MASTER

Improving energy saving decisions by matching recommender type with domain knowledge and mindset

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Award date:
2011

Eindhoven, November 2011

Improving energy saving decisions by matching recommender type with domain knowledge and mindset

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identity number: 0655862

in partial fulfilment of the requirements for the degree of

Master of Science
in Human-Technology Interaction

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TUE: School of Innovation Sciences.
Series Master Theses Human-Technology Interaction (HTI)

Keywords: Energy Saving, Mindset, Recommender Systems, Domain knowledge, Decision Making

Abstract

To save the environment in the future we need to make sacrifices now while the benefits of these actions will reveal itself in the future. But people have a hard time making the tradeoff between sacrifices now and possible gains in the future. A possible explanation why people have difficulties in solving this trade-off is that the two different time perspectives have an impact on how people's assess the situation. Construal level theory states that in the distant future people have a more abstract mindset and focus on the desirability of saving energy, while in the nearby future a more concrete mindset is used and the focus is on the feasibility of saving energy. To help people in their tradeoff between desirability and feasibility, recommender systems can be applied. But the evaluation of the system and the tendency to accept the recommendations has been shown to depend on the fit between the user's domain knowledge and the type of recommender. Whereas experts prefer an attribute-based system, novices are more helped with a needs-based system. Furthermore previous research showed that if the mindset matches the recommender's information abstraction level, combining needs-based with an abstract mindset and attribute based with an abstract mindset, users show more understanding and have stronger behavioral intentions. In other words by providing a good fit between the user's domain knowledge, the mindset and the recommender system, people will process information more fluently, be more satisfied with the system and potentially save more energy.

Based on this premise the main goal of this thesis is to determine where fit or misfit occurs and how this influences the user's intention to save energy and her evaluation of the recommender system. We hypothesize that higher levels of domain knowledge result in more energy to be saved with the attribute-based recommender and a concrete mindset whereas lower levels of domain knowledge result in more saved energy with the needs-based recommender and an abstract mindset. Furthermore a good fit between the system and the participant's mindset is expected to increase the understandability, which in turn leads to an increased intention to save energy. Finally we expect that experts will perceive an attribute-based recommender as most useful, whereas novices will prefer the needs-based recommender.

To test these hypotheses a user study was performed. In this study users were primed to think in an abstract or concrete way and subsequently assigned to use either a needs-based or an attribute-based system. Before using the system, domain knowledge was measured and after using the system understandability, satisfaction with the system, perceived usefulness of the system and choice satisfaction were assessed.

The results of the study show that experts are mostly helped with an attribute-based system in a concrete mindset. They perceive the attribute-based system with a concrete

mindset as most useful and more importantly, they save more energy as they choose more measures. Novices on the other hand perceive the needs-based systems as most useful, regardless of the mindset they are in. Even though they select more measures with the needs-based system (in either mindset), the amount of energy saved using this system does not differ from when they use the attribute-based system with the abstract mindset. This is caused by the high saving measures that are chosen with the attribute-based system in an abstract mindset by both novices and experts. So the mindset to not only influences the behaviors with the system but also the evaluations of the recommender system. As expected increased understandability results in increased savings, but shows no effect of the fit between mindset and system.

Overall our study shows that the application of a well-designed recommender system can help people save energy and thereby help preserve the planet for future generations. However the recommender system should fit the domain knowledge and mindset of the user to help them to consider and select better measures which is an important step in having people save more energy.

Preface

This thesis presents my graduation project in the group Human-Technology Interaction at Eindhoven University of Technology. This report not only signifies the end of my education at the Eindhoven University of Technology but it also marks the end of a decade of studying. My gratitude therefore extends beyond this graduation project.

First of all I would like to thank my supervisors. Martijn Willemsen who had the trust in my abilities to admit me to the pre-master program 3.5 years ago, which in the end led to this thesis. During this graduation project his door was always open to discuss my findings, new ideas or versions of the report, for this I thank him. Thanks to Ron Broeders, my other supervisor, for his insights in the construal level theory, the invaluable discussions about the results and his ability to help in the structuring of the thesis, which was a daunting task. Thank you both for your sincere interest in this research, your abilities to keep pushing me to improve my work and deal with my mocking. This was a luxury which not many other students experience.

I would also like to thank former fellow student Mark Graus for his miniature lecture about matrix factorization, which sadly could not be used in the study, and for sharing his knowledge about multidimensional scaling. I was also lucky to be one of the human testers of his espresso making skills, which I must admit are really improving.

The experiment could not have been done without the help of Bart Knijnenburg who allowed me to use his recommender system and his server for my study. Furthermore I thank him for his help with the labeling of the needs and for the bottle of whisky I expect to receive in the near future.

I would especially like to thank my parents and my girlfriend. Henri and Trudy always supported and encouraged me during the past decade in any way that was needed. And Femke, my girlfriend, who was always ready to provide emotional support and doubled as an advisor whenever I got stuck. Thank you all so much, this would truly have not been possible without you.

And finally thanks to all my friends and family for their interest in my work and the much needed distractions. Some of them have already wondered which study I might end up doing next. Only time will tell.

Niels

Contents

Chapter 1

Introduction

Although many people are increasingly concerned about the effects of energy usage on the environment, the amount of energy consumption in households has not been significantly reduced in the past couple of years (Energie-Nederland & Netbeheer Nederland, 2011). To save energy people are required to incur costs and efforts, sacrificing money or comfort today while the benefits are received in the future (Poortinga, Steg, Vlek, & Wiersma, 2003). According to the construal level theory, the two temporal perspectives, now vs. the future, are in conflict as they focus on a tradeoff between feasibility and desirability respectively (Liberman & Trope, 1998; Torelli & Kaikati, 2009). Actions that are desirable are not always feasible and those which are feasible are not always desirable. It is therefore difficult to make the tradeoff between the feasibility and the desirability when choosing energy-saving measures. This increased difficulty can result in the deferring of choice and therefore preventing people from saving energy (Tversky & Shafir, 1992).

This tradeoff difficulty can be reduced by supporting the decision process with a well-designed recommender system. This would make the choice of energy-saving measures easier and therefore result in stronger behavioral intentions. Previous research has shown that matching the system to the user's domain knowledge (Randall, Terwiesch, & Ulrich, 2007; Knijnenburg, Reijmer, & Willemsen, 2011b) or the systems information abstraction level to the user's mindset (Köhler, Breugelmans, & Dellaert, 2011) has beneficial effects on the behavioral intentions and the evaluation of the recommender. In other words by providing a good fit between the user's domain knowledge, the mindset and the recommender system, people will process the information more fluently, be more satisfied with the system and potentially save more energy.

Based on this premise the main goal of this thesis is to determine where fit or misfit occurs and how this influences the user's intention to save energy and her evaluation of the recommender system. This research therefore contributes to insights in the application of construal level theory and other theories of decision making. Besides the theoretical contributions the results can be used in marketing and the development of systems designed to help and persuade individuals to save the environment.

1.1 Construal level theory

To save the environment in the future we need to make sacrifices now, but the benefits of these actions will reveal themselves in the future. For example to save energy (and money) in the long-term you can thermally insulate your floor. But this requires money to buy the required materials and effort to install it now. Liberman, Trope, McCrea, and Sherman (2007) showed that people have difficulties to tradeoff the uncertain future gains with the losses they need to endure now. People do not perform the right actions because of the time difference between acting and the resulting savings. To help people save more energy, the mechanisms behind this problem need to be understood. One psychological theory, the construal level theory, deals with the impact of distance on the perception of a situation.

According to the construal level theory (CLT) the larger the psychological distance (e.g. time, spatial or social) people perceive the more abstract they think about a concept (Liberman & Trope, 1998; Trope, Liberman, & Wakslak, 2007; Liberman, Trope, McCrea, & Sherman, 2007). This can be illustrated by comparing temporal distance with spatial distance. At an increased distance only the global aspects of the situation are perceived i.e. an abstract view. When being nearer, both temporarily as spatially, the details of the situation and the complex aspects associated with it are seen; i.e. a concrete view (Trope & Liberman, 2000; 2003). In other words, in high-level, abstract mindsets people focus on *why* an action is performed and incorporate the larger meaning of the action instead of the physical manifestation. Whereas in low-level, concrete mindsets the focus is on *how* an action is performed and therefore on the details of the action (Vallacher & Wegner, 1987; Trope & Liberman, 2003). In the earlier example saving energy is *why* the floor should be insulated and installing floor insulation is *how* more energy is saved.

Liberman and Trope (1998) showed that, in line with the findings of Liberman et al. (2007) and CLT, in an abstract mindset the focus is on the desirability (why) and on the feasibility of the situation in a concrete mindset (how). For example to be able to insulate the floor, money and knowledge about the installation are needed. This focus on the feasibility makes the possible problems and complexities of the situation more salient, while the future advantages are less perceived (Trope & Liberman, 2003). On the other hand focusing on the desirable outcome of saving energy, lacks a concrete plan of action to achieve this. In other words thinking about the concrete actions lets people perform actions without any significance to the abstract goal, while thinking about the abstract goal, prevents them from acting concretely (Vallacher & Wegner, 1987; Torelli & Kaikati, 2009).

Both mindsets are needed to have people save energy, as people should choose measures for which the sacrifices are feasible and the results desirable. But feasibility and desirability are often in conflict. Therefore people need to make a tradeoff between the desirability and feasibility of the energy-saving measures. But people have difficulties making this tradeoff and therefore often refrain from making the right decisions as increased choice difficulty results in deferring of choice (Tversky & Shafir, 1992; Payne, Bettman, & Johnson, 1993). By assisting people in their decision making process it will be easier for them to find measures which are both feasible and desirable, and likewise save more energy. For this purpose recommender systems can be applied, which help people making decisions. These systems have helped people choose cameras they should buy (Wang & Benbasat, 2005), movies they should see (Schafer, Konstan, & Riedl, 1999) but also which energy-saving measures should be chosen (Knijnenburg & Willemsen, 2009; 2010; Knijnenburg, Reijmer, & Willemsen, 2011b).

1.2 Recommender systems

Recommender systems assist consumers in their decision making process, by matching the preferences of the consumer to the characteristics of the products (Burke, 2002). The preferences for example involve the importance of an affordable price of a product or the importance of certain functionality. In other words the user can provide input on what is feasibility (price) and what is desirability (functionality), which the system uses to make recommendations. These systems therefore can make it easier to find energy-saving measures by taking over part of the decision process.

According to Edwards and Fasolo (2001) the first steps in the decision process are identifying the needs a product should fulfill and which attributes it should contain to fulfill each need. By weighting the needs and attributes according to their importance the overall utility of the products can be determined. A decision can therefore be composed into a two-step multi-attribute preference model, where a decision maker first takes the importance of her needs and secondly the impact of the attributes on these needs into account in determining the utility of a product (Butler, Dyer, & Jia, 2006; Butler, Dyer, Jia, & Tomak, 2008). According to the rational decision theory, users should pick the measure or product with the highest utility.

As an illustration, Figure 1 shows how an individual's needs for a laptop can be linked to the attributes. For example the utility of the MS-office performance is determined by giving importance weights to the processor and memory. These weights are multiplied by the subjective ratings for the processor and memory and summed to determine to utility of the MS-office performance for a laptop. The utility of the whole laptop depends on the importance of the needs. The importance weights of the needs are multiplied by the utility for each need and summed which results in the utility for the laptop.

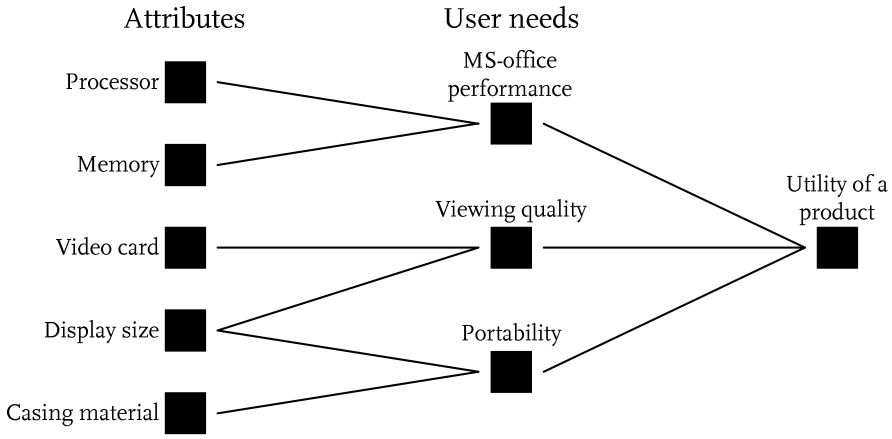

Figure 1: Linking the utility, to the needs and technical attributes of a laptop computer; based on the causal structure by Randall, Terwiesch, and Ulrich(2007).

Based on these principles Randall et al. (2007) developed two types of laptop recommender systems; a needs-based system and an attribute-based system. In the attribute-based system the user weights the attributes, where the system calculates the utility of the product. While in the needs-based system users weights the needs and the system, based on knowledge of the attributes, calculates the user's utility for each product. Randal et al. (2007) performed a user study in which participants were helped with their laptop configurations by either the needs-based or the attribute-based recommender. Their results showed that novices preferred the needs-based system while experts preferred the attribute-based system and made fewer changes to their recommended configuration with it, indicating a higher tendency to accept the recommendation. This is because compared to novices, experts have more knowledge about the technical attributes of the measures and therefore are better capable of making the tradeoffs between them (Xiao & Benbasat, 2007; Shanteau, 1988). With their knowledge, experts know how the needs are affected by the attributes of the product (Hutton & Klein, 1999). Novices on the other hand lack the knowledge required to understand the impact of the attributes (Hutton & Klein, 1999). Therefore experts prefer detailed information, while novices are more helped with general information (Alba & Hutchinson, 1987). This fit between the user and the recommender type is important as it increases the behavioral intentions (Xiao & Benbasat, 2007). Therefore a good fit between the user and an energy-saving recommender should result in more energy to be saved.

The behavioral intentions are not only influenced by the fit between the user's domain knowledge and the type of recommender. Köhler, et al. (2011) tested an attribute-based system and needs-based system with which the user either had to select a product in the distant future (abstract) or near future (concrete). Their results showed that the fit between the abstract mindset and the needs-based system and the concrete mindset and the attribute-based system resulted in higher fluency and a higher likelihood the user accepts the advice. This fit can be explained when looking at the abstraction level of the attribute-based and needs-based recommender. An attribute-based system focuses on the details and more complex structure of a measure and therefore is a more concrete representation. While the needs in a needs-based system are more holistic, goal relevant, more distantly related to the product itself, and thus more abstract. Therefore fitting the mindset with the system type will further strengthen the behavioral intentions of the users of the system. So to help people save more energy, the type of recommender system should fit the user and its mindset.

Using a recommender system to help people find appropriate energy-saving measures is not a novel concept; such a system was developed by Knijnenburg and Willemsen (2009; 2010). They applied two methods of determining the user's preference weights: an attribute-based system in which the user directly sets the attribute weights and an example-based system in which the user sets the weights indirectly by indicating her preference for example products. A user study showed that participants with more domain knowledge (experts) were more satisfied with the attribute-based systems while those with little domain knowledge (novices) preferred the example-based system. A follow-up study confirmed the fit between experts with an attribute-based system and showed that novices were most satisfied with a top-N system (Knijnenburg, Reijmer, & Willemsen, 2011b).

Although these findings confirm that the match between experts and an attribute-based system occurs in the energy-saving measures domain, there has not been a suitable recommender for novices. In the example-based system, users cannot see what their preference settings are and cannot correct them. This makes the process of indicating one's preference less transparent which has been shown to negatively impact the acceptance of the recommendations (Kramer, 2007). Furthermore rating example products is not part of the normative decision process (Edwards & Fasola, 2001). Applying a needs-based system to help novices would therefore make more sense. It allows novices to fully control and perceive their preference settings in a similar fashion as in the attribute-based system, but at a level they can understand.

Another problem of the previous work by Knijnenburg et al. (2009; 2010; 2011b) is that they focused primarily on the user experience. Although a fit has been shown between domain knowledge and system type, the studies with the recommender did not report differences in the amount of energy saved. As the goal of the application of a recommender in this thesis is to help people save more energy, the fit between system, user and mindset will be primarily assessed in terms of the consequences on the user's behavior in selecting measures.

1.3 Hypotheses

People have difficulties making the right decisions when it comes to saving energy. According to the CLT there is a tradeoff between the feasibility of the required sacrifices and the desirable results which are obtained in the future. This tradeoff between the feasibility and the desirability makes the decisions about how to save energy difficult. This tradeoff difficulty can be reduced by supporting the decision process with a well-designed recommender system. To help people save more energy the recommender system should fit with the domain knowledge of the user and its mindset. Randall et al. (2007) showed a fit of the system with user's domain knowledge in that an attribute-based system matches with experts (high domain knowledge) and a needs-based system with novices (low domain knowledge). Köhler et al. (2011) showed that the system (abstraction level of the recommender) should fit with the mindset, i.e. an abstract mindset fits with a needs-based system and a concrete mindset fits with an attribute-based system. By combining these findings the following three-way fit would be expected:

H1: Higher levels of domain knowledge results in more energy to be saved with the attribute-based system and a concrete mindset whereas lower levels of domain knowledge results in more saved energy with the needs-based system and an abstract mindset.

Previous studies have shown that a good fit between the information abstraction level and the mindset results in higher process fluency or understandability of the system (Lee, Keller, & Sternthal, 2010; Köhler, et al., 2011). Furthermore increased understandability results in stronger behavioral intentions (White, MacDonnell, & Dahl, 2011; Köhler, et al., 2011), i.e. more energy to be saved. In other words when the mindset matches with the system type, users understand the system better and therefore have stronger behavioral intentions. Attributes are more detailed and thus more concrete, while needs are more holistic and thus more abstract. Therefore the following fit is expected:

H2: Understandability mediates the effect of the fit between mindset and the system type, where matching a needs-based system with an abstract mindset and combining an attribute-based system with a concrete mindset result in higher understandability, whereas other combinations will result in lower understandability.

Besides influencing the behaviors of the users with the system, the fit between the system type and the user has shown to result in positive evaluations of the system. The findings of Randall et al. (2007) show that the satisfaction and perceived usefulness of the system are influenced by the fit between domain knowledge and the system type.

H3: Higher levels of domain knowledge results in more satisfaction with and perceived usefulness of the attribute-based system whereas lower levels of domain knowledge results in more satisfaction with and perceived usefulness of the needs-based system.

The three hypotheses focus on several constructs of the user experience, such as the understandability, satisfaction with the system and the perceived usefulness of the system. These constructs are not only influenced by the mindset, system and domain knowledge, but also have an effect on each other. To better understand how a (mis)fit influences the user's intention to save energy and her evaluation of the recommender system, a model of the constructs is created.

To get a better understanding of the user experience in recommender systems Knijnenburg, Willemsen, Soncu, Newell, and Gantner (2011a) created a user-centric framework. In this framework objective system aspects (in this case system type) influence the system subjective aspects (the perception of the objective system aspects), which in turn influences the experience and interaction with the system. To put it in other words, what the system does (OSA), influences how a user perceives the system (SSA) and therefore how she perceives the interaction with the system (EXP). These effects are further influenced by situational conditions (SC), e.g. the mindset, and the personal characteristics (PC) of the user, e.g. the domain knowledge. This model can be used to assess how the manipulations influence different concepts of evaluation and thereby create a better understanding of the underlying mechanisms.

Based on previous studies a model of the expected relations between the constructs can be created. Knijnenburg (2009) showed that understandability (SSA) influences the satisfaction with the system (SSA/EXP). And according to Kamis and Davern (2004), increased system satisfaction increases the perceived usefulness (EXP), which in turn increases the satisfaction with the chosen measures (EXP). Based on these findings the following basic model can be constructed: understandability → satisfaction with the system → perceived usefulness → choice satisfaction.

The three hypotheses can be connected to this basic model. Hypothesis 1 predicts that a fit between mindset, domain knowledge and recommender type increases the amount of energy saved (domain knowledge × mindset × system type → amount of energy saved). Furthermore according to hypothesis 2 a fit between the mindset and the system type should result in more understandability which in turn should result in more energy to be saved (mindset × system type → understandability → amount of energy saved). In hypothesis 3 the fit in domain knowledge and the system type is expected to result in more satisfaction (domain knowledge × system type → system satisfaction) and perceived usefulness with the system (domain knowledge × system type → perceived usefulness). Finally as users know the focus is on saving energy, we expect that that they will be more satisfied with the choices if they save more energy (amount of energy saved → choice satisfaction).

These relations are combined in a model as shown in Figure 2. The rectangular boxes represent the different evaluations of users and the different system types and mindsets; the elliptic box represents behavior. An arrow indicates a directional relationship between two variables. The colors represent the different constructs as defined by Knijnenburg et al. (2011a) with the objective system aspects (system type) in magenta, the personal characteristics (domain knowledge) in red, situational characteristic (mindset) in aqua, the subjective system aspects in green, experience constructs in orange and interaction (behaviors) in blue.

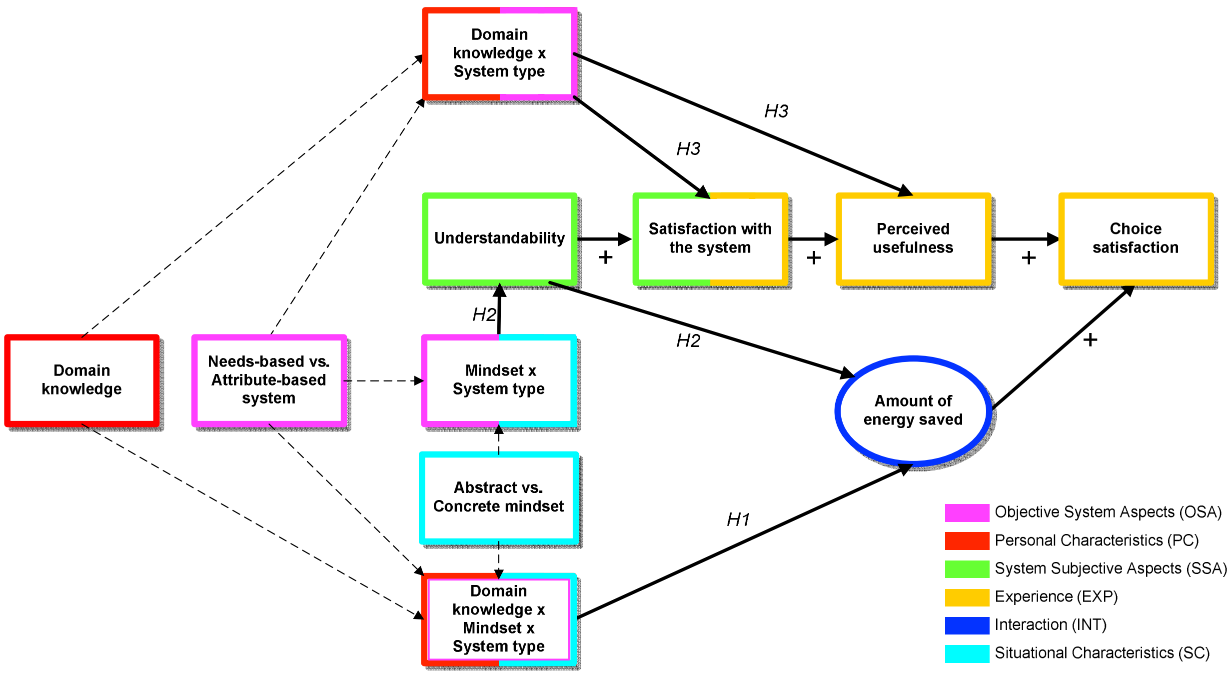

Figure 2: Predicted model of the variables

To test these hypotheses a needs-based system of the energy-saving measures recommender needs to be developed, which requires the identification of the needs users have when selecting energy measures. In the next chapter these needs will be identified.

Chapter 2

Needs-based system

To develop a needs-based system, the needs themselves should be identified. Needs are often identified by doing market research; running focus groups and doing interviews with consumers (Griffin & Hauser, 1993). More recently other procedures such as mining textual reviews of consumers have been applied (Lee, 2007; 2009). These approaches require either consumers which can indicate their need or the availability of reviews. In the domain of energy-saving measures there is a problem of participants giving socially desirable answers, which might not adequately reflect their needs. Therefore in this study the needs will be identified using behavioral data from previous experiments. The needs-based system will be developed based on the attribute-based system. This system and the information that is contained in it will therefore be discussed first.

2.1 The attribute-based system

In the attribute-based system users can indicate their preference by adding weights to the 8 attributes used in the system. As the weights have to be distributed between the attributes, the user is required to make tradeoffs. For example determining whether the comfort of a measure is more important than the amount of energy it saves. All the attributes with their descriptions are shown in Table 1. The system multiplies the preference weights with the attribute values and sums the result to determine the utility of each measure. The measures with the highest utility are recommended to the user.

Table 1: Attributes used in the recommender for energy-saving measures, from Knijnenburg (2009).

Attribute	Description
Effort once	The one-time effort needed to implement the measure (i.e. buying and/or installing the measure).
Continuous effort	The continuous effort needed to perform the measure (i.e. repeatedly defrosting your freezer).
Cost once	The one-time cost involved in buying the measure (i.e. purchase costs). If a non-green alternative exists, these are the additional purchase costs.
‘Real’ Euro savings	The savings in Euros minus the repeated additional

	costs of the measure.
Kilowatt-hour savings	The savings in kilowatt-hours on the electricity bill, or the savings on the gas bill (in m^3 gas) converted to kWh.
Time before return of investment	The time it takes to earn back the initial spending that the measure entails.
Environmental effects	The positive or negative environmental effect that the measure entails, besides the energy-savings (i.e. solar panels have a negative effect, as their production costs more energy than what they save over their lifetime).
Comfort	The increase or decrease in comfort involved in implementing the measure (i.e. taking shorter showers decreases comfort; double glazing increases comfort through noise reduction).

In the needs-based system the preference is indicated for the needs. Based on the two-step multi-attribute utility model (Butler, et al., 2006; 2008), the needs will be identified by applying multidimensional scaling to the behavioral data from previous experiments. Readers who are not interested in the technical details of decision making and multidimensional scaling are advised to skip section 2.2 to 2.5 and continue reading at paragraph 2.6 on page 19. In that paragraph the identification and labeling of the dimensions is discussed.

2.2 Linking needs and attributes

Butler, et al. (2006) model needs in a two-step multi-attribute utility model. In the model the utility u of a product is determined by the set of needs o. For each need o_i the utility is determined and multiplied by a weight w_i which depends on the importance of the need. The resulting scores are summed to come to an overall utility score.

$$u(o) = \sum_{i=1}^{n} w_i u_i(o_i) \tag{1}$$

The score of a product on need o_i is determined by weighting the importance of each attribute for each need k_{ij}. The weight for an attribute can differ for each need. The weights of the attributes for each objective are multiplied with the attribute ratings $f_j(a_j)$ and summed for all attributes, resulting in an overall value for the objective.

$$o_i = \sum_{j=1}^{m} k_{ij} f_j(a_j) \tag{2}$$

By combining (1) and (2) the formula for the two-step approach is represented by (3).

$$u(o) = \sum_{i=1}^{n} w_i u_i (\sum_{j=1}^{m} k_{ij} f_j (a_j)) \quad (3)$$

In previous studies with the recommender for energy-saving measures choices of the participants have been collected (Knijnenburg & Willemsen, 2009; 2010; Knijnenburg, et al., 2011b). According to equation (1), the choice of measures is based on the highest utility which is determined by the weighted sum of the needs utilities. When a participant chooses multiple measures these measures are all expected to score high on the important needs for that participant. Therefore by determining which measures are often chosen together the most prominent needs can be discovered. The needs themselves, according to equation (2), relate to the attributes of the measure. Therefore the most prominent attributes in a need can be determined by regressing the discovered needs on the attributes, which helps in labeling the needs.

2.3 Behavioral data

In four previous experiments with the energy-saving recommender by Knijnenburg and Willemsen (2009; 2010) and by Knijnenburg, et al. (2011b) participants could choose between 80 energy-saving measures. If applicable to the participant, the measures could be classified as either "I-am-already-doing-this" or "I-want-to-do-this" [1]. Both the classifications show a (former) interest in the measure. The other non-classified products do not indicate a preference or dissatisfaction with a measure and therefore will not be used. For each participant the products were scored by giving it a 1 if it was put in one of the lists and otherwise 0, resulting in a fully defined m (number of measures) $\times$ n (number of participants) matrix with 80 measures $\times 546$ participants with binary data.

Item-Item (dis)similarities

The binary data can be transformed into a measure-measure ($m \times m$) (dis)similarity matrix by applying a binary (dis)similarity coefficient (Borg & Groenen, 2005). This coefficient is based on the Operational Taxonomic Units (OTUs) in a 2×2 table, which is shown in Table 2. With these coefficients the (dis)similarity between two measures i and j can be determined.

In Table 2 a indicates the number of times i and j are both chosen, b the number of times i is chosen and j is not, c is the number of times j is chosen and i not and d is the number of times both are not chosen (Dunn & Everitt, 1982). With the current data $a+b+c+d$ equals the amount of participants (n).

[1] In one of the experiments participants could also classify the product as "I-do-not-want-to-do-this", but as the data from four experiments are collapsed, only the identical classification methods are taken into account.

Table 2: Operational Taxonomic Units (OTUs)

	1 (Presence)	0 (Absence)	Sum
1 (Presence)	a	b	$a+b$
0 (Absence)	c	d	$c+d$
Sum	$a+c$	$b+d$	$n=a+b+c+d$

Choi (2008) identified 76 possible similarity coefficients which differed in the main method type they used, feature-based, distance-based or correlation-based, and whether negative matches were taken into account. When negative matches are taken into account a mutual absence indicates similarity between two measures. Coefficients which use negative matches are called symmetric as a and d are equally important (Choi, 2008; Choi, Cha, & Tappert, 2010). In the current data mutual absence does not indicate similarity as participants only classify a limited subset of the measures: the amount of measures classified ranges from 1 to 80 with an average of 19.4.

Due to the limited number of choices that are made the feature-based Dice & Sorensen coefficient is chosen as it is an asymmetric coefficient which adds extra weight to a match in presence. The similarity between measure i and j is calculated by (4).

$$s_{ij} = \frac{2a}{2a+b+c} \tag{4}$$

The application of (4) to the $m \times n$ matrix results in a $m \times m$ similarity matrix with the range $0 \le s_{ij} \le 1$ where 1 indicates completely similar measures. Similarity measures can in this case be transformed in dissimilarity measures by (5).

$$\delta_{ij} = 1 - s_{ij} \tag{5}$$

2.4 Method

The dimensions underlying the dissimilarities will be determined using multidimensional scaling. Multidimensional scaling (MDS) is a mathematical method that searches for a low dimensional space that matches the dissimilarities as good as possible (Kruskal, 1964a; Borg & Groenen, 2005; Cox & Cox, 2001). It can be regarded as a variety of factor analysis, the main difference is that a factor analysis uses a correlation matrix and a MDS used a (dis)similarity matrix. A factor analysis requires the data to be distributes as multivariate normal and tends to extract more dimensions which can make interpretation of the solution more difficult (Hill & Lewicki, 2005).

The aim of using MDS should not be to perfectly match the distances in the spatial solution d_{ij} with the dissimilarities δ_{ij} but match them as equal as possible ($d_{ij} \approx \delta_{ij}$) to take measurement imprecision, unreliability and sample effects into account (Borg & Groenen, 2005). Differences between the distances and dissimilarities will occur as long as the amount of dimensions p is smaller than $m-1$, in this case 79. The normed sum-of-squares of these errors, Stress-I, is used as a badness-of-fit measure used in assessing the dimensional solution (Kruskal, 1964a).

As the stress reduces with increasing dimensions, the choice of number of dimensions can be set to a cutoff value of Stress-I. The cutoff point of Stress-I depends on the ratio of dimensions to measures, where an increase in stress is expected if the amount of measures is at least 10 times as large the amount of dimensions. Borg and Groenen (2005) indicate in such a case Stress-I < 0.15 indicates an acceptable solution.

Metric and nonmetric

Two main types of multidimensional scaling exist: metric and nonmetric. In the metric version the absolute distances are used, while in a nonmetric MDS the ordering of the distances is used (Kruskal, 1964a; 1964b). A metric table is transformed in a nonmetric table by replacing the distances by distance rankings, in which the smallest distance is given the lowest value as can be seen in Figure 3. These new values are used to determine the underlying dimensions. A nonmetric MDS results in lower levels of stress compared to a metric MDS and therefore in fewer dimensions (Borg & Groenen, 2005).

	i	**j**	**k**
i	-	0.2	0.3
j	0.2	-	0.8
k	0.3	0.8	-

	i	**j**	**k**
i	-	1	2
j	1	-	3
k	2	3	-

Figure 3: Transforming a metric distance table to a ranked distance table for products i, j and k

With the transformation into ordinal measures a case can occur in which $\delta_{ij} = \delta_{i'j'}$: a tie. But the ordinal values of the two distances do not necessarily have to be identical. There are two main approaches to handling ties: primary and secondary (Cox & Cox, 2001). The primary approach states that if $\delta_{ij} = \delta_{i'j'}$, d_{ij} does not necessarily have to be equal to $d_{i'j'}$ and the order in which most stress is reduced is used. This approach is called the untying of ties. The secondary approach states that if $\delta_{ij} = \delta_{i'j'}$ then $d_{ij} = d_{i'j'}$, which adds unnecessary constraints on the solution and can lead to less interpretable results (Lingoes & Roskam, 1973). By applying a nonmetric MDS with a primary approach to ties a strong reduction of Stress-I with limited dimensions can be achieved and therefore will be applied[2].

2.5 Results

A nonmetric MDS using SMACOF[3] (a stress minimization strategy using majorization) with simplex start was applied using a primary approach to ties (untying of ties), which achieved a Stress-I < 0.15 (Stress-I = 0.137) with 2 dimensions. The descriptive statistics of the two resulting dimensions are shown in Table 3 and the two dimensional space of the measures is shown in Figure 4. The dimensional values for all the measures can be found in Appendix A.

Table 3: The descriptive statistics of the two dimensions

	Minimum	Maximum	Mean	Std. Deviation
Dimension 1	-1.03	1.67	0.000	0.63
Dimension 2	-0.60	1.14	0.000	0.30

[2] The application of a non-metric multidimensional scaling entails that the similarity coefficient in (4) can be replaced by any coefficient formula in the so called Fichet-Gower family, which in a 2-adic formulation (comparison between 2 items) is: $S^{(2)}_{F-G}(\theta) = \frac{a}{a + \theta(b + c)}$ where θ is a positive parameter (Warrens, 2009).

[3] This algorithm is applied in the PROXSCAL function in SPSS.

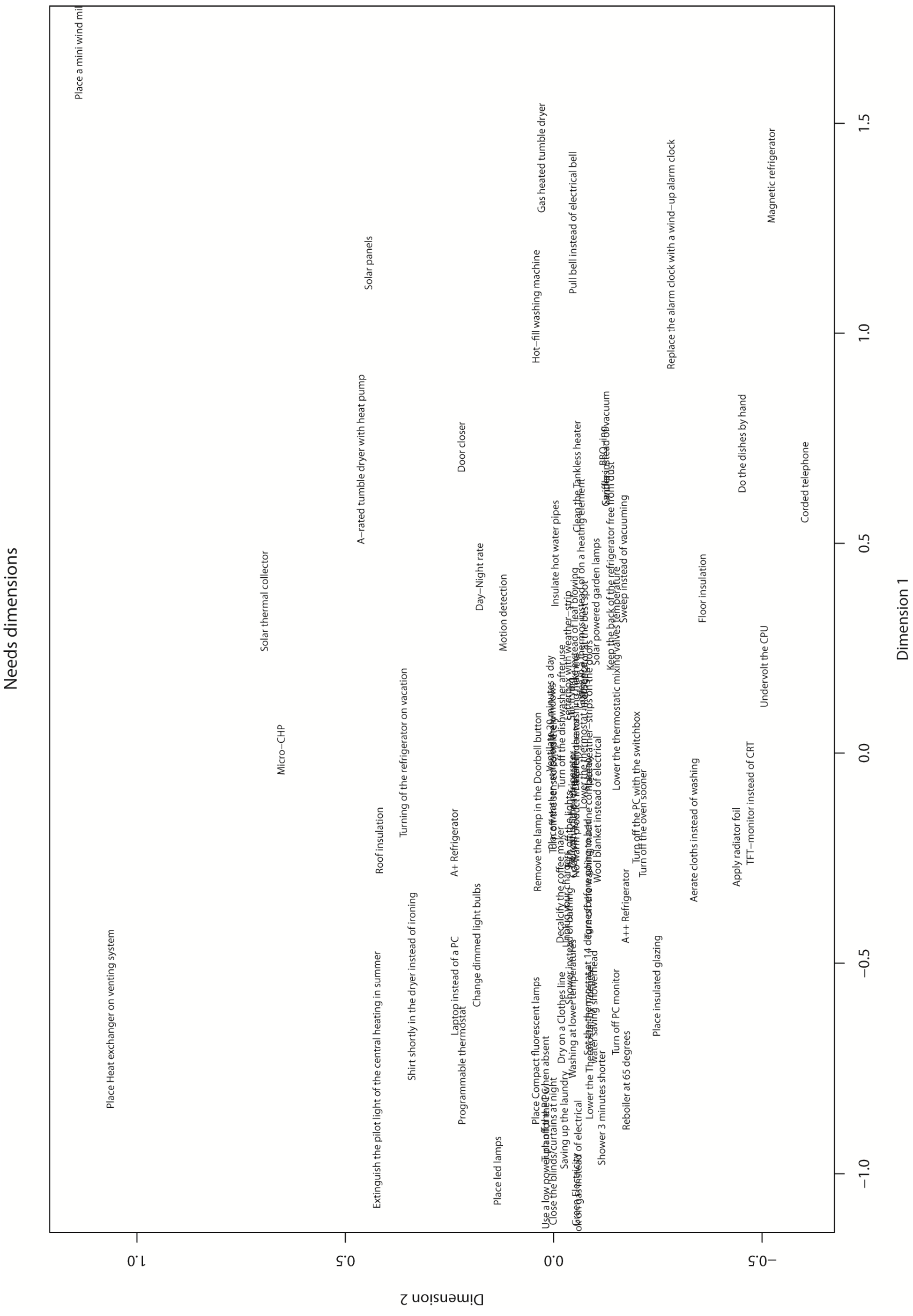

Figure 4: The 2 dimensional space of energy saving measures obtained by running the SMACOF algorithm.

Regressions

The resulting values of the dimensions are regressed on the attribute values of the measures. The descriptive statistics of the attributes are shown in Table 4.

Table 4: Descriptive statistics of the attributes

	Minimum	Maximum	Mean	Std. Deviation
Effort once	0	49	10,81	13,76
Continuous effort	0	46	4,49	8,23
Cost once	0	4765	299,58	860,96
'Real' Euro savings	-43,0	320,0	42,187	68,16
Kilowatt-hour savings	0	3055	305,48	512,13
Time before return of investment	0	9999	554,59	2190,57
Environmental effects	-25	24	-1,63	7,87
Comfort	-22	24	0,69	8,40

Due to the differences in the value ranges of the attributes, the standardized regression coefficients, betas, are used to assess which attribute is most important for that need. The betas indicate the importance of each attribute on the need and therefore are similar to k_{ij} in equation (2). The result of the regression of the first dimension is shown in Table 5.

Table 5: Predicting the first dimension by the attributes (R^2 =0.696)

	Estimate	Std. Error	Beta	t	p
(Constant)	-0.054	0.072		-.750	0.455
Effort once	0.016	0.005	**0.355**	3.542	0.001
Continuous effort	0.010	0.006	**0.135**	1.694	0.095
Cost once	0.000	0.000	**0.221**	2.020	0.047
'Real' Euro savings	-0.005	0.001	**-0.530**	-3.937	0.000
Kilowatt-hour savings	0.000	0.000	**-0.265**	-1.998	0.050
Time before return of investment	0.000	0.000	**0.144**	2.030	0.046
Environmental effects	-0.049	0.008	**-0.609**	-6.200	0.000
Comfort	-0.019	0.006	**-0.252**	-3.171	0.002

The first dimension loads strongly on effort once, real-savings euro and environmental effects. Measures which require more initial effort, do not result in many savings and have negative environmental effects score high on this dimension. For example placing a mini-windmill does save energy, but requires a lot of initial effort and has high aversive environmental effects due to the production of the windmill.

Table 6: Predicting dimension 2 with the attributes (R^2=0.456)

	Estimate	Std. Error	Beta	t	p
(Constant)	-0.088	0.030		-2.971	0.004
Cost once	0.000	0.000	**0.258**	2.257	0.027
'Real' Euro savings	-0.002	0.001	**-0.483**	-2.982	0.004
Kilowatt-hour savings	0.000	0.000	**0.849**	5.112	0.000

The second dimension shows a counterintuitive effect of a strong positive energy-saving but negative impact of euro saving. These two attributes are strongly correlated (r = 0.846), thereby showing signs of multicollinearity. A scatterplot indicated that the negative coefficient of 'Real Euro savings' is mostly due to noise fitting. Due to the strong correlation the effect of kilowatt-hour can also be attributed to the 'Real' euro savings.

2.6 Discussion

Measures which score high on the first dimension require more initial effort, but do not necessarily result in high saving and often have other adverse environmental effects. Looking at the pattern of the measures in this dimensions, it seems that the higher the score, the higher the visibility of the measure to the outside world. These patterns fit with the notion of competitive altruism. Competitive altruism is a form of self-presentation aimed at showing others that they are willing to sacrifice themselves for the greater good (Barr, Gilg, & Ford, 2005; Griskevicius, Tybur, & Van den Bergh, 2010). It is a form of conspicuous consumption, but where conspicuous consumption is focused on the display of wealth (Veblen, 1899), conspicuous altruism is about showing your willingness to self-sacrifice. Van Raaij and Verhallen(1983) described this phenomenon: "Many consumers feel the need to show others their energy-conscious behavior" (p. 139). Overinvesting in solar panels and hybrid cars are examples of this behavior (Sexton & Sexton, 2011), which matches with the high scores of windmills and solar panels on this first dimension. Griskevicius, et al. (2010) showed that people who are focused on their status chose more often for a green product which had pro-environmental features instead of a more luxurious non-green product in a public situation.

In the second dimension measures which have higher initial costs and more energy savings score higher. This dimension shows patterns of the environmentalist versus economist. On the lower end of the scale are measures which have a less favorable ratio of investments versus monetary savings, such as replacing the cordless phone with a corded version. Only someone who is aiming to save the environment, an environmentalist, will perform such a measure. On the high end of the scale are measures which require more investments, but also have much higher payoff, such as thermally insulating your roof. These measures are more interesting for someone focusing on the economic aspects of the measures. This matches with the main motives identified in many studies of concerns for the costs of energy use and the required investments to reduce them (Stern, 1992; Barr, Gilg, & Ford, 2005).

Labeling

For use in the needs-based system, the two dimensions need to be labeled. The labeling should prevent the tendency to give socially acceptable responses as would be expected if the first dimension was labeled "Less visible to others – Clearly visible to others". Competitive altruism focuses on measures which stand out and therefore are not common to have (Woodruff, Hasbrouck, & Augustin, 2008), or in other words the uniqueness of the measures. By labeling the dimension as "Popular measures – Unique measures" the main characteristics of competitive altruism are maintained and it allows participants to choose measures on the far end of the scale without fear of being socially unacceptable.

In another study on the underlying motives of saving energy, Seligman, Darley and Becker (1978) ran a survey on energy attitudes among 56 couples, which after a factor analysis showed 4 factors. Their second dimension was labeled as "high effort – low payoff" which fits the second dimension of the MDS. To make the tradeoff between the two ends of the dimension clearer, the second dimension is labeled "Every saved kWh counts – A lot of savings per invested euro".

2.7 Needs-based system

In the attribute-based system participants indicate their weight for the attributes after which the scores are summed and the highest scoring measures are recommended. The overall utility value of an option increases monotonically with increased attribute values. The weighted system therefore makes it impossible to prefer a lower value of an attribute.

In the needs-based system the dimensional values indicate more intermediate statuses. For example the "Popular measures – Unique measures" dimension indicates how visible a measure is. These are not dimensions that monotonically increase in terms of goodness, rather a user will have a certain ideal point on these dimensions. So, a different approach must be used to recommend items from the need-based dimensions

The two-dimensional space offers a possibility to indicate a preference of the ideal level on each dimension. In other words, users indicate their preferred values on the two dimensions in Figure 4. The best recommendations should be the options closed to these ideal points. By calculating the Euclidian distance between the participant's preference position and the measures, the closest measures can be determined. Instead of making tradeoffs on weights between attributes which is done in the attribute-based system, users of the needs-based system have to make a tradeoff *within* each dimension. For example in the needs-based system the user makes a tradeoff between more or less visibility of the measure.

For more details on the functionality of the two recommender systems see Appendix B.

Chapter 3

Method

To assess how the level of fit between the system, the user and its mindset influences the amount of energy intended to be saved and the evaluation of the recommender system, a user study was performed. The details of how the study was performed will be discussed in this chapter.

3.1 Design

A 2 × 2 between subjects design was used where mindset (concrete versus abstract) and type of system (attribute-based versus needs-based) were manipulated. The study consisted of three parts, a pre-experimental questionnaire (with a mindset manipulation), the use of the recommender and a post-experimental questionnaire.

Participants were invited to go to the main website and were randomly assigned to one of the four conditions. Participants were informed about the topic, the expected time investment and reward for the research. They then proceeded to the pre-experimental questionnaire which consisted of demographics (5 items), domain knowledge (6 items), need for uniqueness (12 items) and mindset manipulation questions (2 items). The domain knowledge and need for uniqueness questions were answered on a 5 point-scale, the mindset manipulation consisted of two open questions as will be discussed in paragraph 3.2. After the questionnaire the participants received a short instruction. They were asked to use the system to find energy-saving measures that are important to do. Furthermore they were told that after using the system they would receive questions about their choices and their experience with the system.

The participants received one of the two systems and were given a step-by-step explanation on how to use it. After the explanation they were free to use the system for any period and in any way they preferred. After using the system they received a post-experimental questionnaire with questions regarding understandability (9 items), satisfaction with the system (5 items), perceived usefulness (6 items), and satisfaction with the chosen measures (4 items).

3.2 Mindset manipulation

After the demographics, domain knowledge and need for uniqueness questions, the participant's mindset was manipulated. Different mindset manipulations have been used in previous research. These manipulation vary in how active they are, from how (why) diagrams which requires the participant to progressively think more abstractly (concretely) by writing down reasons or ways for the behavior (Freitas, Gollwitzer, & Trope, 2004) to receiving a flyer describing ways (concrete) or reasons (abstract) to perform certain behavior (White, MacDonnell, & Dahl, 2011). Another distinction is whether the task or description is specific to the domain. Where in some research the manipulations were specific to the domain (Sanna, Lundberg, Parks, & Chang, 2010; White, MacDonnell, & Dahl, 2011; Freitas, Gollwitzer, & Trope, 2004) others used word association tasks which had no connection to the domain (Fujita, Trope, Liberman, & Levin-Sagi, 2006).

The current study is performed online without any supervision; therefore an active task is needed as a description might not be read attentively in the fast click-through environment of the web. For the same reason it should be short and simple to prevent participants to become frustrated. As the study is a presented as a whole, the task should also be domain specific to prevent confusing people about the task at hand.

Therefore the mindset manipulation in this study consisted of 2 questions for both of the types of mindsets. The questions asked the participant to describe reasons (abstract level) or ways (concrete level) to save energy. The questions are shown below:

The first abstract question:

> There are many reasons why energy should be saved. Before you can start using the system we would like you to indicate why in general it is important to save energy.
> Why should we save energy in general?

The second abstract question:

> Which reasons to save energy are important will depend on the individual. Before you can start using the system we want to ask why it is important to you personally to save energy.
> Why do you want to save energy?

The first concrete question:

> There are many ways how energy can be saved. Before you can start using the system, we would like you to indicate how we in general can best save energy.
> How can we save energy in general?

The second concrete question:

> Which ways to save energy work best will depend on the individual. Before you can start using the system we want to ask how you personally can save energy.
>
> How can you save energy?

3.3 Participants

In total 186 participants completed the study, 143 were recruited through an online panel and received €4 Euros for their participation, and 43 through an event invitation on Facebook, where for every 5 participant a gift card worth €12.50 could be won (contacts with knowledge about the study were not invited). 11 participants were removed from the set as they did not select any measure they were willing to do. Another one was also removed as that participant only selected and chose one measure and directly stopped interacting with the system, which does not indicate serious usage of the system.

The remaining 174 participants consisted of 89 (51%) males and had an average age of 28.0 with a SD of 8.87. On education 4 finished primary school, 71 finished high school, 9 had an intermediate vocational education, 29 had a higher vocational education and 61 finished university. The distribution of participants over the conditions is shown in Table 7.

Table 7: The number of participants in each condition of this study.

	Attribute-based system	Needs-based system	Total
Abstract mindset	43	43	86
Concrete mindset	44	44	88
Total	87	87	174

3.4 Measurements

Domain knowledge and need for uniqueness

Domain knowledge is measured by 6 questions based on the questionnaires by Knijnenburg and Willemsen (2009; 2010). As one of the identified needs involves the uniqueness of the measures, the need for uniqueness (NFU) of the participants is also measured. The short-form NFU scale, developed by Ruvio, Shoham, and Brenčič (2008) and translated in Dutch by Oudenhooven (2009), was used. This scale consists of three dimensions of NFU: creative choice (4 questions), unpopular choice (4) and avoidance of similarity (4). An exploratory factor analysis, with a weighted least squares estimator using a diagonal weight matrix (WLSMV) and a geomin rotation, was performed which resulted in a 4 factor solution as shown in Table 8. One domain knowledge question and two NFU questions were dropped due to crossloadings.

Table 8: Factor loadings of the pre-experimental questionnaire

	Domain Knowledge	Creative choice	Unpopular choice	Avoidance of similarity
I know energy consumption of all devices	**0.579**			
I understand difference between measures	**0.855**			
I know more measures than others	**0.690**			
I know which measures are useful	**0.764**			
I can choose the right measures	**0.802**			
I don't understand most measures	**-0.588**			
I often combine possessions in such a way that I create a personal image that cannot be duplicated		**0.538**	0.242	
I do not enjoy being original by trying to find a more interesting version of run-of-the-mill products		**-0.621**	-0.167	
I actively seek to develop my personal uniqueness by buying special products or brands.		**0.848**		
Having an eye for products that are interesting and unusual assists me in establishing a distinctive image.		**0.933**		
When it comes to the products I buy and the situations in which I use them. I have broken customs and rules		-0.152	**0.405**	
I have not violated the understood rules of my social group regarding what to buy or own.			**-0.742**	
I have rarely gone against the understood rules of my social group regarding when and how certain products are properly used.			**-0.841**	
I often try to avoid products or brands that I know are bought by the general population.		0.153		**0.768**
As a rule. I dislike products or brands that are customarily bought by everyone.				**0.888**
The more commonplace a product or brand is among the general population, the less interested I am in buying it.				**0.919**

The correlations of these factors are shown in Table 9. The highest correlations are found between the NFU scales, which can be expected as they measure a similar concept. The correlations with domain knowledge are more surprising but their size is not troublesome.

Table 9: Correlations between the four factors of the pre-experimental questionnaire

	Domain Knowledge	Creative choice	Unpopular choice	Avoidance of similarity
Domain knowledge	1.000	0.354**	0.034	0.340**
Creative choice	0.354**	1.000	0.408**	0.426**
Unpopular choice	0.034	0.408**	1.000	0.172*
Avoidance of similarity	0.340**	0.426**	0.172*	1.000

*p<0.05, **p<0.01, ***p<0.001

A confirmatory factor analysis, with the same estimator and rotation type as in the EFA, was performed on the remaining 16 questions on 4 factors resulting in a RMSEA=0.064, CFI=0.968, TLI=0.961, and a chi-square(98)=167.965, p<0.01 indicating a reasonable fit[4]. The factors were reliable as shown by the Cronbach alphas; domain knowledge: α=0.802, creative choice: α=0.798, unpopular choice α=0.867 and avoidance of similarity: α=0.651.

The factor scores for individual participants were calculated and were shown to be normally distributed based on the skewness and kurtosis values, and non-significant Kolmogorov-Smirnov tests.

Behavioral measures

The behaviors of the participants were logged to measure whether people performed different behaviors and made different choices with the different mindsets and systems. To test the first hypothesis the total amount of energy saved with the chosen measures was measured. As the total amount of energy saved is influenced by the amount of measures chosen and the amount of energy each measure saves, these were also recorded.

[4] The preferred values are: CFI > 0.95, TLI > 0.96 (for categorical variables), and RMSEA< 0.06 and a non-significant chi-square test, although the chi-square test has shown to be very sensitive (Hu & Bentler, 1999).

System satisfaction, understandability, system usefulness and choice satisfaction

System satisfaction is measured by five questions of the QUIS scale[5]. The scores of the nine points scaled questions were summed (M=26.71, SD=7.29) and this sum score was normally distributed with a Cronbach's alpha of 0.827. Understandability, system usefulness and choice satisfaction were measured by 19 five-point scale questions. An EFA with a WLSMV estimator and geomin rotation was performed, resulting in a 3 factor solution, as shown in Table 10, after the removal of one system satisfaction question and six understandability questions.

Table 10: Factor loadings of the post-experimental questionnaire

	Perceived usefulness	Understandability	Choice satisfaction
The system made me more energy-conscious	**0.740**		
I would use the system more often	**0.831**		
I make better choices with this system	**0.764**		
The system was useless	**-0.859**		
I would recommend the system to others	**0.818**	0.186	
I understood how to indicate my preference		**0.719**	
How difficult/easy was stating your preference		**0.609**	0.239
I understand the system		**0.932**	
I like the measures I've chosen			**0.820**
I think I chose the best measures			**0.541**
The chosen measures fit my preference			**0.770**
How many measures will you implement			**0.676**

A CFA indicated a good fit with RMSEA=0.039, CFI=0.993, TLI=0.991, and a chi-square(51)=64.555,p=0.09. The factors also showed to be reliable with Cronbach's alphas of understandability: 0.768, system usefulness: 0.886 and choice satisfaction: 0.720. The calculated individual factor scores proved to be normally distributed based on the skewness and kurtosis values, and non-significant Kolmogorov-Smirnov tests.

The correlations are shown in Table 11. The correlations are high, but based on the expected relations between the factors (see Figure 2 on page 10), this is not a surprise.

[5] Based on the QUIS, this questionnaire can be found at http://hcibib.org/perlman/question.cgi?form=QUIS. Question 5 was omitted as in a previous study question 5 it proved to be confusing in a pretest (Knijnenburg, 2009).

Table 11: Correlations between the three factors of the post-experimental questionnaire

	Perceived usefulness	Understandability	Choice satisfaction
Perceived usefulness	1.000	0.578**	0.593**
Understandability	0.578**	1.000	0.620**
Choice satisfaction	0.593**	0.620**	1.000

*p<0.05, **p<0.01, ***p<0.001

Chapter 4

Results

To determine whether the fit between domain knowledge, the mindset and the system type influences the amount of energy saved, as was predicted in hypothesis 1, the amount of energy saved will be assessed individually. Hypotheses 2 and 3 which involve the post-experimental questionnaire factors understandability, satisfaction and perceived usefulness, will be assessed using a structural equation model (SEM) which takes all the interdependencies of these factors into account.

For all the analyses the manipulated variables are dummy coded with concrete=0 (baseline) and abstract=1 for the mindset manipulation and attribute-based=0 (baseline) and needs-based=1 for the system type.

4.1 Chosen measures: amounts and energy saved

Participants saved on average 2.38 MWh (se=0.174) with their chosen measures. Hypothesis 1 predicts that higher levels of domain knowledge result in more energy to be saved with the attribute-based system and a concrete mindset whereas lower levels of domain knowledge results in more saved energy with the needs-based system and an abstract mindset. To test this hypothesis we regressed the total amount of energy saved on domain knowledge, mindset and system type[6]. The results show that the more domain knowledge a participant has, the less energy is saved in an abstract mindset ($p<0.1$) and with the needs-based recommender system ($p<0.1$) (see Table 12). In other words, in line with hypothesis 1 more domain knowledge results in more energy to be saved with the attribute-based system and the concrete mindset (see Figure 5). For novices on the other hand, the needs-based system (for both mindsets) and the attribute-based system with an abstract mindset result in higher savings compared to attribute-based with a concrete mindset. This effect is inconsistent with hypothesis 1 which states that novices save more energy with the needs-based system only when in an abstract mindset. Moreover the amount of energy saved with the needs-based system is not

[6] The three factors of need for uniqueness were not included as these measures resulted in irregular results. For example the total amount of energy saved was negatively influenced by 'unpopular choice' but positively by 'creative choice', where the factor scores of these two measures correlate by $r=0.426$, $p<0.01$. Therefore the NFU measures are ignored in the analyses.

influenced by the mindset manipulation. Most surprising is the high result of the attribute-based system with the abstract mindset for novices. Novices are not expected to have a fit with the attribute-based system, and the attribute-based system is expected to have a misfit with the abstract mindset.

Table 12: The total amount of energy saved in MWh with the chosen measures (R^2 = 0.049)

	Estimate	Std. Error	t	p
(Constant)	2.754	0.345	7.975	0.000
Abstract	-0.041	0.492	-0.083	0.934
Needs	-0.774	0.489	-1.582	0.115
Abstract × Needs	0.187	0.696	0.269	0.788
Domain knowledge	0.534	0.340	1.569	0.118
Domain knowledge × Abstract	-0.844	0.496	-1.702	0.091
Domain knowledge × Needs	-0.920	0.490	-1.879	0.062
Domain knowledge × Needs × Abstract	0.938	0.698	1.343	0.181

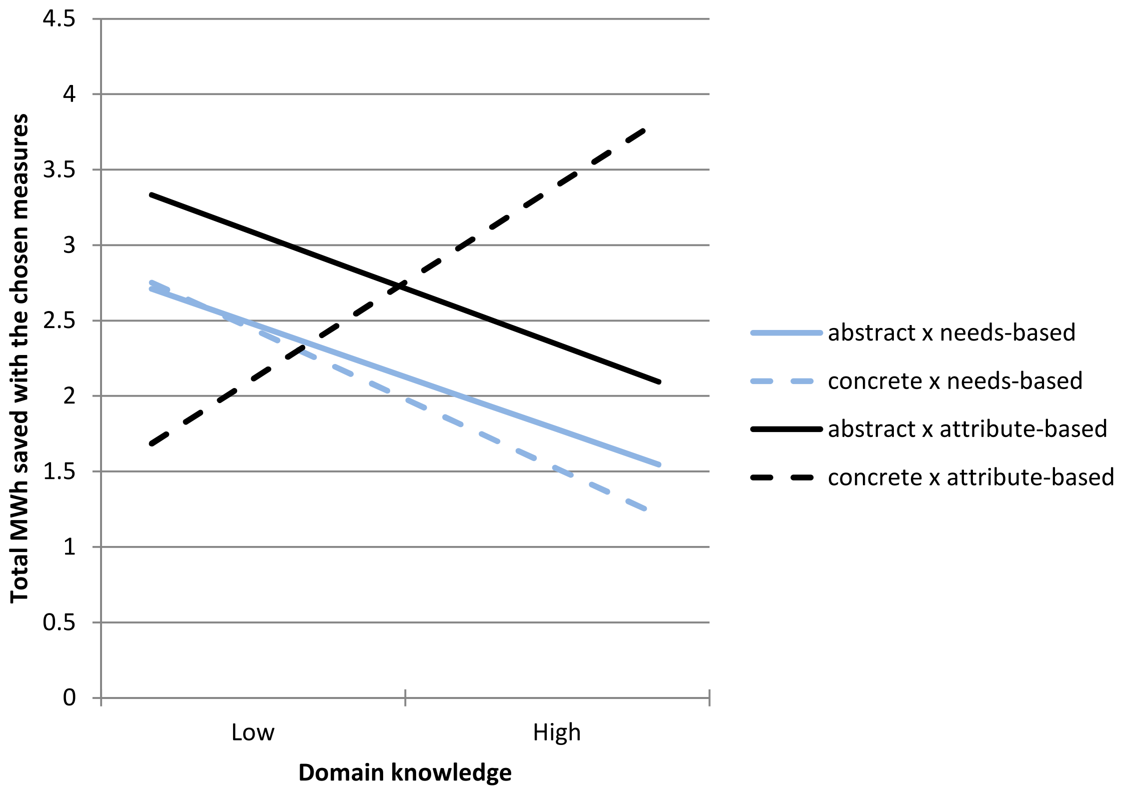

Figure 5: The total amount of MWh saved with the chosen measures for each condition as a function of domain knowledge

Although interaction effects have been found, it is unclear whether the slopes of the different conditions differ. To assess whether the slopes significantly differ between the conditions, a simple slopes test for three-way interactions, developed by Dawson and

Richter (2006), was performed. The tests showed that the concrete mindset with an attribute-based mindset has a marginal significantly different slope than the abstract mindset with an needs-based ($t(166)=1.708$, $p=0.09$), abstract mindset with an attribute-based ($t(166)=1.702$, $p=0.09$) and with concrete mindset with an needs-based ($t(166)=1.878$, $p=0.064$). None of the other slopes have significant differences. This confirms that the slope for the attribute-based system with a concrete mindset is different from the other three conditions.

These differences in the total amount of energy saved can be caused by the amount of measures participants choose or the amount of energy is saved by each chosen measure. This might also explain the lack of mindset effects on the needs-based system and the apparent fit that is seen with the attribute-based system and an abstract mindset for novices.

Amount of items chosen

All participants included in the analyses chose at least one measure they wanted to do. On average participants chose 6.59 measures with a standard error of 0.426. We regressed the number of measures on the domain knowledge, mindset and system type. The results (see Table 13) show that participants in an abstract mindset choose fewer measures, but not when using the needs-based system ($p<0.05$), indicating a fit between the mindset and system. Furthermore increasing domain knowledge result in more chosen measures ($p<0.1$) except when using a needs-based system ($p<0.05$) or when primed with an abstract mindset ($p=0.06$). This further confirms the idea that experts have a misfit with the needs-based system and with an abstract mindset, but there is no substantial three-way interaction ($p=0.236$) to corroborate this. Therefore experts choose most measures with the attribute-based system and a concrete mindset (see Figure 6).

Whereas in the previous analysis the amount of energy novices save with the needs-based system in both mindsets and the attribute-based system with an abstract mindset were similar, the results of the amount of items show different patterns. With the needs-based system, they choose more measures than with the attribute-based system independent of the mindset they are in. This effect is consistent with the expected fit between the needs-based system and novices, but again there is not effect of the mindset manipulation on the behaviors with the needs-based system.

Table 13: Predicting the number of measures chosen ($R^2 = 0.105$)

	Estimate	Std. Error	t	p
(Constant)	7.151	0.816	8.759	0.000
Abstract	-2.576	1.163	-2.215	0.028
Needs	-0.356	1.156	-0.308	0.758
Abstract × Needs	3.730	1.645	2.268	0.025

Domain knowledge	1.456	0.805	1.809	0.072
Domain knowledge × Abstract	-2.183	1.172	-1.862	0.064
Domain knowledge × Needs	-2.965	1.157	-2.562	0.011
Domain knowledge × Needs × Abstract	1.964	1.651	1.190	0.236

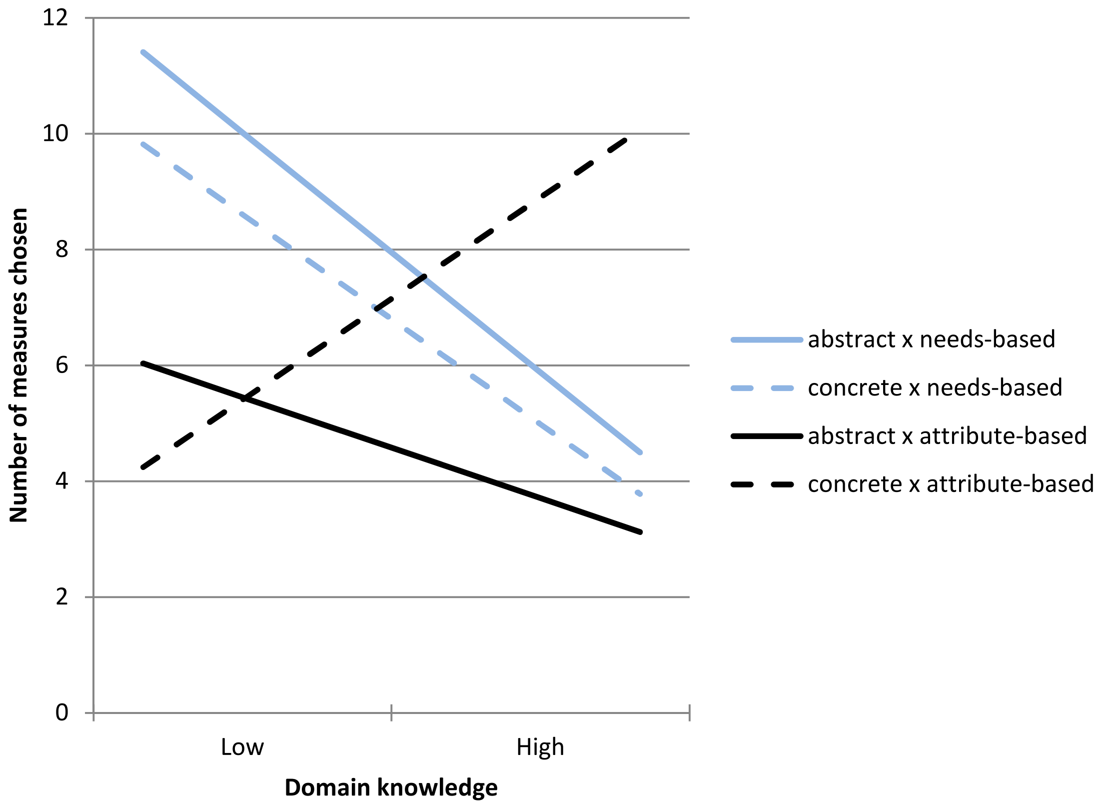

Figure 6: Number of measures chosen as a function of domain knowledge, mindset and system type

Similarly to the total amount of energy-saved a simple slopes test for three-way interactions was performed to determine whether the slopes differ significantly. The tests showed that the concrete mindset with the attribute-based system has a significantly different slope than the abstract mindset with a needs-based system ($t(166)=2.785$, $p<0.01$), concrete mindset with an needs-based system ($t(166)=2.562$, $p<0.05$) and an almost significant effect of the abstract mindset with an attribute-based ($t(166)=1.863$, $p=0.064$). None of the other slopes have significant differences, indicating that the only the concrete-attribute based system condition has a slope significantly different from the others.

Energy saved by the chosen measures

The number of measures chosen is lower with an abstract mindset, but increases when combined with a needs-based system (see Table 13). These effects are not shown in the total amount of energy saved by the chosen measures (see Table 12). Therefore the mindset and system type should have an influence on the amount of energy that is saved by each chosen measure. Combining these two results, the amount of energy-saved by each chosen measure should be positively influenced by an abstract mindset, but negatively when combined with a needs-based system. A regression on amount saved per measure confirms that participants using the needs-based system in an abstract mindset choose smaller energy-saving measures (see Table 14). Whereas the amount of measures and the total amount of energy saved was influenced by the fit between experts, system and mindset, the average amount of energy saved by the measures is not. Only a main effect of domain knowledge occurs, indicating that experts choose measures with larger savings.

Table 14: Predicting the average amount of energy saved with each chosen measure (R^2=0.168)

	Estimate	Std. Error	t	p
(Constant)	492.65	55.870	8.817	0.000
Abstract	136.17	79.541	1.712	0.089
Needs	-160.60	78.987	-2.033	0.044
Abstract × Needs	-229.33	112.343	-2.041	0.043
Domain knowledge	66.39	28.247	2.350	0.020

To further assess the effect of system type, a graph of the average savings per measure and 95% confidence intervals is created. The graph is shown in Figure 7.

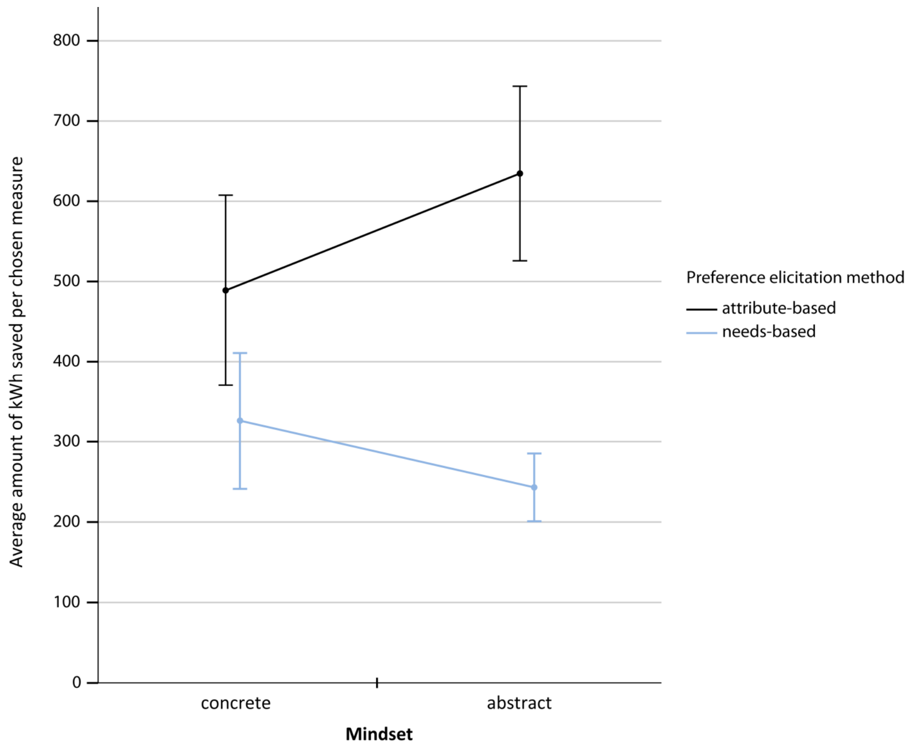

Figure 7: The average amount of energy saved by each chosen measures with the 95% confidence intervals

The graph displays the differences between needs-based and attribute-based system and their interaction with mindset, as indicated by the regression coefficients. A t-test was performed on the participants with an abstract mindset which showed a significant effect of system type ($t(84)=5.521$, $p<0.001$). In a concrete mindset, the system type only showed a marginal significant effect ($t(86)=1.837$, $p=0.07$). So overall the attribute-based system results in a tendency to choose measures which save more energy. But this difference between the needs-based and attribute-based system is smaller in a concrete mindset.

Conclusion hypothesis 1

The results show that, as expected in hypothesis 1, experts save more energy with the attribute-based system in a concrete mindset. This is mainly caused by the amount of measures they choose. For novices the results do not support hypothesis 1 which predicted that they would save more energy with the needs-based system in an abstract mindset. The results of the amount of energy saved in total, the amount of measures chosen and the amount of energy saved by each chosen measure show no (strong) effects of the mindset on the needs-based system. Furthermore novices save a lot of energy with the attribute-based system with an abstract mindset which is caused by the amount of energy saved by each chosen measures. Hypothesis 1 is therefore supported for experts, but not for novices.

4.2 Structural equation model (SEM)

Apart from the behaviors of the participants, their evaluations of the systems are also expected to be influenced by the fit between the domain knowledge, the system type and mindset. This in turn is expected to influence how participants behave with the system. The differences in the amount of energy saved are expected to be partially mediated by the understandability of the systems as proposed in hypothesis 2. Furthermore hypothesis 3 predicts that the satisfaction and perceived usefulness of the systems will be influenced by the fit between system type and domain knowledge.

A structural equation model (SEM) will be used to assess whether these effects occur and how the dependent variables relate to each other. The factors from the CFA of the post-experimental questionnaires were modeled and the predicted path model was implemented with the mindset, system type and domain knowledge (the saved and standardized factor scores) as predictors, and improved by recursively removing non-significant relations. The resulting model has an excellent fit: CFI=0.994, TLI=0.993, RMSEA=0.021 and a chi-square(155)=167.271, p=0.2367[7] and is shown in Figure 8. An arrow indicates a directional relationship between two variables, accompanied by the regression coefficient, the standard error (in parentheses) and the significance of the relation. For clarity reasons questionnaire items are not added to the model, neither are non-significant relations.

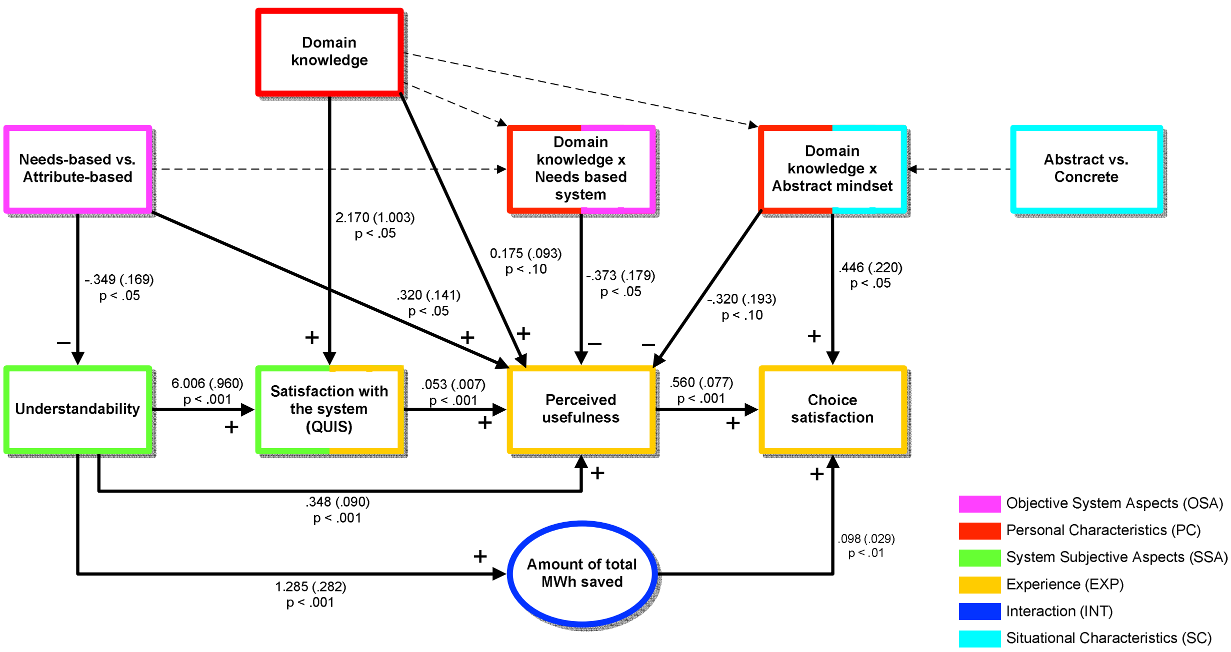

Figure 8: Structural Equation Model

[7] The preferred values are: CFI > 0.95, TLI > 0.96 (for categorical variables), and RMSEA < 0.06 and a non-significant chi-square test, although the chi-square test has shown to be very sensitive (Hu & Bentler, 1999).

Relations of the post-experimental questionnaire constructs

First the predicted relations of the post-experimental questionnaire constructs will be assessed. We predicted the following main model: understandability → satisfaction with the system → perceived usefulness → choice satisfaction. Figure 8 shows that participants with a better understanding of the system are not only more satisfied with the system, they also perceive it as being more useful. The increased system satisfaction also results in higher perceived usefulness, showing that the effect of understandability on perceived usefulness is partially mediated by system satisfaction. And finally the satisfaction with the chosen measures is higher when participants perceive the system as more useful. Compared to the a priory predicted relations of the post-experimental questionnaire construct, only the direct influence of understandability on the perceived usefulness was not predicted. This effect was expected to be fully mediated by the satisfaction with the system.

The model also shows the expected positive effect of the total amount of energy saved on the choice satisfaction. Therefore a participant who saves more energy will, when reflecting on the choices made, be more satisfied with them.

Main effects of the manipulations

The model in Figure 8 shows main effects of the system type and domain knowledge which were not expected. Understandability is directly influenced by the system type, where the needs-based system results in a lower understandability compared to the attribute-based system. Furthermore the needs-based system is perceived as more useful than the attribute-based system. Based on the relations between the constructs the negative influence of the needs-based system on the understandability should result in a lower perceived usefulness of the system. The positive main effect of the needs-based system on perceived usefulness counters this indirect effect. To determine the total effect of system on the perceived usefulness, a test of indirect effects is performed. The total indirect effect of system on perceived usefulness via understandability is significant with $b=-0.233$, $se=0.110$, $z=2.121$, $p<0.05$. But added to the positive direct effect of needs-based on system usefulness the total effect of system on usefulness is no longer significant: $b=0.088$, $se=0.174$, $z=0.505$, $p=0.613$. The needs-based system therefore does result in less understandability, but this does not influence the perceived usefulness of the system.

Another main effect that is shown in Figure 8 is that experts are more satisfied with the recommender and perceive them as more useful, independently of the type of system they used and which mindset manipulation is received.

Understandability and the amount of energy saved

Hypothesis 2 predicted that matching a needs-based system with an abstract mindset and combining an attribute-based system with a concrete mindset would result in higher understandability. The increased understandability was expected to positively influence the amount of energy saved. Consistent with this hypothesis understandability indeed influences the amount of energy saved (see Figure 8). But contrary to hypothesis 2, understandability is not influenced by the fit between the system type and the mindset. So hypothesis 2 is only partially supported.

Satisfaction and perceived usefulness

We predicted in hypothesis 3 that higher levels of domain knowledge result in more satisfaction with and perceived usefulness of the attribute-based system whereas lower levels of domain knowledge result in more satisfaction with and perceived usefulness of the needs-based system. Figure 8 shows that the satisfaction of the system is not influenced by the fit between domain knowledge and the system type, but the perceived usefulness is. Consistent with hypothesis 3 more domain knowledge results in a lower perceived usefulness of the needs-based system ($p<0.05$, see Table 15). Unexpectedly the abstract mindset also lowers the perceived usefulness of the system with increasing domain knowledge ($p<0.1$). As a result experts perceive the attribute-based system with a concrete mindset as most useful, while in an abstract mindset the same system has a low score (see Figure 9). Therefore there is an unexpected influence of the mindset on the evaluation of the system. Figure 9 shows that novices perceive the needs-based system as more useful regardless of the mindset, confirming hypothesis 3. Similarly to the results of the amount of measures chosen and the total amount of energy saved, the needs-based system is not influences by the mindset manipulation. So in summary hypothesis 3 is only partially supported. As predicted, novices perceive the needs-based system as most useful regardless of the mindset, while the perceived usefulness of the attribute-based system for experts is only higher in a concrete mindset.

Table 15: Perceived usefulness of the system in the SEM

	Estimate	Std. Error	z	p
Abstract	-0.013	0.177	-0.072	0.943
Needs	0.320	0.141	2.278	0.023
Domain knowledge	0.175	0.093	1.882	0.060
Abstract × Needs	-0.005	0.252	-0.021	0.984
Domain knowledge × Needs	-0.373	0.179	-2.085	0.037
Domain knowledge × Abstract	-0.320	0.193	-1.664	0.096
Domain knowledge × Abstract × Needs	0.339	0.259	1.310	0.190

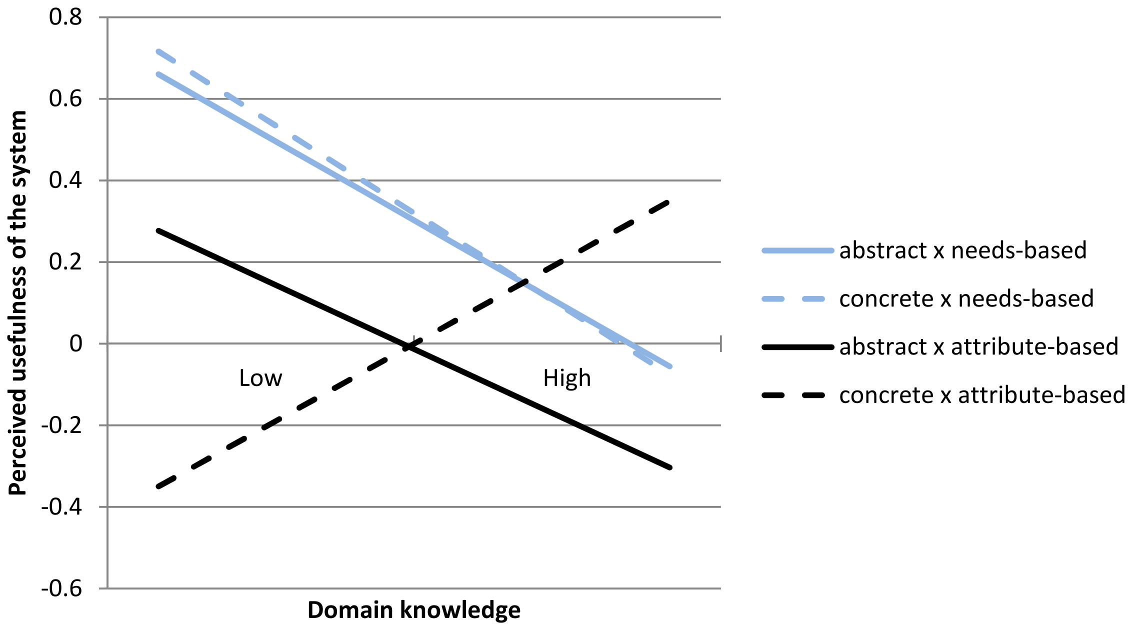

Figure 9: Perceived usefulness as a function of domain knowledge

Choice satisfaction

For choice satisfaction we observe an unexpected positive influence of domain knowledge with an abstract mindset (Table 16). The table only shows a significant positive effect of the domain knowledge with an abstract mindset. In an abstract mindset experts are more satisfied with their choices independently of the system type they used (see Figure 10). So where the total amount of energy saved, the number of measures chosen and the perceived usefulness show a negative effect of domain knowledge with an abstract mindset, the effects is positive for choice satisfaction.

Table 16: Satisfaction with the chosen measures in the SEM

	Estimate	Std. Error	z	p
Abstract	-0.006	0.210	-0.027	0.979
Needs	-0.043	0.200	-0.217	0.829
Domain knowledge	0.022	0.150	0.147	0.883
Abstract × Needs	0.077	0.291	0.265	0.791
Domain knowledge × Needs	0.257	0.241	1.067	0.286
Domain knowledge × Abstract	0.446	0.220	2.024	0.043
Domain knowledge × Abstract × Needs	-0.253	0.330	-0.767	0.443

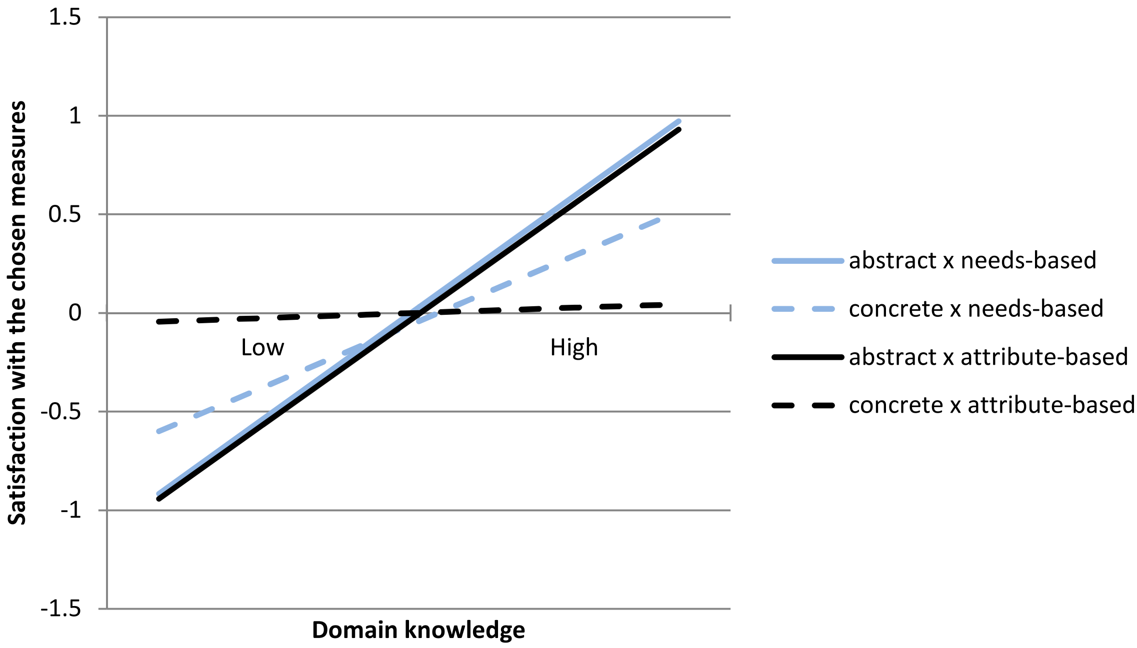

Figure 10: Satisfaction with the chosen measures as a function of domain knowledge

4.3 Needs underlying the chosen measures

To get a better understanding of the nature of the chosen measures in the different conditions, we project these measures per condition on the two dimensional (needs) space. This is done by averaging the value for each of the needs of the chosen measures for each participant. As the two-dimensional space is not setup to clearly distinguish different types of measures, there are no hypotheses for this test. This analysis is therefore purely exploratory to further understand the behaviors of the participants in the different conditions. The mean value and standard error for the average position of the chosen measures in the dimensional space is shown in Table 17.

Table 17: The mean value and standard error for the average position of the chosen measures in the dimensional space

	Mean	Std. Error
Popular measures - Unique measures	-0.283	0.029
Every kWh counts – A lot of kWh per invested euro	0.051	0.014

A regression of the “Popular measures - Unique measures” scale resulted in significant effects for the mindset and system type and their interaction and also shows a main effect of the amount of domain knowledge (Table 18). Experts tend to choose more unique measures, i.e. they score higher on the “Popular measures - Unique measures” scale. More interesting are the significant effects of mindset and system type on the type of measures chosen. In an abstract mindset participants tend to choose more the popular type of measures. In a needs-based system participants tend to choose more unique measures.

Table 18: Predicting the average value of the "Popular measures - Unique measures" scale of the chosen measures (R^2=0.385)

	Estimate	Std. Error	t	p
(Constant)	-0.395	0.046	-8.653	0.000
Abstract	-0.211	0.065	-3.240	0.001
Needs	0.337	0.065	5.228	0.000
Abstract × Needs	0.193	0.092	2.102	0.037
Domain knowledge	0.066	0.023	2.855	0.005

Experts also choose measures which are higher on the "Every kWh counts – A lot of kWh per invested euro" scale. This indicates that experts are more willing to invest more as long as the benefits weight up to the investments. The significantly negative interaction effect of abstract mindset with a needs-based system (see Table 19) suggests that when a participant uses a needs-based system in an abstract mindset, measures which require less investments, but also result in less energy to be saved are chosen. This is consistent with the findings of the average amount of energy saved by each chosen measure in Figure 7.

Table 19: Predicting the average value of the "Every kWh counts – A lot of kWh per invested euro" scale of the chosen measures (R^2=0.089)

	Estimate	Std. Error	T	p
(Constant)	0.057	0.026	2.178	0.031
Abstract	0.056	0.037	1.516	0.131
Needs	-0.013	0.037	-0.363	0.717
Abstract × Needs	-0.111	0.052	-2.106	0.037
Domain knowledge	0.030	0.013	2.253	0.026

To gain a better understanding of these results and the area in which participants made their choices, the average positions and 95% confidence intervals of the chosen measures can be plotted in the two-dimensional space. The resulting graph is shown in Figure 11.

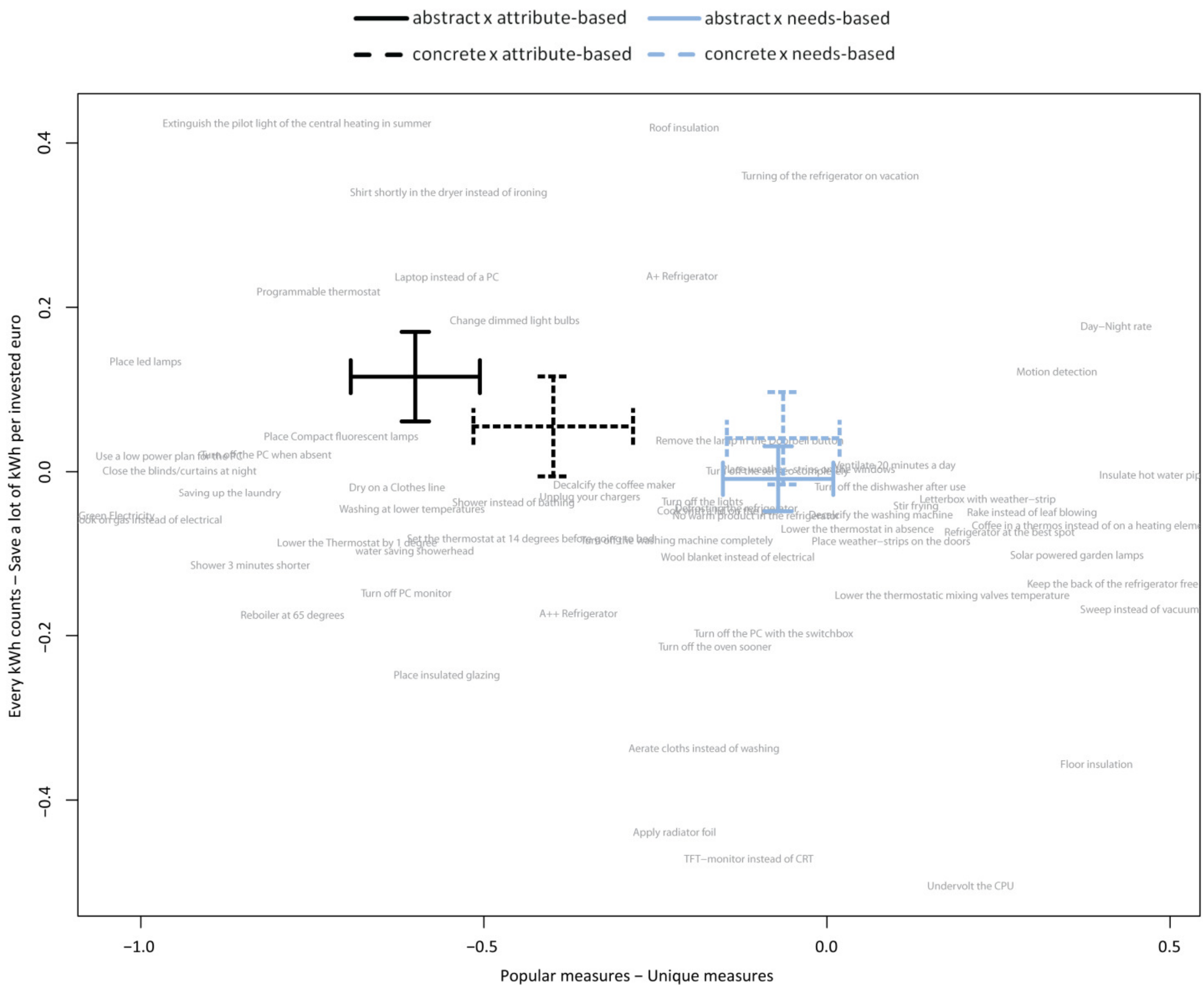

Figure 11: A zoomed in part of the 2-dimensional space with for each condition the 95% confidence interval of the chosen measures

The graph shows that participants in the needs-based system on average choose measures around the center points (0.0) of both dimensions. This indicates that the needs are well balanced as a similar amount of participants chose measures at the high or low end of the scale.

On the first dimension ("Popular measures - Unique measures"), the graph indicates a potential significant effect of the mindset on the attribute-based system. With the attribute-based system and an abstract mindset, participants choose more popular, less visible measures. Whereas with the attribute-based system and a concrete mindset more unique, visible measures are chosen. A t-test confirmed this difference, $t(85)=2.704$, $p<0.01$ with a mean difference of 0.201. The other differences in the graph have been accounted for by the regressions in Table 18 and Table 19.

Chapter 5

Discussion

To save the environment we need to make sacrifices now while the benefits of these actions will reveal itself in the future. According to the construal level theory this difference in temporal distance lets people focus on different aspects of an action. When an action is situated in the near future the focus is on the feasibility while it is on the desirability in the distant future. People have difficulties making the tradeoff between feasibility and desirability when choosing energy-saving measures (Liberman, et al., 2007). Recommenders can be used to help people solve this tradeoff. Randall et al. (2007) showed that the evaluation of the recommender and the intentions to act depends on the fit between the user's domain knowledge and the type of recommender (needs versus attribute-based). On the other hand Köhler et al. (2011) showed that matching the mindset with the type of recommender also has beneficial effects on the behavioral intentions and the evaluations. Based on these results the fit between domain knowledge and the type of recommender is expected to be amplified by a matching mindset. The main goal of this study is thus to determine how fit between recommender type, domain knowledge and mindset influences the user's intention to save energy (in terms of measures selected) and the evaluation of the recommender system. This was tested by a user study in which the participants' mindset was manipulated and the participants were randomly assigned to either an attribute-based or a needs-based recommender system. In this chapter we summarize the main findings and assess their implications and limitations.

5.1 Main findings

Influencing the amount of energy saved

Based on Randall et al. (2007) and Köhler et al. (2011) hypothesis 1 predicts that higher levels of domain knowledge result in more energy to be saved with the attribute-based system and a concrete mindset whereas lower levels of domain knowledge result in more energy saved with the needs-based system and an abstract mindset.

For the attribute-based system we expect that the amount of energy saved will increase with increasing domain knowledge and that this effect is amplified by a concrete mindset. The results show (see also Figure 5 in chapter 4) that in the attribute-based system the amount of energy saved indeed increases with expertise when in a concrete mindset, which is mainly due to the fact that more energy-saving measures are chosen in this condition (see Figure 6). We would expect a reduced effect of increased saving with increasing domain knowledge for the abstract mindset (due to the misfit between mindset and system), but we even observe a decrease in energy saved with expertise for the abstract mindset. In other words, when in an abstract mindset, novices save more with the attribute-based system than experts. Overall with the attribute-based system and an abstract mindset very few measures are chosen (and even less by experts than by novices which correlates with the lower total savings), but the measures that are chosen save a lot of energy.

This tendency to choose larger energy saving measures only occurs with attribute-based system with an abstract mindset. A reason for this effect is that, according to the CLT, the abstract mindset lets users focus on the desirable outcome of their intended behaviors (Liberman & Trope, 1998). The desirable outcome of an energy-saving measure is the amount of energy it saves. This suggests that users tend to focus on the amount of energy a measure saves when they are in an abstract mindset. The attribute-based allows users to deliberately indicate a preference for large saving measures, supporting the focus on the desirability of a measure.

For the needs-based system we expect that the amount of energy saved increases with decreasing domain knowledge and that this effect is amplified by an abstract mindset. The results (see Figure 5 in chapter 4) confirm that the total amount of energy saved with the needs-based system decreases with increased domain knowledge but the mindset does not influence this effect. Similarly the amount of measures chosen with the needs-based system also decreases with increasing domain knowledge without any effects of the mindset. A possible cause for the lack of mindset effects on the needs-based system is that the needs-based system asks the participant's preference at an abstract level, while also showing the concrete attributes in the information about the measures. Participants with an abstract mindset might perceive a fit with the preference indication of the system, while those in a concrete mindset might have a fit with the attribute descriptions of the measures. This might have reduced the effects of the mindset on the amount of energy saved and the number of measures chosen.

Understandability and the amount of energy saved

Previous research reports an increased understandability when the abstraction level of the information or system matches with the mindset, which in turn led to stronger behavioral intentions (Köhler, et al., 2011; White, et al., 2011). Therefore hypothesis 2 predicts that matching a needs-based system with an abstract mindset or an attribute-based system with a concrete mindset should result in higher understandability. The increased understandability in turn is expected to result in more energy to be saved by the chosen measures. The structural equation model (SEM) shows that increased understandability indeed results in more energy to be saved, but it does not show the expected fit between mindset and system. The understandability is not influenced by the interaction of the system type with the mindset. Although hypothesis 2 is based on the findings of Köhler, et al., (2011) and White, et al., (2011) their understandability questionnaires measure different aspects. White et al. (2011) measured the understandability of the written information on a flyer, whereas our research involves the understandability of a recommender system. Where Köhler et al. (2011) did measure the understandability of a recommender system, the interaction with their system was very limited compared to our recommender. In their study users first indicated their preference in one screen and then received a single recommendation in another screen without being able to see or alter their preference (there was no active interaction with a real recommender). Understandability in these two studies therefore mostly measures information processing fluency. In our study the application of the recommender allows multiple preference changes and shows multiple recommendations. Users interact in a complex way with a real recommender and select multiple measures. The understandability of the system therefore involves more than just the information processing fluency. In the understandability of our recommender these other aspects play a bigger role than the information processing fluency. It is therefore not surprising that in our study the fit between the mindset and the system did not result in increased understandability.

Perceived usefulness

Hypothesis 3 predicts that higher levels of domain knowledge result in more satisfaction with and perceived usefulness of the attribute-based system whereas lower levels of domain knowledge result in more satisfaction with and perceived usefulness of the needs-based system. These effects were assessed as part of the SEM. We found that only perceived usefulness and not system satisfaction was impacted by the independent variables. Consistent with hypothesis 3 novices perceived the needs-based system as more useful in both mindsets, whereas the attribute-based system with a concrete mindset was most useful for experts. The mindset of a participant thus not only influences the behaviors as was expected but also the evaluations of the system. Furthermore there is no influence of the mindset on perceived usefulness of the needs-based system, as was also seen in the total amount of energy saved and the number of chosen measures. This further confirms that the needs-based system is not influenced by the mindset manipulations.

Choice satisfaction

Although not predicted, choice satisfaction was higher for participants with higher levels of domain knowledge and an abstract mindset, while novices had the lowest choice satisfaction with an abstract mindset. Literature supports the idea that an abstract mindset might lead to more choice satisfaction. In general an abstract mindset is associated with the desirability of the decision (Liberman & Trope, 1998) and with the possible gains of the measure (White, et al., 2011). Therefore the abstract mindset can be seen as a positive view of the situation. The concrete mindset is focused on the losses that need to be endured (White, et al., 2011) and the complexity of the situation (Trope & Liberman, 2003). Therefore a general more positive view on the chosen measures in an abstract mindset would be expected, but this does not explain why novices have a lower choice satisfaction in an abstract mindset.

Perhaps because novices lack the ability to understand the underlying effects of their choices (Hutton & Klein, 1999) they are less able to see how well they did on a global level, which results in a misfit with the abstract mindset. Alba and Hutchinson (1987) indicate that those with increased domain knowledge have the ability to categorize products at levels above and below the level novices use. This might indicate the experts' ability to switch the level at which they think. During the decision making process they prefer the concrete attributes as they have the ability to understand the consequences of the measures themselves (Hutton & Klein, 1999). The choice satisfaction questions focus on the overall impact of the chosen measures. This requires a more global and abstract view on ones behavior. Experts have the ability to assess this and a mindset which fits this abstract view of the decision results in a fit and therefore more satisfaction.

5.2 Implications

People refrain from saving energy as they have difficulties making the tradeoff between sacrifices to be made today and the gains which will be received in the future. A recommender system can help making this tradeoff between the feasibility and desirability of energy-saving measures. Our study shows that people are best helped when there is a fit between the user's domain knowledge, the system type and the mindset. More specifically, experts show a fit with the attribute-based system and a concrete mindset and novices with a need-based system regardless of the mindset. This fit not only positively influences the user's perceptions of the recommender, but more importantly lets them save more energy with their decisions.

Our findings confirm and extend those of Randall et al. (2007). We replicate their finding that experts prefer an attribute-based system while novices would rather use a needs-based system. In addition our results show that the mindset can strongly influence these results. A mindset that matches the abstraction level of the system results in a more positive experience for the user. The abstraction level of the information in a system can therefore have a serious impact on how it is evaluated. This mindset effect on the attribute-based system is consistent with CLT.

CLT states that differences in mindset influence how a situation is perceived (Trope & Liberman, 2003). Our findings with the attribute-based system show that the mindset indeed influences the behaviors and evaluations of users, which confirms the main ideas of the CLT (Liberman & Trope, 1998; Torelli & Kaikati, 2009). But although many studies focus on the perceptions of situations, our research is the only one which determines the effects of mindsets on real decisions. CLT studies often involve the description of a scenario in which the participant has to imagine how satisfied she would be with the described decision (for example see study 3 by Liberman and Trope (2000)). These findings are often interpreted as though they are real decisions. But a real decision involves multiple products which need to be assessed and tradeoffs that have to be made between them. The recommender system used in our study contains a large set of energy-saving measures. Participants are therefore required to make tradeoffs between measures. Furthermore the participants in our study were not restrained in their behaviors. They could use the recommender for as long as they wanted and in any way that they wanted. Our study therefore shows that the effects of mindset can indeed influence the behaviors and evaluation of people in a real decision making task. Our findings therefore also confirm and extend the main findings of Köhler et al. (2011).

Köhler et al. (2011) showed that a good fit between mindset and system result in stronger behavioral intentions but they tested this with a system that only mimics the functionality of a recommender. Our study, with a fully functional recommender, confirms their results indicating that mindset and system match have an impact in more realistic systems. Our results show a clear fit of a concrete mindset in an attribute-based system, but no effect of the mindset on the needs-based system. Even though our results show an impact of the mindset manipulation, this only influences the evaluations and behaviors of the attribute-based system. The needs-based is not influenced by the mindset as would be expected according to the CLT. Where CLT research often uses artificially created situations in which there is a distinct abstraction level, we take on a more realistic approach. For example Köhler et al. (2011) compared a completely abstract and completely concrete system, the realism of such a distinction is questionable. The evaluation and behavior with our needs-based system, which mixes concrete attribute information with abstract preference elicitation, is not influenced by the mindset manipulation. We suggest this is caused as neither mindset has a clear fit or misfit with the system. This mixture of abstract and concrete information is more realistic. For example people will always consider the concrete price of a laptop even when the purchase is expected to be done in a year and therefore abstract. In other words in real life situations we cannot prevent that concrete aspects are part of an abstract system.

With our findings we therefore indicate that the findings of the CLT might be easily disrupted by small differences in the context.

The impact of the mindset manipulation on the attribute-based system might explain the lack of behavioral results found by Knijnenburg et al.(2009; 2010; 2011b). In their studies they assessed the fit between the system type and the user's domain knowledge, and only observed differences in the evaluation of the system not in the measures that were selected. Our findings suggest that the lack of behavioral differences between the fit of the recommender with the user's domain knowledge is caused by the influence of the participant's mindset. When in our study the amount of energy saved with the attribute-based system would be collapsed for both mindsets, the amount of energy saved with the attribute-based system would no longer differ between experts and novices (see Figure 5).

Action identification theory

Combined the results show that experts have the best fit with a concrete mindset and an attribute-based system. Although this is consistent with the findings by Randall, et al. (2007) and Köhler, et al. (2011), it contradicts what would be expected from another theory about the mental construal of events: the action identification theory (AIT). Similarly to CLT, the AIT states that an action can be identified (construed) at different levels of abstraction ranging from low-level to high-level identities (Vallacher & Wegner, 1987). The levels are connected in a hierarchy, the action's identity structure. People have the tendency to move towards and maintain high-level identities in this hierarchy (Vallacher & Wegner, 1987; 1989). Higher levels can be reached when there is sufficient experience with the detailed execution of an action to combine the individual parts into new informative clusters. Or in other words an expert maintains a high-level identification (abstract), while novices have a low-level identification of an action (concrete). We would therefore expect a fit between novices and a concrete mindset and between experts and an abstract mindset. The findings of the current study contradict this as experts save more energy and select more measures with the attribute-based system in a concrete mindset compared to the abstract mindset. This contradiction is probably caused by the different aspects which are discussed in the CLT compared to the AIT. The AIT has a background in automaticity where increased experience with an action reduces the need for conscious control when executing the action. An example of automaticity for example is switching gears in a car. A novice driver needs to mentally focus on the individual action involved in switching gear, pushing the clutch, move the gears in the correct position depending on the speed and slowly release the clutch again. A more experiences driver does not have to be conscious of every individual action required to shift the gears, the expert automatically perform the right actions. In the current study the focus is not performing an action but on one's preference. Studies about experts showed they prefer more detailed, concrete information as they automatically cluster the individual pieces into larger, more abstract chunks (Hutton & Klein, 1999). Therefore the AIT which states that experts think at a higher level is not incorrect, but does not necessarily mean that they prefer abstract information of a product.

Limitations and future research

The first limitation of the current study is the needs-based system. The needs were identified based on previous behaviors. The labeling of the two dimensions was done by us and not verified by a user study. Therefore the position of (some) measures might not be consistent to what a user would expect based on the labeling of these dimensions. Even though this constraints the usefulness of the needs-based system, the results do not show that participants perceive this to be the case. But for a recommender to really help users, it should recommend measures which do not surprise the user.

Secondly we only applied two mindset manipulations and did not have a control group. It is possible that experts and novices have a default mindset. Our findings suggest that experts have a fit with a concrete mindset when choosing a product as they have the ability to determine the abstract consequences themselves. While novices on the other hand are not able to use detailed concrete information and therefore prefer high-level abstract information. Knowing the default mindset would make it possible to tailor a recommender system to the user without the need for a deliberate mindset manipulation.

Thirdly even though we urged participants to find measures they are willing to do, the choice of energy-saving measures is still hypothetical. They might not be committed to really execute their chosen measures. The findings illustrate that in an abstract mindset the focus in on the desirability of the action, i.e. the amount of energy saved. The tendency to focus on the desirability of an action reduces feasibility considerations, thus making it less likely the consumer is able to perform the action. For example a participant can choose to insulate its roof because it results in a high amount of energy saved (desirability) but ignores the amount of money, time and effort that is required to do it (feasibility). The balance between these two mindsets at different stages of the decision making process is important. Where one mindset might work in the choosing of measures another might be needed to actually convince people to act (Liberman & Trope, 1998). At the moment of acting, other parts of the decision making and judgment play a role, such as the risks involved. Research on the interplay between decision making and CLT can help in knowing how decisions are best supported and how people can be persuaded to perform certain behaviors. However using a recommender system that fits the domain knowledge and mindset of the user will help them to consider and select better measures, which is an important first step in having people save energy.

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Appendix A

Measures and dimensions

The 80 measures are shown ordered on each needs dimension in the table below.

Table 20: The 80 measures ordered on the values for the two dimensions with the "Popular measures - Unique measures" dimension on the left and the "Every saved kWh count - A lot of saving per invested euro"

Measure	Popular measures – Unique measures
Place a mini wind mill	1.671
Gas heated tumble dryer	1.427
Magnetic refrigerator	1.380
Pull bell instead of electrical bell	1.274
Replace the alarm clock with a wind-up alarm clock	1.205
Solar panels	1.168
Hot-fill washing machine	1.069
Do the dishes by hand	0.746
Swiffer instead of vacuum	0.736
BBQ-ing	0.732
Door closer	0.729
A-rated tumble dryer with heat pump	0.706
Clean the Tankless heater	0.674
Corded telephone	0.645
Candles	0.630
Insulate hot water pipes	0.483
Sweep instead of vacuuming	0.473
Keep the back of the refrigerator free from dust	0.461
Day-Night rate	0.424
Coffee in a thermos instead of on a heating element	0.398
Floor insulation	0.393

Measure	Every saved kWh counts – A lot of savings per invested euro
Place a mini wind mill	1.140
Place Heat exchanger on venting system	1.062
Solar thermal collector	0.695
Micro-CHP	0.655
A-rated tumble dryer with heat pump	0.461
Solar panels	0.443
Extinguish the pilot light of the central heating in summer	0.423
Roof insulation	0.419
Turning of the refrigerator on vacation	0.359
Shirt shortly in the dryer instead of ironing	0.339
A+ Refrigerator	0.237
Laptop instead of a PC	0.236
Door closer	0.222
Programmable thermostat	0.218
Change dimmed light bulbs	0.183
Day-Night rate	0.176
Place led lamps	0.133
Motion detection	0.122
Place Compact fluorescent lamps	0.042
Hot-fill washing machine	0.041
Remove the lamp in the Doorbell	0.037

Solar powered garden lamps	0.371
Solar thermal collector	0.369
Motion detection	0.335
Rake instead of leaf blowing	0.306
Refrigerator at the best spot	0.272
Letterbox with weather-strip	0.237
Undervolt the CPU	0.214
Lower the thermostatic mixing valves temperature	0.191
Stir frying	0.131
Ventilate 20 minutes a day	0.106
Place weather-strips on the doors	0.101
Turn off the dishwasher after use	0.101
Decalcify the washing machine	0.085
Lower the thermostat in absence	0.051
Turning of the refrigerator on vacation	0.012
Micro-CHP	0.008
Place weather-strips on the windows	-0.020
Turn off the senseo completely	-0.065
Turn off the PC with the switchbox	-0.070
No warm products in the refrigerator	-0.099
TFT-monitor instead of CRT	-0.105
Remove the lamp in the Doorbell button	-0.106
Wool blanket instead of electrical	-0.123
Defrosting the refrigerator	-0.129
Turn off the oven sooner	-0.157
Cook with a lid on the pan	-0.159
Aerate cloths instead of washing	-0.172
Turn off the lights	-0.178
A+ Refrigerator	-0.208
Roof insulation	-0.208
Turn off the washing machine completely	-0.211
Apply radiator foil	-0.220
Decalcify the coffee maker	-0.303
Unplug your chargers	-0.341
A++ Refrigerator	-0.359
Set the thermostat at 14 degrees before going to bed	-0.421

button	
Gas heated tumble dryer	0.028
Turn off the PC when absent	0.021
Use a low power plan for the PC	0.018
Ventilate 20 minutes a day	0.007
Place weather-strips on the windows	0.002
Turn off the senseo completely	0.000
Close the blinds/curtains at night	0.000
Insulate hot water pipes	-0.005
Decalcify the coffee maker	-0.017
Turn off the dishwasher after use	-0.018
Dry on a Clothes line	-0.020
Saving up the laundry	-0.027
Unplug your chargers	-0.032
Letterbox with weather-strip	-0.035
Turn off the lights	-0.038
Shower instead of bathing	-0.039
Stir frying	-0.043
Pull bell instead of electrical bell	-0.045
Defrosting the refrigerator	-0.046
Washing at lower temperatures	-0.047
Cook with a lid on the pan	-0.049
Rake instead of leaf blowing	-0.051
Decalcify the washing machine	-0.054
No warm products in the refrigerator	-0.055
Green Electricity	-0.055
Clean the Tankless heater	-0.055
Cook on gas instead of electrical	-0.060
Coffee in a thermos instead of on a heating element	-0.067
Lower the thermostat in absence	-0.070
Refrigerator at the best spot	-0.075
Set the thermostat at 14 degrees before going to bed	-0.083
Turn off the washing machine completely	-0.085
Place weather-strips on the doors	-0.086
Lower the Thermostat by 1 degree	-0.088
Water saving showerhead	-0.098
Solar powered garden lamps	-0.103

Change dimmed light bulbs	-0.451
Shower instead of bathing	-0.452
Shirt shortly in the dryer instead of ironing	-0.545
Laptop instead of a PC	-0.554
Place insulated glazing	-0.554
Water saving showerhead	-0.595
Washing at lower temperatures	-0.598
Turn off PC monitor	-0.608
Place Heat exchanger on venting system	-0.615
Dry on a Clothes line	-0.621
Lower the Thermostat by 1 degree	-0.677
Place Compact fluorescent lamps	-0.708
Programmable thermostat	-0.737
Extinguish the pilot light of the central heating in summer	-0.764
Reboiler at 65 degrees	-0.779
Turn off the PC when absent	-0.809
Shower 3 minutes shorter	-0.835
Saving up the laundry	-0.866
Close the blinds/curtains at night	-0.938
Use a low power plan for the PC	-0.949
Cook on gas instead of electrical	-0.982
Place led lamps	-0.993
Green Electricity	-1.031

Wool blanket instead of electrical	-0.104
Shower 3 minutes shorter	-0.114
BBQ-ing	-0.120
Swiffer instead of vacuum	-0.124
Candles	-0.124
Keep the back of the refrigerator free from dust	-0.138
Turn off PC monitor	-0.148
Lower the thermostatic mixing valves temperature	-0.152
Sweep instead of vacuuming	-0.169
A++ Refrigerator	-0.174
Reboiler at 65 degrees	-0.176
Turn off the PC with the switchbox	-0.197
Turn off the oven sooner	-0.213
Place insulated glazing	-0.249
Replace the alarm clock with a wind-up alarm clock	-0.283
Aerate cloths instead of washing	-0.338
Floor insulation	-0.356
Apply radiator foil	-0.440
Do the dishes by hand	-0.454
TFT-monitor instead of CRT	-0.471
Undervolt the CPU	-0.504
Magnetic refrigerator	-0.524
Corded telephone	-0.604

Appendix B

System functionality

Two systems are used in this study, an attribute-based system and a needs-based system. Receiving a recommendation from a recommender system consists of three stages: the input (which is used for the preference elicitation), process (generate the recommendations based on the input) and output (presenting the recommendations) (Xiao & Benbasat, 2007). The preference elicitation is the process of understanding the preferences of the user. Screenshots of the two systems are shown in Figure 12. The top part shows the preference elicitation method (input) which is the only aspect of the system that is visually different for the systems. The input is used to match measures which match the preference best. The 10 best measures are recommended (process) and shown (output) in the middle. These can be chosen or classified otherwise.

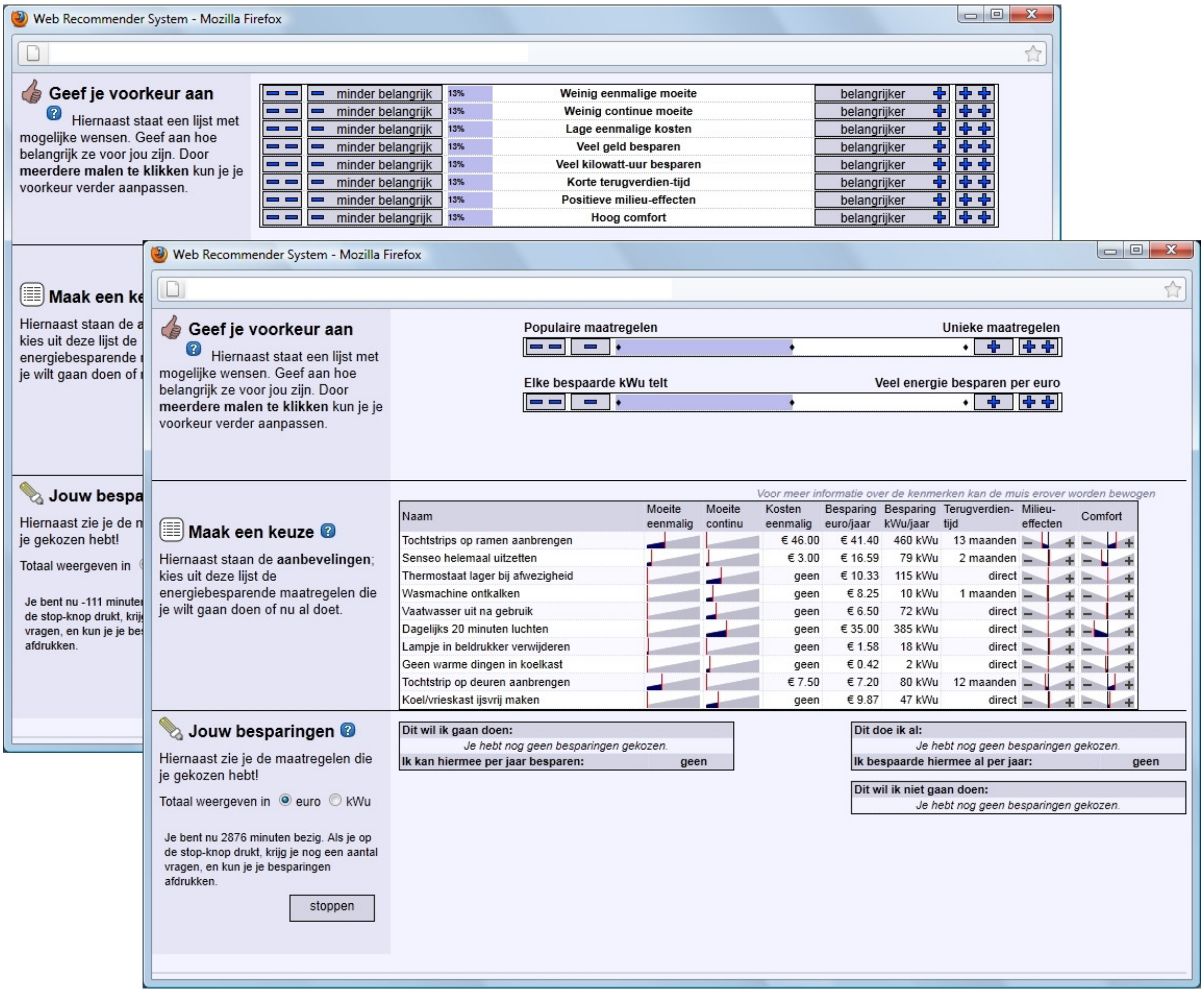

Figure 12: Screenshots of the attribute-based system (top) and needs-based system (bottom)

Input: Preference elicitation

Users can indicate their preference by setting attribute weights or by indicating where they position themselves on the needs dimensions. In the attribute-based system clicking on the single plus/minus makes the factor grow/shrink by a factor 1. With the double buttons the growth/shrinkage is performed with factor of 5.

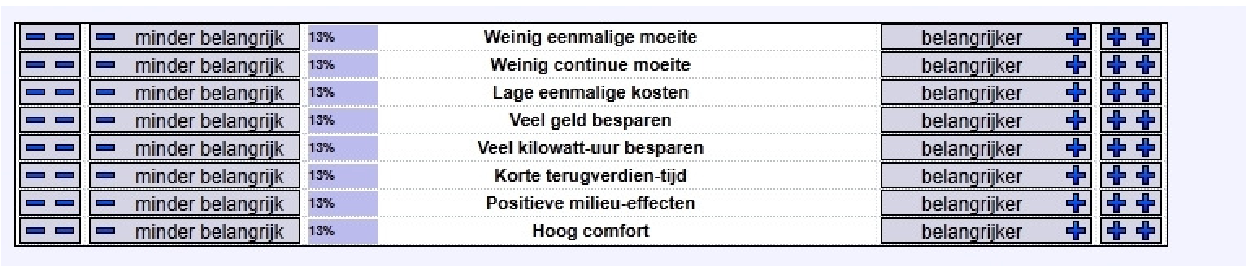

Figure 13: The attribute-based preference elicitation method

In the needs-based system the preference can be indicated on the two dimensions. The step size on the dimension is 0.125. Depending on the whether the single or double preference buttons are used a single (0.125) or double step (0.250) is applied.

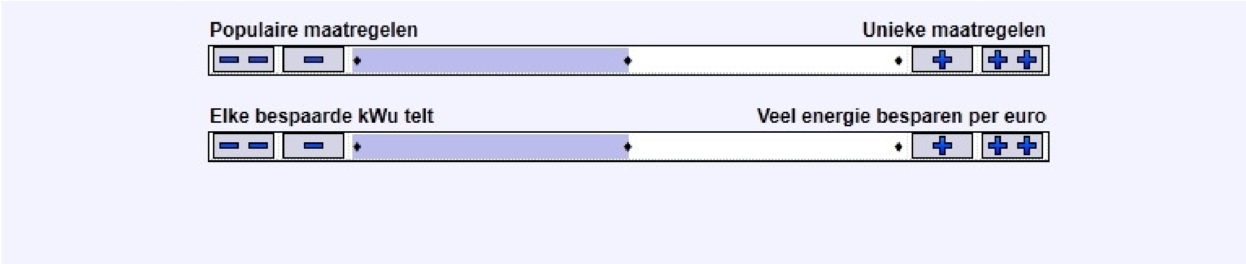

Figure 14: The needs-based preference elicitation method

Process: Matching preference and measures

The preferences are matched to the measures. With the attribute-based system the weight of each attribute is multiplied by the value of the attribute and summed. The 10 highest scoring measures are recommended to the user.

With the needs-based system, the Euclidian distance between the position of the user's preference and the measures is determined. The 10 measures which are closest to the users position in the two-dimensional space are recommended.

Output: Recommendations

The recommended measures are shown in the table in the middle of the screen with the values for the 8 attributes displayed for each measure.

Naam	Moeite eenmalig	Moeite continu	Kosten eenmalig	Besparing euro/jaar	Besparing kWu/jaar	Terugverdien-tijd	Milieu-effecten	Comfort
LED lampen plaatsen			€ 105.00	€ 121.20	537 kWu	11 maanden	– +	– +
PC energiebeheer inschakelen			geen	€ 67.20	320 kWu	direct	– +	– +
Warmtewisselaar op ontluchting plaatsen			€ 1139.50	€ 261.06	3055 kWu	5 jaar	– +	– +
Koken op gas ipv elektrisch			€ 190.00	€ 75.00	210 kWu	31 maanden	– +	– +
Groene stroom			geen	geen	0 kWu	direct	– +	– +
PC uitzetten bij afwezigheid			geen	€ 96.28	458 kWu	direct	– +	– +
Was opsparen			geen	€ 57.75	275 kWu	direct	– +	– +
Laptop in plaats van PC			€ 95.00	€ 31.50	150 kWu	3 jaar	– +	– +
`s Avonds gordijnen/luiken sluiten			geen	€ 57.47	639 kWu	direct	– +	– +
3 minuten korter douchen			geen	€ 50.00	450 kWu	direct	– +	– +

Figure 15: The table with the recommended measures

When users click on a measure a popup screen with information about the measure, both a written description and an overview of the attribute values, is shown (see Figure

16). Information about a measure can be viewed in either a general description which is in plain language or in a detailed description in which technical terms are not avoided. The user can switch between the two options, whereby the last chosen option is maintained until the user chooses to change it.

Figure 16: The pop-up screen with information about the measure and at the bottom the buttons to classify the measures

On the bottom of this pop-up buttons are shown through which users can classify the measure. When a user want to do a measure she clicks on the “I want to do this”, if she is already doing the measure she can remove it from the recommendation list clicking on “I am already doing this” and if it is a measure she does not want of cannot do she can click on “I do not want to do this”. The measure will be put in one of the three tables at the bottom of the screen as can be seen in Figure 17.

Figure 17: The three classification tables, with the "I want to do this", "I am already doing this" and "I don't want to do this"

Appendix C

Questionnaires

In this appendix the questions of the pre-experimental and post-experimental questionnaires are shown. Questions in italic are not included in the factor scores.

Pre-experimental questionnaire

Domain knowledge

Dutch wording	Translation	Scale
Ik weet precies hoeveel energie elk apparaat in mijn huishouden verbruikt.	I know energy consumption of all devices	disagree/agree
Ik begrijp het onderscheid tussen verschillende soorten energiebesparende maatregelen.	I understand difference between measures	disagree/agree
Ik ben bekend met energiebesparende maatregelen waar de meeste mensen nooit van gehoord hebben.	I know more measures than others	disagree/agree
Ik weet welke energiebesparingen zinvol zijn om uit te voeren.	I know which measures are useful	disagree/agree
Ik ben in staat om goede energiebesparende maatregelen te selecteren.	I can choose the right measures	disagree/agree
Ik begrijp niets van de meeste energiebesparende maatregelen.	I don't understand most measures	disagree/agree
Ik twijfel wel eens of ik goede energiebesparende maatregelen heb gekozen.	*I doubt whether I choose the right measures*	*disagree/agree*

Need for uniqueness

Dutch wording	Translation	Scale
Vaak combineer ik dingen op een zodanige manier, dat ik een uniek imago creëer dat niet kan worden nagedaan.	I often combine possessions in such a way that I create a personal image that cannot be duplicated	disagree/agree
Ik ben niet iemand die het leuk vind om origineel te zijn, door een interessantere versie van standaard/doorsnee producten te zoeken.	I do not enjoy being original by trying to find a more interesting version of run-of-the-mill products	disagree/agree
Ik ben actief bezig met het ontwikkelen van mijn unieke persoonlijkheid, door speciale producten of merken te kopen.	I actively seek to develop my personal uniqueness by buying special products or brands.	disagree/agree
Een oog hebben voor producten die	Having an eye for products that are	disagree/agree

interessant en ongebruikelijk zijn, helpt me in het creëren van een onderscheidend imago.	interesting and unusual assists me in establishing a distinctive image.	
Ik probeer vaak producten of merken te vermijden waarvan ik weet dat een groot deel van de bevolking ze koopt.	I often try to avoid products or brands that I know are bought by the general population.	disagree/agree
Ik heb voor mezelf de regel dat ik niet van producten of merken houd die door iedereen gekocht worden.	As a rule, I dislike products or brands that are customarily bought by everyone.	disagree/agree
Hoe gangbaarder een product of merk is onder de bevolking, des te minder geïnteresseerd ik ben in het kopen ervan.	The more commonplace a product or brand is among the general population, the less interested I am in buying it.	disagree/agree
Als het gaat om producten die ik koop en de situaties waarin ik ze gebruik, dan heb ik ongewone gebruiken en regels.	When it comes to the products I buy and the situations in which I use them, I have broken customs and rules	disagree/agree
Ik schend de ongeschreven regels van mijn sociale groep niet, als het gaat om wat ik koop of bezit.	I have not violated the understood rules of my social group regarding what to buy or own.	disagree/agree
Ik ben zelden tegen de ongeschreven regels van mijn sociale groep ingegaan, als het gaat om wanneer en hoe bepaalde producten gebruikt zouden moeten worden.	I have rarely gone against the understood rules of my social group regarding when and how certain products are properly used.	disagree/agree
Ik houd ervan om de heersende smaak van mensen die ik ken uit te dagen/te prikkelen, door het kopen van dingen die zij niet zouden accepteren.	*I enjoy challenging the prevailing taste of people I know by buying something they would not seem to accept.*	*disagree/agree*
Wanneer een product dat ik bezit populair wordt bij de rest van de bevolking, dan ga ik het niet minder gebruiken.	*When a product I own becomes popular among the general population, I will not use it less*	*disagree/agree*

Post-experimental questionnaire

System satisfaction (QUIS)

Dutch wording	**Translation**	**Scale**
Het systeem is	The system is	Terrible/wonderful
Het systeem is	The system is	Complex/easy
Het systeem is	The system is	Frustrating/satisfying
Het systeem is	The system is	Dull/stimulating
Het systeem is	The system is	Rigid/flexible

Understandability

Dutch wording	**Translation**	**Scale**
Ik begreep goed hoe ik mijn voorkeur kon aangeven.	I understood how to indicate my preference	disagree/agree
Ik begrijp hoe het systeem werkt.	I understand the system	disagree/agree
Hoe moeilijk of makkelijk vond je het om	How difficult/easy was stating your	difficult/easy

je voorkeur aan te geven in het systeem?	preference	
Het systeem begreep mijn voorkeur volledig.	*The system understood my preference*	*disagree/agree*
Het systeem gaf slechte aanbevelingen.	*The system made bad recommendations*	*disagree/agree*
De aanbevelingen van het systeem pasten bij mijn voorkeur.	*The recommendations fitted my preference*	*disagree/agree*
Hoe moeilijk of makkelijk vond je het om met hulp van dit systeem energiebesparende maatregelen te vergelijken?	*How difficult/easy was comparing measures*	*difficult/easy*
Hoe moeilijk of makkelijk vond je het om verschillende attributen van de energiebesparende maatregelen te vergelijken?	*How difficult/easy was comparing attributes*	*difficult/easy*
Ik heb vooral naar de naam van de maatregelen gekeken, en nauwelijks naar de overige attributen	*I looked primarily at the name of the measures not at the attributes*	*disagree/agree*

System usefulness

Dutch wording	Translation	Scale
Het systeem heeft mij milieubewuster gemaakt.	The system made me more energy-conscious	disagree/agree
Ik zou dit systeem vaker gebruiken als dat mogelijk was.	I would use the system more often	disagree/agree
Met dit systeem kan ik beter milieuvriendelijke keuzes maken.	I make better choices with this system	disagree/agree
Ik vond het systeem nutteloos.	The system was useless	disagree/agree
Ik zou dit systeem aan anderen aanraden.	I would recommend the system to others	disagree/agree
Het systeem beperkte me in mijn vrijheid om keuzes te maken.	*The system restricted my options to make decisions*	*disagree/agree*

Choice satisfaction

Dutch wording	Translation	Scale
Ik ben blij met de maatregelen die ik gekozen heb.	I like the measures I've chosen	disagree/agree
Ik denk dat ik de beste maatregelen uit de lijst heb gekozen.	I think I chose the best measures	disagree/agree
De door mij gekozen maatregelen passen precies bij mij.	The chosen measures fit my preference	disagree/agree
Hoeveel van de door jou gekozen maatregelen ga je daadwerkelijk uitvoeren?	How many measures will you implement	none/all