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The authors bear the entire responsibility for the content of this report and for the conclusions drawn therefrom.

Zusammenfassung

Dieses Projekt untersucht die Kombination von individuellem Feedback und sozialen Vergleichen mit monetären Anreizen, um den Stromverbrauch zu beeinflussen. Um die Auswirkungen zu untersuchen, nutzen wir ein Feldexperiment, das in Partnerschaft mit einem Stromversorger durchgeführt wird. Wir entwickeln eine digitale Plattform und eine mobile Anwendung, die Daten aus intelligenten Zählern nutzen, um Feedback zu realistischen und angepassten potenziellen Einsparungen zu geben. Unser Ansatz beruht auf Zielsetzungen mit monetären Belohnungen und ermöglicht es, ausgewählte Behandlungseffekte sowie moderierende Effekte von Energiewissen und umweltfreundlichen Werten zu identifizieren. Darüber hinaus werden wir eine Methode der erklärten Präferenzen verwenden, um die Präferenzen verschiedener Haushaltstypen für nachhaltige Maßnahmen wie Bewahrung, Investitionen in Energieeffizienz oder die Einführung von Ökostrom zu identifizieren, was die Quantifizierung der Auswirkungen von Interventionen auf ein inklusives Spektrum von Bevölkerungssegmenten und psychologischen Profilen ermöglicht.

Résumé

Ce projet étudie la combinaison de feedback individuel et de comparaisons sociales avec des incitations monétaires afin d'influencer la consommation d'électricité. Pour étudier l'impact des interventions, nous utilisons une expérience de terrain menée en partenariat avec un fournisseur d'électricité. Nous développons une plateforme numérique et une application mobile alimentées par les données des compteurs intelligents pour fournir du feedback sur des économies potentielles réalistes et adaptées. Notre approche repose sur la fixation d'objectifs avec des récompenses monétaires et permet d'identifier une sélection d'effets de traitement ainsi que des effets modérateurs des connaissances énergétiques et des valeurs pro-environnementales. Nous utiliserons également des expérimentations de choix discrets (une méthode de préférences déclarées) pour identifier les préférences de différents types de ménages concernant les actions durables comme la préservation, l'investissement dans l'efficacité énergétique, ou l'adoption d'électricité verte. Ceci nous permet de quantifier les effets des interventions sur divers segments de population et de profils psychologiques.

Summary

This project studies how individual feedback and social comparisons can be combined with monetary incentives to influence residential electricity consumption. To study the impact of interventions, we rely on a field experiment conducted in partnership with an electricity provider. We develop a digital platform and a mobile app fed by smart meter consumption data to provide feedback based on realistic saving potentials tailored to each participating household. The experimental design relies on a goal setting task with monetary rewards and will allow us to identify a selection of policy treatment effects as well as moderating effects of energy literacy and pro-environmental values. We will moreover use a choice experiment to identify the preferences of various household types regarding sustainable actions namely conservation, efficiency investment, or adoption of green electricity. This allows us to quantify intervention effects across an inclusive range of population segments and psychological profiles.

Contents

Abbreviations

CoSi	Co-Evolution and Coordinated Simulation of the Swiss Energy System and the Swiss Society
CREST	Competence Center for Research in Energy, Society, and Transition
DCE	Discrete Choice Experiment
DCE 2023	The DCE conducted in 2023 (integrated in SHEDS)
DCE 2024	The DCE planned to be conducted in 2024 (on La Goule customers)
DiD	Difference in Differences
DSRM	Design Science Research Methodology
EES	Energy – Economy – Society
FE	Field Experiment
HES-SO	University of Applied Sciences and Arts Western Switzerland
HH	Household
INFINEED	The Interplay of Feedback and Incentive Effects on Electricity Demand
La Goule	Société des Forces Electriques de La Goule
LSTM	Long Short Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
RP	Revealed Preferences
RQ	Research question
SCCER	Swiss Competence Centers for Energy Research
SFOE	Swiss Federal Office of Energy
SHEDS	Swiss Household Energy Demand Survey
SM	Smart Meter
SMART (project)	The Smart Meter Rollout as an Experimental Setting: Promoting Energy-Saving Behaviors with Target Group Specific Interventions
SP	Stated Preferences
SWEET	SWiss Energy research for the Energy Transition
UniNE	University of Neuchâtel
WP	Work Package
WS	Workshop

Introduction

1.1 Background information and current situation

Despite a large and growing literature on non-price interventions such as feedback, there are significant research gaps in identifying causal effects and in distinguishing the mechanisms underlying specific responses (Andor & Fels, 2018; Schwartz et al, 2019). For instance, in the case of commitment devices, most studies use a combination of treatments, failing to disentangle the specific effect of commitment. Moreover, many studies examine hypothetical responses in discrete choice experiments (DCE) rather than in real setups, or focus on short-term effects neglecting the evolution of behavioral changes over time. Helping people achieve sustained energy conservation behaviors through the use of nudges has received mixed results (Caballero & Della Valle, 2021), prompting researchers from different disciplines to find explanations. One such explanation points to psychological values modulating long term commitment and consumption habits (Puntiroli et al., 2022), as will be investigated in this project.

Concerning monetary incentives, literature suggests that small but salient price signals could be effective (Wagner, 2017). Comparing monetary incentives with nudges, a few studies (Holladay et al., 2019; Weber et al., 2017) point to potentially significant effects of both measures. There is, however, little research about the effect of policies combining multiple interventions, in particular, on the interplay between non-monetary and monetary incentives (Schwartz et al., 2019) and their long-term effects. In line with the Behavioral Reasoning Theory (Claudy et al., 2013), we expect that information on saving potentials and how these can be achieved, will have a positive effect on sustainable behavior. Monetary incentives might cause a motivation-crowding-out effect, by “legitimizing” antisocial behavior (Lanz et al., 2018) but could be effective if they can provide a salient price signal (Wagner, 2017; Brandon et al., 2018). Recognizing the importance of peer effects, many studies identify observation of other community’s members and normative social influences as a main channel for behavioral change (e.g., Wolske et al., 2020).

1.2 Purpose of the project

The main purpose of this project is to understand how monetary and non-monetary incentives can motivate consumers to engage in sustainable behavior. To do so, we will study how consumers rely on and assess information that is communicated thanks to digital devices (i.e., an app linked to a smart meter monitoring their electricity consumption) and how these pieces of information interact with monetary incentives. Hence, we investigate the causal effect of combining monetary and non-monetary interventions on energy reduction. Given that monetary incentives can be effective in the short run, but may have little effect on long term behavior (Mantzari et al., 2015), we aim to identify the interplay of monetary and non-monetary interventions and find an optimal way of targeting consumers in order to maximize the long term impact of our interventions.

1.3 Objectives

The project has three interdependent objectives, each linked to a specific research question and addressed with its own tailored scientific approach. First, we aim to investigate sustainable actions from different perspectives. We focus on a more complex interplay between various sustainable behaviors and human psychology. In particular, we study conservation behavior, efficiency investment and the adoption of green electricity. Considering various sustainable actions with different costs and information requirements allows us to accommodate heterogeneous preferences, including for instance low-income groups interested in conservation, as well as affluent households opting for high-cost/high-information actions such as efficiency investments. This novelty helps assess inclusive policies based on monetary and non-monetary incentives and to adapt them to the individuals' own information requirement levels.

Second, we assess the impact of our interventions on actual and long term behavior. Following the literature (e.g., Andor & Fels, 2018), we will focus on a selection of non-monetary interventions that target various cognitive biases. Specifically, we consider information cues (via individual feedback), norm-based interventions (via social comparison), and commitment (via goal setting). Among these three categories, social comparisons are the most commonly investigated, and reportedly the most effective intervention with significant reduction of energy consumption, followed by the goal-setting interventions that are considered as promising. We will assess how the repeated interaction with this non-monetary information will impact behavior over time.

Finally, an important objective is to identify the effects of personal characteristics such as energy literacy, information overload as well as pro-environmental values on the type of sustainable behavior (or lack thereof). Our past research (Schubert et al., 2022) suggests that habits and routines play an important role in energy demand, while energy literacy is not necessarily correlated with higher intentions (Farsi et al., 2020). This observation, in conjunction with previous disappointing observations on the intention-behavior gap (Park & Lin, 2020) raise the question about how to best engage consumers in the desired behavior thanks to the information at hand. We argue that two key mechanisms are at play here. The first one concerns consumers' personal level of desired information and literacy. Thanks to our surveys, we will test how to best calibrate the quantity and type of information to communicate. The second mechanism concerns consumers' engagement. Our past research (Holzer et al., 2020) has demonstrated that properly designed feedback motivates individuals to engage in a desired behavior. We aim, thanks to the feedback mechanism that we will implement and the personalized information it will deliver, to trigger sustainable action aligned with the consumers' energy consumption goals.

Description of facility

SHEDS

The project's first discrete choice experiment (DCE) has been integrated in wave 2023 of the Swiss Household Energy Demand Survey (SHEDS). SHEDS is an online survey established in 2015 and conducted for six annual waves between 2016 and 2021 by the Competence Center for Research in Energy, Society, and Transition (SCCER CREST). SHEDS interviews a rolling panel dataset of about 5,000 respondents (except in 2021 when sample size was reduced to 4,250 respondents for budget reasons). The 2023 wave is part of activities within the new consortium Co-Evolution and Coordinated Simulation of the Swiss Energy System and Swiss Society (SWEET CoSi). SHEDS is fielded in collaboration with the survey company Intervista, mandated to conduct the sampling; namely, contacting potential respondents and offering them a participation bonus. Only respondents who report being involved (at least partly) in their household's expenses qualify for the survey. The final sample is constructed to be representative of the Swiss population (excluding Ticino) according to the following pre-selected characteristics and quotas:

- Age: 18-34 = 30%, 35-54 = 40%, 55+ = 30%;
- Gender: male = 49%, female = 51%;
- Region: French-speaking = 25%, German-speaking = 75%;
- Living situation: tenants = 62.5%, owners = 37.5%.

SHEDS global objective is to analyze energy-related behaviors of Swiss households and their evolution. The survey is designed as a series of modules whose questions are drawn from the established and cutting-edge research literature. The core modules are dedicated to eliciting energy-related, psychological, social context, and socio-economic information. The energy-related modules collect information about equipment and usage in three energy domains: electricity, heating, and mobility. Additional modules containing DCEs targeting specific research questions are implemented in each wave. In wave 2023, the only DCE included in SHEDS was the one designed for INFINEED.

La Goule Data Platform

The project will benefit from SM data from 7,938 end users provided by energy provider La Goule (*Société des Forces Électriques de La Goule*). About 6000 among these customers are residential, which will be the focus of this study. All customers of La Goule are equipped with SM that transmit electricity consumption every 15 minutes. The reliability and the transmission of such a large amount of SM data is a serious challenge. During the first phase of this project, a lot of effort went into discussing the SM data and how to make it available to the research team.

At this stage we have access to SM data for a three-year period from August 2018 through July 2023, which including the following information:

- SM's identification number;
- Date and time of record;
- kWh consumed during the time interval (hour or 15-minute interval);
- Index value of the SM at the beginning and end of the time interval;

In addition to SM readings the data include a series of customer characteristics,namely:

- Further information regarding households, in particular zip code and type of heating system.
- Type of electricity product (blue, green, gray, etc.)
- Type of consumer (consumption, self-consumption, production, self-consumption community)
- Specification of the presence of renewable production (solar, hydraulic, none, etc.)

Procedures and methodology

We use the design science research methodology (DSRM) in six sequential steps: (1) identify the problem, (2) define the objectives, (3) design, (4) implement, (5) evaluate, and finally (6) communicate. The design phase provides two independent treatments (social nudges and financial incentives) that will be evaluated separately or in combination. Our central hypotheses concern the effectiveness of the goal setting device under 3 types of policy treatments: 1) no intervention, 2) social comparison, 3) social comparison plus financial rewards. We propose a two-stage procedure for the evaluation step. While adopting a stated-preferences (SP) approach in the first stage (WP2), we follow a revealed-preferences (RP) analysis in the second stage (WP3).

The SP evaluation stage consists of two DCEs: The first one (DCE 2023) has been conducted in May 2023 on a subsample of 621 respondents in SHEDS 2023. The second DCE (DCE 2024) is planned to be conducted prior to the FE in early 2024, on a sample of La Goule's customers. DCE 2023 has been developed with three treatment groups. We will elaborate and fine-tune the design of DCE 2024 based on the results of DCE 2023 and the lessons learned from that experiment. We expect to run the experiment on a sample of about 400 to 800 households (corresponding to a response rate of 5 to 10% within the pool of La Goule's customers).

As compared to DCE 2023, we aim at making the provided information (individual and social feedback) more accurate through the use of individual SM data. Considering that the DCE participants are invited to the FE, we thrive to provide a series of simple and reasonably short choice tasks (numbers to be decided) in order to minimize non-response and various attrition risks. Moreover, the main purpose of DCE 2024 is to prime the respondents for the upcoming FE. DCE 2024 and the goal-setting experiment proposed in the FE are interrelated: While the respondents are subject to the same type of treatment in both experiments, the DCE provides respondent with the possibility to adopt various objectives (behavioral changes and reduction targets), while the FE will provide the real ground for achieving their stated goals and, depending on their treatment group, could be financially rewarded according to their achievement at the end of the study period.

During the study period the respondents will receive several levels of information treatments as well as a dynamic feedback system conveying messages about individual performance and social comparison. The frequency of this feedback will be determined according to La Goule’s boundary conditions, with a special care to minimize intrusion known to trigger negative reactions. In fact, increasing evidence in the field of nudging and social interventions indicates that people stop complying with requests when they feel their freedom is reduced in some way (Zemack-Rugar et al., 2017) and may even begin to act in opposition to an intervention (Osman et al., 2020). In addition, the design of our experiments allows us to identify the potential effects of energy literacy and environmental values as well as present bias and procrastination on the adopted sustainable action, but also the relative importance of each on formation of sustainable habits over time. Finally, at the end of field study we plan a short survey with a series of follow-up questions in order to identify among other factors, the mechanisms through which the reduction goals are achieved or not.

We acknowledge that respondents in the DCE and participants in the field experiment are likely to show different characteristics than the general population. In particular, because the DCE is held online and the field experiment involves using a smartphone app, average age will certainly be lower in our sample than in the population. We account for this sample bias in two steps. First, in all experiments, we create control and treatment groups randomly, which ensures that both are composed by similar individuals and therefore ensures internal validity of our experiments. Second, in the field experiment, we will have access to consumption data from non-participants (we call it a “reference group”), making it possible for us to investigate potential differences between the general population and the control group.

The collected data will be analyzed by advanced econometric methods with adequate modeling of heterogeneity. Conditional logit and mixed logit models will be implemented to analyze the SP data. Such models make it possible to unravel preferences for different alternatives and to evaluate relative importance of different attributes. Mixed logit models account for heterogeneity in the preferences. To analyze the FE data, we will rely on difference-in-differences (DiD) techniques (i.e., regression analyses that compare the before-after outcome for a treatment group of households against that of a control group). Such an approach allows to credibly estimate causal impacts of an intervention and benefit from strong internal and external validity.

Activities and results

WP0: Understanding usage and saving potential

Following a productive collaboration with La Goule, we have recently received a complete version of the historical dataset featuring cleaned SM readings as well as anonymised consumer details with some relevant household characteristics, for about 6,000 households over a five-year period from 2018 to 2023. Note however that most of the analyses in WP0 (reported below) are performed on an initial data set with limited SM data for about 1,000 households over a 3-year period (2020-2022). The results are therefore preliminary in their scope but quite useful for fine-tuning our models and specification strategies.

Missing data

The prediction of the next (missing) value for a given input sequence is of interest. In distinction to other supervised learning problems where the order of observations may not be significant, sequence prediction necessitates preserving the inherent order of the input sequence. Standard recursive neural networks can be considered for predictions; however, they have difficulties retaining information from previous inputs while processing a sequence. This limitation impedes their capacity to recognize and learn long-term patterns in data, which is particularly important in energy consumption data (Géron, 2022). Long Short-Term Memory (LSTM) networks are designed to prevent this problem by their architecture. LSTM cells excel at capturing long-term patterns due to their special structure that allows the LSTM cells to learn which information to store, which to discard, and which to read from their memory. In this study, we take inspiration from Brownlee (2018) and common applications of LSTM for series prediction.

We performed a study to investigate the potential of LSTM neural networks to predict daily consumption. The analysis is performed on the initial data set. We use a reduced dataset containing 212 selected households that meet the data quality criteria required for training of ML algorithms. We also included relevant information such as the weekday, daily average regional temperature measured by MeteoSuisse. A univariate LSTM model, which utilizes only past energy consumption data, alongside a multivariate LSTM model, that incorporates the engineered features is designed and trained.

We assessed the model performance by usual metrics namely, Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE), in comparison to the best-performing baseline model that assumes that the prediction of today's energy consumption is equal to the average of the past two energy consumption values observed on the same weekday. These preliminary results suggest that both LSTM models performed slightly better than the baseline models. Therefore, these models appear promising to help fill in the missing data in the complete data set.

Usage profiles and Saving potential

Using both consumption data and socio-demographic characteristics, we tried to identify segments of households using cluster analyses. Identifying recognizable consumption patterns and the important structural determinants of the latter (such as demographics and dwelling characteristics) is essential to the project. This will enable us, during the field experiment, to make relevant comparisons across households who can be genuinely compared. Our exploratory study was performed in two steps.

First, we used the sample of data received from La Goule containing electricity consumption data for about 1,000 households over a 3-year period (2020-2022). In this preliminary analysis, we tackled the issue by simply removing households with a high proportion of missing values.

The K-means technique belongs to the distance-based clustering methods. It is one of the most widely used clustering techniques for clustering electricity consumption data, as it is generally quick and easy to implement (Rajabi et al., 2020). This method corresponds perfectly to our needs regarding the analysis of smart meter data. K-means clustering was performed considering the following six features: HH's average daily consumption, average normalized consumption of 4 periods of the day (night, morning, daytime, evening), standard deviation over the normalized periods for each HH (a measure of consumption disparity). The clusters show important differences in their level of consumption and in their consumption patterns, as displayed in Figure 1. On average, all clusters have a typical camel-shaped load curve with a consumption spike in the middle of the day and another one in the evening, but the magnitude of these spikes differ considerably across clusters. The importance of night consumption also varies across clusters.

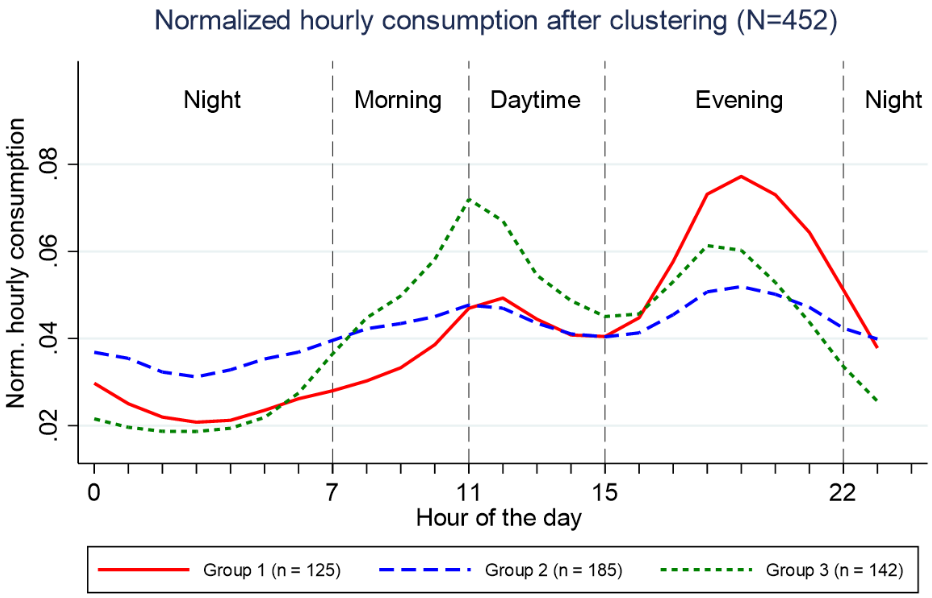


Figure 1: Normalized hourly consumption, by cluster (based on 452 households).

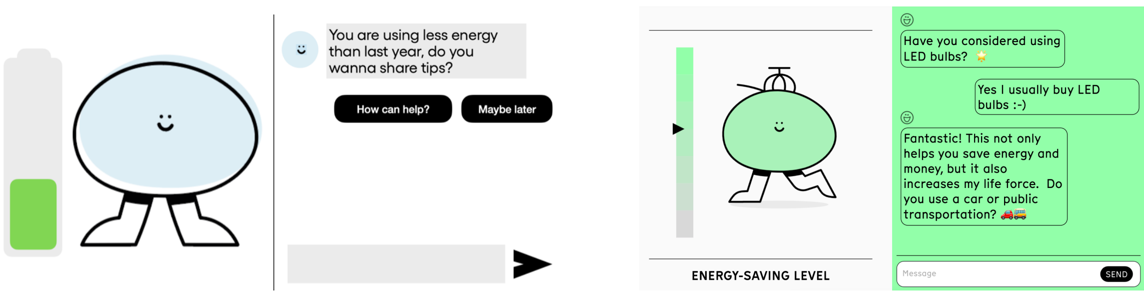
Second, we used data from wave 2021 of SHEDS, which contains data from around 4,250 respondents. Among others, SHEDS collected information regarding personal and household characteristics, dwelling, and annual electricity bills. We performed a hierarchical clustering on these data and selected the number of clusters using the Calinski-Harabasz index. We obtained five clusters, whose characteristics seem relevant in determining electricity consumption level and patterns. In particular, the clusters differ significantly according to household size and number of children, residential status (tenants or owners), and the respondent's age.

WP1: Solution design

The participatory design task started in Year 1 with several notable achievements. We conducted a first half-day Co-Design workshop (see Figure 2 below) with 9 participants including our partner from the utility provider. The workshop was led by professional user experience designers. The primary objective of the workshop was to initiate the participatory design task by (1) better understanding electricity consumption behavior and goals and (2) ideating over potential feedback design solutions to help consumers reach these goals. The activities of the workshop generated discussions and artifacts (e.g., drawings, voting, post its), which were collected and analyzed. The results, combined with insights from scientific literature on eco-feedback were used to design a first feedback concept for the INFINEED system. In particular, we chose to pursue a care-based approach, where energy-saving is shown as the lifeforce of a digital avatar, called INFI, similar to a Tamagotchi (see Figure 3 below). That is, the more energy is saved by the user, the more energized the avatar's life force. The goal of this design is twofold. First, the goal was to show the reduction of consumption as a positive metric, that is the more you reduce, the more the metric (the avatar life force) increases. This is visible in Figure 4 as you move from an avatar with a low level of life force on the far left, to a high level of life force on the far right. Second, the goal was to create some emotional attachment to the feedback system to make it more appealing and potentially more effective. The initial designs also include a conversational interaction feature, powered by a Generative AI system. The goal of the feature is again twofold. First, it can convey information to consumers about energy saving tips in a piecemeal fashion rather than through a potentially overwhelming fact sheet. Second, it can provide increased emotional attachment to the system.

We have started an iterative and incremental process to validate and improve the design through extensive pilot testing with online participants followed by analyses and discussions with designers and researchers. For instance, we have iterated through five online experiments with 150 users per pilot to adjust the conversational interaction through prompt engineering. Then we have evaluated how the care-based designs enhanced with conversational interactions can increase emotional attachment and potential energy saving behavior through a larger online experiment (N=450). Our preliminary findings suggested that our approach enhances emotional attachment and subsequently increases users' willingness to adopt energy-saving actions. As such these findings provide a promising starting point on which to build the full eco-feedback system design which will integrate social and monetary incentives for the field experiment in Year 2.

Figure 2. Co-design workshop



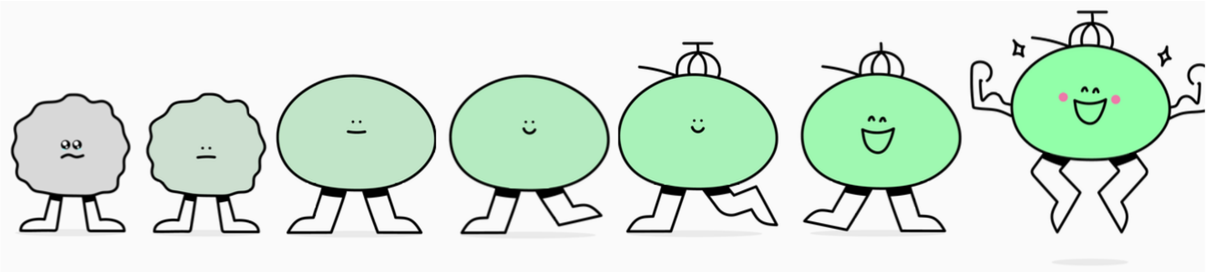


Figure 3. Initial care-based eco feedback design mockups. The Avatar of the system, called INFI visualizes the energy saving level. The more consumers save energy, the more life force INFI receives.

WP2: Choice experiment and user survey

The first survey and choice experiment (DCE 2023) has been completed. We plan a second survey and a choice experiment immediately before the FE (DCE 2024), on a sample of La Goule's customers who will thereafter be invited to participate in the FE. DCE 2023 benefits from all information collected in SHEDS, not only from wave 2023 but also former ones. Further specific questions were formulated to tailor individual social comparisons and were given to respondents immediately before the choice tasks. We also included follow-up questions after each task to capture insights into the participants' intentions and motivations. Lastly, we added questions related to specific psychological attitudes regarding environmental concerns to uncover the underlying drivers behind the participants' preferences. We ensured the DCE is concise yet comprehensive, minimizing potential participants fatigue. Figures 4 and 5 illustrate a sample choice task in two situations.

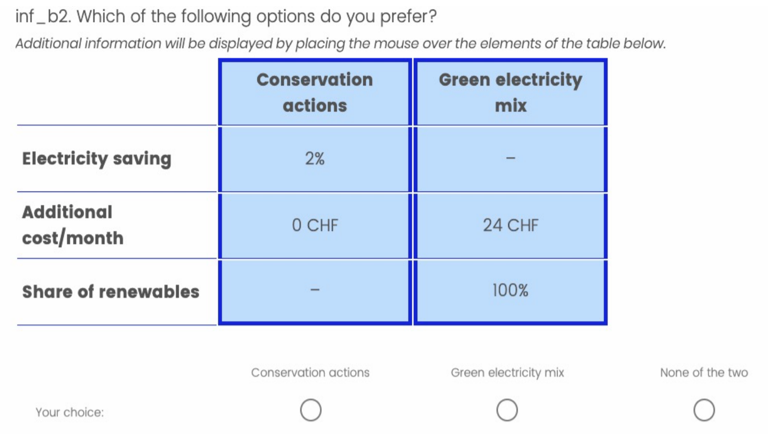
inf_a2. Which of the following options do you prefer?

Additional information will be displayed by placing the mouse over the elements of the table below.

	Conservation actions	**Efficiency investment**
Electricity saving	8%	11%
One-off price	0 CHF	160 CHF

	Conservation actions	Efficiency investment	None of the two
Your choice:	○	○	○

Figure 4. Choice task – situation A.



inf_b2. Which of the following options do you prefer?

Additional information will be displayed by placing the mouse over the elements of the table below.

	Conservation actions	Green electricity mix
Electricity saving	2%	–
Additional cost/month	0 CHF	24 CHF
Share of renewables	–	100%

	Conservation actions	Green electricity mix	None of the two
Your choice:	○	○	○

Figure 5. Choice task – situation B.

DCE 2023 is composed of six choice tasks which were presented to 621 respondents. For each task, they faced a trade-off between various energy-related decisions: conservation actions, investing in efficiency, opting for green electricity, or simply maintaining their current consumption (status quo). To discern the nuanced effects of social comparison and framing, we divided the participants into three groups – one control group and two treatment groups, each randomly assigned. The first treatment group was exposed to a social comparison that provided them with information on whether their consumption was higher or lower than that of similar households, framed in terms of kilowatt-hours (kWh). The second treatment group experienced a similar comparison, but the framing was done in terms of Swiss Francs (CHF) instead, thus adding information on monetary savings. Additionally, to understand the underlying mechanisms operating throughout the decision, a variety of control variables were included, covering socio-demographics, dwelling characteristics, energy literacy, values, norms. This design allowed us to estimate the specific impact of different social comparisons and framings on household energy decisions.
Globally, social comparisons produce mixed results. When socially compared, households who consume less than average are more motivated to commit to conservation actions. However, for those who consume more than average, the social comparison leads to lower preferences for electricity reductions. Further introducing monetary information affects individuals' intrinsic motivation to act sustainably. When presented with monetary gains associated with their choices, participants seem less motivated by their intrinsic or internal reasons to act sustainably.

Given that monetary information can reduce intrinsic motivation, it is vital to carefully design any financial incentives or information campaigns. Social comparisons can be an effective incentive but need to be used strategically. For households that consume more than average, social comparison would not be recommended as it may discourage them. For those consuming less than average, social comparison can act as a motivating tool.

WP3: Field experiment

This WP will formally start next year. However, the involved researchers have already started to work on it. Thanks to some explorations described in WP0 and to results from WP1 and WP2, we already have a preliminary design that should be assessed and finalized before the FE (more on this in section 5 below).

Evaluation of results to date

Thus far, the results of WP0 are based on preliminary analyses obtained on a subset of the existing data. Our analyses nevertheless already point to several observations that are encouraging and helpful for the rest of the project and other WPs: First, the issue of missing values is not as considerable as we had expected. The daily reading procedure helps mitigate the problem for our study. However, the issue remains a fairly significant obstacle for high-frequency data such as hourly consumption, as well as for applications such as accurate estimation of load profiles. The performed analyses suggest a great potential for ML models as opposed to simple averaging based on previous average values.

With respect to usage profiles and saving potentials, the results remain inconclusive. While suggesting three distinctive clusters based on load profiles and an indicative number of fundamental variables for a clear segmentation, the estimation of saving potential remains a challenge requiring further analysis. As far as our FE is concerned, we favor reasonable approximation based on large reference groups with a limited number of variables. The main candidates are household size, type of heating equipment and dwelling ownership. We continue the research on user profiles and saving potentials with complete SM data. We aim at a triangulation strategy linking results from SM data with household survey data (here, SHEDS). We will moreover benefit from the full dataset from La Goule, which not only contains SM data but also provides some socio-demographic characteristics (in particular heating system, geographic location, and type of electricity product) to investigate relationships between the cluster analyses conducted independently on the two types of data.

From the first co-design workshop, most of our preliminary observations point to the importance of simplicity of intervention design. A tedious design with too much quantitative information could be extremely counterproductive. There is also a fairness criterion as far as financial rewards are concerned. Moreover, if failing to achieve an ambitious saving goal results in no reward, the respondents might choose more modest goals.

DCE 2023's findings point to significant moderating effects of social norms and environmental values on individuals' preferences regarding sustainable actions. Moreover, we find that social comparisons and monetary incentives could show some opposing effects. The effects on tradeoffs between conservation actions and purchase of green electricity appear to be relevant and should be further investigated in DCE 2024 and the following FE.

Next steps

The project's 2nd year has started with great progress in solving the administrative issues regarding access to SM data. The next step here is to get regular access (ideally a "real-time" access) to SM data from La Goule's residential customers. Given the technical restrictions and administrative constraints this access could be limited to weekly intervals, which will be totally compatible with the field experiment In case data can be accessed more frequently, the design of the field experiment could be adapted, but this is not a sine qua non condition.

In order to estimate realistic potential and realized savings for individual households (HH), we need to define a reference group for each HH type. The next step is to use the SHEDS and SM data to define a number of HH typologies based on a number of characteristics. We aim at a maximum size of reference groups in order to have meaningful comparisons while ensuring the number of households in each group remains sufficient to obtain robust statistics for each.

The FE design is in a fairly advanced stage. The design of interventions needs some testing and fine tuning, which is planned for the coming months. In particular we need to assess our feedback messages as well as concrete financial-incentive instruments. In addition to financial rewards for conservation we explore a lottery for promoting participation.

In parallel, we will develop the DCE 2024 building upon the DCE 2023. We adapt the design in order to establish a solid link with the FE especially regarding treatment groups and intervention strategies. The design of FE and DCE 2024 will be complemented by a short questionnaire prioritizing essential variables for our analyses. We do our best not to compromise participation over the study period.

We continue our exploration of various designs. At this stage, after several rounds of internal discussions and tests we favor a design with three groups, respectively representing 1) control group with individual feedback, 2) social-comparison treatment, and 3) social comparison plus financial incentives. We also favor a goal-setting approach based on two complementary definitions: The first one is a quantitative goal that specifies a saving percentage (formulated either in Francs or in kWh), and the second one is a qualitative goal that specifies one or several conservation behaviors (e.g. lowering washing temperature, turning off lights). The DCE 2024 will be based on quantitative goals in comparison with a purchase or upgrading the electricity product to a "greener" electricity. The FE design on the other hand will focus on qualitative goals that are relatively tangible for respondents. The respondents are provided with some information on the relationship between the two measures before responding to choice tasks. The respondents in the financial treatment group are primed to consider financial savings during their DCE.

We work on a promotion campaign in order to attract La Goule's customers to participate in our experience. This will be conducted shortly before the launch of the experience. We will also complete the econometric analysis of the data from DCE 2023, and we will apply our clustering approach to the complete SM data and SHEDS. We plan to present the final results in the next INFINEED's workshop to be organized in May or June 2024.

National and international cooperation

We have developed two collaboration channels. The first one is a collaboration with a research team from University of Bern, working on another EES project SMART. The exchange between the two research teams allowed us to share experience regarding targeted interventions. The second channel is a cooperation with SWEET CoSi in order to use the SHEDS survey. We have integrated the DCE 2023 in SHEDS. We will continue this cooperation in order to utilize the synergies between the two projects regarding behavioral change and energy conservation.

Publications

Three publications are planned to be prepared by the middle of 2024. The first one is on sustainable behaviors leveraged by design. The second publication documents the results of our first DCE, which will appear as a working paper by the end of 2024. The third one will be a working paper by the end of 2024 on the clustering of load curves derived from residential consumption data from La Goule.

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