Saving energy in 1-D: Tailoring energy-saving advice using a Rasch-based energy recommender system

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Abstract. Although there are numerous possibilities to save energy, conservation initiatives often do not tailor their content to the consumer. By considering energy conservation as a one-dimensional construct, where different behaviors have different execution difficulties, we have set out a Rasch-based energy recommender system that provides tailored conservation advice to its users.

Through an online choice experiment among 196 users, we found that users prefer energy-saving measures that fit their Rasch-profile, rather than ones that fit their conservation attitude.

Keywords: Recommender systems, energy advice, Rasch model, energy efficiency, energy curtailment

1 Introduction

Initiatives that promote energy conservation, such as mass-media campaigns, often fail to effectively persuade individuals to change their energy-saving behavior [1,2,3]. A main cause for this is that such initiatives do not tailor their content to individual consumers, e.g. through tailored advice or feedback [3], but are rather general instead [4]. An additional shortcoming is that providing general information to consumers leaves them unaware of all the possible conservation measures [2,5].

Recommender systems can overcome these issues by tailoring advice to users based on their choices, preferences, and behavior [6]. Energy recommender system research has already pointed out the effectiveness of tailoring choice interfaces to users' knowledge levels by adapting the method of preference elicitation [7], and showed that increased levels of user satisfaction lead to more energy savings [8].

Although such an adaptive interface ensures compatibility with a recommender system user's goals and knowledge level [8], it does not personalize the conservation advice itself. How advice should be tailored is unclear, as researchers disagree of the dimensionality of energy conservation and are inconsistent in their findings [9].

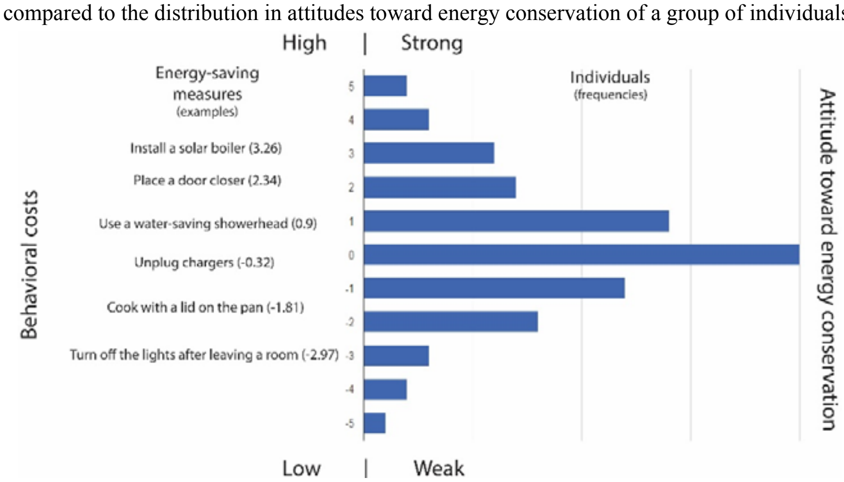
To tailor energy-saving advice, we will explore how to conceptually differentiate between energy-saving measures and subsequently perform a user experiment using an energy recommender system.

2 Dimensionality of energy conservation

The heterogeneity of conservation measures has led to various conceptual differentiations of energy-saving behaviors [9,10]. The most dominant conception of energy-saving dimensionality is a two-dimensional approach, differentiating between efficiency and curtailment [1,3,5,11]. Efficiency comprises one-time investments in home equipment, such as installing double-glazed windows, while curtailment involves reductions in energy-related behaviors, such as lowering one's thermostat.

A few authors have taken a different view on the dimensionality of energy-saving behavior [10]. Rather than discerning between behaviors based upon the nature of their activity, they argue that we must conceptualize energy-saving behavior as goal-directed behavior [10,12], in which conservation behaviors form a specific class pertaining to a single goal, saving energy, and that an individual's willingness to reach that very goal can be revealed by the behavioral steps that person is willing to take [12]. For instance, if one commits to execute a behavior carrying large costs, such as installing a solar boiler (cf. figure 1), one will also be likely to perform a behavior with fewer costs, such as turning off the lights after leaving a room [10,12].

Fig. 1. An example quantification of a few energy-saving behaviors and the costs they carry, compared to the distribution in attitudes toward energy conservation of a group of individuals.



The values depicted above were derived using the Rasch model [12], a model commonly used in psychometrics [13]. Rasch provides a mathematical formalization of the theory of goal-directed behavior, equating the costs δ of a behavior i with the conservation attitude θ of an individual n in a probabilistic model (cf. equation 1) [12].

$$\ln\left(\frac{P_{ni}}{1-P_{ni}}\right) = \theta_n - \delta_i \tag{1}$$

By quantifying behaviors in terms of costs and differentiating between them, as well as gauging the different propensities to save energy of a group of individuals, it is possible to tailor energy-saving advice based on this common dimensionality.

We have two main research expectations. First, in contrast with curtailment and efficiency, we expect that energy-saving behaviors form a one-dimensional scale. Second, we expect that tailored energy-saving advice, i.e. behaviors that match a user's attitude, are perceived as more appropriate than those that are easier or more difficult.

3 Creating a one-dimensional scale of energy-saving measures

We performed a pre-study to fit a one-dimensional scale of conservation measures. 263 participants interacted with our conservation web-tool, containing 88 energy-saving measures. Each participant had to indicate which measures they already executed by either responding 'yes', 'no', or 'does not apply' to each measure presented.

After controlling for misfit persons and items [cf. 13], we fitted a scale of 79 energy-saving measures with medium to high reliability, ranging in difficulty levels from -5.73 to 5.49 ($M = 0.06$; $SD = 2.14$). In line with our expectations, curtailment and efficiency measures were mapped onto a one-dimensional scale, with curtailment bearing less behavioral costs than efficiency measures ($M_{cur} = -0.67$; $M_{eff} = 1.03$).

4 Method - Energy recommender system user experiment

We used the constructed scale in an online energy recommender system to estimate users' abilities and recommend them tailored conservation measures accordingly.

Each user had to indicate for 13 semi-randomly sampled energy-saving measures whether he already executed them, by either responding 'yes', 'no', or 'does not apply'. Using their answers, we estimated user attitudes and provided them two tailored lists of nine energy-saving recommendations, whose execution difficulty levels were either 1 logit above, equal to, or 1 logit below the user's estimated attitudinal level.

To test which relative difficulty level is perceived as most appropriate, each user had to rank-order both lists in preference order, placing the preferred measures at the top. Users were only required to rank-order items that they did not already execute.

5 Results

Our web-tool was distributed among the members of the participant database of the virtual lab at Eindhoven University of Technology. 196 users (51.6% female; M_{age} = 27.3 years) completed our user experiment.

To test whether users perceived the tailored energy-saving measures as the most appropriate, we performed multiple rank-ordered logistic regression analyses on the ranked-ordered lists. Our analyses indicated that the relative difficulty level of a conservation measure had a significant effect on a measure's rank-order position. Contrary to our expectations, we found that relatively easy measures were perceived as the most appropriate, topping the rank-ordered lists ($p < 0.001$). This effect was rather linear: the mean relative difficulty level per ranked position increased while moving down the list. In other words, users preferred easy measures over more difficult ones.

6 Conclusions & future work

We have demonstrated two things: First, a diverse set of conservation measures can be mapped onto a one-dimensional scale according to the measure's difficulty levels. Second, from the provided tailored recommendations, users perceived the relatively easy ones as the most appropriate, suggesting that good energy-saving recommendations should fit a user's Rasch profile, rather than its attitude. This confirms the validity of the Rasch model, as individuals tend to exert more low-cost behaviors [12].

Future research must explore two things. First, how Rasch-based, energy-saving recommendation sets compare to non-personalized baselines, such as a set that consists of the most popular items (i.e. the easiest ones in a Rasch scale). Such a comparison should not only be made through choice, but also in terms of user experience concepts, such as system satisfaction [14]. Second, while we have employed a choice-support system, future systems must be more persuasive and use conservation nudges.

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