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Working Paper

Online-based energy auditing and incentive mechanisms to reduce domestic energy consumption.

Domestic energy consumption accounts for about 20-30% of total energy use in western countries [1], [2]. On the level of single households, however, energy consumption tends to vary greatly. This is particularly due to differences regarding behavior and decisions made by individuals. For example, heating and ventilation behavior, the intensity of the use of electrical appliances and hot water, as well as home insulation and weatherization provisions affect total energy consumption. Therefore, in the context of energy transition, interventions targeting energy-relevant behaviors and decisions on the level of single individuals are promising tools to increase domestic energy efficiency on a large scale [3].

In this regard, interventions providing individually tailored means and information on how to decrease energy consumption exhibit larger effects on energy savings compared to generalized interventions providing the same means and information to all participants [4]. However, tailored interventions (such as, for example, a personal energy consulting) often lack scalability due to high financial and labor costs. Indeed, a large scale intervention providing tailored information and suggestions to save energy has so far not been applied as a cost efficient way to cause moderate energy savings on a large scale.

In recent years, IT-based information systems (IS), such as online-platforms, could diminish the existing conflict between a scalable intervention on one and the level of detail and the degree of customization of the classical instruments on the other hand [5], [6]. Thus, it has to be investigated how individually tailored energy efficiency campaigns can be implemented in a scalable IS solution.

In this context, incentive mechanisms to promote target behaviors (such as financial rewards) are widely applied across fields. Incentive mechanisms are used to promote the compliance to psychotherapeutical interventions [7–9], to increase business sales and to support customer retention [10] and as a motivator for private households to reduce their energy consumption [11]. However, effects of incentive mechanisms to promote energy conservation campaigns show to be rather inconsistent and temporary [11]. A reason for this might be that most interventions incentivize actual energy savings rather than actions and decisions which directly or indirectly contribute to the superior, somewhat abstract goal of saving energy. It is promissing to reward concretely defined actions rather than abstract achievements by rewarding them within a scheme of a reinforcement schedule. Such a schedule directly links the actions and decisions to the reward and thus serves as a positive reinforcer in a operant learning paradigm [12].

Consequently, it has to be investigated how an individually tailored energy efficiency campaign can be integrated in a largely scalable IS and how incentive mechanisms can be applied to motivate the long-term usage of such a system on one and the execution of the recommended actions on the other hand.

Therefore, we designed a large-scale field-experiment (n > 2000) in which we will develop an IS solution providing users with tailored information and recommendations to decrease their energy consumption. Furthermore, we will evaluate the effects of incentive mechanisms, measuring how the different reward-schemes influence the IS usage-patterns and the electricity consumption of the participants. Additionally, we will check for rebound effects and if the effects vary as a function of reward types.

The study is conducted in a highly realistic environment with customers of a utility company using the IS as a real product. Thus, the inferences based on the data are limited to the specific group of potential users of the IS but are characterized by high external validity.

Methods

Procedure

The field experiment takes place in a real world buisness-setting. Therefore, the study design itself is a real world energy-efficiency campaign. The experimental procedure is shown in Fig. 1. The basic idea of the setting is to motivate people to execute suggested actions. The suggestions are selected according to the individual interests, household characteristics and prospects of the participants. We test whether a contingent rewarding of the execution exhibits an effect on the probability of the execution of the actions and what kind of rewards work best.

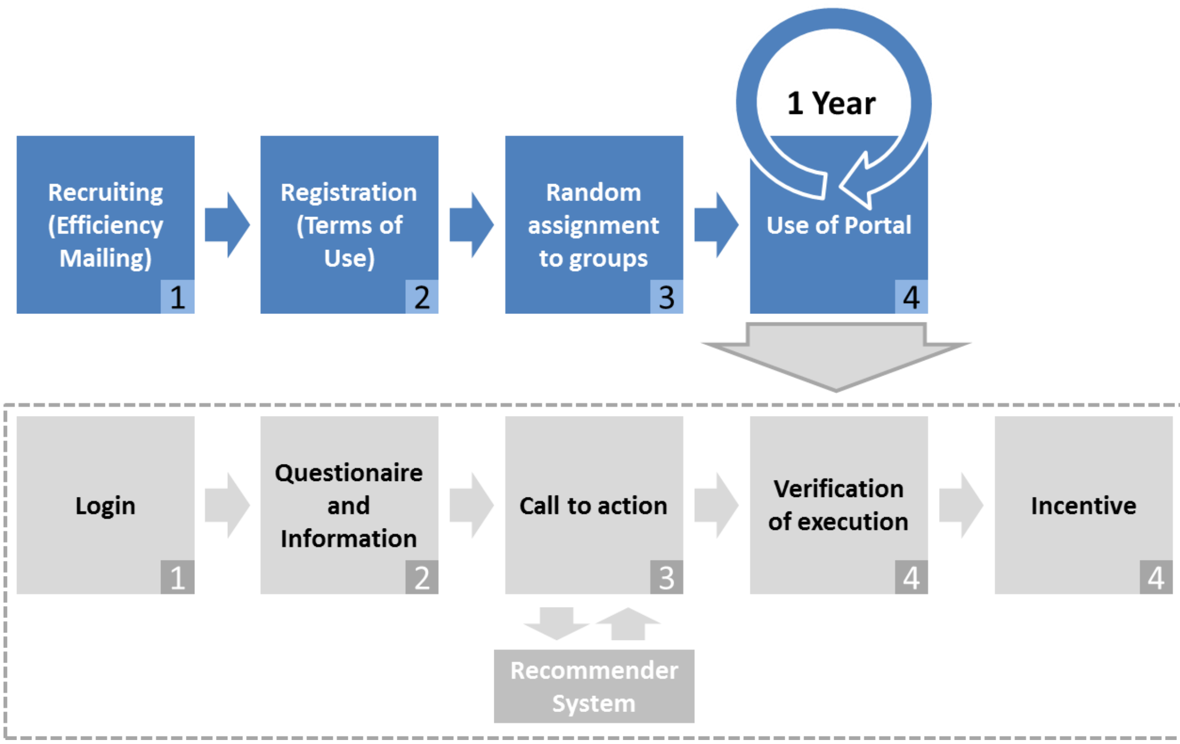

Figure1. Experimental Procedure

Recruiting and sample

In an initial step 20 000 randomly selected customers of a swiss utility company are recruited via an energy efficiency mailing of the utility company. The mailing shows information concerning the historical electricity consumption of the customer in comparison to the consumption of his respective neighbors (street-level at most to ensure anonymity) and promotion of a new online product the customer can use to decrease energy consumption. The mailing does, however, not contain any information concerning the scientific nature of the product to (as in all phases) ensure high external validity of the data. Also, no information about the testing of incentives is given. This ensures the realism of the setting which strongly contributes to the high external validity of the dataset.

Registration

Subsequently, participants visit the online-platform, register with a valid email address and an “efficiency-code” provided on the efficiency-mailing. The “efficiency-code” enables the system to identify every participant as a specific customer of the utility company and load historical consumption data into the user-profile. The participants then agree the terms of use which include the advice that data are used for scientific purposes.

Group assignment

In the next step participants get randomly assigned to one of four experimental groups. Group assignment determines the reward participants get for executing actions (online or offline) they are asked to perform and which directly or indirectly decrease total energy consumption in their home. Groups are displayed in fig. 2.

Experimental-group	**Non-Material reward**	**Material reward**	**Financial reward**	**Sample Size (n)**
E1	**X**	-	-	500
E2	**X**	**X**	-	500
E3	**X**	-	**X**	500
E4 (Control-Group)	-	-	-	500

Figure 2: Experimental Groups.

The non-material reward is a compliment for the effort the user showed performing the action. Also, a descriptive feedback of what the users achieved performing the action is added.

The material reward is transferred into bonus points the user can use to select from a defined set of presents. Again the reward is given for the effort the user showed. The presents are energy-efficiency products, such as LED light bulbs or smart water-meters. The monetary value of the bonus points is not shown to the user but limited to about 10% of the mean yearly electricity bill (40 CHF).

The financial reward comes in form of real money. The user gets the reward when he verifies the execution of the action. The financial bonus is also limited to a maximum of about 10% of the yearly electricity bill (40 CHF).

For the user the usage of the portal is an ongoing process. Data collection for the experiment runs for one year but the portal is not limited to this period. Users have no information on when the experiment actually stops.

Portal use

From a user's perspective the ongoing process of usage can be described as a continuous loop and is divided into the following steps.

The login loads the individual user profile in which information concerning the historical electricity consumption and information's collected on the platform is saved.

The user then gets directed to an interactive questionnaire part in which, in a play like manner, we measure information concerning household characteristics, performance of energy relevant behaviors and generally relevant attitudes. The information serves as a data base for the recommender-system and is integrated in the user-feedback. Subsequently, the user gets a descriptive feedback showing his historic achievements.

Subsequently, the recommender-system selects a set of 2-4 actions the user can take and which directly or indirectly decrease the energy consumption in his home. The functional principles of the recommender-system are described in the following section.

The recommended actions can either take place online (e.g. watching an educational video or buying efficiency-products) or in the real world. Real-world actions can either be short-term oriented (e.g. "count all 100W light-bulbs") or stretch over a defined period of time (e.g. "turn off lights whenever you leave a room for the next week"). Email a sms reminders can be set to keep attention on the actions and the portal.

In a next step the execution gets verified by the user, if the action was not imbedded in the use of the portal. If the execution is verified positively, the reward (depending on the assignment to one of the incentive-systems) is given. The user then gets redirected to the interactive questionnaire.

Recommender-System

The recommender-system is a hybrid system combining a content-based and a collaborative-filtering algorithm [13]. The systems recommendations are integrated into a Bayes model to estimate the overall fit of user and content.

The content-based filtering estimates the fit of participants and content by directly and indirectly matching user specific variables (household characteristics, interests, etc.), relevant exogenous variables (time of year, weather, etc.) and variables characterizing the content (for home-owners, relevant in spring, etc.) [14]. The Collaborative-filtering approach identifies similarities of different users and weights recommendations based on the assumption that similarities in past behavior predict common interests in general [15]. Also similarities in content is considered and weighted in the same way. The weighting of the different variables is a major contribution of the study and gives insights into the ongoing debate of which features determine similarities in energy-relevant behavior and electricity consumption.

Data collection

Data is collected whenever users enter the efficiency-platform. Usage-patterns and the execution of the recommended actions (as the central dependent variable) are tracked. Consumption data (electricity) is provided by the providing utility company.

To quantify the quality of the recommender-system we perform an additional experiment on the efficiency-platform with users across all groups. Users are presented six sets of three conservation actions and have to judge whether they think the actions are selected in respect to their personal means and interests on a five point likert-scale. Half the sets are selected randomly the other half according to recommendations made by the recommender-system.

Additionally, two questionnaires measure variables concerning moral licensing, interests, consumption behavior and purchasing behavior to quantify possible rebound-effects. The questionnaires are sent simultaneously to all users in a temporal distance of eight month.

Data Analysis

Data is analyzed using multivariate statistics. ANOVAS are used to analyses non-repetitive data. For repetitive measurements linear mixed models are used for analysis[16]. We thereby prevent possible statistical problems of repeated measurements ANOVA (rmANOVA) with more than two measures. In particular we compensate for possible problems which occur when applying rmANOVA on data that is characterized by high dropout rates, unbalanced data and violation of the assumption of sphericity made by the rmANOVA [16].

Expected results

The contingent rewarding has a significant effect on both, the probability of the execution of the recommended actions as well as reductions in electricity consumption on the level of experimental groups. Experimental-group1-3 show a significantly higher probability of executing recommended actions, compared to the control group. However, effects in the non-material reward group are significantly smaller compared to the material reward and financial reward group. Significant savings in electricity consumption are measured for all experimental groups compared to a non-treatment sample (about 7%). However, savings are substantially higher for the reward-associated groups 2 and 3 and highest for the material-reward group. Additionally, users in the material- and financial reward groups used the system significantly more frequent and significantly lower dropout-rates have been measured.

The probability of the execution of recommended actions correlates significantly with the predicted probability of the recommender-system. Actions selected by the recommender-system match the personal means and interests significantly better than randomly selected actions. The randomly selected actions are significantly rated above chance showing the relevance of all actions.

Recommended energy-saving actions are ranked by overall popularity, showing a general preference for curtailment- compared to efficiency behavior, supporting findings of related studies [17]. However, the financial bonus significantly raises the probability of the execution of efficiency-actions. An important remark is that efficiency-behavior is mostly associated with investments in products and services.

All groups show hints of effects of moral licensing. Particularly changes regarding mode of travel are observed.

Discussion

The study provides important theoretical and practical contributions each relevant for scientists as well as practitioners.

The important practical contribution of the study is a cost effective solution to decrease domestic energy consumption on large scale. The efficiency-portal is an innovative approach to tailor online energy-audits by means of an IS and make it easily accessible to a large user-basis. All experimental groups (also non-reward) are expected to significantly save energy. Thus, comparable efficiency portals can be applied to substantially reduce domestic energy consumption and contribute to realizing the energy-transition to renewables.

Rewards are expected to effectively motivate the frequent and long term usage of the IS when they are convertible into a monetary value. Contingent rewarding exhibit its influence by means of operant learning. Thereby, rewarded actions are transformed into habitual responses to characteristic situations and integrated into the daily routines of the users [12].

The technical contribution of the study is how an IS system can effectively operate by means of a tailored energy auditing. Therefore, the criteria as well as the semantical structure of the recommended actions are analyzed. Furthermore, the algorithms of the recommender-system and the performance of the system are evaluated and optimized.

The presented study also gives insights into possible mechanisms (possibly on the basis of individuals) which can cause rebound effects.

[1] European Environment Agency, "Environmental signals 2001 - Chapter Households," Copenhagen, 2001.

[2] U.S Energy Information Administration, "Annual energy review 2009," Washington, DC, 2009.

[3] J. Dimitropoulos, "Energy productivity improvements and the rebound effect: An overview of the state of knowledge," *Energy Policy*, vol. 35, no. 12, pp. 6354–6363, Dec. 2007.

[4] W. Abrahamse, L. Steg, C. Vlek, and T. Rothengatter, "The effect of tailored information, goal setting, and tailored feedback on household energy use, energy-related behaviors, and behavioral antecedents," *Journal of Environmental Psychology*, vol. 27, no. 4, pp. 265–276, Dec. 2007.

[5] R. Daft and R. Lengel, "Organizational information requirements, media richness and structural design," *Management science*, 1986.

[6] P. Evans and T. Wurster, "Getting real about virtual commerce," *Harvard Business Review*, pp. 84–94, 1999.

[7] A. Giuffrida and D. Torgerson, "Should we pay the patient? Review of financial incentives to enhance patient compliance," *Bmj*, vol. 315, no. September, 1997.

[8] K. G. Volpp, L. K. John, A. B. Troxel, L. Norton, J. Fassbender, and G. Loewenstein, "Financial incentive-based approaches for weight loss: a randomized trial.," *JAMA : the journal of the American Medical Association*, vol. 300, no. 22, pp. 2631–7, Dec. 2008.

[9] A. J. Budney, B. a. Moore, H. L. Rocha, and S. T. Higgins, "Clinical Trial of Abstinence-Based Vouchers and Cognitive-Behavioral Therapy for Cannabis Dependence.," *Journal of Consulting and Clinical Psychology*, vol. 74, no. 2, pp. 307–316, 2006.

[10] R. N. Bolton, P. K. Kannan, and M. D. Bramlett, "Implications of Loyalty Program Membership and Service Experiences for Customer Retention and Value," *Journal of the Academy of Marketing Science*, vol. 28, no. 1, pp. 95–108, Jan. 2000.

[11] W. Abrahamse, L. Steg, C. Vlek, and T. Rothengatter, "A review of intervention studies aimed at household energy conservation," *Journal of Environmental Psychology*, vol. 25, no. 3, pp. 273–291, Sep. 2005.

[12] J. E. R. Staddon and D. T. Cerutti, "Operant conditioning.," *Annual review of psychology*, vol. 54, pp. 115–44, Jan. 2003.

[13] L. M. de Campos, J. M. Fernández-Luna, J. F. Huete, and M. a. Rueda-Morales, "Combining content-based and collaborative recommendations: A hybrid approach based on Bayesian networks," *International Journal of Approximate Reasoning*, vol. 51, no. 7, pp. 785–799, Sep. 2010.

[14] M. Pazzani and D. Billsus, “Content-based recommendation systems,” *The adaptive web*, pp. 325–341, 2007.

[15] X. Su and T. M. Khoshgoftaar, “A Survey of Collaborative Filtering Techniques,” *Advances in Artificial Intelligence*, vol. 2009, no. Section 3, pp. 1–19, 2009.

[16] J. Landwehr and A. Herrmann, “Zeitliche Dynamik im Marketing: Neue Verfahren zur Auswertung,” *Marketing Review St. Gallen*, 2008.

[17] S. Attari and M. DeKay, “Public perceptions of energy consumption and savings,” *Proceedings of the …*, 2010.