reducing the temperature or switching off lamps that are not used (Stern & Gardner, 1981). The distinction is psychologically important according to Stern and Gardner (1981), as people tend to be more receptive to energy efficiency behaviour than curtailment behaviours. SMs aim to change both of these two kinds of energy behaviours by reducing users information deficit.

The information deficit problem relates to the *Information Paradigm*, which suggests that "asymmetric information can be an impediment to welfare-enhancing" (Micklitz, Reisch, & Hagen, 2011, p. 1) and that there are consumers who are willing and capable to digest the provided information and use it for rational decisions (Micklitz et al., 2011). Consequently, new information from SMs should, according to the paradigm, lead to new knowledge that can be used for rational decisions that leads to behavioural change. The information paradigm is in line with the model of rational choice that is the dominant theory behind most of the existing energy-economic policies (Jackson, 2005; Mundaca, 2008).

However, people are not capable to process all information for rational choices (Jackson, 2005; Tversky & Kahneman, 1974). To cope with this limitation people enact a habitual behaviour (Jackson, 2005). The consumption patterns for electricity are often habitual and routinized without any reflection on when and where the electricity is consumed (Fischer, 2008; Verplanken & Wood, 2006). Habitual electricity use behaviour includes, for example, switching on and off lights, washing a full load of clothes, having lower temperatures in the living area and in the fridge and freezer and reduced stand-by use. Habitual behaviour is practical as it spares us the time and effort of making conscious decisions; however, the habits may also lead to undesired, suboptimal results (Fischer, 2008). The more often the habit is repeated and the more positive reinforcement that is received from the habit, the harder it is to break the 'bad' habit (Jager, 2003). According to Fischer (2008), to break a habit the person must first realise that there is a problem and after that understand that his or her problem is related to the behaviour and finally become conscious that it is possible to change his or her behaviour.

The information provided via the feedback mechanisms can lead to conscious decisions to make habitual changes and use less electricity use (Abrahamse et al., 2005; Darby, 2006; Staats, Harland, & Wilke, 2004). However, conscious decisions are not the only way to change habits. The literature of behavioural economics focuses on how people are influenced by biases and make unconscious decisions with low cognitive efforts (See e.g. Kahneman, Knetsch, & Thaler, 1991; Thaler, 1999; Tversky & Kahneman, 1974). One example of findings within this strand of literature is that people are more concerned about losing a certain amount of money than they are pleased about winning the same amount (loss aversion) (Kahneman, Knetsch, & Thaler, 1990; Weber, 2013). Another example that has been demonstrated is that by 'priming' respondents in a survey with images of nature resulted in more positive answers regarding recycling behaviour (Biel, 2004). Some scientists within behavioural economy tend to treat rationality as a dichotomous variable instead of as degrees of rationality (Etzioni, 2014). Etzioni (2014) argues that there is clear evidence that people act irrational in many cases but that the science has not clarified the degree of rationality and in which cases people tend to be more or less rational. The thesis at hand has not done any experiments within behavioural economics but acknowledges that the literature of behavioural economics presents important explanations of irrational human behaviour.

2.2 Rational Choice Theory

Neoclassical economical theory, practiced in most market-based countries, builds on the assumption that individuals are rational and have perfect information of the goods that are purchased (Mundaca, 2014). The idea is that each individual makes a brief cost benefit analysis for all choices and selects the choices with lowest costs (not necessarily in monetary terms) in order to maximise utility (Scott, 2000). The lack of information is seen as one kind of market failure and shall be corrected as it prevents people from making the correct decisions (Micklitz et al., 2011).

The rational choice theory has, however, met substantial criticism in the last decades (Hargreaves, 2011; Jackson, 2005; Thaler, 2000). Jackson (2005) lists three main categories of criticism to rational choice: people act irrationally, they are not purely individualistic and they (people) do not act without moral considerations.

The first criticism of rational choice theory is that people do not always act rationally (to what extent is not described or debated). People have limited cognitive skills and are unable to process all provided information and therefore take cognitive shortcuts by for example acting according to routines. Uncertainties concerning the future and the costs of gaining information are also potential barriers to people acting rationally (Simon, 1957). All the critique from the literature of behavioural economics lies, of course, also within this category of critique. People tend to behave according to their habits and do what they are used to without reflecting on making any new choices (Aarts, Verplanken, & van Knippenberg, 1998; Bourdieu, 1990).

The second category of criticism according to Jackson (2005) is that people are not acting purely individualistically; instead, they are deeply influenced by their social context. Mead (1934) claims that 'social conversations' are forming the self, and Granovetter (1985) argues that interpersonal relations are embedded in making decisions to such a degree that the assumption that they are independent from the behaviour, as claimed by rational choice theory, is a "grievous misunderstanding" (p. 482).

The third and final category of criticism of rational choice theory concerns the lack of moral considerations. People do not always act out of their own self-interest but also due to purely altruistic reasons (Schwartz, 1973). Results from four American studies made by Schultz (2001) provided "strong evidences" (p. 336) that people had environmental concerns organized around altruistic and biospheric concerns in addition to egoistic concerns. Jackson (2005) discussed two possible reasons for why social structures that limits self-interest actually are accepted. The first idea was that the social structures are the antecedents to individual behaviour and that "we, as individuals are socialised automatons, helpless in the face of institutional structure" (Jackson, 2005, p. 40) and the second alternative was that people recognise that a moral behaviour is optimal for the protection of long-term success of the society. Regardless which of the alternatives are most correct, both of the two rejects central parts of the rational choice theory (Jackson, 2005).

The amount of criticism of rational choice theory from many different areas of research has resulted in efforts to develop new models that at least partly mitigate recognised limitations of rational choice theory (Jackson, 2005). Two of those theories, extensively used within energy behaviour research, are introduced in the following sections.

2.3 Theory of Planned Behaviour

The Theory of Planned Behaviour (TPB) (Ajzen, 1991) has been one of the mostly used models to predict peoples behaviour (Jackson, 2005; Turaga, Howarth, & Borsuk, 2010). The studied behaviours come from a range of areas, such as health and consumption where examples include smoking behaviour, blood donations and sunscreen use (Armitage & Conner, 2001), but TPB has also been used to predict pro-environmental behaviour (Bonnes & Bonaiuto, 2002; Jackson, 2005), including recent studies on electricity use (Abrahamse & Steg, 2009; Botetzagias et al., 2014).

TPB is an extension of the theory of Reasoned Action (Ajzen & Fishbein, 1980) that suggests that a persons *intention* is a central antecedent to the actual behaviour. The intention in turn can be predicted by *attitudes* towards the behaviour and the *subjective norms*. Some scientists call TPB a rational choice theory (Abrahamse & Steg, 2009; Turaga et al., 2010), but it differs in the important aspect that it also includes the factor subjective norms (Jackson, 2005). Ajzen (1991) added the factor *perceived behavioural control* (PBC) to the Reasoned Action theory, and the new theory became TPB. According to the theory PBC influences both the intention to behave in a certain way as well as the actual behaviour (Ajzen, 1991).

The *attitude* towards the behaviour describes how positive or negative a person is to enact a specific behaviour and is formed by the evaluation and the beliefs of the outcome of the behaviour (Ajzen, 1991). The *subjective norm* describes the pressure that an individual feels from others, important for the individual, to behave in a certain way (Ajzen, 1991). Each belief of each person is called the normative belief and the subjective norm is the sum of the strength of each normative belief multiplied with the motivation to comply with that individual (Ajzen, 1991). The subjective norm is different from the *personal norm* that describes the own personal view of the behaviour regardless of what others think.

Ajzen (1991) found that the theory of Reasoned Action was applicable only when a person believed that he/she had the possibility to perform the action; therefore, the predictor perceived behavioural control (PBC) was added to the model. In the context of this thesis, a user who has confidence that saving electricity is possible is more likely to accomplish results than a user who does not perceive it possible to save more electricity.

Figure 2-1 illustrates a schematic view of how the different factors are supposed to influence behaviour. Note that the intention is only a proxy for the actual behaviour, and the correlation between the intention and behaviour has been found to be 0.47 (Armitage & Conner, 2001). According to Jackson (2005), most studies that use TPB only measure the relation between the predictive factors and the intention and not the actual behaviour, which seems a bit odd since it is the actual behaviour that is important in the end. The relative strength of the predictors is context dependent, meaning that for some behaviours, the attitudes are larger determinants while in others it can be the subjective norms or PBC (Ajzen, 1991). The subjective norm is often seen as the weaker predictor of behaviour. Abrahamse and Steg (2009) decided, based on poor results of previous studies, to remove the factor from the model.

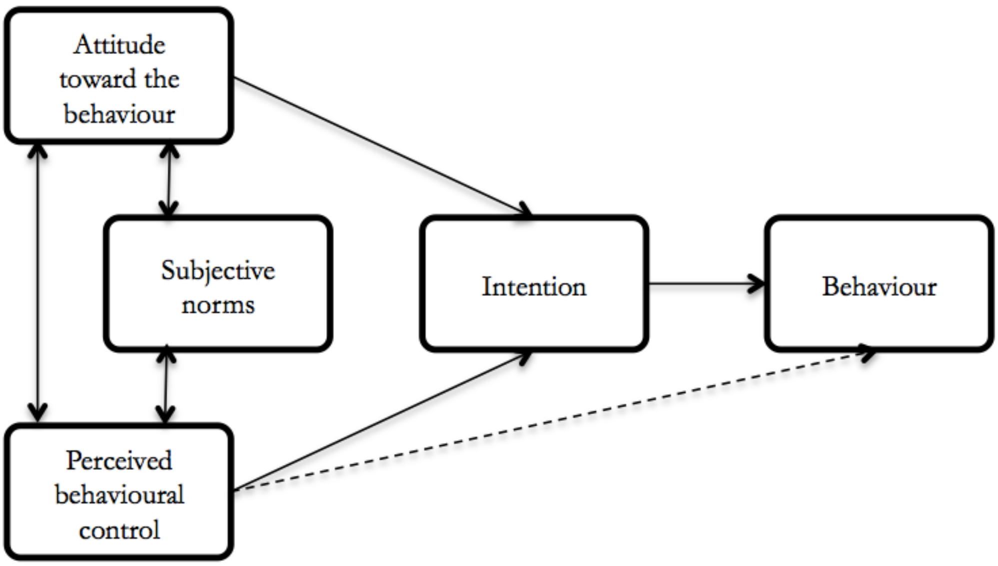

Figure 2-1. Schematic view of TPB. The arrows denote the relation between two factors/behaviour.

Source: Author, after (Ajzen, 1991)

In a meta-review of TPB, Armitage and Conner (2001) studied 154 different reports and found that TPB has managed to explain 20% of the variance of the actual behaviour. It was also found that self-reported behaviour (from surveys) is easier to predict with these factors than actual behaviour (Armitage & Conner, 2001; Jackson, 2005).

Recent studies have found that PBC and attitudes are significant predictors for energy saving (Abrahamse & Steg, 2011; Botetzagias et al., 2014). A Dutch study of energy use in households found that PBC was a significant predictor for energy savings (Abrahamse & Steg, 2009), and Botetzagias et al. (2014) concluded a comparable result that found that the factor had a significant contribution to several energy curtailment behaviours in Greek households. Botetzagias et al. (2014) also found a contribution from the attitudes factor for some of the behaviours, but no contribution from the subjective norms were found in that study.

As explained earlier, one of the limitations of rational choice theories is that moral considerations are not taken into account. The TPB model, which is highly related to rational choice theories, does not include this aspect. Morality is, however, a central concept in the theories described in the following section.

2.4 Norm-Activation and Value-Belief-Norm theories

People that are aware of environmental issues and feel responsible for the causes of these do sometimes act irrationally according to rational choice theories. Instead of just behaving in the interest of their own personal satisfaction they are acting in the best interest of other people or living organisms. This way of acting is called pro-environmental behaviour. The value-beliefs-norm (VBN) theory, developed by Stern (2000), is trying to explain how values, beliefs and norms steer this kind of behaviour. VBN was based on another theory called the Norm-Activation theory, which will be the first to be described below.

The Norm-Activation theory (Schwartz, 1973, 1977) suggests that behaviour is steered by personal moral norms that are an outcome of two different psychological antecedents. The first antecedent is the awareness of the consequences or threats to others, pro-environmental or altruistic behaviour is activated (awareness of consequences, AC). The second antecedent is that an individual must feel that he/she has the ascribed responsibility (AR) to act. Schwartz (1977) stresses that the ascribed responsibility is a defensive tendency whereby the individual tries do deny his/her responsibility rather than an impulsive tendency to feel responsible for certain events. This means that if the denial is low, a person's norms and altruistic behaviour are stronger. As can be seen in Figure 2-2, the awareness of responsibility and the ascribed responsibility are not only determining the personal norms, but also the behaviour directly, which implies that the two antecedents are also influencing the strength between the personal norms and the behaviour (Jackson, 2005).

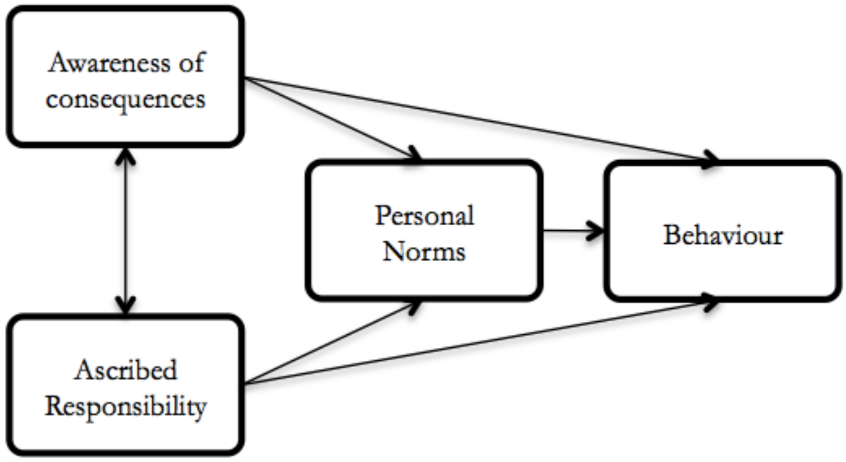

Figure 2-2. Schematic view of the Norm-Activation theory.

Source: Author, after (Jackson, 2005)

The VBN theory extends the moral Norm-Activation theory with the New Environmental Paradigm (NEP) perspective which is a survey-based metric, designed to measure the environmental concerns of people (Dunlap, Van Liere, Mertig, & Jones, 2000). The survey consists of 15 statements to which the respondents are asked to indicate the level of agreement or disagreement (Dunlap et al., 2000). The total score of the NEP survey is affected by the biospheric, altruistic and egoistic values. Stern (2000) argues that research has shown that the different factors are linked via a causal chain according to Figure 2-3, which differs from Schwartz (1977) who argued that AC and AR are also direct antecedents of the actual behaviour. In the VBN model, the NEP factor is an antecedent to AC and is influenced by biospheric, altruistic and egoistic values of a person (Figure 2-3).

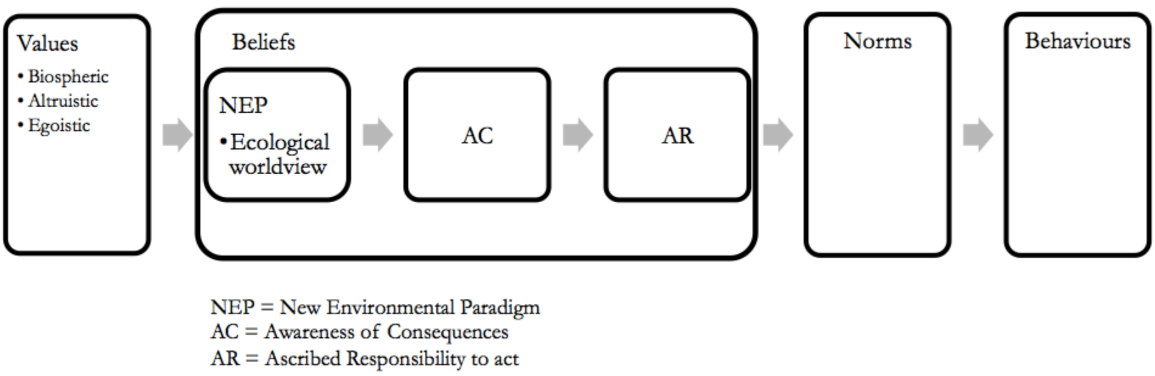

Figure 2-3. Schematic view of the VBN theory.

Source: Author, after (Stern, 2000)

Stern (2000) also acknowledge that there are other variables that influence behaviour, such as contextual factors, personal capabilities and habits (Stern, 2000). Within the contextual factors monetary incentives and costs are included. In the SM case, the monetary incentives are related to the amount of money that can be saved on the electricity bill, while the costs include transaction costs for keeping track of the savings and the costs for buying energy efficient appliances.

VBN and the Norm-Activation theories have been used in several studies that aim to understand the underlying factors behind environmental activity, both for estimating the behaviour for electricity curtailment (Abrahamse & Steg, 2011; Black, Stern, & Elworth, 1985; Botetzagias et al., 2014) and for other kinds of environmental behaviours such as consumer recycling behaviour (Park & Ha, 2014), yard burning behaviour (Van Liere & Dunlap, 1978) and student´s car use (Bamberg & Schmidt, 2003).

Many of the studies have used surveys or interviews to estimate the behaviour of the individuals (Jackson, 2005). A problem with surveys are that the 'Hawthorne effect' may cause unreliable results (see e.g. Adair, 1984). This effect implies that the participants change their behaviour because they are aware that they are being monitored (Adair, 1984).

2.5 Contextual variables influence on behaviour, energy use and energy saving

Contextual variables does also influence the electricity and energy use behaviour (Stern, 2000; Thøgersen & Grønhøj, 2010; Wilson & Dowlatabadi, 2007). These variables are behavioural determinants that are not personal or psychological (Wilson & Dowlatabadi, 2007). Wilson & Dowlatabadi (2007) further divides the contextual variables into individual variables, such as socioeconomic status, technical skills and individual resources, and shared variables, such as regulations, available technologies and social norms[6]. According to this definition the availability of a SM and the amount and type of electricity feedback falls within the category of contextual variables.

The literature provide evidence that contextual variables are important factors for predicting the total energy use (Abrahamse & Steg, 2009; Brandon & Lewis, 1999; Thøgersen & Grønhøj, 2010). Black et al. (1985) demonstrated that contextual factors were influencing the behaviour indirectly and can also constrain energy efficiency measures. One example is that people with less income may not afford to upgrade to effective heating or improve the insulation (Black et al., 1985). Home size, family composition and income are contextual parameters that have been found to significantly impact the total energy use (Thøgersen & Grønhøj, 2010).

With regards to energy efficiency investments many studies are consistent with the not so surprising result that wealthier households are doing more energy efficiency investments than poorer ones (Black et al., 1985; Karlin et al., 2014; Urban & Ščasnỳ, 2012). Different results have been found with regards to the impact from the education level on the electricity saving behaviour (Karlin et al., 2014). Black et al. (1985) found a positive correlation between higher education and energy curtailment behaviour in contrast to Nair et al. (2010) and Poortinga et al. (2003) that both found negative correlation. Botetzagias (2014) that tested determinants for different electricity curtailment behaviours found that people with higher education are more likely to wash clothes with lower temperature but no statistically significant contribution from the education variable was however found for any of the other seven behaviours studied. It has also been found in both more recent and older studies that senior persons tend to do more energy curtailment activities (Black et al., 1985; Urban & Ščasnỳ, 2012).

[6] The subjective norm is closely related to the social norm but differs in the specificity of the behaviour: "While a social norm is usually meant to refer to a rather broad range of permissible, but not necessarily required, behaviors, NB [Normative Belief] refers to a specific behavioral act the performance of which is expected or desired under the given circumstances" (Ajzen & Fishbein, 1972, p. 2). While it makes sense that the social norm is a contextual norm the subjective norm is the personal subjective view of the individual and will in the thesis at hand be referred to one of the psychological factors of the individual.

2.6 Feedback studies and smart meter effectiveness

Since the last oil crisis in the early 70s multiple studies have been performed to understand how to reduce energy use and to identify different drivers of energy use (Ehrhardt-Martinez et al., 2010). This section provides a brief overview of what kind of feedback intervention studies that have been done, different ways of conducting the studies, where and when they have been conducted and the main results with regards to effectiveness.

2.6.1 Overview of studies and methods

Feedback of energy use can be categorised in different ways. Darby (2006) divided them into *direct feedback* where the feedback is delivered without being processed by anyone, *indirect feedback* where the consumption is treated before it reaches the customer (typically together with the bill) and *time of day pricing* where the user gets higher prices during peak hours and can then steer the consumption to the time of day when prices are low. Ehrhardt-Martinez (2010) further divided the indirect feedback systems into *enhanced billing*, *estimated feedback* (meaning that the utility company estimates and disaggregates the energy usage) and (*daily/weekly feedback*) via for example mail or self-meter reading. The direct feedback was divided into *real-time feedback* and *real-time plus,* where the difference between the two is that real time-plus also receives disaggregated consumption for individual appliances (See table 2-1).

Table *2-1. Different grades of feedback and their effectiveness (Ehrhardt-Martinez et al., 2010)*

Direct/Indirect	**Feedback**	**Description**	**Estimated Effectiveness**
Indirect	Enhanced Billing	Household specific billing, advice	3,8%
Indirect	Estimated Feedback	Web-based energy audit with info on on-going basis	6,8%
Indirect	Daily/Weekly Feedback	Household specific info, advice on daily or weekly basis	8,4%
Direct	Real-Time Feedback	Real-time premise level info	9,2%
Direct	Real-Time Plus Feedback	Real-time inform down to application level	12,0%

Ehrhardt-Martinez (2010) categorised large studies as having more than 100 users in the sample and long duration period as more than six months. Fischer (2008) categorised the feedback interventions into what kinds of comparisons are provided in the feedback.

All feedback studies identified in this literature review have been done in North America, EU, Australia and Japan (Abrahamse et al., 2005; Darby, 2006; Ehrhardt-Martinez et al., 2010; Fischer, 2008; McKerracher & Torriti, 2013). In a meta-review of feedback interventions from gas and electricity use, Darby (2006) found that direct feedback reduces the energy use by 5-15%, whereas feedback reduces energy use by 0-10%. These figures were then supported by the research done by Ehrhardt-Martinez et al. (2010) that found savings between 3.8% for enhanced billing up to 12% for real-time information (including disaggregation on appliance level) (Table 2-1). However, Schleich et al. (2013) could not find any significant difference in reduction between those users that had enhanced billing compared to those that had interactive web feedback.

In their review of 19 studies based on feedback from SMs, Bager & Mundaca (2015) found more modest reductions of 1.6% (*Mdn* = 2.9, *N* = 19). When the studies that included IHDs were removed, even lower reductions of 0.7% were found. The study was based on more recent interventions undertaken between 2002 and 2013 (Bager & Mundaca, 2015). Another recent meta review that studied solely direct feedback from IHDs conducted from 33 interventions found that the average reduction was not more than 3-5% (McKerracher & Torriti, 2013). According to the authors, the reason for this lower figure was that previous meta-analyses omitted data from the newest trials and included trials on gas use, time of use billing and prepayment. Another reason given was also that the presence of the smart grid, including installed SMs, has made trials like this easier and less costly, which has enabled a more representative sample (McKerracher & Torriti, 2013).

There are different results regarding the effects of normative comparisons between users. Two older studies report high effects of 10% and 18% from normative comparison (Midden, Meter, Weenig, & Zieverink, 1983; Nolan, Schultz, Cialdini, Goldstein, & Griskevicius, 2008) while more recent and larger trials have showed more marginal reductions of 1% and 2.2% (Klos, 2009; Raw & Ross, 2012). Two studies that have tested this comparison did not find any significant reductions in use at all (Egan, 1999; Haakana & Sillanpää, 1998). Fischer (2008) argues that normative comparisons do not provide any improved savings and that users that find that they are consuming below average may think that they have no reason to take any further actions for energy reduction.

The vast majority of the feedback studies have used a control group that has not received the same feedback as the intervention group (Abrahamse et al., 2005; Darby, 2006; Ehrhardt-Martinez et al., 2010; Schleich et al., 2013), some have used both a control group and a historic baseline (e.g. Brandon & Lewis, 1999; Mountain, 2006; Nilsson et al., 2014; Ueno, Inada, Saeki, & Tsuji, 2005) and a few have only used a historical baseline (Nielsen, 1993; Ueno, Sano, Saeki, & Tsuji, 2006). The consumption data gathering is done on various ways, such as, meter readings, self-reporting of electricity meter, surveys, self-reporting of energy saving behaviours and interviews (Fischer, 2008). The studies varies between large field studies that measure a specific feedback intervention and more experimental studies that randomly pick out the sample and expose different groups to different kind of feedback mechanisms (Abrahamse et al., 2005; Bager & Mundaca, 2015; Ehrhardt-Martinez et al., 2010; Fischer, 2008; McKerracher & Torriti, 2013).

Ehrhardt-Martinez (2010) found that earlier studies in the 70s and 80s (called the energy crisis era) report 2.1% (percentage points) higher savings than those more recent studies in the 90s and the first decade of the new century (the climate change era). It is also found that larger studies (N >100) tend to report lower reductions of energy use than smaller ones (6.6% versus 11.6%). Bager and Mundaca (2015) also found in their meta-review that such a trend may be correct but only with a significance level of 85%. However, Gans et al. (2013), which present findings from a large study on Northern Ireland with approximately 2 800 households between 2002 and 2009, found significant reductions of 11-17%. These reductions are found for pre-paid customers that had a "key-pad meter" installed in their houses. Two other recent and large studies report more modest electricity reductions: a study in Austria found reductions of 4.5% (Schleich et al., 2013), and 3% reductions were found in a 2007-2010 study with 60 000 households in the UK (Raw & Ross, 2012).

2.6.2 Feedback studies in Scandinavia

Since this thesis studied a feedback service in Sweden a more thorough review is done on interventions done in in Scandinavia. Ten of the feedback studies that were found have been done in Scandinavia. Most of those interventions related to indirect feedback via improved billing or mailings and not direct real-time feedback. Only three feedback studies that are using displays, and not enhanced billing, have been identified in Scandinavia (Bager & Mundaca, 2015; Nilsson et al., 2014; Uggmark, 2013). Bager & Mundaca (2015) demonstrated that the introduction of 47 SMs in Copenhagen residences reduced the electricity use by 6,7% (±41%) while Nilsson et al. (2014), in a Swedish feedback experiment where the users got IHD installed in their homes, did not measure any statistically significant effect at all. Both of the two studies suffered from fairly low number of participants (47 and 40), which reduced the possibility to get statistically significant results.

One study that did not suffer from few participants was the E.ON energy saving experiment that initially had 9 771 participants (Uggmark, 2013). The experiment combined several interventions including consumption feedback on phone, IHD and five different motivational interventions: economical motivation that stressed the amount of money that has been spent on electricity, a social comparison where the users competed with four to five other similar households, reminders and status information regarding success or failure and the fifth intervention that targeted the kids in the households that included an app with the cuddly character Bongo, who was happy when electricity was reduced and sad when it increased. Even though the experiment included a lot of ingenuity, praising efforts to reduce electricity in the households and interesting results regarding electricity saving in different segments of the society, it gave no information regarding the contribution from each individual intervention including the isolated effect from the increased feedback. However, all the interventions together resulted in a decrease of electricity use of 2.2% compared to the control group. The intervention group reduced the electricity use by 0.7% compared to historical use, while the control group increased electricity use by 1.5% compared to historical use (Uggmark, 2013).

Another Swedish study of 400 households aimed to study the potential of reducing electricity use by providing the users with a web service that presented monthly statistics of their electricity use (Jurek Pyrko, 2009). The study concluded that the users of the service only reduced their use with 0.04% and that the change was not statistically significant (Jurek Pyrko, 2009).

To summarize, a lot of feedback studies have been made, and all have different geographical, social and temporal contexts. It is difficult to compare these studies as they all have different kinds of interventions and starting points before the interventions take off. Except for the E.ON energy experiment (Uggmark, 2013) no larger study of real-time feedback in Scandinavia has been found.

3 Research methodology

This chapter describes the methodology used to be able to answer the two research questions defined for this thesis. First the case under study, 100Koll, is described. The next section describes the methods used to collect the data and it also includes the conceptual framework that guided the design of the survey. The third section presents the methods used for the analysis.

3.1 Case study: 100Koll

Case studies have become a fundamental basis for social-economic research and evaluation theory, bridging research and practice, sharing good practice experiences and identifying the scalability and replicability of solutions. This unit of analysis is the most flexible and valuable component of research design for evaluation research (Yin, 2014).

100Koll is a service provided by the utility company E.ON. It allows monitoring user's electricity use on a smartphone, a tablet or a web page. The feedback is provided in (close to) real-time with up-to one minute delay from the actual electricity use until it is actually is presented on the display. In order to use 100Koll, each user has to install an optical eye, connected to the SM that normally is mounted in the property where the electricity use takes place. To transmit the electricity use data to the 100Koll database, the optical eye is also connected to the user's Wireless Local Area Network (WLAN). 100Koll can also monitor the users electricity use on individual appliances in the home by the use of smart plugs that are connected between the electricity outlet and the electric appliance. The smart plug measures the electricity use and can also be programmed to switch on and off electricity supply to the appliance according to the need of the user. The smart plugs communicate with the 100Koll service via the user's WLAN and the Internet.

Figure 3-1. The 100Koll smart phone app in the middle, the smart plug (left) and the optical eye (with the wire) that is connected to the communication box (to the right)

Source: E.ON, (used with consent from E.ON)

Fischer (2008) identifies some features for effective feedback that both stimulates energy efficiency/conservation measures and is appealing to users. The feedback shall according to Fischer (2008) be based on actual consumption, given frequently, involve interaction, allow for appliance specific breakdown, given over a long period, have historical or normative comparisons and be presented in an appealing way. 100Koll fulfils many of these features as it is based on actual consumption, and the electricity consumption can be monitored anytime anywhere provided that the user has a smartphone or tablet. The feedback is given with one minute delay, which means that the feedback is close to real-time. Historical consumption is provided in a graph and can show the consumption back on an hourly, daily and monthly level. No normative comparisons (e.g., with national average, similar households or households in the neighbourhood) are presented by the service. The actual and the historical consumption data reported by the smart plugs are also given as a feedback. The user can choose to see the feedback in either kWh or in monetary value of the electricity consumed; however, the user has to manually enter the electricity price (in öre/kWh). No feedback regarding environmental impact of electricity use is provided, but the application includes the animated mascot, Bongo, who becomes happier the more electricity that is saved. 100Koll was introduced in Sweden in February 2014 and the number of users of the service has gradually increased since then.

3.2 Methods for data collection

Except for the literature reviewed, two methods were used for collecting the data. The first method used was to collect electricity use data from an E.ON database and the second method was to collect additional information about the electricity users via a survey.

3.2.1 Electricity use data

By collecting electricity use data, it will be possible to measure how the consumption has changed due to the introduction of the 100Koll service and from that calculate the effectiveness of 100Koll and answer the first research question defined in section 1.3. This data is also, together with data collected from the survey, used to answer the second research question that aims to find factors that can predict electricity behaviour.

Electricity use data was collected from two groups of E.ON customers: the intervention group that had installed the 100Koll service in 2014 and a control group that had not installed 100Koll. The sample size of the 100Koll group was 2 751, and only users that started with the service before 30 September 2014 were included in the sample. Electricity use data up until April 2015 was collected, which means that all users in the sample had used the service for 8 to 14 months. The sample included buildings that have had different users during the sample period. These were removed to avoid strange consumption patterns. Moreover, users that lived in different houses or apartments (i.e., used different residential IDs) were removed from the sample since it would have resulted in odd electricity use and saving results. Households with a consumption equal to zero in any month were also scrapped from the sample, as it seemed unrealistic for a normal household. Finally, only users that had consumption data between January 2011 and April 2015 were kept in the sample since the historic consumption data was needed as a baseline to estimate the expected consumption after 100Koll was introduced. With all these users removed from the original sample, 1 753 users were kept for the calculation of the effectiveness. The households were all based in Sweden with the majority of users in the southern part of the country. With 4.7 million households in Sweden (Statistics Sweden, 2013) and a sample size of 1 753, the margin of error in the calculations is as low as 2.34% with a 95% confidence level. The collected data from the database included the monthly electricity use from January 2011 up until April 2015 and the date the individual residence installed the 100Koll service.

The sample of the control group was selected by E.ON, which tried to find a socio-economic mix that mimicked the intervention group. The geographical mix was also regarded in the selection. This thesis did not include any measures to find the difference in the socio-economic mix but the fact that the average monthly consumption differed with 35% between the two groups suggested that there were some differences between the two groups. The sample size of the control group was 2 048. After users that lacked data in any of the months from January 2011 to April 2015 were removed, 1342 users remained.

3.2.2 Consumer Survey

This section describes the method for the data collection of survey questions. As a guide for the design of the survey a conceptual framework was developed (Figure 3-2), which is presented in this section. The framework was also used for the model specification that is described in section 3.3.2.

The survey was conducted in June 2015 to capture the underlying factors for the electricity use. Due to time limits there were no time to pilot the survey as other wise is recommended (Oppenheim, 2000). An E.ON web based tool was used for the survey, and the questionnaire was sent to all 2 751 households that were included in the sample of 100koll users except for those that had not recently answered any other E.ON survey, which resulted in that the questionnaire was distributed to 2 173 households. As the whole population was targeted a random sample technique was not needed. After one week 543 responses were retrieved. The full questionnaire can be found in Appendix I. In addition to questions related to this thesis, other questions of interest for E.ON were also included in the survey[7]. These included, for example, why the service was ordered, how the smart plugs are used and if they would recommend the service to others.

Each question in the survey is a kind of test. The more tests that are done on a measurement the more the result can be trusted (Cronbach, 1951). Hence, to make sure that the survey really captures the factors correctly, multiple questions per factor should be used. The more questions that are provided for the same factor, the more valid the factor is (i.e. the more it is possible to believe that the factor really reflects what it claim to reflect) (Cronbach, 1951). An obvious drawback with including a lot of questions is, however, that it may lead to a lower response rate and irritation from the respondents. This is the reason why three of the psychological and moral factors were captured with only one test/question.

Most of the questions in the survey were designed with a Likert scale (Likert, 1932), which means that the respondent selects the answer from a discrete scale where the ends describe extreme values such as "does not agree at all" and "completely agree". All the questions for the psychological and moral constructs were constructed with a five-degree Likert scale.

Conceptual framework

From the theories presented in chapter 2 it was found there are many things that influence behaviour. Figure 3-2 below is a simplification of the relations between the SM, electricity behaviour, electricity use and its determinants with the discussed theories incorporated. The dotted parts, although they are interesting, were not within scope of the study. The SM may cause an impact on the psychological factors but a recent study found that electricity meters have not changed peoples cognition about monitoring and their environmental believes and suggested that the monitoring does not change the user to such an extent that it leads to spill-over effects of other pro-environmental behaviours (Webb, Benn, & Chang, 2014). It may therefore be a reasonable assumption that 100Koll has not influenced the psychological and

[7] E.ON added questions to this questionnaire to avoid submitting too many surveys to their customers.

moral factors of the users. The level of influence depends on the kind of information that is provided and in this case the information consists of user data.

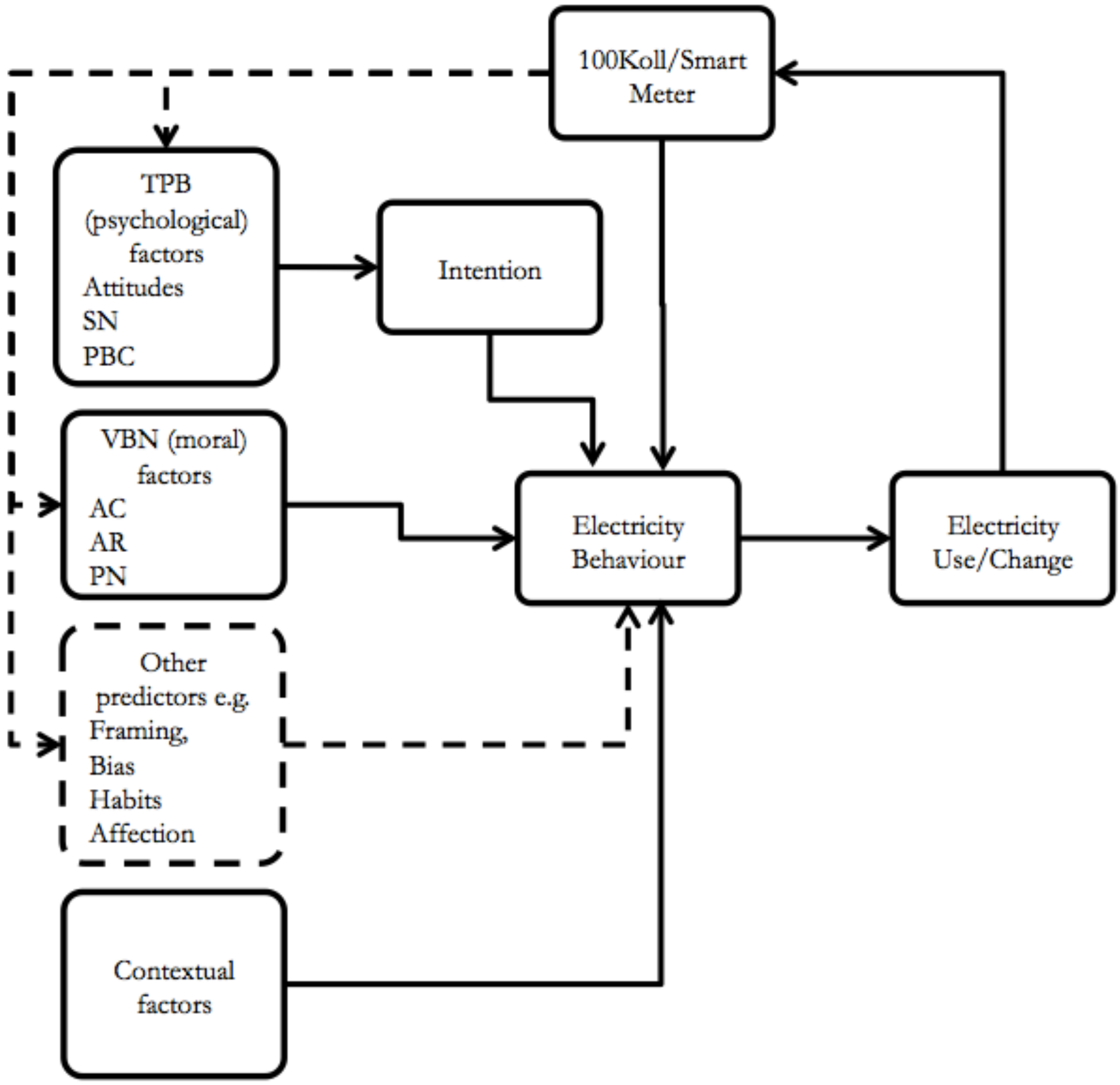

Figure 3-2. A simplified illustration of electricity behaviour with multiple theories synthesized into one graph, whereby the dotted lines describe the parts not studied in this thesis.

Psychological factors from Theory of planned behaviour

The TPB factors captured in the survey were attitude, subjective norms and perceived behavioural control, as they are, according to the theory (Ajzen, 1991), supposed to predict the intention of the user that in turn predicts the behaviour (see section 2.3)

The questions in the survey related to these factors were formulated after inspiration from Thøgersen and Grønhøj (2010). All questions were distributed in Swedish and are translated to English in this section. Care was taken when translating since nuances in how the question is understood may distort the result.

The *attitude* factor was captured by two questions: “It is important for me to save electricity to reduce the global warming” and “It is important for me to save electricity to reduce my costs”.

Even though there are more reasons to reduce electricity such as to increase energy security, reduce nuclear power with risks for radioactive leaks and reduce water power with less impact on rivers, it was decided to simplify the questionnaire and submit only these two questions in accordance with other surveys (see e.g., Botetzagias et al., 2014; Thøgersen & Grønhøj, 2010).

The *subjective norm* (SN) factor was captured by one question: "My acquaintances expect me to push myself to save electricity in my home". Even though this is a single-item question, it is assumed that it captures the subjective norms regarding electricity saving of the respondent.

The *perceived behavioural control* (PCB) factor was also captured by only one question: "I believe that I have large possibility to influence the electricity use of my household".

Moral factors from the Value Base Norm theory

The VBN factors that were captured in the survey were awareness of consequences, ascribed responsibility and personal norms. As described in section 2.4, VBN also includes the NEP factor that explains the ecological worldview of a person (Dunlap et al., 2000). To get a valid result for this factor, 15 questions would have been required. These questions, in addition to all the other questions were deemed to be too much for the respondents to handle with lower response rate as a result. According to Stern (2000), the NEP factor was the first factor of the beliefs in a causal chain leading to the behaviour. This means that it should also have the least correlation with the actual behaviour. It was therefore decided to remove that factor from the survey and the analysis. The questions were formulated after inspiration from the survey used by Abrahamse and Steg (2011).

The *awareness of consequences* (AC) factor that was supposed to reflect how large problems the respondent believe that energy use causes, was captured by two questions: "I think that global warming is a problem for the society" and "By saving electricity you contribute to a reduction of global warming".

The *ascribed responsibility* (AR) factor captured the respondents feeling of responsibility to reduce the greenhouse effect and was captured with only one question: "I feel jointly responsible for the global warming".

The *personal norm* (PN) factor aimed to reflect the magnitude of moral obligation to reduce electricity use and was captured by two questions: "I feel like a better person when reducing electricity use" and "I feel guilty when I use a lot of energy".

Contextual factors

Five contextual factors were captured in the survey: size of the residence (*Living area*), amount of persons that live in the household (*Household size*), monthly disposable income of the household (*Income*), level of education of the respondent (*Education*) and the age of the respondent (*Age*). These were selected since they, or a subset of them, are commonly used in several studies (Abrahamse & Steg, 2011; Black et al., 1985; Botetzagias et al., 2014; Karlin et al., 2014; Thøgersen & Grønhøj, 2010). Two factors that were not included even though they are also commonly used in the literature were gender (e.g. Abrahamse, Steg, Vlek, & Rothengatter, 2007; Botetzagias et al., 2014; Poortinga, Steg, Vlek, & Wiersma, 2003) and number of teenagers (e.g., Thøgersen & Grønhøj, 2010). The respondents were given intervals to choose from (see table 3-1 below) to avoid the need to type the exact numbers.

Table 3-1. Intervals for the five contextual factors captured in the survey and used to explain the behaviour of the users.

Factor/Variable	Interval number	Interval
Living area	1	0-49 m^2
	2	50-99 m^2
	3	100-149 m^2
	4	150-199 m^2
	5	200-249 m^2
	6	More than 250 m^2
Household size	1-6	1-6 persons
	7	7 or more
Income (Household)	1	0-20 000 SEK
	2	21 000-50 000 SEK
	3	51 000-80 000 SEK
	4	More than 80 000 SEK
Age (respondent)	1	18-29 years
	2	30-39 years
	3	40-49 years
	4	50-59 years
	5	60-69 years
	6	70-79 years
Education	1	Elementary school
	2	High school, Vocational training, Folk high school
	3	Qualified vocational school
	4	College/university

Questions regarding electricity saving behaviour and 100Koll

One multiple-selection question was added to understand how much energy efficiency measures a respondent had taken: "Have you undertaken any of the following measures in your residence the last three years?" The tick box choices that were supplied included the following alternatives: new windows, sealing windows, insulating the garret, added insulation to the facade, added insulation on the roof, installed heat pump, new kitchen appliances, steering appliances, reduced temperature, installed solar panels, changed heat system, recovery of air ventilation change lamps, shorter showers and other measures. For each measure the respondent could choose between "Partially", "Yes completely" and "No". The answer of this question was used to describe the electricity saving behaviour of the respondent and is referred to as the ES_behaviour variable in this thesis. The variable was given two points for each measure that was answered with "Yes completely" and one point for each measure that was answered with "Partially". Twelve of the measures to select from were energy efficiency measures that entail investments while only three of them entail energy curtailment measures, which means that the variable mainly described energy efficiency measures. The cumulative answers of this question will in following sections be referred to as the variable *ES_behaviour*.

Asking for measures in the last three years and not for the period after 100Koll was introduced did not help to explain the influence that 100Koll had. However, one additional question captured if 100Koll had contributed to take any decisions regarding the selected measures. That gave an indication if the respondent felt that 100Koll has been to any help. The question was formulated "Did 100 Koll contribute to decisions about the measures above?" The respondent could choose from the following options: "I have not done any measures", "Yes, partly caused by knowledge gained from 100Koll", "Yes, solely caused by knowledge gained from 100Koll", "No, other things caused the decision". The answers of this question will in following sections be referred to as the variable *100K_action*.

Another question that was similar to the one previously discussed but with the distinction that it captures whether the users believe that 100Koll can reduce electricity in their home in contrast to the previous question that asked if any of the mentioned energy efficiency actions had been inspired by 100Koll. The question was formulated as follows: "I believe that I with help from 100Koll can reduce unnecessary consumption in my home". The answers of this question will in following sections be referred to as the variable *100K_reduces*.

The two variables 100K_action and 100K_reduces acts as proxies for how much 100Koll have helped the users to reduce electricity.

3.3 Methods for data analysis

This section describes how the collected data was analysed to provide the results. The first part describes the methods used to estimate the effectiveness of 100Koll and the second part presents the methods to understand what psychological, moral and contextual factors predict the electricity use and the effect of the 100Koll real-time feedback service.

3.3.1 Estimating average effectiveness of the feedback from 100Koll

The effectiveness of the feedback was calculated with three different methods. The first method compared the actual use of electricity with the historic baseline without using the control group, and the following two used the electricity use from a control group to estimate the effectiveness. The differences between the two last methods concerns what periods that was used to calculate the expected and actual consumption and how the expected electricity use was assessed.

Method 1 – Historical baseline comparison

Comparing with a historic baseline means that it is assumed that the consumption pattern would be repeated if no intervention occurs. The electricity use is highly dependent on the climate, which is evident from Figure 4-1 where the consumption is almost four times as high during the winter months than during the summer months. However, the impact from the climate was not in the scope of this research, which implies that the consumption figures measured must be climate compensated to be comparable. When compensating for climate impact, concepts such as degree-days and energy index are used. The idea behind the energy index and the degree days is fundamentally the same, however, the energy index takes, in addition to the temperature also more parameters, such as wind and insolation, into account (Heincke, Jagemar, & Nilsson, 2011). Based on this fact it was decided to use climate correction instead of temperature correction in this study.

The climate correction of the electricity figures was done with a method described by the Swedish Meteorological and Hydrological Institute (SMHI). The method includes three basic steps. In the first step, the base load not affected by the temperature is removed. In the second step, the remaining part is divided with the energy factor (retrieved from SMHI) and in the third step, the base load is added to the corrected part again (SMHI, n.d.). The energy factor was calculated by dividing the actual energy index with the normal index[8]. The base load for a user was calculated by the average use in June, July and August 2011-2013 (2014 was excluded since the 100Koll was introduced in that year). Since there are different energy indexes depending on where you live, each user was given factors corresponding to the closest city in latitude of 20 different places spread over Sweden[9]. The users that had higher electricity use in summertime than in wintertime were not climatic corrected.

The measured monthly use after the 100Koll installation (E_{actual}) was compared with an expected electricity use ($E_{expected}$) that was calculated by an average for that specific month over the three previous years. (E.g., if the use in May the three previous years were 500 kWh, 490 kWh and 480 kWh, $E_{expected}$ would be 490 kWh.)

To calculate the relative electricity saving effectiveness (ESE) for a specific month (m) and a specific user (u), the following formula was used:

$$ESE_{m,u} = ((E_{expected,m,u} - E_{actual,m,u}) / E_{expected,m,u}) * 100 \quad (1)$$

The average change for a user was then calculated by taking the sum of all months.

$$ESE_{average,u} = (\Sigma E_{expected,m,u} - \Sigma E_{actual,m,u}) / \Sigma E_{expected,m,u} \quad (2)$$

The average change for the whole sample was then calculated by using the sum of all users.

$$ESE_{average} = (\Sigma\Sigma E_{expected,m,u} - \Sigma\Sigma E_{actual,m,u}) / \Sigma\Sigma E_{expected,m,u} \quad (3)$$

Other ways to calculate the expected electricity use were also tested. One of them was to use the trend of the electricity use for the previous years. By doing this, the tendency of the change in the use was also taken into account. This resulted however in some of the users getting negative $E_{expected}$, which was corrected by not allowing lower $E_{expected}$ than half of the minimum value the three earlier years. Another way to calculate $E_{expected}$ was to use a weighted average. This was motivated by the belief that the consumption three years back should not have as predictive power as for the consumption only one year back. $E_{expected}$ for a month was then calculated with the weights 0.5, 1, 1.5 according to (4) below.

$$E_{expected,\ m} = (0,5 * E_{expected,\ m-36} + 1 * E_{expected,\ m-24} + 1,5 * E_{expected,\ m-12}) / 3 \quad (4)$$

It was decided to calculate $E_{expected}$ according to the mean of the same months the previous years as it resulted in the least variation between the different users and therefore was perceived to be the method that gave the most realistic result.

Method 2 – Control group comparison

Although the effectiveness calculations made by using a historic baseline, as described in the previous section, indicated a minor electricity reduction in line with the research done within the field, it was not possible to say for sure that this reduction was due to the 100Koll intervention. Since the consumption was climatic corrected, that contextual factor should not

[8] These indexes can be bought by SMHI.

[9] The places used were Falsterbo, Tomelilla, Hässleholm, Älmhult, Borgholm, Göteborg, Linköping, Norrköping, Järfälla, Österåker, Enköping, Sundsvall, Härnösand, Sollefteå, Luleå, Boden and Haparanda. These places were used since they were available and seemed to be spread somewhat evenly over Sweden.

influence the result, but there could be other non-identified changes in the society that may cause changes in the electricity use. Such shared contextual factors could be caused by societal changes in technology, regulations or economy (Wilson & Dowlatabadi, 2007). To check this, it was decided to compare the result with a control group that should have been influenced by the same shared contextual factors as the intervention group.

Normally when calculating the effectiveness by using a control group, the consumption for the intervention group is compared with the consumption for the control group (that was not exposed by the intervention). This was not possible in this case since the control group had 34.3% less average consumption. The large difference in the average consumption between the 100Koll group and the control group shows that the two groups were not very similar, which would have been the ideal. However, by assuming that the electricity change of the two groups was supposed to be the same without an intervention and by using historical data from both groups, it was still possible to retrieve indicated results. The different periods that have been used to calculate the effects are shown in Figure 3-3 below. The base line period (BLP) and the intervention period (IP) were used in method 3 while the period just before the implementation period (JBP) and the period just after the implementation period (JAP) were used in method 2.

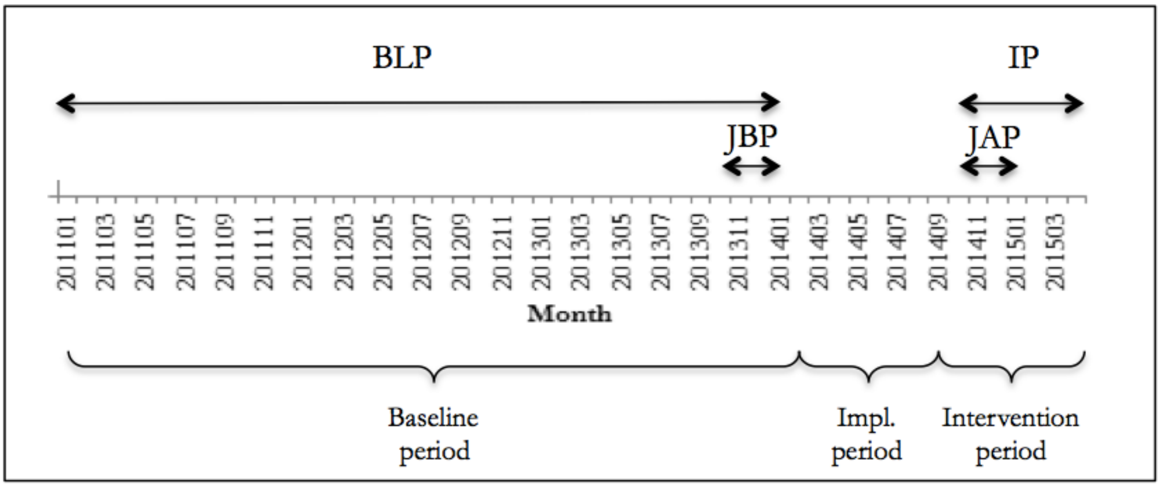

Figure 3-3. The periods used to calculate the effectiveness of the feedback mechanism include the baseline period (BLP), the intervention period (IP), the period just before the intervention (JBP) and the period just after the intervention (JAP).

The effectiveness was calculated by comparing the expected energy use with the actual energy use. (Figure 3-4 below illustrates the different variables used in the following four formulas)

$$ESE = 100 * \frac{E(Expected) - E(Actual)}{\mathrm{E(Expected)}} \qquad (5)$$

The actual energy use was the same as the average energy use of the intervention group (IG) during the intervention period (IP).

$$\mathrm{E(actual) = E(IG{,}JAP)} \qquad (6)$$

It was assumed that the IG should have the same relative change in average electricity use (Δ(Expected)) as the control group (CG). This change was calculated by comparing the change from the BLP with the IP.

$$\Delta(\text{Expected}) = \frac{E(CG,JAP) - E(CG,JBP)}{\text{E(CG,JAP)}} \quad (7)$$

E(Expected) was then calculated by using the expected change.

$$\text{E(Expected)} = \text{E(IG, JBP)} * (1 + \Delta(\text{Expected})) \quad (8)$$

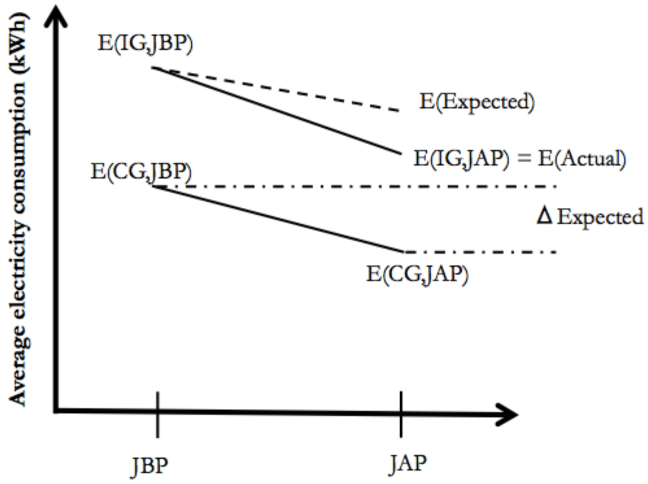

Figure 3-4. An illustration of the different electricity use figures that were used to calculate the effectiveness.

Method 3 – Historical base line and control group comparisons

A third method was tested for the calculation of the effectiveness. This method used the same approach as the first method by using the baseline period to estimate the expected use of the full IP. This was done for both the control group to get E(CG, BLP) and for the intervention group to get E(IG, BLP). No temperature correction was needed since both groups had the same weather on average and were equally spread over the country.

$$\text{E(actual)} = \text{E(IG,IP)} \quad (9)$$

$$\Delta(\text{Expected}) = \frac{E(CG,BLP) - E(CG,IP)}{\text{E(CG,BLP)}} \quad (10)$$

$$\text{E(Expected)} = \text{E(IG, IP)} * (1 + \Delta(\text{Expected})) \quad (11)$$

ESE was then calculated using equation (5) in method 2 above.

3.3.2 Econometric analysis and model specification

This section describes the five econometric models that were used for the analysis of determining factors of electricity use, electricity change, electricity behaviour and 100Koll use. The section also describes how the models were analysed with statistical methods.

The models were developed with guidance from the conceptual framework described in section 3.2.2 and are illustrated in Figure 3-5. Each model has one dependent variable and 12 to 14 independent variables that may predict the variance of the dependent variable. The independent variables for all five models included three psychological factors from the TPB theory, three moral factors from the VBN theory and five contextual variables described in section 3.2.2.

The first model was specified to explain the total *electricity use* (Elect_use). The independent variables that were included in the model were all the eleven psychological, moral and contextual variables (described in section 3.2.2). Additionally the two variables 100K_action and 100K_reduces were added to the model as they act as proxies for how well 100Koll helps to reduce electricity. It is expected that the higher these two are, the lower the total electricity use should be. The electricity saving behaviour was not added to this model, as it would not have helped to answer any of the research questions.

The second model was specified to explain the *electricity change* (Elect_change) of the user. The value of this variable was calculated for the users according to formula (1) and (2) in section 3.3.1. In this model Elect_use was added as an independent variable in order to investigate if the variance in electricity use can explain the electricity change. The other dependent variables in this model were the same as for the model that explained electricity use.

Having calculated the individual electricity change for all the users it was found that the standard deviation of the effectiveness was significant (M = *1.4%*, SD = 31%, N = 1753). When looking at individual consumption curves, it was evident that many of the users (but less then half) turned out to have significantly different consumption between different years. This may be explained by many different reasons. People may, for example, have made a large renovation with lots of electricity needs, have moved in or out of the dwelling or have installed an electric heat pump or solar panels. To overcome this issue, the half of the sample that had the least variation between the different months was selected as representative of the electricity-change variable in the regression models. This resulted in a significantly lower standard deviation (M = *1.4%*, SD = 7.7%, N = 876).

The third model specified aimed to explain the variation of the *electricity saving behaviour* (ES_behaviour). It included the same independent variables as the model for electricity change. It may seem strange to include the electricity use in this model since according to the conceptual framework the causality is in the opposite direction (i.e. it is the behaviour that should predict the electricity use and not the other way around). Nevertheless, electricity use was added in order to explore if higher electricity use led to more electricity saving activities. Based on this reasoning, caution must be taken before concluding on causalities between these two variables.

The fourth and the fifth models were specified to explain the two variables *100K_action* and *100K_reduces*. Since it was not possible to measure the actual amount of electricity in kWh each individual user had saved with the use of 100Koll, these two variables were the best available proxies for the estimation of how the feedback actually worked. They do however not explain to which extent, in terms of kWh or percentage decrease, 100Koll has helped. Both models have the eleven psychological, moral and contextual variables as independent variables. Additionally they also have electricity use as an independent variable. The same caution with causality must be taken for these variables and electricity use as had to be taken for the electricity saving behaviour and electricity use.

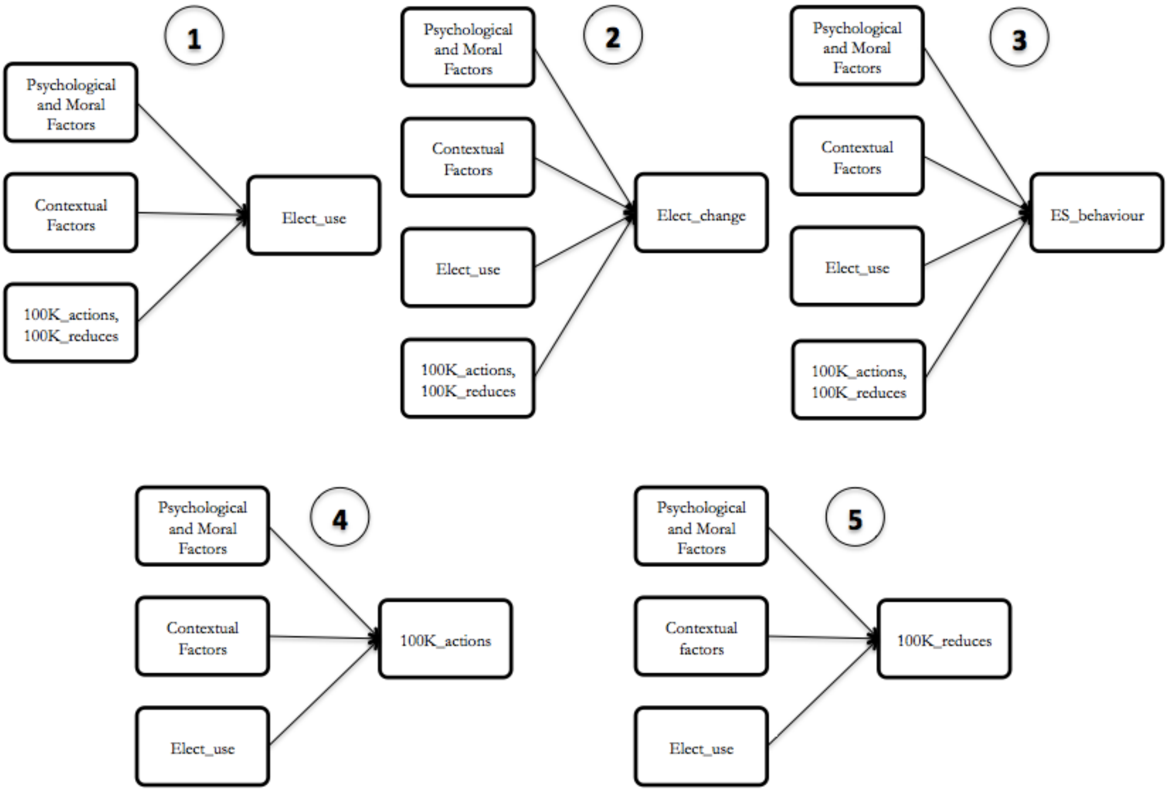

Figure 3-5. The five models that were specified with the dependent variable to the right and the independent variables to the left.

In similar studies, the models have been fitted in consecutive steps (See e.g., Abrahamse & Steg, 2009; Botetzagias et al., 2014; Karlin et al., 2014). In both Abrahamse and Steg (2009) and Botetzagias et al. (2014), the models were fitted into three steps, where the first step only had the psychological factors included in the model, followed by the second step where the moral factors were added and the final step where the contextual factors were supplemented. This probably has been done to explore the explanatory power of different theories. However, that method would not have helped to answer the research questions in this thesis. It was therefore decided to fit all the selected variables in the models directly.

Variables can have different kinds of relations. They can have no relation at all, be related between each other as a curve (a non linear relation) or have a linear relation. Non-linear relations can be shaped, for example as a sinus curve or as a u-curve where the largest values of Y are when the X variable is smallest and largest in the interval. To simplify the analysis in this research, only the linear relation between the variables has been investigated. A linear relation between an X and a Y variable can be described with the linear equation.

$$Y = k*X + m \tag{12}$$

An equation can have many different variables and still be linear, as in the following example where there are two X variables that are linearly related to Y.

$$Y = k_1{*}X_1 + k_2{*}\,X_2 + m \qquad (13)$$

Bivariate correlation analysis was done between all the variables to see the degree of association. The correlation between two variables describes to which extent they have a linear relation. Two variables can have a non-linear relation, such as a curve, but still lack correlation. Although two variables are highly correlated, the correlation does not say anything about the causality (i.e. which variable that cause the variation of the other). Bivariate correlation does not take into consideration that two correlated variables (e.g., A and B) may both be influenced by a third variable (e.g., C) which may lead to the conclusion that A causes B, while it is C that causes both A and B. This phenomenon is also called multicollinearity. To make sure that multicollinearity does not lead to wrong inferences a partial correlation can be done. That means that the correlation between two variables is checked while controlling for the effect of one or many other variables.

The five models described above were tested with linear regression. Linear regressions have frequently been used in many studies (Abrahamse et al., 2007; Black et al., 1985; Botetzagias et al., 2014; Gans, Alberini, & Longo, 2013; Stern, 2000). Since the aim was to understand which factors/variables that can explain the variance of the dependent variable, a stepwise forward multiple regressions was used. For each step, the factor with the highest explanatory power (i.e., the one with the lowest p-value) was added. These steps were repeated until no more factors that were statistically significant (i.e., p-value < 0.05) could be added to the model. The adjusted R^2 described the explanatory power of the regression model and the p-value for the F-test describes whether the model is statistically significant (i.e., if it is possible to trust the model). The estimated coefficients for the variables *(β)* indicate how much the dependent variable changes if one unit of the dependent variable is changed. A negative β-value consequently means that the larger the independent value is, the smaller the dependent variable becomes.

During the regressions, multicollinearity was monitored to make sure that independent variables were not mutually correlated which would have resulted in unreliable results and no possibility to draw any conclusions from the regression. The variance inflation factor (VIF) was used to detect multicollinearity. A VIF value lower than five was used as a sign of no multicollinearity.

In order to test the internal consistency of a multiple-item construct (i.e., a factor that is measured with two or more questions) a method called Cronbach's α (Cronbach, 1951) was used. Three of the moral and psychological factors were constructed from the average of two questions. The method seem to be the most practiced method for these kind of analyses as it has been practiced in many of the reviewed studies (Abrahamse & Steg, 2009; Black et al., 1985; Botetzagias et al., 2014; Harland, Staats, & Wilke, 1999). The internal consistency of a multiple-item construct is based on the correlations between the different items of the same test. The value normally ranges from .00, which means no consistency in measurement and 1.00, which means perfect consistency between the different tests. A value of .80 means that 80% of the variance in the measurement is a reliable variance. There are no scientific studies that say what values are supposed to be satisfactory, but according to a guide for the statistical tool SPSS, rules of thumb according to table XXX should be applied (George & Mallery, 2002).

Table 3-2. Rules of thumb for judgement of the values for Cronbach's α (George & Mallery, 2002)

Cronbach's α	**Approximate judgement**
.0 - .5	Unacceptable
.5 - .6	Poor
.6 - .7	Questionable
.7 - .8	Acceptable
.8 - .9	Good
.9 – 1.0	Excellent

SPSS statistics version 2.3 was used as a tool for both calculations of bivariate and partial correlations as well as for the regressions. The tool was also used to calculate Cronbach's α (i.e., the internal consistency reliability of the multiple-item constructs where two questions were used to test one single factor).

3.4 Ethical considerations

Electricity use patterns on an individual level can explain a lot regarding users' lifestyles and major lifestyle changes (Siddiqui, Zeadally, Alcaraz, & Galvao, 2012). This information must obviously be handled with care as it can impinge on people's integrity (Siddiqui et al., 2012). Spreading the information may be used, for example, by businesses for advertising campaigns or by criminals that may use information about unusually low consumption as an indication of when people usually are away from home (Siddiqui et al., 2012).

Moreover, the collected data from the survey discloses private behaviours and norms that must be handled with care to avoid connecting the answers to specific persons.

The collected electricity data that has been used does not reveal any information about the users other than their electricity use and postal code. This information alone makes it impossible to map a consumption profile to a specific household. Information regarding the users under study was collected via a web survey provided by E.ON. This data does not include more information about the users than their actual answers to the survey questions, their postal number and an encrypted id that made it possible to associate the response data from the questionnaire with the electricity use data collected from the E.ON database. By answering the survey, the respondent agreed that E.ON might use the results for research without disclosing any individual answers.

4 Results and analysis

This chapter provides the results from the analysis of the collected data. The first part of the chapter presents the results and analysis of the SM effectiveness and the second part includes the results from the survey and the econometric analyses.

4.1 Smart meter effectiveness

Three methods were used to calculate the electricity saving effectiveness of 100Koll according to the methods described in the previous methodology chapter. First the results from these three are presented followed by a sub-section describing the key discrepancies between those methods. An analysis of the effectiveness results is provided in the end of this section.

4.1.1 Method 1 – Comparing with historical baseline

After temperature correction, the actual monthly average consumption for the intervention group was 1269 kWh (*M* = 1269, *SD* = 815, *Mdn* = *1080*, *N*=20475). This was compared with the expected average consumption that was 1287 kWh (*M* = 1287, *SD* = 805, *Mdn* = *1091*, *N*=20475). This resulted in a total reduction of 1.4%. The users gradually started to use 100Koll between February and September 2014 and had on average, used 100Koll in 11.7 months in April 2014.

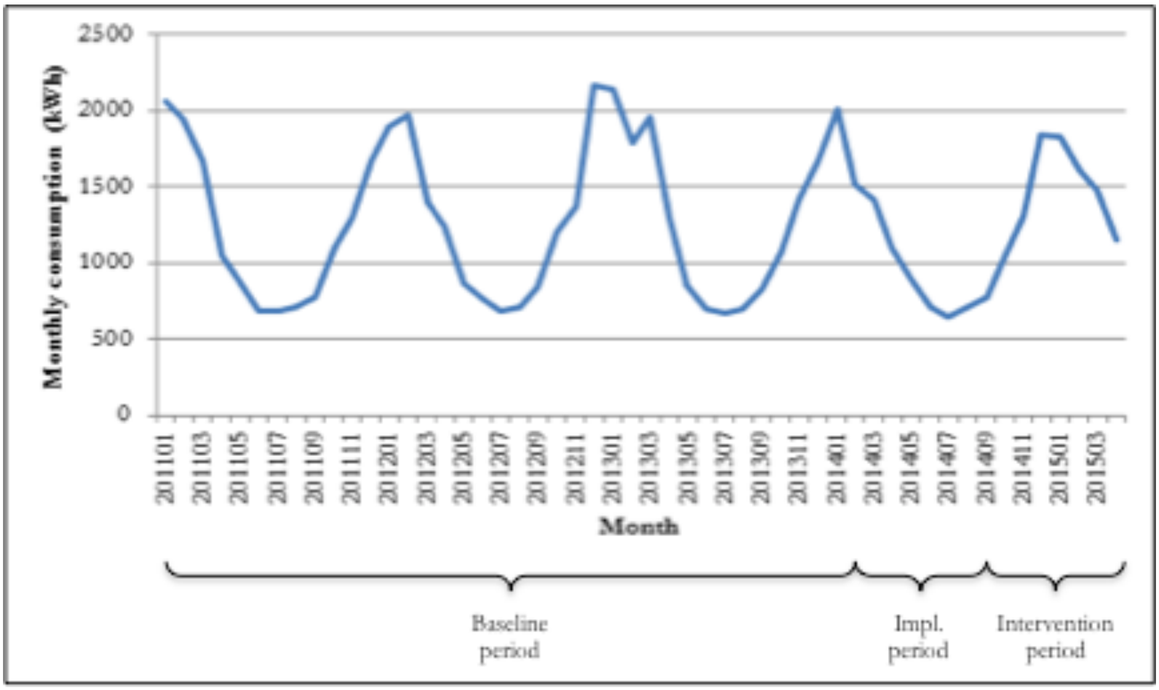

Figure 4-1. Monthly average consumption for the intervention group (not corrected for climatic differences). Large variations between summer months and winter months shows that electricity use is dependent of the climatic conditions. N=1753

Figure 4-1 shows how the average consumption varied between Jan 2011 and April 2015. The variation shows that the winter and summer seasons with their climatic differences have a significant influence on the electricity use. This means that comparing different years with different climatic conditions requires climatic corrections.

4.1.2 Method 2 – Comparing with control group

The control group had the same consumption pattern as the intervention group; however the control group had considerably lower average monthly consumption between Jan 2011 and April 2015 (*M* = 926, *SD* = 278, *Mdn* = *955*, *Max* = 2159, *Min* = 8, *N*=1342) than the intervention group (*M* = 1281, *SD* = 570, *Mdn* = 1259, *Max* = 6428, *Min* = 92, *N*=1753).

The intervention group had an average consumption of 1 542 kWh the four months before the implementation period started. The average consumption after the implementation period when the users had used 100Koll for 1-9 months was 1 501 kWh. The corresponding consumption figures for the control group were 1 130 kWh before the implementation period and 1 121 kWh after.

Therefore, the control group reduced their consumption by 0.80%. Under the assumption that 100Koll would have had the same percentage change without any intervention as the control group, the expected electricity use was estimated to 1 530 kWh, which compared to 1 501 indicated a reduction of 1.9%.

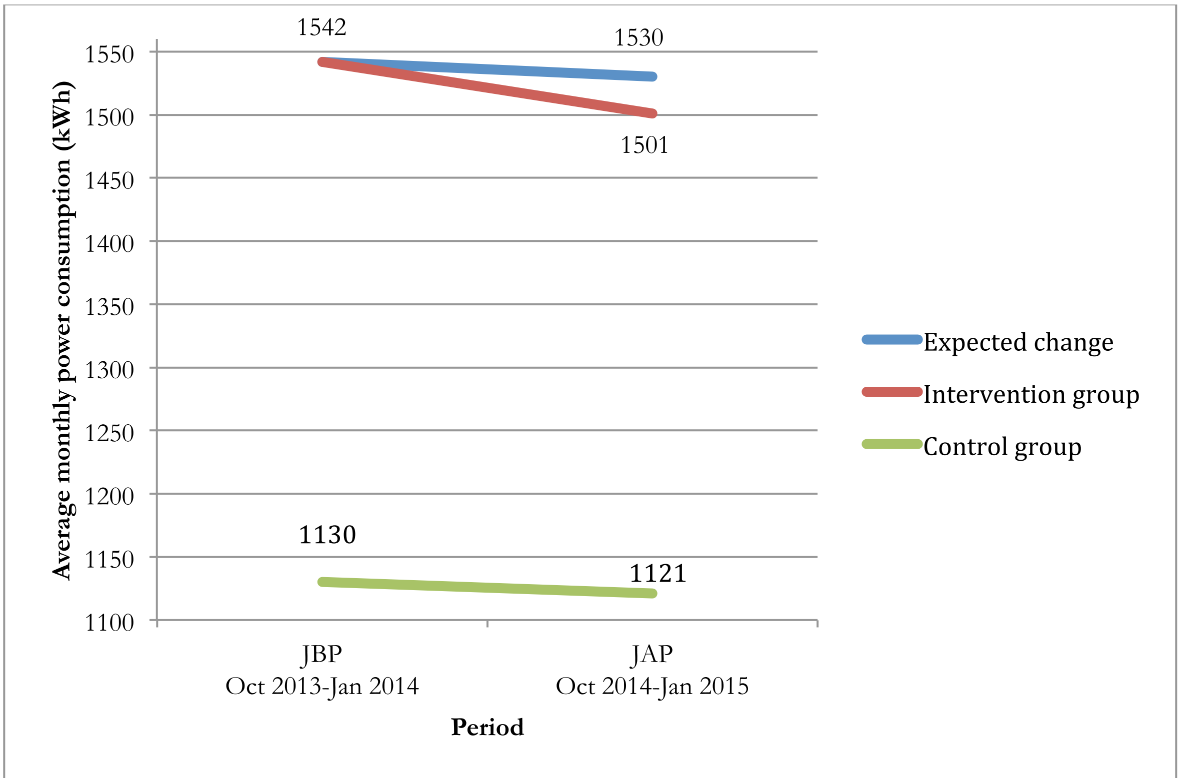

Figure 4-2. Changes in average monthly power consumption comparing the four months just before the implementation period with the four months after the implementation period.

4.1.3 Method 3 – Historical base line and control group comparisons

The actual average monthly consumption for the intervention group was 1 480 kWh while the calculated expected consumption was 1 605 kWh. This resulted in a reduction of 7.7%.

The actual average monthly consumption for the control group was 1 091 kWh, while the calculated expected consumption was 1 165 kWh. This resulted in a reduction of 6.3% for the control group.

Under the assumption that the 100Koll would have had the same percentage change without any intervention as the control group, the expected electricity use was estimated to 1503 kWh, which compared to 1480 indicated a reduction of 1.5%.

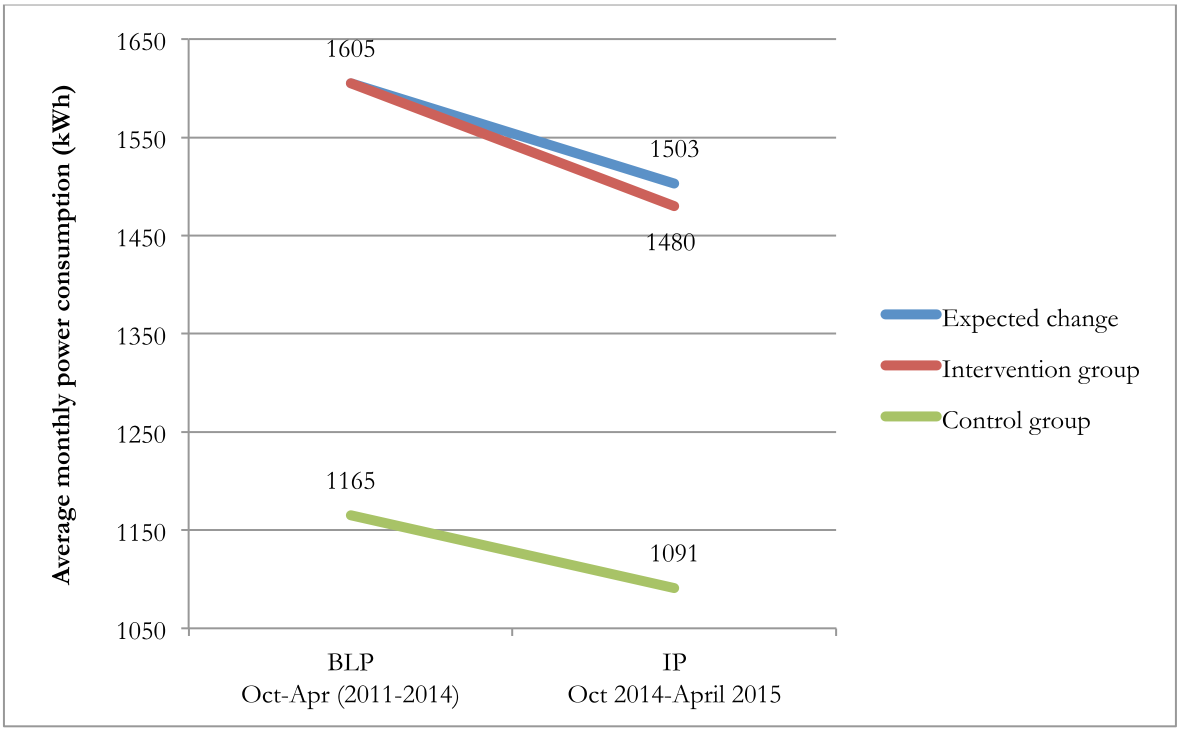

Figure 4-3. Changes in average monthly electricity consumption comparing the expected electricity use with the actual electricity use during the whole IP.

4.1.4 Key discrepancies between the three methods

The three methods differ in how the expected electricity use was estimated. All the methods use the same function (function (1) in section 3.2.1) once the expected electricity use is estimated.

Different from methods 2 and 3, method 1 applies climatic correction to correct for differences in the climate between the base line period (BLP) and the intervention period (IP) and does not use any control group. The main limitation with method 1 is that it is not possible to conclude that the result is only due to the 100Koll introduction. Other shared societal contextual influences may also have influenced changes in the total electricity use. Examples of such influences could be information campaigns, change in electricity price or a technology introduction that has been implemented in many households. This issue was eliminated by comparing with a control group that was supposed to be influenced by all other interventions in the same way as the 100Koll group.

Method 2 and 3 differ in two aspects, the period that is examined and which historical data that is used to estimate the expected electricity use. Method 2 uses only four months before the implementation period to estimate the expected electricity use and examines only the four first months of the intervention period while method 3 uses the average consumption data October to April, February 2011 to January 2014 to estimate the expected electricity and examined the change during the whole seven months of the implementation period. Both method 2 and 3 assumes that the intervention group would have had changed equally much, percentage wise, as the control group without the intervention.

Figure 4-4 illustrates the indicated effectiveness calculated with the three different methods.

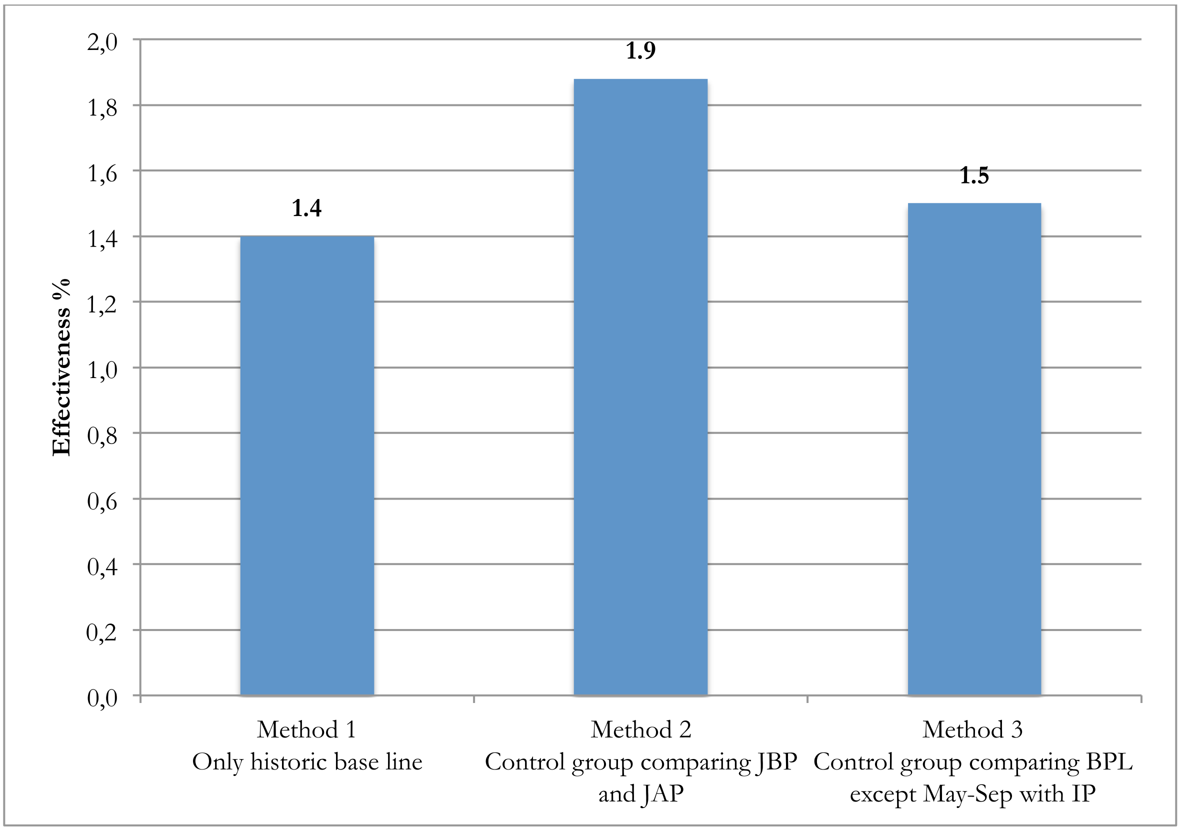

Figure 4-4. Estimated effectiveness of 100Koll calculated with different methods.

It is likely that method 3 resulted in the most accurate outcome since that method used the full seven months of the intervention period and compared to a control group. Since the difference of the average electricity use was as high as 34,3% between the control group and the intervention group it is impossible to rule out that there is no other unknown reason for the caused electricity change than the 100Koll service. However, since method 1 and method 3 that were calculated with two completely different methods resulted in very similar results and the assumptions made[10] are deemed to be reasonable, the results points to very strong indications that the reductions caused by 100Koll after 11.7 months are 1.5%. The reason that Method 2 showed a result that was slightly higher than method 1 and 3 may be explained by the fact that method 3 measures the effect after the four first months of the intervention period, (i.e., after an average of 8.7 months of use) while the two other methods measure the full seven months of the intervention period. This is inline with existing literature that have found that the effect from new feedback often is higher the period closest to the intervention and lower after the feedback have been provided a longer period. Ehrhardt-Martinez (2010) found that the average effect were higher for shorter studies (10.1%) than for longer ones (7.7%). A consistent result was found in a study in Netherlands where the initial reductions in electricity use of 7.8% after four months could not be sustained (Van Dam, Bakker, & Van

[10] Two main assumptions were made. For method 1, the result relied on the assumption that no major societal change influenced the change. For method 2 and 3, the results relied on the assumption that the control group were supposed to change as much as the intervention group if it had not been for the intervention.

Hal, 2010). After 15 months the average reductions was not more than 1.9% (Van Dam et al., 2010).

4.2 Driving factors for electricity use

This section provides the results for how the selected independent variables influenced the five selected dependent variables. Additionally all bivariate correlations as well as selected partial correlations

4.2.1 Descriptive statistics

Of the 543 persons who responded to the survey, 226 respondents answered all the questions. With the intervention group of 1 753 persons, a margin of error of 5% and thus a confidence level of 95%, the recommended sample size is 308. The filtered sample of 226 increases the margin of error by only 1.02% (i.e. up to 6.02%). Descriptive statistics including the number of responses for the users are shown in Table 4-1. The survey showed that the users were quite aware of the consequences of electricity use, and they also felt responsibility for these consequences. The users also had positive attitudes towards electricity saving. Regarding norms for saving electricity, people tended to feel higher pressure from themselves (PN) than from important persons around them (SN). The respondents provided the most consistent answers for the attitude factor that had the lowest standard deviation (SD) and had the highest deviation with regards to personal norms that had the highest SD.

Table 4-1. Descriptive statistics for the variables used in the regression models. The five first variables are used as dependent variables in the models. The following three are the moral variables, followed by the psychological variables. The five variables at the bottom depict the contextual variables. The intervals for the contextual variables can be found in table 3-1.

Variable	Unit	*N*	*M*	*SD*	*Min*	*Max*
Elect change	% Change	176	-1.30	12.64	-32.26	62.44
Elect_use	kWh	342	14 229	6 513	2 939	53 173
ES_behaviour	Scale (0-30)	543	5.32	4.16	0	29
100K_reduces	Scale (1-5)	497	3.40	1.22	1	5
100K_action	1/0	493	0.28	0.45	0	1
AC	Scale (1-5)	501	4.00	0.95	1	5
AR	Scale (1-5)	523	4.04	1.05	1	5
PN	Scale (1-5)	519	3.02	1.07	1	5
Attitudes	Scale (1-5)	522	4.00	0.79	1	5
PBC	Scale (1-5)	530	3.62	1.04	1	5
SN	Scale (1-5)	493	2.53	1.06	1	5
Living area	Scale (1-6)	503	3.49	0.97	1	6
Household size	Scale (1-7)	503	2.76	1.18	1	7
Income	Scale (1-4)	435	2.34	0.67	1	4
Age	Scale (1-6)	496	3.95	1.27	1	6
Education	Scale (1-4)	484	2.76	1.06	1	4

Table 4-2. Survey results for the questions that pairwise constructed a variable (See section 3.2.2). For all questions in this table a 5-point Likert scale was used.

Question	Variable	*N*	*M*	*SD*
I think that global warming is a problem for the society.	AC	514	4.01	1.08
By saving electricity I contribute to a reduction of global warming.	AC	519	3.91	1.13
I feel guilty when I use a lot of energy.	PN	525	2.88	1.21
I feel like a better person when reducing electricity use.	PN	522	3.16	1.20
It is important for me to save electricity to reduce global warming.	Attitudes	523	3.54	1.21
It is important for me to save electricity to reduce my costs.	Attitudes	536	4.46	0.79

4.2.2 Consistency and reliability of the constructs

Three of the six psychological and moral factors were constructed by two questions (Table 4-3). When making these kinds of constructs, Cronbach's α is used as a measure of the reliability and consistency of the construct. The value is normally between 0 and 1. The higher the value is, the better consistency and reliability it has (Table 3-2).

Table 4-3. Cronbach's α for the three variables that were constructed from two questions.

Construct/Variable	Cronbach's α	N (both questions answered)
AC	.659	501
PN	.736	519
Attitudes	.309	522

Based on the rules of thumb for Cronbach's α (Table 3-2) provided by George & Mallery (2002) the AC construct would be regarded as 'Questionable', the PN construct as 'Acceptable' and the attitudes construct as 'Unacceptable'. The low α of the attitudes construct raises some statistical concerns regarding the consistency and reliability. The result is also significantly lower compared to .667, which was what Botetzagias et al. (2014) found, using the same 2-item construct.

4.2.3 Bivariate correlation between variables

This section describes the results of the correlation between all the variables. The correlation itself does not say anything about the causality (i.e., which variable that has influenced the other). To understand the direction of the causality, theory and empirical evidences must be applied. The correlation (r) is described as a value between 1 and -1 and the further the value is from 0, the larger correlation. The sign of the correlation describes whether the variables are increasing together ($r > 0$) or decreasing ($r < 0$). The p-value (p) describes whether the correlation is significant and ranges between 1 and 0. If the p-value is small the hypothesis that the correlation is due to random sampling can be rejected. It is customary within science to call a correlation with a p-value less than .05 as statistically significant (Nuzzo, 2014)[11]. Table 4-4 below shows the bivariate correlations between all the variables.

[11] Nuzzo highlights, however, also that many scientists are making wrong inferences from the p-values and that replication of findings are important before being too sure that the result is in accordance with the reality.

Table 4-4. Bivariate correlations between all variables. Variables 1-5 were used as dependent variables in the regressions according to Figure 3-5. Variables 6-8 constitute the moral factors, 9-11 the psychological variables and 12-16 the contextual variables.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Elect_change	1														
2. Elect_use	.111	1													
3. ES_behaviour	-.075	.023	1												
4. 100K_reduces	-.04	-.158**	.164**	1											
5. 100K_action	-.064	-.007	.054	.388**	1										
6. AC	.176*	-.068	.031	.147**	.049	1									
7. AR	.157*	-.082	.047	.097*	.013	.739**	1								
8. PN	.170*	-.022	.099*	.280**	.201**	.418**	.322**	1							
9. Attitudes	.064	-.074	.090*	.233**	.160**	.623**	.507**	.467**	1						
10. PBC	.017	-.089	.214**	.305**	.142**	.187**	.135**	.205**	.261**	1					
11. SN	.088	-.039	.074	.212**	.175**	.222**	.204**	.382**	.345**	.268**	1				
12. Living area	.029	.379**	.042	-.023	-.052	.009	.019	.018	-.002	-.01	-.064	1			
13. Household size	.185*	.223**	.012	.015	-.053	.075	.083	.053	-.021	-.072	-.049	.158**	1		
14. Income	-.138	.271**	.03	-.071	-.045	-.038	.001	-.036	-.139**	-.059	-.110*	.215**	.214**	1	
15. Age	-.007	-.112*	-.034	.01	.117*	.005	-.02	.103*	.186**	.119**	.276**	-.061	-.548**	-.118*	1
16. Education	-.128	.130*	.001	-.07	-.064	.029	.068	-.05	-.083	-.130**	-.002	.170**	.118**	.313**	-.022

* Correlation is significant at the .05 level (2-tailed).

** Correlation is significant at the .01 level (2-tailed).

4.2.4 Partial correlations and regression results per model

This section describes partial correlation results and regressions per model described in section 3.3.2. Even more detailed descriptions of the regression results than presented in this section can be found in Appendix II – Regression Details.

All five models included all the three psychological variables (Attitudes, SN and PBC), the three moral variables (AC, AR and PN) and the five contextual variables (Living area, Household size, Income, Age and Education). In addition to that, the models also included specific predictor variables according to table 4-5 below.

Table 4-5. Specific predictor variables for the five tested models in addition to the other 11 psychological, moral and contextual variables

Dependent Variable	**Specific Predictor Variables**
Electricity Use	100K_action 100K_reduces
Electricity Change	100K_action 100K_reduces Electricity Use
ES_behaviour	100K_action 100K_reduces Electricity Use
100K_reduces	Electricity Use
100K_action	Electricity Use

Table 4-6. Overview of the Regression results from the five tested models. The results presented in this table are discussed in detail in the following sections

Dependent Variable	Predictor Variables	β	p (variable)	Adjusted R^2	F	p (model)
Electricity Use	Living area Household size Income	2284 1051 1940	< .001 = .008 < .001	.176	F(3,225) = 17.0	< .001
Electricity Change	Household size	2.2	= .025	.035	F(1,114) = 5.16	= .025
ES_behaviour	PBC Education	.87 .51	< .001 = .019	.074	F(2,225) = 9.9	< .001
100K_reduces	PBC PN	.24 .37	= .001 < .001	.167	F(2,230) = 24.1	< .001
100K_action	PN	.11	< .001	.052	F(1,231) = 13.8	< .001

The model that described the electricity change had the lowest F-value meaning that it presented the model that was most likely to be due to chance. The model that described 100K_reduces had the highest F-value, meaning that it was the model that was *least* likely to be due to chance.

Electricity Use

The stepwise multiple regressions resulted in three dependent variables that were statistically significant. In the first step *Living area* was added which alone explained 12% of the variance in electricity saving behaviour. In the second step *Income* was increasing the explanation value to 16% and in the third step *Household size* was added. The three variables *Living area* (β = 2276, p < .001), *Income* (β = 1900, p = .003) and *Household size* (β = 1032, p = .003) together explained 18% of the variation (F(3,230) = 17, p < 0.001). No multicollinearity identified. Highest VIF value was less than five (VIF = 1.11).

As explained in the methodology section (3.3.2) the β value explains how much the predictor variable impacts the dependent variable. This means, for example, that by increasing *Living area* with one unit, the yearly *Electricity use* is estimated to increase (since the β value is positive) by 2 274 kWh. Note that the *unit* of *Living area* is not square meters but instead the interval as described in table 3-1 in the methodology chapter.

The *electricity use* had statistically significant bivariate correlations to *100K_reduces*, and all the five contextual variables. When controlling for all other variables *Living area* and *Income* were still statistically significant. *100K_reduces* was almost statistically significant with a p-value close to .05 (table 4-8). This indicates that those that believe that 100Koll helps reduce electricity tend to have lower electricity use. Additionally, the *electricity use* and the variable *100K_action*, which described if the respondent perceived that 100Koll contributed to energy effective measures, had a minor but insignificant statistical partial correlation (r = -.008, p = *.91*). This minor negative correlation from 100Koll is, although it is not statistically significant, in line with the results of the total, albeit marginal, effectiveness of 100Koll, which pointed to minor electricity savings of 1.4-1.9%.

Table 4-7. Partial correlations between the electricity use and the dependent variables that had bivariate correlations to electricity use (Table 4-4). All other variables in the model were controlled for.

Variable	Partial Correlation (r)	Statistical significance (p)
100K_reduces	-.12	.07
Living area	.30	< .001
Household size	.13	.07
Income	.19	.01
Age	-.05	.48
Education	.02	.74

People that have an electricity saving behaviour should have lower electricity use. At the same time people with higher electricity consumption should have more incentives to adopt more electricity saving behaviour. A partial correlation test between the *electricity use* and the *ES_behaviour* showed that there was no correlation at all between the two variables (r = .001, p = .99). No inference more than that there is no linear association between those two can be made.

The result that the contextual factors and not the psychological and moral factors are determinants for energy use confirms the findings from other studies (See e.g., Abrahamse & Steg, 2009; Brandon & Lewis, 1999; Thøgersen & Grønhøj, 2010).

Electricity Change

The stepwise regression only allowed one of the dependent variables, *Household size* (β = 2.2, p = .03) in the model (F(1,114)=5.2, p = 0.03) that only explained 3.5% of the variance in *electricity change*. No multicollinearity identified since VIF value was less than five (VIF = 1.00).

The low explanatory value of *electricity change* proves that the model did not capture the significant determinants.

The electricity change had statistically significant bivariate correlations to *AC*, *AR*, *PN* and *Household size*. When controlling for all other variables none of them were statistically significant (4-7). *Household size* was however almost statistically significant with a p-value close to .05 and a correlation of .19.

Table 4-8. Partial correlations between the electricity change and the dependent variables that had bivariate correlations to electricity change (Table 4-4). All other variables in the model were controlled for.

Variable	Correlation (r)	Statistical significance (p)
AC	.01	.90
AR	.06	.55
PN	.12	.23
Household size	.19	.06

Table 4-4 indicates that there are small negative bivariate correlations between the electricity use and the two variables *100K_action* (r = -.06, p = .42) and *100K_reduces* (r = -.04, p = .62), which indicate that the SM helped in the reduction. When controlling for all moral, psychological and contextual variables the partial correlation between electricity change and

100K_action is actually higher than what is indicated by the bivariate correlation (r = -.13, p = .19). The same pattern is found for *100K_reduces* that have a higher partial correlation (r = -.13, p = .17) than bivariate correlation. The negative correlations indicate that 100Koll has helped to reduce the electricity use and supports the theory behind SMs presented in section 4.1.

The result indicated that the number of persons in the household had a statistically significant, although small, impact on the electricity change. A possible and simple explanation of this could be that smaller households had lost one member of the household and larger households may have increased the number of consumers in the household during the intervention time. From the regression with total electricity use in the previous section it was found that the number of persons in the household was a significant determinant for total electricity use. Since teenagers are high consuming members of electricity in a household (Thøgersen & Grønhøj, 2010) it would give a significant change in electricity if they leave the household. This effect did not have anything to do with the introduction of the 100Koll.

The positive correlations between the *electricity change* and the moral values indicate that users with higher environmental morality have increased their electricity use since 100Koll was introduced. The only possible explanation to these indications is that they have been electrifying their energy use and abandoning other energy sources. Such examples could be to start using an electrical lawn mower instead of using one running on gas or using an electrical bike instead of using the car. However, this is just speculation, and more research is needed to draw these kinds of conclusions.

Electricity saving behaviour

The stepwise multiple regressions resulted in two dependent variables that were statistically significant. In the first step *PBC* was added which alone explained 5.5% of the variance in electricity saving behaviour and in the second step *Education* was added. The two variables *PBC* (β = 0.87, p < .001) and *Education* (β = 0.51, p = .02) together explained 7.4% of the variation ($F(2,225) = 9.9$ $p < 0.001$). No multicollinearity identified. Highest VIF value was less than five (VIF = 1.11).

The electricity saving behaviour had statistically significant bivariate correlations to *100K_reduces*, *PN*, *Attitudes* and *PBC*. When controlling for all other variables only *PBC* was still statistically significant with an even higher correlation than the corresponding bivariate correlation (Table 4-9).

Table 4-9. Partial correlations between the ES_behaviour and the dependent variables that had bivariate correlations to ES_behaviour (Table 4-4). All other variables in the model were controlled for.

Variable	Correlation (r)	Statistical significance (p)
100K_reduces	-.04	.60
PN	.10	.14
Attitudes	.00	.99
PBC	.23	.001

PBC has been shown in many other studies of electricity saving to be an important determinant for electricity saving behaviour (e.g. Abrahamse & Steg, 2009; Botetzagias et al., 2014), which is consistent with the findings in this study.

Education was also a statistically significant predictor of the electricity saving behaviour, which means that higher educated respondents tended to do more electricity saving measures. As described in section 3.2.2 the *ES_behaviour* variable included mostly energy efficiency measures. Hence, this result confirms the existing literature, which also has found that higher educated people are more acceptable to behaviours entailing energy efficiency measures (Nair, Gustavsson, & Mahapatra, 2010; Poortinga et al., 2003).

The moral factors did not add any explanatory power to the electricity saving behaviour, which is in line with what is found by, for example, Botetzagias et al. (2014) and Heath and Gifford (2002) but in contradiction to results found by other studies where at least one of the moral factors increased the explanation of the variance (Abrahamse & Steg, 2009; Harland et al., 1999). Abrahamse and Steg (2009) suggest that these differences may be a result of how the situation is framed. If the situation looks more like a cost-benefit situation, the psychological variables are more influential, while in other studies, where the environmental or moral issues may be more highlighted, the moral factors have higher impact. Another possible explanation for the non contribution of the moral factors is that these are interwoven in the psychological factors (Botetzagias et al., 2014; Kaiser & Scheuthle, 2003).

The *subjective norm*, which describes the perception of how people important for the user think about the behaviour, was not statistically significant. This was expected, since in general this factor has been found to be the weakest of the predictors for energy behaviour (Armitage & Conner, 2001). It is perhaps more surprising that no statistical significance was found for the *attitude* variable, both in light of what the theory says (Ajzen, 1991) and in light of results from previous studies (Abrahamse & Steg, 2009; Botetzagias et al., 2014; Karlin et al., 2014). However, Karlin et al. (2014) found that *attitudes* were associated primarily with curtailment behaviour and not with energy efficiency behaviour. Botetzagias et al. (2014) also measured only curtailment activities. The dependent variable used for this regression included mainly energy efficiency behaviour, which may be an explanation why the results differed with the other studies in this aspect.

Note that the variable explained the electricity saving behaviour independently from the impact of 100Koll service; hence this model did not provide any new information about 100Koll as such. There were no statistically significant correlation between *100K_action* and the *ES_behaviour*, which may be explained by the fact that the ES_behaviour described electricity saving behaviour the last *three* years and not the behaviour during the period of 100Koll. To understand which factors influence the 100Koll use, two other regressions were made which are discussed in the following two sections.

100K_reduces

The stepwise multiple regressions resulted in two dependent variables that were statistically significant. In the first step *PN* was added which alone explained 13% of the variance in *100K_reduces* and in the second step *PBC* was added. The two variables *PN* ($\beta = 0.37$, $p < .001$) and *PBC* ($\beta = 0.24$, $p = .02$) together explained 16.7% of the variation ($F(2,230) = 24$, $p < 0.001$). No multicollinearity was identified. Highest VIF value was less than five (VIF = 1.33).

100K_reduces had statistically significant bivariate correlations to all moral and psychological factors. When controlling for all other variables, *PN* and *PBC* were still statistically significant (Table 4-10), but not the other variables.

Table 4-10. Partial correlations between 100K_reduces and the dependent variables that had bivariate correlations to electricity use (Table 4-4). All other variables in the model were controlled for.

Variable	**Correlation (r)**	**Statistical significance (p)**
AC	.00	.97
AR	-.08	.25
PN	.27	< .001
Attitudes	.11	.11
PBC	.21	.002
SN	-.03	.67

These results means that people that believe that they have possibilities to influence the electricity use in their household (*PBC*) and people that feel better when saving energy (*PN*) also believes that 100Koll really helps them to save electricity. As mentioned earlier the partial correlations between *100K_reduces* and *electricity change* (r = -.13, p = .17) and between *100K_reduces* and *electricity use* (r = -.12, p = .07) both indicates that *100K_reduces* actually can work as a proxy for the effectiveness of the 100Koll service.

100K_action

The stepwise regression only allowed one of the dependent variables, *PN* (β = .11, p < .001), in the model ($F(1,231)=14$, p < .001) that only explained 5.2% of the variance in *100K_action*. No multicollinearity was identified. The highest VIF value was less than five (VIF = 1.309).

100K_action had in addition to *PN,* statistically significant bivariate correlations to all psychological factors and *age*. After having tested all these associations with partial correlation only *PN* had statistical significance.

Table 4-11. Partial correlations between the 100K and the dependent variables that had bivariate correlations to electricity use (Table 4-4). All other variables in the model were controlled for.

Variable	**Correlation (r)**	**Statistical significance (p)**
PN	.21	.002
Attitudes	.03	.63
PBC	.08	.25
SN	.002	.98
Age	.06	.93

This result further strengthened the result in the previous section that indicated that people with high moral norms (*PN*) tend to change behaviour based on the feedback from 100Koll. *PBC* was not a statistically significant predictor for this variable as it was for *100K_reduces.*

5 Discussion

Before making any conclusions from the results it is well worth to discuss to which degree the results can be trusted, if the research should have been done in another way and implications based on the results. This chapter starts with a comparison of the effectiveness with existing studies, followed by a discussion of the validity of the results. Reflections over the methodology are presented and the chapter ends with a discussion regarding potential policy implications.

5.1 Comparison of effectiveness findings with existing studies

This section sets the achieved results from the effectiveness study in perspective to results of other similar studies and presents possible explanations to why the electricity savings due to 100Koll was 1.4 to 1.9%.

5.1.1 The result compared to other studies

The result presented in this study showed a reduction of 1.4 to 1.9%. This is in line with a recent meta-study of 19 SM interventions that found that these interventions in average led to a reduction of 1.6% (Bager & Mundaca, 2015). Another recent study of 33 trials involving an IHD concluded that effects of 3-5% should be expected for larger rollouts, which is slightly more than the findings from this study. However, compared to older studies, the result from this study can be considered very low (Compare e.g. Darby, 2006; Ehrhardt-Martinez et al., 2010). Darby (2006) concluded that real-time feedback should result in reductions in the higher range of 5-15%. The outcome is also considerably lower than the 12% for real-time disaggregated feedback that Ehrhardt-Martinez et al. (2010) has estimated as an average.

This study shows results lower than many other larger recent studies such as Schleich et al. (2013) that reports 4.5% for web or text feedback in Austria, Gans et al. (2013) with 11-17% for users with a key-pad meter in Northern Ireland, 3% reduction with real-time displays for different fuels in the UK (Raw & Ross, 2012) and a 3% reduction in Denmark where 1 397 users received SMS and e-mail warning messages after exceptionally high electricity use (Gleerup, Larsen, Leth-Petersen, Togeby, & others, 2010).

However, Matsukawa (2004) reports an electricity reduction of 1.5%, which is fully in line with the results retrieved in this study. An experiment with IHDs showing electricity use with a one-hour delay was installed in 319 Japanese households. Matsukawa (2004) argues that the low result may be caused by a complex user interface together with lack of helpful information. It was not elaborated on what kind of information was missing from the displays; however, one of the conclusions was that the large transaction cost (i.e., the effort needed to grasp the information from the IHD) reduced the effects.

The result of 2.24% electricity reduction from the energy experiment that E.ON did in 2012-2013 (Uggmark, 2013) was slightly higher than the outcome of this study. This is however reasonable as the energy experiment combined feedback from the SM with more interventions as explained in section 1.2 (Uggmark, 2013). A Swedish web service that presented non-real-time consumption statistics in 2008-2009 did not help to reduce the electricity consumption (Jurek Pyrko, 2009). The result from the measurement showed an infinitesimal reduction of 0.04% (Jurek Pyrko, 2009). This may be explained by the non-real-time feedback and the limited accessibility restricted to web pages designed for PCs.

5.1.2 Possible explanations for the effectiveness result

The effort needed to obtain the feedback may also be an explanation for the low results of this study. To access the feedback, the user will have to make a conscious decision and select the 100Koll application on the smart phone or tablet or navigate to the web page where the information is available. This may not seem like a large effort but the service competes with a multitude of other services, web pages and applications that also draw attention from the user. Every extra click the user has to do to find the interesting information increases the effort to obtain the information from the service. Even though the IHD used by Matsukawa (2004) did not give any larger effect, an IHD that is a separate device for the electricity feedback and also used in many other studies (Gans et al., 2013; Mountain, 2006; Raw & Ross, 2012) may present information that is easier to attain and the device itself reminds the user of the electricity use. It is suggested that further analysis of 100Koll investigates the correlation between of how often people use the service and the electricity savings to see if it the electricity reduction could be larger by increasing the use of the application.

The persistence of feedback has been discussed in the literature (Darby, 2006; Ehrhardt-Martinez et al., 2010; Fischer, 2008; Van Dam et al., 2010). This study indicated that the effect from the feedback was reduced after having been used for a longer time. The effect after 8.7 months of average use was found to be 1.9% but after 11.7 months the effect had decreased to 1.4 – 1.5%. The same pattern, but more significant was found by Van Dam et al. that reported that the effect from the SM had decreased from 7.8% after four months to 1.9% after 15 months. Ehrhardt-Martinez et al. (2010) did also find that longer studies concluded lower effects from feedback than shorter studies. In contrast, Fischer (2008) found no clear indication that the initial feedback should be higher than after a long period and Darby (2006) argues that the effect is persistent over time. The lower result of effectiveness in this study should there for not be attributed to the duration of the feedback.

Studies have also indicated that more recent larger studies have received lower figures for effectiveness (Bager & Mundaca, 2015; Ehrhardt-Martinez et al., 2010; McKerracher & Torriti, 2013). With measurements from 3 095 households, this study would in those meta-reviews be considered as a large study. Ehrhardt-Martinez et al. (2001) categorized a larger study as involving more than 100 persons, which is very low compared to this study. McKerracher and Torriti (2013) discussed the reasons for this effect. They argue that the larger the study is, the lower the risk is for the Hawthorne effect, which means that in smaller studies, people have a higher awareness that they are under study and are trying to perform ‘better’ than what they would have done other wise. The other reason for the lower effects of larger studies may be the sampling method (McKerracher & Torriti, 2013).

If a study requires that people opt-in to participate it is likely that only the ones that are highly interested in the subject participate and perform ‘better’ than what can be expected from a larger study, such as a national, roll-out of a similar service (McKerracher & Torriti, 2013). From their analysis of 27 feedback studies, McKerracher and Torriti (2013) found that studies with participants that opt-out result in a conservation effect of 2.6% compared to the ones that have participants that opt-in with an effect of 4.5%. In the initial phase of 100Koll, many user’s received the service for free (A. Widmark Sjöstedt, personal communication 26 August 2015), which means that for the case studied in this thesis the sampling method can be seen as an opt-out whereby people were opting out by choosing not to use it.

Although it is important to compare different studies and find patterns for different results these comparisons must be handled with care. All interventions differ in how the feedback is provided as has been discussed in this thesis, but what has not been discussed and what is often not clear in many studies is the state of the people exposed to the intervention (i.e., which kind of awareness of electricity use the users already have and what kind of information they received before the new feedback was introduced). The intervention that was studied in this thesis was targeting households that already had SMs and accurate monthly bills but lacked real-time feedback of electricity use. The participants in other studies that have been compared in this thesis may have had a less understanding of their consumption before they received the new feedback than what the Swedish users in this study had. The 100koll may not have reduced the information deficit as much in this case as it has for many of the other studies.

The level of information that users have received before the intervention is only one of the contextual parameters that may influence the effectiveness of the feedback. Many other shared contextual parameters may also influence the results such as laws and regulations, electricity price for the consumers, social norms in the society and available technologies (Wilson & Dowlatabadi, 2007).

Fischer (2008) provides a list of properties of feedback mechanisms that are both stimulating for the users and effective in conserving energy:

> "is based on actual consumption, is given frequently (ideally, daily or more), involves interaction and choice for households, involves appliance-specific breakdown, is given over a longer period, may involve historical or normative comparisons (although these are appreciated by households, the effects are less clear) and is presented in an understandable and appealing way". (p. 101)

100Koll fulfils all of these properties except for the normative comparisons. However, comparisons with other users have shown mixed results, which means that it may not give any significant improvements in terms of effectiveness but it may be well worth to try it out especially as users have claimed that they like that kind of information (Garay & Lindholm, 1995; Haakana & Sillanpää, 1998).

To summarize, the possible reasons for the relatively low effectiveness may be that the Hawthorne effect was not present, the sampling method was more like an opt-in than an opt-out, people had to make an effort to open the 100Koll application, and the level of knowledge about electricity use the users already had. The real-time feedback of the electricity use and appliance specific breakdown, should lead to more electricity savings which it did at least compared to earlier Swedish interventions that lacked these features (Jurek Pyrko, 2009).

5.2 Validity of the results

A framework developed by Morgan and Gliner (1997) was used to evaluate the validity of the results. The framework distinguishes between internal validity that describes how strong the causal effect is and external validity that describes how generalizable the results are (Morgan & Gliner, 1997).

5.2.1 Internal validity

The internal validity is dependent on the three factors: "instrument reliability and statistics", "equivalence of participants characteristics" and "control of experiences and environment variables" (Morgan & Gliner, 1997, p. 18).

Instrument reliability and statistics

This dimension concerns how reliable the instruments and measurements were, the appropriateness of statistical techniques and interpretation of the statistical analysis. The instrument reliability is high for the effectiveness calculations since the data used for the measurements is billing data captured from SMs installed in the houses and should reflect the actual electricity use with high precision. The sample size of 1 753 is deemed to be representative for the 4.8 million house households (Statistics Sweden, 2013) in Sweden. With a confidence level of 95% the margin of error is as low as 2.34%.

A survey was used to measure the psychological, moral and contextual factors that predicted the electricity behaviour, electricity use and the 100Koll use. Three of the factors, SN, AR and PCB, were only single item constructs (section 3.2.2), which should lead to lower reliability in that the factor really captures what it is meant to do. Additionally the attitudes factor resulted in a relatively low value for Cronbach's α (section 4.2.2).

Three of the moral and psychological and moral factors, SN, AR and PCB, were single-item constructs meaning that the factors were only constructed by one question. Having multiple items is, however, preferred since they averages out measurement errors (Nunnally & Bernstein, 1994) and provides a better representation of a complex concept (McIver & Carmines, 1981). The drawback with multiple item constructs is that it implies an increase in total number of questions that may result in a lower response rate. The low value (α = .31) of the multi item construct of the attitudes factor raised concerns regarding the validity of the attribute. The construct was supposed to measure the attitudes to electricity saving based on two main reasons, reduce global warming and reduce costs. As it was obvious that these two could lead to inconsistent answers while at the same time the construct seemed sound in theory it was decided to keep this construct as it was. Caution with inferences from the results that involve those four factors must however be taken.

Equivalence of participants characteristics

For this dimension, the validity suffers from the fact that the control group was not similar to the intervention group in all aspects (except from the independent variable, 100Koll). It was found that in addition to the intervention, the average electricity use also differed which made it impossible to just compare the difference between the two groups. A historic baseline was used, and under the assumption that the control group and the intervention group had the same relative variation, a result could be calculated.

Control of experiences and environment variables

This dimension concerns whether extraneous effects may have affected the result. For the effectiveness measurements the people in the households that were measured were not aware of the measurements as the data was taken from a database. The use of a control group ensured that the electricity change was not caused by anything else than the treatment (i.e., the 100Koll introduction).

For the survey, the Hawthorne effect (Adair, 1984) cannot be ruled out as people may have responded in a certain way to influence the results. This effect is however not specific to this survey but a general issue for all surveys. Partial correlations have been practiced to make sure that the independent variable causes the effect and not another variable.

5.2.2 External validity

The external validity, the generalizability, is according to Morgan and Gliner (1997) dependent on three dimensions, "operations and instrument validity", "population validity" and "ecological validity" (p. 18).

Operations and instrument validity

This dimension describes whether the variables are "appropriately measured/defined and are representative of the concepts or constructs under investigation" (Morgan & Gliner, 1997, p. 10). For the effectiveness calculations, the independent variable, 100Koll, and the dependent variable, electricity use, are both well-defined parameters and the concept of reduced energy from improved feedback is an acknowledged concept used in several studies as described in the literature review of this thesis.

The dependent variables that were tested were measured in different ways. The electricity use was simple to understand and measure and should be questioned with regards to this dimension. The electricity change that was calculated for each individual user did not provide any additional information and did not contribute to any significant knowledge. The result from that regression does not contribute to answer any of the two research questions. 100K_reduces and 100K_action should, under the assumption that the users are telling the truth, indicate how much 100Koll helps to save electricity.

Population validity

This dimension is about how well the selected sample can represent the target population, which in this case study were Swedish households. The sample was selected from 100Koll customers that installed the service between February and September 2014. The majority of users were from the southern part of Sweden. The average yearly electricity consumption for the households of the intervention group was 15.4 MWh and 11.1 MWh for the control group. This is lower than the national average consumption 2012 for Swedish single-family houses using electric resistance heating, that have an average yearly consumption of 16.9 MWh but much higher than the national average household consumption when excluding the electricity used for heating, which was 6.2 MWh in 2012 (Swedish Energy Agency, 2013). This indicates that the sample represented high electricity consuming households but not only households with electric resistance heating. Since the service initially was provided for free (A. Widmark Sjöstedt, personal communication 26 August 2015), it is likely that both interested customers and customers that are less interested in electricity use have installed 100Koll. It could therefore be assumed that the sample was a good representation of larger electricity consuming households in southern part of Sweden.

Ecological validity

The third dimension describes how close to real life outcomes the conditions for the research was. The research was designed as a field study where real life conditions were analysed which means that the validity was high regarding this aspect. Some of the variables were however captured from a survey, which means that those to some extent are artificial and may not fully reflect the actual values of a real life scenario.

5.3 Discussion of methodology

This section discusses the methodology used and highlights alternative methods that could have been used to increase the level of validity and to be able to draw more inferences.

Several methods were used for the calculation of the total effectiveness of 100Koll. These methods gave somewhat different results, but all were consistent in the sense that they were within a rather small span, lower than most other feedback studies. The control group was not (close to) identical to the intervention group, which would have been ideal. The electricity consumption differed significantly between the two groups, which should have been avoided. Potentially a fourth method could have been used to avoid this issue. For that method, two samples would have been selected, one from the control group and one from the intervention group, whereby ensuring that the two samples had the same average electricity consumption before the intervention took place. The two new subsets could then have been compared. However, the feasibility of that method was not assessed during this. Further research may try out this possibility.

The survey was submitted only to the intervention group. A similar survey (without specific 100Koll questions) should have been sent to the control group as well. This would have made it possible to find out whether 100Koll had any influence on any of the psychological and moral factors. That effect could therefor not be tested in this study; instead, it was assumed that 100Koll did not have any effect on these factors and that they stayed constant during the intervention. Moreover it was assumed that the new information from 100Koll in combination with the existing attitudes values, norms and awareness of issues would cause changes in the behaviour of the users and thus reduce the consumption. Having submitted the survey to the control group as well would probably have avoided the need for these assumptions.

Method one used climatic correction for the effectiveness result. The method for the climatic correction used was retrieved from SMHI (SMHI, n.d.). No references to any scientific literature regarding the theoretical background or empirical results from the use of the method were provided. For the energy saving experiment, undertaken by E.ON, a method called 'the LTH-method' was used for the temperature correction of the electricity use (Uggmark, 2013). This method, potentially more scientific, may have provided more reliable results.

No method was found to measure the electricity reduction that 100Koll yielded (in kWh) for each individual household. The first idea was to use the electricity change variable, calculated according to the methods described in section (3.3.1), as a proxy, but as there were large variations in the electricity change for the sample, with almost as many households increasing their electricity use during the intervention period as households that were decreasing the electricity use, it was apparent that other factors disturbed the signal from the 100Koll so much that it was not possible to use the calculated result. It was decided to include the electricity change model to explore and demonstrate any possible relations between the independent variables and the electricity change. The regression did, however, not yield any results important for answering the research questions.

The survey included questions related to global warming and electricity use. However, the electricity use from the residential sector in Sweden only represent 1.1% of the total green house gas emissions (EC, 2014), which means that global warming may not be the major negative effect from electricity use in the Swedish households. For that reason it may not have been correct to ask about global warming in the survey but instead ask about other negative consequences from electricity use.

5.4 Policy implications

This study shows that introducing real-feedback via, PCs, smartphones and tablets only marginally reduce the electricity use in Sweden. The UK has set a target that all households in the country shall have smart meters with display monitors installed by 2020 (J. Pyrko & Darby, 2011). The results from this study indicate that a similar target in Sweden would not result in any significant effects. However, as one ingredient in a mix of multiple policies it may give much better results. Gardner and Stern (1996) described four possible types of interventions: (1) Governments incentives and regulations, (2) education to change attitudes, (3) small community management and (4) moral, ethical or religious appeals. These four types will lead the following discussion.

The first type of intervention includes incentives, and a typical incentive to stimulate or depress consumption is to change the price. Electricity has traditionally been inelastic (Allcott, 2011; Ito, 2012), which means that consumption has not changed much based on changes in the price. Since 2008, the electricity prices in Sweden have been reduced with approximately 50% for the flat price plans (see Figure 5-1). According to the theory behind SMs, described in section 2.1, the increased awareness of electricity use and corresponding monetary losses should trigger a more rational behaviour and reduce electricity. The price elasticity (i.e., the amount of change in electricity due to change in one unit of price) should therefore be larger with increased feedback and greater awareness. A 2014 study in Connecticut supported this reasoning (Jessoe & Rapson, 2014). The group that had an IHD installed in their homes reacted more to price changes than the control group (Jessoe & Rapson, 2014). Both groups received the same information about the price changes via the same communication channels, which means that the price salience was not tested. The only thing that differed was the increased feedback of consumption (Jessoe & Rapson, 2014). Hence, if 100Koll had been introduced in 2008 when the electricity price was much higher, a higher result of the effectiveness would probably have been received. Policies increasing the cost for the end user may be a more effective instrument if increased feedback, such as 100Koll, is available. In the Nordic countries the market price of electricity is settled by Nord Pool Spot[12]. One policy instrument to increase the cost for the electricity users in Sweden is to increase energy taxes.

A Swedish study has found that users were willing to reduce electricity with 50% during peak hours if the end user electricity cost was three times higher (Lindskoug, 2006). However, a Swedish survey carried out in 2006 indicated that 70% of the customers that had tried a dynamic tariff wanted to have their flat tariff back (Jurek Pyrko, 2005).

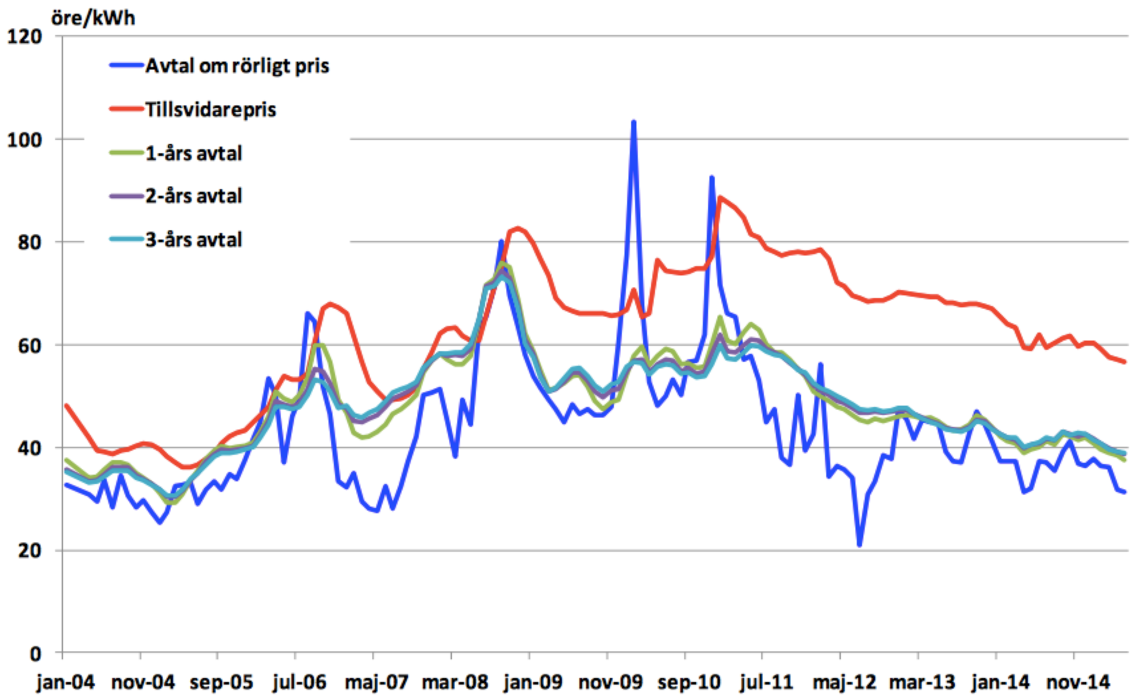

Figure 5-1. Swedish electricity end-user prices between January 2014 and May 2015.

Source: Swedish Statistics and Swedenergy via The Swedish Consumer Energy Markets Bureau.

[12] Nord Pool Spot is a marketplace for electricity and operates in the UK, Germany, Estonia, Latvia, Lithuania, Sweden, Norway and Sweden ("Nord Pool Spot," n.d.).

The second type of policy intervention included education or information (Gardner & Stern, 2002). Based on the results in this study, any informational policies combined with SMs should not target people's attitudes, their awareness of negative consequences from electricity use or the responsibility that they think that they have for the global warming. These factors did not have any measurable impact on any of the dependent variables. However, the results indicated that people who perceive that they can influence the electricity use in the household tend to perform more energy reducing activities and also believe that 100Koll can help them to take action. Information campaigns that describe how easy it is to take action and examples on what to do may therefore give more effects together with increased feedback. Information on other users 'successful' behaviour has shown to be effective in stimulating pro-environmental behaviour (Abrahamse et al., 2005; Schultz, Nolan, Cialdini, Goldstein, & Griskevicius, 2007). Other policy instruments that, according to Egmond and Bruel (2007), have primary effect when perceived behavioural control is a determinant for the behaviour are personal advices and demonstrations.

The third type of intervention, 'small community management', is applicable for locally controlled resources with local resource dependency (Gardner & Stern, 2002) and therefore not applicable in this context.

The fourth type of intervention that was discussed by Gardner and Stern (1996) included an appeal to people's moral values. However, with the increasing level of moral relativism in Western countries those kind of interventions may be less effective (Jackson, 2005). Nevertheless, the results from this research indicated that personal norms, one of the moral factors, seemed to have both an influence on actions taken due to 100Koll and on the beliefs that 100Koll helps to reduce electricity use. Hence, policies that moralize with regards to electricity use may have an effect in combination with increased feedback. Oikonomou et al. (2009) also suggest that policies that increase morality could be a viable strategy to achieve end-use energy efficiency. These kinds of strategies involve "convincing people that they should protect collective environmental qualities (despite it may also involve some individual costs), and that their contribution will be socially helpful" (Oikonomou, Becchis, Steg, & Russolillo, 2009, p. 4795).

6 Conclusions

The aim of this study was to better understand how effective, in terms of reduced electricity use, real-time feedback is in Sweden and in that way contribute to reduce the energy efficiency gap. Additionally the study aimed to get a better understanding of whether the feedback is more effective for people with different psychological, moral and contextual characteristics. The case under study was a Swedish feedback service, called 100Koll, launched by E.ON in 2014. As was described in section 3.1, the service provides the user with real-time electricity use data for the whole dwelling as well as for individual appliances. The case is interesting since only a few studies have been done in Sweden, which also differs from other countries in its capabilities to produce electricity with low CO_2 emissions, high average electricity use for the households and an aggressive energy roadmap. In order to reach these aims, two research questions were defined.

1. What effectiveness with regards to reduced electricity use has 100Koll had on Swedish households?
2. How do people's psychological, moral and contextual characteristics determine the electricity use and the effect of the 100Koll real-time feedback service?

6.1 Main findings

When it comes to the *first research question* it was found that the effectiveness of 100Koll was 1.4 to 1.9% compared to the control group and historical use. The energy savings from the feedback was found to be 1.9% after 8.7 months and 1.4 to 1.5% after 11.7 months of use. This result is consistent with reductions from existing literature that found an effect of 1.6% (Bager & Mundaca, 2015). Earlier studies have found that real-time feedback like 100Koll should result in considerably larger reductions (Darby, 2006; Ehrhardt-Martinez et al., 2010). However, existing knowledge also displayed a tendency implying that the larger the study's sample and the more recent the study sample was, the smaller the reductions in electricity use was found (Ehrhardt-Martinez et al., 2010).

Possible explanations to the relatively lower level of reduction being found in this thesis could be that the feedback was not as visible as it would have been with a separate device providing feedback. It could also be that Swedish households already had a good starting point (i.e., a fairly good understanding of their consumption due to the monthly metering that has been mandated since 2009) or that the electricity cost for the households was relatively low compared to the earlier years. In addition one could also question the actual design of 100Koll and how salient (and useful) the given information is to electricity users.

With regard to the validity of the effectiveness result, the fact that two different methods lead to almost the same result increases the validity of the result. The first method used climatic correction to calculate the result while the other method used a control. The first method was based on the assumption that no larger societal changes caused a decrease in the electricity use of the intervention group. The second method (method 3) was based on the assumption that the control group, with 34% lower average electricity use than the intervention group, would have changed consumption as much as the control group if the intervention did not occur. Since two different methods lead to the same result, since the assumptions made were realistic and since the result also was very consistent with the literature the result is deemed as reliable.

The result may not be generalizable for the whole population of Sweden but, based on the sample method, the average electricity use and the geographical use of 100Koll, the result should be applicable to high electricity consuming households in southern part of Sweden.

With regard to the *second research question* it was found that the contextual factors, living area, household size (number of persons in the household) and income, had statistically significant impact on the total use of electricity. The results also indicated that the personal norms and the perceived behavioural control had impact on how effective the real-time feedback was. Five of the factors that were tested, attitudes, subjective norms, awareness of consequences, ascribed responsibility and age, did not contribute with any explanation to the variance of electricity use, electricity change, electricity saving behaviour or 100Koll effectiveness.

In line with the existing literature, this study found that the psychological and moral factors could not predict the level of electricity use. Instead, the contextual factors living area, the number of persons in the household and the income explained 17.6% of the variation. The results also indicated[13] that people claiming that 100Koll help them to reduce electricity also had lower total use of electricity.

Perceived behavioural control together with the moral obligations people feel for saving electricity, their personal norms, explained as much as 16.7% of the variation in the level of belief that people have that 100Koll helps to reduce electricity use. It was assumed that the more a user believes that 100Koll can help to reduce electricity, the more effective in terms of electricity saving the service actually is. The personal norm could also explain a part of the variation of the actions that the 100Koll users already had taken based on the feedback from 100Koll. With due limitations, these two results suggest that higher perceived behavioural control and increased feelings of moral obligations give higher reductions in electricity use when 100Koll is used.

It was also found that people that perceive that they can control the electricity use (i.e., a higher PBC) and people that have a higher education level have more tendencies to perform energy efficiency actions.

With regard to the validity of the answer to the second research question, it must be seen as an indication rather than proof based on two limitations. Firstly, the number of questions used for the psychological and moral factors were too few to guarantee that the factors were fully reliable and described what they were set out to do. Secondly, the result is based on the assumption that the feedback did not influence the psychological and moral determinants. This has not been proved and must be left for further research.

6.2 Recommendations and suggestions for further research

Based on the results from this study, *policy makers* in Sweden should be aware that an intervention like this in isolation only results in marginal electricity savings. It is, however, possible that increased feedback of electricity use in combination with other interventions such as information campaigns or tariff interventions can increase the effect as discussed in section 5.4.

From the survey, it was found that the 100Koll users had low average values on PBC and personal norms, which indicates that it may be possible to increase these within the 100Koll users. As mentioned in the main findings, the results also indicated, with due limitations, that by increasing these two characteristics among the users the effectiveness of 100Koll may be increased. Hence, potential information campaigns that are combined with enhanced feedback of electricity use, similar to 100Koll, should have two main purposes: to increase the perceived

[13] A partial correlation, controlling for all other independent variables resulted in a p-value of .07, which is very close to .05, which is the level often used to say that it is statistically significant.

behavioural control and the personal norms as regards electricity-saving activities. This means that users should be educated in how easy it is to reduce electricity use and that anyone can do something to contribute to the reduction. Additionally, awareness campaigns that make electricity users feel that they contribute to something important when reducing electricity use would according to the results have positive effect when it is combined with the increased feedback. Exactly how the education and awareness campaign should be implemented and what effect it may give has not been assessed in this thesis. The cost-effectiveness of an information campaign must be taken into consideration before launching it since they can be very expensive[14].

To *researchers,* the results from this thesis should be interesting as it complements the energy feedback literature with new results from a comparably large study in Sweden. Few real-time feedback studies have been done in the country and no other similar study of this size has, as far as the author knows, been done in Sweden.

The result is important for *energy companies* that are interested in helping their customers to reduce electricity. The findings from this research indicate that other measures than real-time feedback of electricity use may be more effective to achieve such reductions. Energy companies that have a service similar to the one studied in this thesis may be able to increase the effectiveness by tailored education and awareness programs similar to those suggested for policy makers above.

It is suggested that further research investigate the effects of combining real-time feedback with other interventions, such as prices changes and specific information campaigns in order to see if the effect becomes significantly higher. Ideally, several groups with different combinations of interventions should be used to clearly see which combinations that result in most electricity saving. Further investigations regarding the price sensitivity with and without SMs could be of interest.

One of the discussed reasons for the low result of effectiveness was that the effort needed to monitor 100Koll on a PC or a smart phone was higher than the expected gain and that perhaps a dedicated device like an IHD would provide a higher result since no specific app or web page needs to be opened. Further research could investigate if an IHD would enhance the reduction significantly in Swedish households.

As was clearly demonstrated by Bager and Mundaca (2015), the effectiveness of the feedback heavily depends on how it is presented (Bager & Mundaca, 2015). Hence, it is suggested that the user interface for 100Koll is further reviewed and designed to maximise the effect of the service. Different ways to frame the message of the consumption also deserves more research. Trials with different designs may yield useful insights in this respect.

Finally, this thesis focused on the moral, psychological and contextual impact on electricity use, behaviour and 100Koll use. The results indicated that some of the factors are important predictors of electricity behaviour; however, they only explained a limited part of the total variation. Moreover, this study assumed that there was no impact from meter-reading on the psychological and moral characteristics of the users, but did not prove it and thus it is impossible to conclude that increased perceived behavioural control and personal norms really would help to increase the effectiveness of the feedback. Therefore, more research regarding

[14] A Californian company once spent more money on an information campaign about the benefits of insulation than it would have cost to insulate the homes directly (McKenzie-Mohr, 2000).

the impact of predicting factors other than those studied in this thesis is recommended and further conceptualisation and specification of models (to be tested) are needed.

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Appendix I: Survey questions

Number	Question	Answer alternatives
1	Jag anser att global uppvärmning är ett problem för samhället.:	5 grade Likert scale: 1. Instämmer inte alls to 5. Instämmer helt;,Vet ej
2	Tillsammans med andra har jag ansvar för att minska den globala uppvärmningen.:	5 grade Likert scale: 1. Instämmer inte alls to 5. Instämmer helt, Vet ej
3	Genom att spara el bidrar man till en minskad global uppvärmning.:	5 grade Likert scale: 1. Instämmer inte alls to 5. Instämmer helt, Vet ej
4	Det är viktigt för mig att spara el för att minska den globala uppvärmningen.:	5 grade Likert scale: 1. Instämmer inte alls to 5. Instämmer helt, Vet ej
5	Det är viktigt för mig att spara el för att kunna minska mina kostnader.:	5 grade Likert scale: 1. Instämmer inte alls to 5. Instämmer helt, Vet ej
6	Vad av följande är den störst bidragande faktorn för att du ska spara el?:	1. Endast spara på miljön, 2. Mest för att spara miljön. 3 Miljö och pengar är lika starka, 4. Mest för att spara pengar, 5. Endast spara pengar, Inget av alternativen, Vet ej
7	Vad av följande är den störst bidragande faktorn för att du ska spara el?:Kommentar	Free text
8	Jag upplever att jag har stor möjlighet att påverka min (hushållets) elanvändning.:	5 grade Likert scale: 1. Instämmer inte alls to 5. Instämmer helt, Vet ej
9	Personerna i min omgivning förväntar sig att jag ska anstränga mig för att spara el i mitt hem.:	5 grade Likert scale: 1. Instämmer inte alls to 5. Instämmer helt, Vet ej
10	Jag får dåligt samvete när jag slösar på el i mitt hem.:	5 grade Likert scale: 1. Instämmer inte alls to 5. Instämmer helt, Vet ej
11	Jag känner mig som en bättre person när jag sparar el. :	5 grade Likert scale: 1. Instämmer inte alls to 5. Instämmer helt, Vet ej
12	Stämmer det att du beställt tjänsten 100Koll?:	Ja, Nej, Vet ej
13	Vilken var den främsta anledningen till att du beställde 100Koll?:	Annat, Få bättre koll på hur mycket enskilda prylar i hemmet drar, Få bättre koll på min totala elförbrukning, För att jag är intresserad av ny teknik, För att kunna stänga av och sätta på olika prylar, Spara el och därmed minska min energikostnad, Spara el

		och därmed minska påverkan på miljön.
14	Vilken var den främsta anledningen till att du beställde 100Koll?:Om Annat, vänligen uppge:	Free text
15	Vilken var den främsta anledningen till att du beställde 100Koll?:Kommentar:	Free text
16	Hur använder du huvudsakligen din/dina smartplugs?:	Mäta hur mycket energi olika prylar i hemmet drar, Styra prylar i hemmet (stänga av/sätta på), Sätta schema på prylar, Få varning om någon pryl drar för mycket el, Annat, Använder ej smartplugs, Vet ej
17	Hur använder du huvudsakligen din/dina smartplugs?:Om Annat, beskriv gärna vad	Free text
18	Vilka prylar har du satt din/dina smartplugs på?	Lampa, Dator, TV, Stereo, Strykjärn, Annat, Använder ej smartplugs, vet ej
19	Hur använder du huvudsakligen din/dina smartplugs?:Om annat, beskriv gärna vad	Free text
20	Hur använder du huvudsakligen din/dina smartplugs?:Kommentar kring din användning av Smartplugs:	Free text
21	Jag tror att jag med hjälp av 100Koll kan minska onödig förbrukning i mitt hem.:	5 grade Likert scale: 1. Instämmer inte alls to 5. Instämmer helt, Vet ej
22	Jag tror att jag med hjälp av 100Koll kan minska onödig förbrukning i mitt hem.:Kommentar:	Free text
23	På en skala mellan 1-10, hur troligt är det att du skulle rekommendera tjänsten 100Koll till vänner och bekanta?:	11 grade Likert scale: 0. Instämmer inte troligt to 10. Väldigt troligt, Vet ej
24	På en skala mellan 1-10, hur troligt är det att du skulle rekommendera tjänsten 100Koll till vänner och bekanta?:Förklara gärna ditt svar här:	Free text
25	Har du utfört någon/några av följande energieffektiviserande åtgärder i din bostad under de senaste TRE åren?:Nya fönster	Delvis, Ja helt, Nej
26	Har du utfört någon/några av följande energieffektiviserande åtgärder i din bostad under	Delvis, Ja helt, Nej

	de senaste TRE åren?:Tätat fönster	
27	Har du utfört någon/några av följande energieffektiviserande åtgärder i din bostad under de senaste TRE åren?:Tilläggsisolerat vind	Delvis, Ja helt, Nej
28	Har du utfört någon/några av följande energieffektiviserande åtgärder i din bostad under de senaste TRE åren?:Tilläggsisolerat fasad	Delvis, Ja helt, Nej
29	Har du utfört någon/några av följande energieffektiviserande åtgärder i din bostad under de senaste TRE åren?:Ökat isolering på tak	Delvis, Ja helt, Nej
30	Har du utfört någon/några av följande energieffektiviserande åtgärder i din bostad under de senaste TRE åren?:Installerat värmepump	Delvis, Ja helt, Nej
31	Har du utfört någon/några av följande energieffektiviserande åtgärder i din bostad under de senaste TRE åren?:Köpt nya vitvaror	Delvis, Ja helt, Nej
32	Har du utfört någon/några av följande energieffektiviserande åtgärder i din bostad under de senaste TRE åren?:Styr belysning/annan apparatur med timers/smartplugs	Delvis, Ja helt, Nej
33	Har du utfört någon/några av följande energieffektiviserande åtgärder i din bostad under de senaste TRE åren?:Sänkt inomhustemperaturen	Delvis, Ja helt, Nej
34	Har du utfört någon/några av följande energieffektiviserande åtgärder i din bostad under de senaste TRE åren?:Installerat solceller	Delvis, Ja helt, Nej
35	Har du utfört någon/några av följande energieffektiviserande åtgärder i din bostad under de senaste TRE åren?:Bytt värmesystem	Delvis, Ja helt, Nej
36	Har du utfört någon/några av följande energieffektiviserande åtgärder i din bostad under de senaste TRE åren?:Värmeåtervinning ventilationsluften	Delvis, Ja helt, Nej
37	Har du utfört någon/några av följande energieffektiviserande åtgärder i din bostad under de senaste TRE åren?:Bytt till energisnåla lampor	Delvis, Ja helt, Nej
38	Har du utfört någon/några av följande energieffektiviserande åtgärder i din bostad under	Delvis, Ja helt, Nej

	de senaste TRE åren?:Kortare dusch tid	
39	Har du utfört någon/några av följande energieffektiviserande åtgärder i din bostad under de senaste TRE åren?:Annat	Free text
40	Har du utfört någon/några av följande energieffektiviserande åtgärder i din bostad under de senaste TRE åren?:Vet ej	
41	Har du utfört någon/några av följande energieffektiviserande åtgärder i din bostad under de senaste TRE åren?:Om du kryssar i annat, vänligen ange vad:	Free text
42	Har 100Koll varit en bidragande faktor till beslut om ev. åtgärder ovan?	Har ej gjort några åtgärder de senaste tre åren, Ja delvis pga insikter från 100Koll, Ja enbart pga insikter från 100Koll, Nej andra orsaker påverkade beslutet, Vet ej.
43	Har du utfört någon/några av följande energieffektiviserande åtgärder i din bostad under de senaste TRE åren?:Kommentar:	Free text
44	Vad var anledningen till de energieffektiviserande åtgärderna?:Fler val möjliga	Minskade energikostnader, Minskade värmeförluster, Behagligare inomhustemperatur-/miljö, Miljöaspekter, Gamla uppvärmningssättet föråldrat/trasigt, Bekvämlighet, Skapa ett smartare hem, I samband med renovering, I samband med inflytt i ny bostad, Annat
45	Vad var anledningen till de energieffektiviserande åtgärderna?:Om Annat, vänligen ange vad:	Free text
46	Vilket är bostadens byggnadsår?:	1909 eller äldre; 1910-1930, 1931-1940, 1941-1950, 1951-1960, 1961-1970, 1971-1980, 1981-1990, 1991-2000, 2001-2010, 2011 eller nyare. Vet ej
47	Vilket är bostadens byggnadsår?:Kommentar:	Free text
48	Hur många kvm boyta har bostaden?:Ange storleksintervall	0-49 kvm, 100-149 kvm, 150-199 kvm, 200-249 kvm, 250+ kvm, Vet ej
49	Hur många personer bor i hushållet (inklusive dig	1, 2, 3, 4, 5 eller fler

	själv)?:Antal vuxna (16 år och äldre)	
50	Hur många personer bor i hushållet (inklusive dig själv)?:Antal barn (under 16 år)	0, 1, 2, 3, 4, 5 eller fler
51	Vad är hushållets ungefärliga månadsinkomst (efter skatt)?:	0-20 000 kr, 21 000-50 000 kr, 51 000-80 000, 80 000 +, Vet ej, Vill ej uppge.
52	Hur gammal är du?:	18-29 år, 30-39 år, 40-49 år, 50-59 år, 60-69 år, 70-79 år, Vill ej uppge
53	Vilken är din högst avklarade utbildningsnivå?:	Annan yrkesutbildning, Folkhögskola, Grundskola, Gymnasium, Högskola/Universitet, JY-Utbildning, Vill ej uppge

Appendix II – Regression Details

This appendix describes the detailed results from the regressions made with SPSS and target readers with extensive statistical knowledge. All parameters presented are not explained as it is expected that the reader of this appendix already have that understanding. The most important parameters are described in the methodology chapter (3.3.2) and the results are explained in section 4.2.4.

Electricity Change

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.209[a]	.044	.035	11.1394

a. Predictors: (Constant), Household size

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	640.239	1	640.239	5.160	.025[b]
	Residual	14021.849	113	124.087		
	Total	14662.088	114			

a. Dependent Variable: Elect change

b. Predictors: (Constant), Household size

Coefficients[a]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF

1	(Constant)	-7.757	3.038		-2.553	.012		
	Household size	2.187	.963	.209	2.271	.025	1.000	1.000

a. Dependent Variable: Elect change

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics		
						Tolerance	VIF	Minimum Tolerance
1	Elect_use	.081[b]	.866	.388	.082	.960	1.042	.960
	100K_reduces	-.099[b]	-1.071	.286	-.101	.990	1.010	.990
	100K_action	-.138[b]	-1.502	.136	-.141	.999	1.001	.999
	AC	.025[b]	.267	.790	.025	.984	1.017	.984
	AR	.025[b]	.265	.792	.025	.992	1.008	.992
	PN	.117[b]	1.277	.204	.120	.998	1.002	.998
	Attitudes	-.057[b]	-.617	.539	-.058	.999	1.001	.999
	PBC	.026[b]	.282	.778	.027	.974	1.027	.974
	SN	.147[b]	1.591	.114	.149	.980	1.020	.980
	Living area	.043[b]	.461	.646	.044	.985	1.015	.985
	Income	-.166[b]	-1.812	.073	-.169	.988	1.013	.988
	Age	.063[b]	.507	.613	.048	.546	1.830	.546
	Education	-.179[b]	-1.944	.054	-.181	.978	1.022	.978

a. Dependent Variable: Elect change

b. Predictors in the Model: (Constant), Household size

Electricity Use

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.347[a]	.121	.117	6481
2	.403[b]	.163	.155	6338
3	.433[c]	.188	.177	6256

a. Predictors: (Constant), Living area

b. Predictors: (Constant), Living area, Income

c. Predictors: (Constant), Living area, Income, Household size

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1318459695.373	1	1318459695.373	31.381	.000[b]
	Residual	9621475172.831	229	42015175.427		
	Total	10939934868.20	230			
2	Regression	1779676674.858	2	889838337.429	22.148	.000[c]
	Residual	9160258193.346	228	40176571.023		
	Total	10939934868.20	230			
3	Regression	2053692679.921	3	684564226.640	17.487	.000[d]
	Residual	8886242188.283	227	39146441.358		
	Total	10939934868.20	230			

a. Dependent Variable: Elect_use

b. Predictors: (Constant), Living area

c. Predictors: (Constant), Living area, Income

d. Predictors: (Constant), Living area, Income, Household size

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	5115.789	1701.192		3.007	.003		
	Living area	2650.604	473.167	.347	5.602	.000	1.000	1.000
2	(Constant)	884.636	2080.122		.425	.671		
	Living area	2401.451	468.505	.315	5.126	.000	.975	1.025
	Income	2164.918	638.962	.208	3.388	.001	.975	1.025
3	(Constant)	-904.532	2161.778		-.418	.676		
	Living area	2275.552	464.902	.298	4.895	.000	.965	1.036
	Income	1900.009	638.616	.182	2.975	.003	.951	1.051
	Household size	1032.337	390.193	.162	2.646	.009	.960	1.042

a. Dependent Variable: Elect_use

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics		
						Tolerance	VIF	Minimum Tolerance
3	100K_reduces	-.092[d]	-1.528	.128	-.101	.976	1.024	.947

AC	-.008[d]	-.127	.899	-.008	.999	1.001	.951
AR	-.065[d]	-1.083	.280	-.072	.999	1.001	.951
PN	-.002[d]	-.037	.970	-.002	.995	1.005	.950
Attitudes	-.023[d]	-.380	.705	-.025	.987	1.014	.939
PBC	-.047[d]	-.777	.438	-.052	.976	1.024	.945
SN	.032[d]	.531	.596	.035	.963	1.039	.946
Age	-.014[d]	-.199	.842	-.013	.696	1.437	.674
Education	.040[d]	.632	.528	.042	.886	1.129	.880

a. Dependent Variable: Elect_use

b. Predictors in the Model: (Constant), Living area

c. Predictors in the Model: (Constant), Living area, Income

d. Predictors in the Model: (Constant), Living area, Income, Household size

Electricity Saving Behaviour

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.243[a]	.059	.055	3.3943
2	.286[b]	.082	.074	3.3601

a. Predictors: (Constant), PBC

b. Predictors: (Constant), PBC, Education

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	161.407	1	161.407	14.009	.000[b]
	Residual	2580.841	224	11.522		
	Total	2742.248	225			
2	Regression	224.489	2	112.244	9.942	.000[c]
	Residual	2517.759	223	11.290		
	Total	2742.248	225			

a. Dependent Variable: ES_behaviour

b. Predictors: (Constant), PBC

c. Predictors: (Constant), PBC, Education

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2.455	.809		3.034	.003		
	PBC	.814	.218	.243	3.743	.000	1.000	1.000
2	(Constant)	.830	1.056		.786	.433		
	PBC	.874	.217	.260	4.032	.000	.986	1.014
	Education	.513	.217	.153	2.364	.019	.986	1.014

a. Dependent Variable: ES_behaviour

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics		
						Tolerance	VIF	Minimum Tolerance
2	100K_reduces	.016[c]	.234	.815	.016	.912	1.097	.901
	AC	.047[c]	.702	.484	.047	.920	1.086	.913
	AR	-.023[c]	-.346	.730	-.023	.968	1.033	.960
	PN	.100[c]	1.512	.132	.101	.940	1.063	.927
	Attitudes	.019[c]	.277	.782	.019	.921	1.086	.911
	SN	-.029[c]	-.435	.664	-.029	.926	1.080	.914
	Living area	.061[c]	.939	.349	.063	.977	1.023	.972
	Household size	.029[c]	.443	.658	.030	.953	1.050	.953
	Income	.081[c]	1.193	.234	.080	.900	1.111	.888
	Age	-.076[c]	-1.177	.240	-.079	.992	1.008	.979
	100K_action	.050[c]	.769	.442	.052	.983	1.018	.970
	Elect_use	.045[c]	.687	.493	.046	.970	1.031	.966

a. Dependent Variable: ES_behaviour

b. Predictors in the Model: (Constant), PBC

c. Predictors in the Model: (Constant), PBC, Education

100K_reduces

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.361[a]	.131	.127	1.105
2	.418[b]	.175	.167	1.079

a. Predictors: (Constant), PN

b. Predictors: (Constant), PN, PBC

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	41.947	1	41.947	34.379	.000[b]
	Residual	279.412	229	1.220		
	Total	321.359	230			
2	Regression	56.080	2	28.040	24.100	.000[c]
	Residual	265.279	228	1.164		
	Total	321.359	230			

a. Dependent Variable: 100K_reduces

b. Predictors: (Constant), PN

c. Predictors: (Constant), PN, PBC

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2.130	.238		8.949	.000		
	PN	.430	.073	.361	5.863	.000	1.000	1.000
2	(Constant)	1.439	.306		4.708	.000		
	PN	.370	.074	.312	5.038	.000	.947	1.056
	PBC	.244	.070	.216	3.485	.001	.947	1.056

a. Dependent Variable: 100K_reduces

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics		
						Tolerance	VIF	Minimum Tolerance
2	AC	.004[c]	.055	.956	.004	.776	1.288	.776
	AR	-.034[c]	-.518	.605	-.034	.860	1.163	.833
	Attitudes	.076[c]	1.104	.271	.073	.754	1.326	.754
	SN	-.023[c]	-.350	.727	-.023	.839	1.191	.839
	Living area	-.102[c]	-1.694	.092	-.112	.991	1.009	.938
	Household size	.070[c]	1.146	.253	.076	.974	1.027	.925
	Income	-.059[c]	-.980	.328	-.065	.998	1.002	.946
	Age	-.098[c]	-1.634	.104	-.108	.990	1.010	.942

Education	-.008[c]	-.136	.892	-.009	.985	1.016	.932
Elect_use	-.111[c]	-1.836	.068	-.121	.989	1.011	.937

a. Dependent Variable: 100K_reduces

b. Predictors in the Model: (Constant), PN

c. Predictors in the Model: (Constant), PN, PBC

100K_action

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.238[a]	.057	.052	.4317

a. Predictors: (Constant), PN

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.570	1	2.570	13.793	.000[b]
	Residual	42.861	230	.186		
	Total	45.431	231			

a. Dependent Variable: 100K_action

b. Predictors: (Constant), PN

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-.056	.092		-.616	.538		
	PN	.105	.028	.238	3.714	.000	1.000	1.000

a. Dependent Variable: 100K_action

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics		
						Tolerance	VIF	Minimum Tolerance
1	AC	-.053[b]	-.728	.467	-.048	.788	1.270	.788
	AR	-.095[b]	-1.384	.168	-.091	.868	1.152	.868
	Attitudes	-.009[b]	-.123	.902	-.008	.764	1.309	.764
	PBC	.078[b]	1.192	.234	.079	.945	1.058	.945
	SN	.026[b]	.383	.702	.025	.865	1.156	.865
	Living area	-.119[b]	-1.875	.062	-.123	1.000	1.000	1.000
	Household size	.012[b]	.183	.855	.012	.997	1.003	.997
	Income	.029[b]	.457	.648	.030	.997	1.003	.997
	Age	.014[b]	.213	.831	.014	.995	1.005	.995
	Education	.027[b]	.420	.675	.028	1.000	1.000	1.000
	Elect_use	-.029[b]	-.445	.657	-.029	1.000	1.000	1.000

a. Dependent Variable: 100K_action

b. Predictors in the Model: (Constant), PN