Effective Visualizations of Energy Consumption in a Feedback System – A Conjoint Measurement Study

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Abstract. Sustainable use of energy is one of the guiding principles of today's society. But there is a lack of comprehensive analysis solutions for the energy consumption of private households to provide real insights. In order to provide useful information, feedback systems may be the answer. Numerous studies about feedback systems have been conducted so far and each individual component of such a system has been tested. The combination of these components leads to a dashboard for decision support of private households. Within this study the individual components were combined in several configurations and implemented as a prototype dashboard. A Conjoint measurement is used for evaluation and observation of user preferences collected in over 1,000 questionnaires. The result, an evaluated dashboard, combines several effective feedback elements based on user preferences and helps to save energy based on decision support and transparency.

Keywords: Feedback system · Smart metering · Energy intelligence · Decision support · Conjoint

1 Introduction

Sustainability is one of the core concepts in economics and social research. A big focus within these fields of research relates to energy suppliers. These companies are responsible for shaping the future in terms of replacement of fossil fuels and nuclear power sources by renewable energy sources. Besides supporting the shift to renewable sources in the future, they are also able to create incentives towards responsible boundaries for energy consumption in private households [1]. A problem that often occurs in that context is the lack of information provided by the supplier companies. Information are often sparse and not suitable for detecting inefficient energy consumption patterns [2]. This mainly concerns the fact that billing is only provided on an annual level, at least, in Germany. That leads to unspecific, time delayed reactions on the consumer side. With the comprehensive rollout of smart meter technology a new

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data source is available that yields high potential when it comes to optimization on the consumer side as well as the development of new business models on the supplier side [3, 4].

In order to supply consumers with the required information, energy feedback systems are designed. These systems can help to reduce energy consumption up to 20 % [4]. However, the research field of feedback systems in the area of energy consumption is comprehensive. Therefore we conducted a systematic review [5]. We found that while most of the systems suggest visualization concepts in order to give feedback to the consumer, they were limited to a certain part of feedback rather than looking at the whole system. The latter is important to optimize energy savings and present optimal visualization depending on the data and customer preferences. For example, a study examined the consumption reduction over a test period of 100 days using only an in-home display [5]. In this preliminary study of feedback systems all described elements were characterized and a systematic overview of possible components for feedback and goal setting systems was presented (Fig. 1):

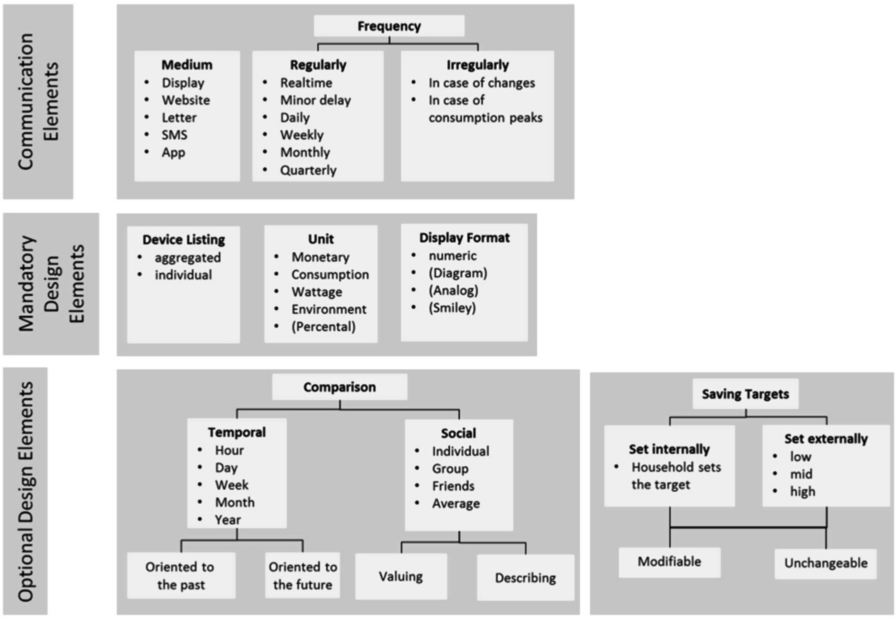

Fig. 1. Systematic overview over feedback system elements [5]

The problem of single components not being integrated into a feedback system which is able to visualize information for the consumer poses a challenge and acts as a basis for this paper.

According to [6], feedback systems are a special case of decision support systems and should employ rules of visualization in order to generate added value on the consumer side. Concepts of user friendly software and usability have to be applied to create an advantage for the consumer using these systems. This is an important factor considering the technology acceptance level of the consumer and the consumer motivation to use feedback systems.

2 Research Design and Methodology

Considering the information in [5], our goal can be stated as the evaluation of visualization components and their combination in order to design an energy feedback system for private households.

To evaluate user preferences for certain combinations of components we conduct a choice-based conjoint measurement analysis [7]. The conjoint measurement enables us to access a user's preferences for each component in the context of the whole feedback system [8]. We will refer to the feedback system as a product and the components as attributes of that product, since this terminology is more common in conjoint analysis.

2.1 Choosing the Attributes

The first step of developing conjoint measurements is to select product attributes which the user is required to access according to his preferences. First, the attributes selected for conjoint measurement have to be checked on the fulfilment of the general requirements of the conjoint analysis [8]. Table 1 shows the attributes according to [5] and their applicability according to the requirements of the study.

Table 1. Alignment of feedback elements with the conjoint measurement analysis [5]

Attribute	Description
Media and frequency	These attributes are highly correlated and cannot be separated. According to [5], electronic media has the highest potential for energy savings and will therefore be used in the study. As a representative media we choose "Website"
Device listing	Details on every electronic device are somewhat difficult from a technological perspective, so we only use aggregated figures over all devices
Units	Mainly monetary units are preferred by the users, as well as consumption- and environmental-focused units are used. To evaluate these findings the monetary unit "Euro" and consumption unit "kWh" are chosen
Visualization	Visualization concepts depend on the statement that should be visualized and therefore vary varied using a conjoint measurement
Social comparisons	User preferences regarding comparisons between households are very different. Therefore the attribute "Social Comparison" is included in the study with the values "Yes" or "No". We use comparisons between the target household and an average consumption of households with the same number of persons

(*Continued*)

Table 1. (*Continued*)

Attribute	Description
Comparisons over different time periods	Using information in order to make decisions regarding energy consumption in past periods can decrease energy consumption. Therefore this attribute acts as a basic element of every feedback system. While it is uncommon to vary this during the conjoint measurement we will later implement different visualizations for hourly, monthly and annual comparisons. Since there are no studies concerning consumption prognosis, we will vary future prognosis between annual and monthly comparisons. These time intervals were chosen because the month is a basic billing interval for monthly bills like rent, phone bill or salary. Summarizing the above, we used the attribute "Time Comparison" with the values of "Yes" and "No"
Goals	We only conduct the analysis with personal goals rather than pre-set goals from external sources. Since users do have different preferences concerning goals we choose to include this attribute in the analysis as the attribute "Goals" with the values "no goals", "detailed description", "rough description"

2.2 Visualization of the Components

We combined the attributes described above to products which had to be evaluated. In order to yield realistic visualizations we used standard consumption profiles from real households [9]. Figure 2 shows combinations of the attributes "Time Comparison" with monthly and annual comparisons.

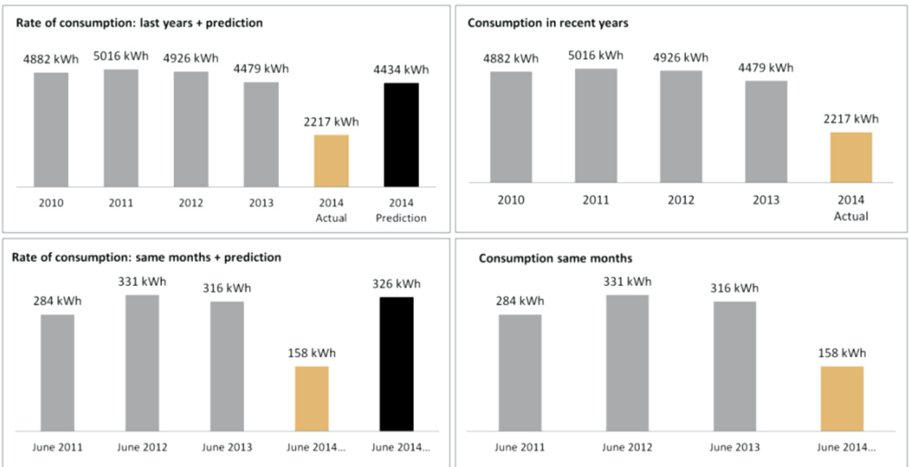

Fig. 2. "Time Comparison" with monthly and annual comparisons

2.3 Empirical Survey

An empirical survey for conjoint measurements consists of choice situations which themselves are orchestrated from certain stimuli. The subject chooses the product variation that earns the highest utility. In order to keep up motivation during the experiment only two stimuli are presented [10]. We used SPSS to generate the choice situations. We have included four attributes with two or three values and two stimuli per choice situation which results in a total of 16 choice situations. Since these are too many choice situations for one subject, we split the situations in two blocks of eight. You can find all stimuli in the appendix [14].

2.4 Quality of the Measurement

In order to measure the quality of the empirical design we use D-efficiency criteria [10]. In order to yield the design matrix with orthogonal coding we transform the original matrix, which is important to evaluate the balance and accuracy. The results are shown in Table 2 respectively for the first four stimuli. Now we calculate the D-efficiency of a $N_D \times p$ design matrix X as [10]:

$$D - \mathit{efficiency} = 100 \frac{1}{N_D \left| \mathrm{X}'\mathrm{X}^{-1} \right|^{1/\mathrm{p}}} \quad (1)$$

Our design results in an efficiency value of 98.5 which is fairly close to the optimal value of 100 that represents perfect orthogonality of the design matrix. We can therefore proceed to parameter estimation of our conjoint model in order to create the stimuli for the conjoint analysis (please mind: this is a snapshot).

Table 2. Snapshot of the design matrix with binary coding (0: element variation not present, 1: variation present)

Comparisons over different time periods	Social comparison	Goals	Units	Selection situation – stimulus (block, please check [14] for a visual impression of the stimuli)
1	1	1 0	0	1-1 (1)
1	0	1 0	0	1-2 (1)
1	0	0 1	0	2-1 (1)
0	0	0 1	1	2-2 (1)

2.5 Model Specification and Estimation

Preference Model: In order to explain a subject's preferences we use the part-worth-model. This entails in comparison to the vector model or the ideal-point model to apply the variation onto qualitative attributes as well. The part–worth model only describes the utility of an attribute. The utilities are later aggregated to yield the overall utility model, so that we can calculate the utility of a stimulus.

Choice Model: In addition to the preference model, we need to define a choice model that describes how subjects based on the preference model will select certain products. We will employ the most common model at this, which is the multinomial logit choice model [10].

Estimation: We use maximum likelihood estimation to yield probabilities for the choice of a certain stimulus [10].

3 Executing the Survey

3.1 Survey Questionnaire

Introduction questions serve the purpose of familiarizing the subject with the topic and ease the participant into the questionnaire. For this purpose, we defined six questions about personal energy consumption that were personal, topic-based and easy to answer.

After introducing that the questionnaire is about energy consumption, we offer the subjects the possibility to monitor their energy consumption in an online dashboard (that serves as the feedback system). At this point the choice situations are presented and the choice based utility is measured in regard to the stimuli of every choice situation. The subjects are confronted with a detailed description of each choice situation that represents the main part of the questionnaire. Since we split the subjects up in two groups each subject was given eight choice situations. We choose the two blocks and choice situations in each block at random in order to avoid order effects. Following those choice situations a subject is confronted with five questions regarding comparison of energy consumption over time (comparison to historical data). The last part of the questionnaire consists of demographic items in order to match the answers of the preceding questions with a profile.

3.2 Pretest and Sample

We conducted a pretest according to [11] before conducting the study in an online survey tool. The pretest was conducted with 13 participants and led to marginal alterations of the questionnaire. Since the medium is an electronical feedback system implemented via website, we expect the main users to be digital natives who prefer graphical visualizations instead of plain text [12]. Therefore we focus our survey on that target group. We choose our subjects so that they make up a representative sample regarding the target groups of digital natives which in this case is our population with focus on motivated students [13]. We conducted the survey within 3 months collecting 1,207 questionnaires from which 1,072 were completed and contained no missing values.

4 Results

4.1 Demographics

The most important information about the subjects are given below:

– Gender: 40.5 % female, 57.6 % male
– Age: 84.1 % 20–29 years old
– Education: 49.6 % High school, 26.7 % College Degree
– Size of household: 21.6 % 1 person, 39.6 % 2 persons, 21.2 % 3 persons
– Type of household: 89.3 % rented apartment
– Monthly net income: 73.4 % below 1,000 Euro

4.2 Results of Introduction Questions

Only 13 % of the subjects have a clear understanding or knowledge of their annual power consumption and only 19 % of all subjects know what their annual energy bill states in terms of energy costs. This is supported by the facts that only 18 % look at their meters more frequently than once a year. However, more than 70 % of the subjects want to reduce their energy consumption. Also, 70 % of the subjects plan to reduce consumption due to environmental awareness.

4.3 Preliminary Rating of the Features

The feature rating uses a scale from 1 (I do not like it) till 5 (I like it very much). The result of the rating was shown in Table 3. This table shows the arithmetic mean and the standard deviation of the separate features in three dimensions. The first one gives the average-score for the appearance, the second one for the content and the third calculates the average for both categories (in case of mean).

Table 3. Results of the separate feature-rating

Feature	Arithmetic mean			Standard deviation	
	Appearance	Content	Both	Appearance	Content
Rate of consumption: last years	3.43	3.73	3.58	0.97	1.06
Rate of consumption: same months	3.43	3.74	3.58	0.98	1.03
Additional prediction	3.36	3.77	3.57	1.08	1.18
Comparison households with same size	2.99	3.46	3.22	1.17	1.24
Saving target: bar chart	3.16	3.39	3.28	1.07	1.16
Saving target: speedometer	3.49	3.39	3.44	1.20	1.18

With exception of the social comparison all features reach a score bigger than 3 in the dimensions appearance and content. The highest score of the appearance with a score average of 3.49 shows the saving target shown in a speedometer, followed by the rate of consumption of the last years and the rate of consumption of the same months about the last years with a score of 3.43.

In the dimension of content, the feature of prediction reached with 3.77 the highest score, even followed by the rate of consumption of the last years and the rate of consumption of the same months about the last years.

Weighted both categories with 0.5 the retrospective comparisons get with 3.58 the highest scores, followed by the prediction with 3.57. Whereas the social comparisons get the lowest score with 3.22. But this score is bigger than the average evaluation point 3 and shows in this way a positive trend as well.

The rating results of the feedback features show a mainly positive judgement. But especially the dimension of appearance offers potential for improvements as this category shows the worst results in comparison to the other dimension.

4.4 Results of the Conjoint Measurement

Table 4 shows the results regarding the attributes in product combinations.

Table 4. Part-worth utility of all attributes

Attribute j	Value m	Part-worth utility b_{jm}
Time comparison	1 Yes	$b_{11} = 0.285$
	2 No	$b_{12} = -0.285$
Social comparison	1 Yes	$b_{21} = 0.160$
	2 No	$b_{22} = -0.160$
Goals	1 No goals	$b_{31} = -0.343$
	2 Detailed goals	$b_{32} = 0.012$
	3 Rough goals	$b_{33} = 0.331$
Measurement unit	1 Euro	$b_{41} = -0.002$
	2 kWh	$b_{42} = 0.002$
None-option		$b_5 = -1.386$

We yield an increased utility for prognosis on a monthly or annual basis. The same result is true for the social comparison. Highest utility values within the goal category were achieved when visualizing “rough goals”. The measurement unit “kWh” is preferred. We can now calculate overall utility values from the part-worth values. The highest utility (0.54) is given by stimulus 2 (see Fig. 3) in choice situation 3 in block two, using “kWh”, “social comparison” and “prognosis”. This is followed by stimulus 1, which is described exactly as above but using “Euro” as the unit of measurement.

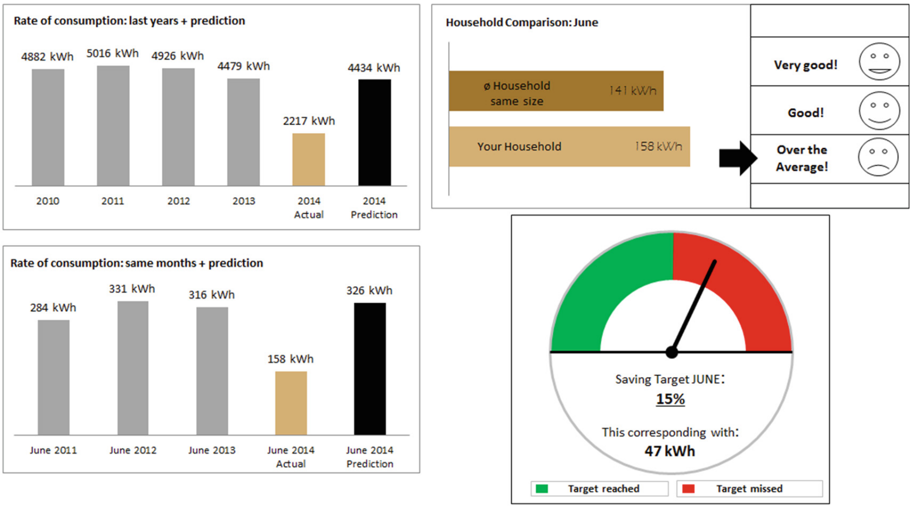

Fig. 3. Stimulus 2 in choice situation 3 with highest utility (Color figure online)

To yield attribute weights from the choice based analysis we use the range of the part-worth utility counts in order to derive relative importance of each attribute. The relative importance is shown in Fig. 4.

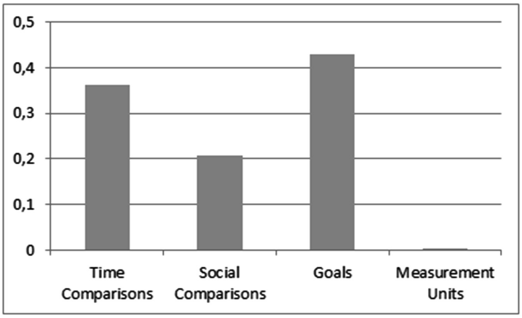

Fig. 4. Relative importance of attributes

From Fig. 4 we can state that, while the goals are the most important attribute, the measurement unit importance is only marginal (0.003).

4.5 Evaluation of Results

We employ a likelihood ratio test in order evaluate the goodness of fit regarding the model.

Therefore, we compare our model to the random choice model. The LLR test statistic yields the following results:

$$LLR = -2 \cdot (LL_0 - LL) = -2 \cdot (-9,430.488 + 7,993.058) = 2,839.558 \quad (2)$$

This results in a p-value close to zero. The hypothesis that the random model holds can be rejected. Furthermore we check the significance of the part-worth utility counts that are presented in Table 5.

Table 5. Likelihood ratio test for utility values

Utility	LLR_j	p-value
b_{11} (Prognosis "yes")	353.552	0.000 %
B_{21} (Social comparison "no")	102.037	0.000 %
b_{31} (No goals)	256.950	0.000 %
b_{32} (Detailed goals)	0.229	0.640 %
b_{41} (Euro)	0.023	0.882 %
b_5 (None-option)	2298.717	0.000 %

While the utility values of prognosis of the attributes "yes", social comparison "no" and "no goals" are highly significant, the attributes "detailed goals" as well as measurement unit "euro" are not significant.

5 Conclusion

5.1 Summary

We conducted a conjoint measurement analysis among n = 1,072 students that naturally were assumed to be digital natives. A feedback system was designed according to principals of visualization in IS research. The subjects assessed the components with above average ratings.

The assessment of the visualization elements mostly revealed positive feedback, yet there is potential for improvement. Based on the gathered data we can suggest using saving goals, social comparisons and consumption prognosis as components for a feedback system. The relative importance of the attributes goals and social comparisons contradict the rejection of those components within the meta-study that was conducted as a preliminary research project [5]. A feedback system designed for digital natives should therefore contain the feedback elements prognosis, social comparison, saving goal which is visualized by a speedometer, history based comparisons of energy consumption visualized by bar charts as well as daily consumption visualized by line plots. The measurement units should be kWh as well as Euro.

5.2 Limitation

While conducting the analysis it was apparent that assessment of the content was more positive than assessment of the visualization. For future research we suggest improving visualization in feedback systems. Using final comments of the subjects, they often complained about the colors. This observation leads to the conclusion, that the standards of the visualization of information in business [6] are not fully applicable to private households, although they both follow similar goals. Furthermore, consumers have a low readiness to pay for a feedback system. On one hand, this can correlate with the opinion of the subjects that such system has to be provided for free as an additional benefit by the supplier companies. On the other hand, the small income of the subjects in this study can explain the low willingness to pay.

Another issue that the subjects mentioned in connection with feedback system was the worry of a potential lack of security of the private data by data transmission through a website. To be able to give answers on how data security can be guaranteed further research needs to be undertaken.

In general, to increase the acceptance for such systems by the consumer the benefits of using them need to be clarified and communicated in an appropriate way. Furthermore the developed feedback system didn't have only investigated about the user preferences but also regarding about the effect on the energy consumption of the households.

This study uses the theoretical concept of digital natives although the social science criticizes the quality and empirical evidence of this concept. Nevertheless this study has preferred a prototypical way to generate data and the technical affinity of the target group which is connected to this theoretical concept. This analysis can be used as a first step for the construction of an evaluation of a feedback system for energy consumption of private households. Further research should transfer this concept to other groups of consumer, besides the target group of this study.

Moreover, the possibilities and contribution of such a feedback system to the sustainability in energy consumption have to be explored. The focus for this research should lay on the effect of a feedback system for a long-term change of energy consumption by consumers.

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