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Federal Department of the Environment,
Transport, Energy and Communications DETEC

Swiss Federal Office of Energy
Energy Research and Cleantech

Interim report from 21 October 2024

INFINEED

The Interplay of Feedback and Incentive Effects on Electricity Demand

Source: own design

Publisher:
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SFOE contract number: SI/502530-01

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.

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.

Contents

List of abbreviations

CoSi	Co-Evolution and Coordinated Simulation of the Swiss Energy System and 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 2023)
DCE 2024	The DCE conducted in 2024 (prior to the field experiment)
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
PV	Photovoltaic
RP	Revealed Preferences
RQ	Research Question
SCCER	Swiss Competence Centre for Energy Research
SEP	Swiss Energy Park
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

1 Introduction

1.1 Context and motivation

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; Cellina et al., 2024). For instance, in the case of commitment devices, which are tools that individuals voluntarily use to help achieve their goals (Rogers et al., 2014), 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. Individual feedback and energy saving tips via digital devices have been found effective in the short run, but with no long-lasting effect (Cellina et al., 2024).

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 Project 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-type, linked to significant reductions in energy consumption. That is followed by the goal-setting interventions that are also considered 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.

2 Approach, method, results and discussion

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 (WP1) builds on pre-processed data (WP0) and 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). Below, we present the state of each Work Package at the end of Year 2.

WP0: Understanding usage and saving potential

WP0 focused on the consumption data preprocessing (missing data, usage profiles and potential savings). It started in Year 1 and was completed in Year 2.

Missing data

SM readings contain a non-negligible share of missing data. In Year 1 we used a set of high-frequency SM data from about 6'000 households over five years to develop a model for imputing missing values. We use SM readings as well as anonymized consumer details with some relevant household characteristics, for about 6'000 households over a five-year period from 2018 to 2023. These households are private clients of La Goule. The 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.

While the missing data remain an important issue in high-frequency estimates such as hourly consumption, our assessments suggest that the most important factors influencing the volume of missing data impacting our project are related to the data processing and data transformations by La Goule.

In Year 2, following these observations, we collaborated intensively with La Goule, Swiss Energy Park, and HE-Arc researchers towards developing a methodology to handle smart meter consumption so that missing data are plausibly and robustly filled. Eventually, this collaboration made it possible to establish a smooth and efficient process, whereby smart meter consumption data are extracted once a week from La Goule's database, and made available to us. Eventually, the issue of missing data has therefore not been consequential for our daily estimates of consumption and weekly estimates of savings used in WP3.

Usage profiles and realized saving

In the field experiment (FE), realized savings (rather than potential savings) are provided as feedback to the participants and used to rank them accordingly. Because of seasonal variations and other external factors influencing electricity consumption, determining savings requires a reasonable methodology whereby each participating household is compared to a reference group of comparable households that do not participate in the experiment.

In Year 2, we refined this methodology. We use historical electricity consumption (from SM readings) to cluster households into comparable segments. Ideally, the clustering could be enhanced by socio-demographic data. However, we only had access to a dataset composed of electricity consumption and few other technical variables. Our approach differs from that adopted by a recent study by Mari et al. (2025) in two main respects. First, as opposed to that study we aim at estimating savings for each individual household. Moreover, we use a DiD approach thus abstracting from estimating the effect of external effects such as weather as well as various seasonal and global trends. In particular, the realized saving in each household for a given week is estimated by double-differencing with respect to a reference week and a reference group, in a four-step algorithm described below:[1]

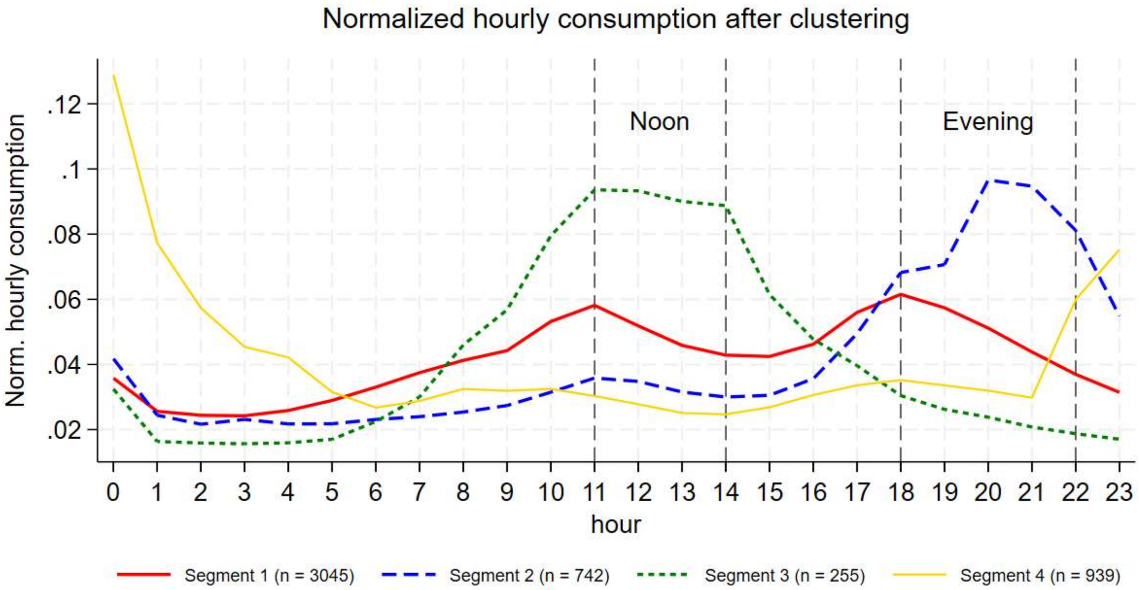
1. We compute the HH's consumption change compared to their weekly consumption in the reference week prior to the experiment (denoted by $Diff_1$).
2. For each HH, we compute the median[2] of the consumption change using all comparable households from the reference group as the counterfactual (denoted $Diff_0$), i.e., the change that would have been observed in absence of treatment.
3. The HH's realized saving is then estimated as the difference $Diff_0 - Diff_1$., i.e., the counterfactual change minus the actual change of consumption in the HH.
4. We compute average savings over the weeks since the beginning of the experiment.

Some days before the FE started, we received from La Goule a dataset with hourly electricity consumption for all their customers (about 5,000 households) over 1.5 years (from the beginning of 2023 to the start of August 2024). We partitioned this dataset using the k-means method, which belongs to the distance-based clustering methods. It is one of the most widely used techniques for clustering high-frequency electricity consumption data, as it is generally quick and easy to implement (Rajabi et al., 2020). This method perfectly applies to our dataset, composed of smart meter recordings for a large number of households. We have explored several clustering variables and compared the results. Extreme variations and the relatively high incidence of missing values prompted us to use daily and hourly mean consumptions rather than extreme values such as daily peak loads. Comparing various clustering strategies showed a reasonable consistency across various specifications. Our final clustering was performed considering six features: mean daily consumption (in kWh), noon (11:00 - 14:00) normalized consumption (in % of daily consumption), and evening (18:00-22:00) normalized consumption, separately for summer (April to September) and winter (October to March) periods.

The Figure below shows the average consumption for each segment identified in the cluster analysis. The consumption is normalized to make it more easily comparable across segments. We observe substantial differences in patterns across segments. The largest segment shows a typical camel-shaped load curve with a consumption spike in the middle of the day and another one in the evening. Segment 2 also has two spikes, but the magnitude of the evening one is considerably larger, whereas the opposite is true for segment 3. Segment 4 has a radically different consumption profile, with a very important night consumption.

[1] The reference week is the week before the start of the experiment (12 to 18 August 2024) and the reference group is selected from all households that are La Goule's customers but do not participate in the experiment. A document providing an intuitive explanation of the savings' calculation is available through the project's webpage: https://infineed.app/wp-content/uploads/2024/09/calculs_savings_expl_participants.pdf

[2] Given the relatively small savings we plan to use the 3rd quartile in the upcoming FE.



Potential savings

An auxiliary objective of this project is to develop a model for estimating electricity saving potential for each individual household. To achieve this, we used all seven waves of the Swiss Household Energy Demand Survey (SHEDS) data from 2016 to 2023. We focus on households' self-reported annual electricity consumption in kWh. After excluding outliers and invalid values, the dataset allows a comparison among 6,302 households. Using three determinants of electricity demand - 4 HH size categories, 3 heating system classes and apartment-vs-house indicator - we specified 24 HH typologies. These data retrieved from SHEDS include many other factors and HH characteristics that could potentially be used. However, our strategy based on 24 typologies allows for a reasonable number of HHs per segment (ranging from 48 to 1,728). In fact, including more variables would imply segments with fewer than 30 HHs. After running several quantile regressions with various specifications for each one of the 24 segments, we converged to a quantile frontier model at 20th percentile (1st quintile) of logarithm of yearly consumption, controlling for location indicators (city agglomeration, countryside, French-speaking region) and dwelling size, as well as household income and respondent's education. This specification gives us the best overall goodness of fit while assuming 20% of HHs in each segment are "perfectly efficient" with negligible saving possibility. The saving potential for the remaining HHs is computed as their consumption difference with the first consumption quintile (the "ideal" HH) in their respective segment. Formally, each HH's saving potential in percentage, is computed as a function of that HH's specific quantile residual (ε), which is the HH's extra consumption (in logarithms) compared to an efficient HH in that segment. Noting the logarithmic specification of quantile regressions, this function can be written as $1-\exp(-\varepsilon)$. A descriptive summary of these savings is given in the table below.

	Household type	Saving potential (median)	Saving potential (mean)
1	House, 1 person, non-electric heating	40%	38%
2	House, 2 person, non-electric heating	40%	36%
3	House, 3 person, non-electric heating	39%	37%
4	House, >3 person, non-electric heating	36%	33%
5	House, 1 person, electric hot water	44%	40%
6	House, 2 person, electric hot water	36%	35%
7	House, 3 person, electric hot water	29%	27%
8	House, >3 person, electric hot water	35%	33%
9	House, 1 person, with heat pump	36%	40%
10	House, 2 person, with heat pump	49%	40%
11	House, 3 person, with heat pump	29%	28%
12	House, >3 person, with heat pump	42%	36%
13	Apartment, 1 person, non-electric heating	38%	35%
14	Apartment, 2 person, non-electric heating	34%	33%
15	Apartment, 3 person, non-electric heating	36%	33%
16	Apartment, >3 person, non-electric heating	36%	34%
17	Apartment, 1 person, electric hot water	45%	40%
18	Apartment, 2 person, electric hot water	43%	37%
19	Apartment, 3 person, electric hot water	46%	44%
20	Apartment, >3 person, electric hot water	42%	37%
21	Apartment, 1 person, with heat pump	35%	34%
22	Apartment, 2 person, with heat pump	33%	32%
23	Apartment, 3 person, with heat pump	35%	34%
24	Apartment, >3 person, with heat pump	38%	38%

The estimated savings suggest that a majority of households in each segment could achieve significant savings, with an overall average saving of 27 to 40 percent, depending on the HH segment. Part of these reductions might however be related to factors beyond the households' control such as outdoor temperature. In other words, there is a strong within-segment heterogeneity among individual households, which could bias savings-potential estimates. This implies that the clustering could be improved with larger samples allowing more homogenous segments of a reasonable size (e.g. 50 HHs per segment). In fact, the measure of our model's goodness-of-fit (pseudo R-squared) is quite variable, ranging from 5% to 44% depending on the given segment. In order to avoid an overestimation of aggregate savings through unobserved heterogeneity, we propose to focus on specific savings that are plausible in the short run. Based on the individual saving estimates, we can compute the share of households that can achieve a given reduction such as 10%. The following table lists the share of HHs in each segment that can achieve a 10% or 20% reduction in their electricity consumption. According to these estimates a majority of households (more than 2/3) can achieve 10 percent savings.

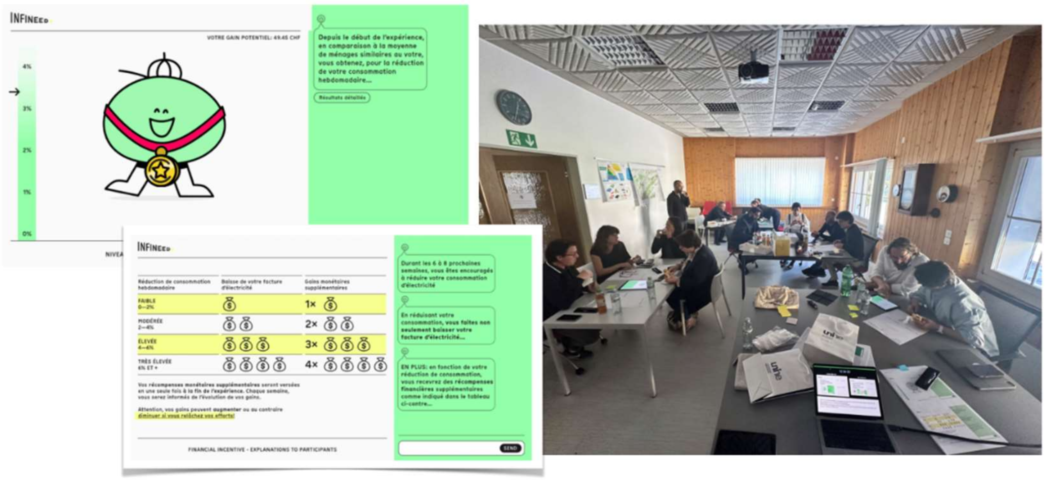
Household type		Fraction (%) of households that can achieve 10% or 20% reduction in their electricity consumption	
		10%	20%
1	House, 1 person, non-electric heating	77%	71%
2	House, 2 person, non-electric heating	75%	68%
3	House, 3 person, non-electric heating	73%	67%
4	House, >3 person, non-electric heating	72%	68%
5	House, 1 person, electric hot water	72%	69%
6	House, 2 person, electric hot water	74%	66%
7	House, 3 person, electric hot water	68%	59%
8	House, >3 person, electric hot water	70%	67%
9	House, 1 person, with heat pump	60%	55%
10	House, 2 person, with heat pump	72%	68%
11	House, 3 person, with heat pump	67%	62%
12	House, >3 person, with heat pump	71%	66%
13	Apartment, 1 person, non-electric heating	74%	68%
14	Apartment, 2 person, non-electric heating	75%	67%
15	Apartment, 3 person, non-electric heating	71%	63%
16	Apartment, >3 person, non-electric heating	72%	64%
17	Apartment, 1 person, electric hot water	74%	67%
18	Apartment, 2 person, electric hot water	74%	66%
19	Apartment, 3 person, electric hot water	72%	69%
20	Apartment, >3 person, electric hot water	73%	70%
21	Apartment, 1 person, with heat pump	68%	64%
22	Apartment, 2 person, with heat pump	70%	64%
23	Apartment, 3 person, with heat pump	73%	68%
24	Apartment, >3 person, with heat pump	70%	66%

Overall, the results suggest that a reasonably accurate estimation of saving potential for an individual HH requires large samples that can allow a much greater number of HH segments. In this context, given the relatively small number of FE participants in our study, we can conclude that individual feedback about a specific HH's saving potential is not realistic. We therefore propose to use generic feedback for all HHs based on generally available information as illustrated in figure below.

Mesures d'économies	Economies d'électricité	
Éteindre les lumières en quittant une pièce	1 – 2%	★
Augmenter la température du réfrigérateur/congélateur	1 – 2%	★
Ne pas préchauffer le four	1 – 2%	★
Cuire vos aliments avec un couvercle	1 – 2%	★
Utiliser le lave-vaisselle/lave-linge rempli entièrement	2 – 3%	★★
Utiliser le lave-vaisselle/lave-linge en mode éco	2 – 3%	★★
Débrancher les appareils électroniques	3 – 4%	★★★
Sécher les vêtements à l'air libre	5 – 8%	★★★★

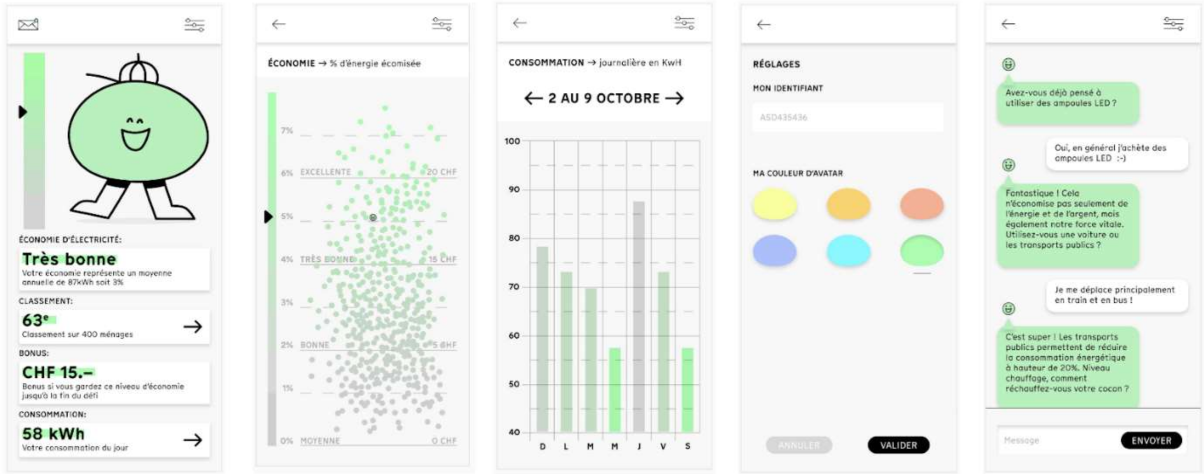
WP1: Solution design

The participatory design task and the implementation task started in Year 1 (see INFINEED's first interim report dated 30.09.2023) and have been completed in Year 2. We adopted an iterative and incremental agile development approach, incorporating feedback in frequent cycles to refine the user experience (we started early with proof of concept implementations of the designs to get a sense of the system). A second participatory design workshop (see image below) was conducted with 12 stakeholders at La Goule, where we explored various design aspects of the mobile app, including different conditions such as monetary incentives and social scoring. The workshop highlighted that statistical data like the percentage of electricity saved or kWh might be challenging for users to understand. Therefore, it is essential to present qualitative textual information on electricity savings (e.g., "Excellent savings," "Good savings," "Moderate savings," or "No savings"). Nonetheless, it was agreed that including kWh information remains important for raising user awareness about their energy consumption.



The workshop also gathered feedback from specialists at La Goule regarding the app's chat interaction, specifically addressing concerns around potential hallucinations from the generative AI component. The feedback was generally positive. However, it was suggested that we further enhance the chat interaction by providing specific tips and more detailed project information. This input was integrated into the subsequent design of the app.

The figure below shows the final mockups of the mobile app for the full condition (with social and monetary incentives). The home screen (first screen on the left) shows Infi, the user's avatar that represents the level of energy saved. The more energy is saved the more life energy Infi has. Next to Infi is a gauge that shows the level of energy saved in an abstract sense (we removed numbers/percentage form the gauge following feedback from the workshop). This screen also summarizes the level of savings qualitatively (e.g., "Très bonne"). Then it offers a section on social ranking that shows the user's position compared to similar households (e.g., 15th among 52 households). Then a section on monetary rewards is displayed (e.g., CHF 10) that indicates how much reward the user would get if they continue saving as they have done so far. Finally, there is a standard consumption section that shows the number of kWh consumed. When clicking on the first three sections users get to the second screen where the savings are displayed visually on a scale with visualizations of thresholds that combine percentages, qualitative indicators, social comparison and monetary rewards. When clicking on the last section, the user gets to the third screen which shows a standard electricity consumption graph that users expect to have on a smart meter app. In addition to these core features, users can change the color scheme of the app in the settings pane (4th screen) by pressing the settings button (top right of the home screen) and a chat screen (5th screen) by pressing the chat button (top left of the home screen).



We have since implemented these design solutions in a web-based Android application, supported by an analytics backend. The code was subsequently ported to two native mobile applications for iOS and Android. The app's backend was deployed on an Azure server to ensure scalability and accessibility throughout the field experiment.

Significant efforts were made to design and implement the infrastructure required for the field study. This pipeline enables users to access their weekly electricity consumption data by linking their app login information to their La Goule account. To enable this link, participants were asked to share their phone numbers during the field study signup, which were then used as their app login credentials. La Goule matched these phone numbers (along with additional names and addresses that we collected) with their client IDs, allowing them to send us weekly electricity consumption data. The pipeline is also required to define a procedure to process the data, update it in the database, and share the update with participants.

For participant updates and communication, we opted to use SMS as the primary channel. Each week, we sent batch SMS messages to all participants to inform them of updates regarding their electricity consumption and other relevant information. Finally, we have also designed a project website for dissemination purposes: https://infineed.app

WP2: Choice experiment and user survey

The SP evaluation stage consists of two discrete choice experiments (DCE): The first (DCE 2023) was conducted on a subsample of 621 respondents from SHEDS 2023. The second (DCE 2024) was conducted prior to the field experiment (FE) in 2024, on a sample of 280 respondents including 261 respondents from La Goule's customers. DCE 2023 contains two social-comparison treatment groups: one framed in terms of kilowatt-hours (kWh) and the other in terms of monetary savings. The design of DCE 2024 has been elaborated based on the results of DCE 2023 and the lessons learned from that experiment. We streamlined our treatments focusing on social comparison and dynamic social norms. The actual number of participants in DCE 2024 and the FE was below our expectation. We observe an especially low participation rate for the FE, with 164 participants. Given the low response rate, we plan to repeat the FE in the Winter. This allows us to increase the sample size used for DCE 2024.

DCE 2023 sheds light on the effects of social comparisons and financial information on preferences for three sustainable actions: conservation, investment, and purchase of green electricity. The results suggest that social comparisons are effective only in one specific situation: increased preferences for *conservation actions* among HHs with below-average consumption, with no detectable effect for *efficiency investment* and *green electricity*. The results provide suggestive evidence of crowding out for financial information: First, adding financial information alongside social comparisons adversely affects the below-average consumers away from sustainable behavior. Secondly, individuals who perceive conserving energy as important respond negatively to financial information, as if they would not appreciate being perceived to save electricity for financial purposes. Concerning HHs with above-average consumption, who have presumably the greatest potential for savings, both types of comparisons result in higher preferences for *no action*. These households respond negatively to comparisons. However, the inclusion of financial information may attenuate the negative effects of social comparisons, suggesting a crowding-out effect but in an opposite direction.

Overall, DCE 2023 illustrates that incentivizing households' behavior could be challenging, with a limited effect for social comparisons and an asymmetric crowding-out effect for financial information. These results prompted us to explore alternative interventions that leverage the power of social norms. Given that social comparisons might fail to enhance preferences for electricity conservation––particularly among HHs with above-average consumption—we propose a different approach to social norms that emphasizes change. Instead of providing normative information about the current situation, we aim to inform that the context is evolving and specify the direction of this change. Drawing upon an emerging literature, we refer to this type of normative feedback as *dynamic norms*. We focus on two treatments as illustrated in the figure below.

Energy security	**Climate change**
According to a recent survey, more and more Swiss are concerned about energy security and are committed to saving electricity.	According to a recent survey, more and more Swiss are concerned about climate change and are committed to saving electricity.

There are theoretical grounds for dynamic norms to facilitate behavioral change. Psychological barriers that prevent individuals from adjusting their preferences include perceived capability, importance, and consistency. Dynamic norms enhance the salience of the potential for change, which may encourage individuals to reconsider these psychological barriers. Therefore, the primary objective of the DCE 2024 is to estimate the effects of dynamic norms on households' preferences for electricity conservation. Additionally, given the importance of electricity conservation for ensuring the energy supply security and, more broadly, for mitigating the effects of climate change, we evaluate how the effects of dynamic norms differ based on whether the focus is made on energy supply security or climate change.

The designs of the choice task in DCE 2023 and DCE 2024 are similar, with a significant difference related to labeling. In DCE 2023, the alternatives were labeled as three electricity-saving strategies: *conservation actions, efficiency investment,* and *green electricity*. In contrast, the options presented to in DCE 2024 are unlabeled and are based on three attributes as shown in figure.

Electricity savings [%]	2; 5; 10; 15; 20
Price [CHF]	0; 100; 500; 1000; 3000
Effort	Low; Moderate; High

Respondents are asked to make a trade-off between more ambitious saving goals and the associated higher investment costs and effort. They make six choices among four options (A, B, C, or no saving). Prior to the choice situations, participants are randomly assigned to one of the three groups: one control group and the two dynamic norms groups. We hypothesize that participants exposed to dynamic norms will select higher saving goals, investments, and effort levels. Furthermore, we expect that the focus on climate change, which is more prominent in public debate than energy security, will have a stronger impact on households' preferences.

In addition to the experiment, the survey includes various questions regarding demographic and housing characteristics, as well as individuals' phone usage, energy literacy, values, norms, beliefs, and attitudes toward environmental preservation and resource conservation. This information will help us to understand the preferences stated throughout the DCE. Furthermore, we can anonymously match the answers from the survey with the smart meter electricity consumption data. Every participant in the FE has previously completed the survey. Finally, we conduct a survey at the end of the FE to gather suggestions for enhancing the next wave (Winter edition) and to assess how participants interact with the smartphone application and the avatar Infi. Importantly, participants are asked to reflect on the feasibility of the savings goal they previously set and to establish a new savings goal based on the experience gained during the experiment.

WP3: Field experiment

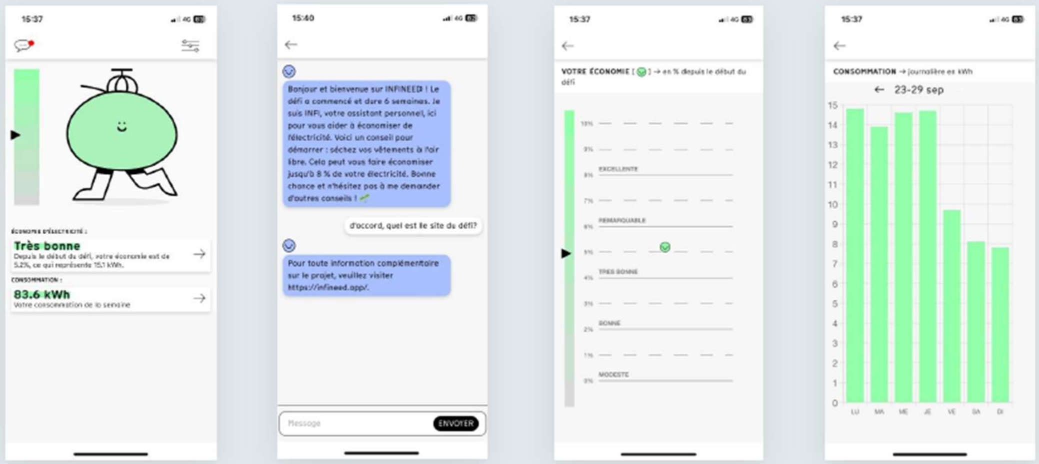
The field experiment took place in August and September 2024. Before that, we organized a promotional campaign to recruit as many participants as possible. The invitation to participate was formatted as an attractive flyer designed with the help of a professional designer. It enclosed a QR-code allowing the participants to register to the experiment. A number of lottery prizes were available to the participants: 20 Galaxus vouchers worth CHF 100 each and an electric bike worth CHF 3,000. La Goule sent the flyer to all its customers with its June 2024 invoice. Moreover, the flyer was sent to the letterboxes at the beginning of August to all households in the concerned regions. Posters were placed in the train stations of the localities concerned, and flyers were distributed in the street at the same occasion. A press conference was held for all the relevant media in the region (television, newspapers). An official letter was sent to all the municipalities to encourage their citizens to participate in the project. Finally, a social media campaign was set up, mainly using the project’s Facebook page, posts on the villages' Facebook pages, and the social media of the University of Neuchâtel and HEG Geneva. A professional promotional video (https://youtu.be/sT9xFOcqSy8?si=zy0mvXVK14yAAFUB) was widely distributed through these channels. Our website (www.infineed.app) has also been an essential way to encourage participation and provide information.

Registration for the experiment was possible until the 11th of August 2024, by completing the initial questionnaire. The survey was distributed anonymously and open to anyone, but the following conditions were mandatory to participate in the field experiment: be a customer at La Goule and provide personal information allowing identification (in particular an address and a phone number). The identification data were then sent to La Goule for validation and linked to their smart meters and consumption data. All respondents who were not recognized as La Goule customers or could not be linked to their consumption data for technical reasons were excluded from the next part of the experiment. For technical reasons, only one INFINEED app account per household could be created. Around 301 respondents completed at least 94% of the initial survey (a level allowing us to contact them again if necessary, using their email addresses). Of these 301, 200 met the above-mentioned conditions and were included in the field experiment. Eligible participants were randomly allocated to the treatment groups using a stratified sampling based on age, household size, and segment belonging (obtained from the cluster analysis described in WP0).

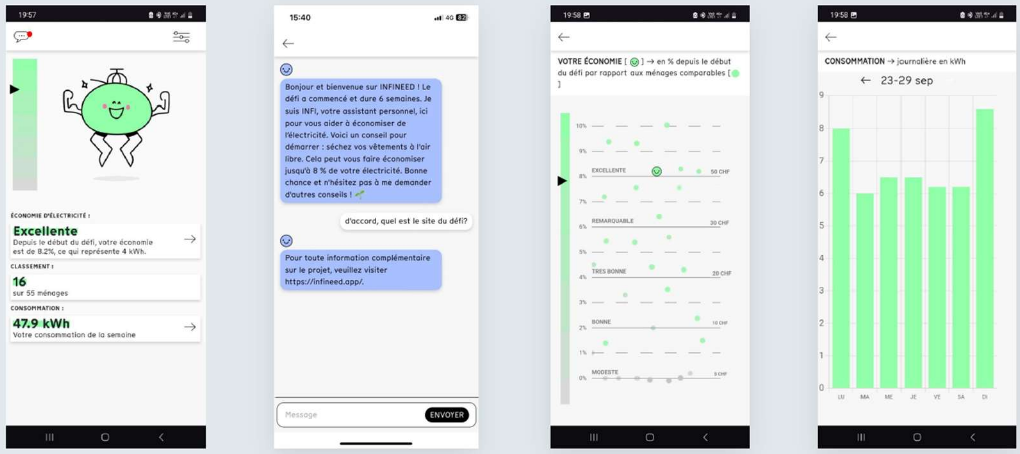
One of the main objectives of this project is to determine the effect of financial and social incentives and their interaction on electricity consumption. It was therefore planned to have a control group, a group with a financial incentive, a group with a social comparison, and a last group with an interaction between the financial and the social incentive. However, because of the relatively small number of registered and identified participants, we finally had to drop the financial incentive group. Indeed, we preferred to drop one group while increasing the probability of detecting clear treatment effects for the remaining groups.

The treatments (group 1 = control, group 2 = social, group 4 = social + financial) consisted of a series of information related to electricity consumption and electricity savings made available through the application (see the three Figures below). All participants (including the control group) received information about their weekly and daily electricity consumption and the savings (in %) they had made since the start of the experiment. They also had access to the chat, which could provide them with personalized advice. In addition, participants included in the social incentive group were ranked according to their electricity savings with all the participants in the same segment. Participants included in the social and financial incentives were not only ranked along participants in the segment but in addition incentivized to save electricity with the following rewards: depending on the savings achieved at the end of the experiment (0-2%, 2-4%, 4-6%, 6-8%, >8%), they received a (supermarket) voucher worth CHF 5, 10, 20, 30, 50.

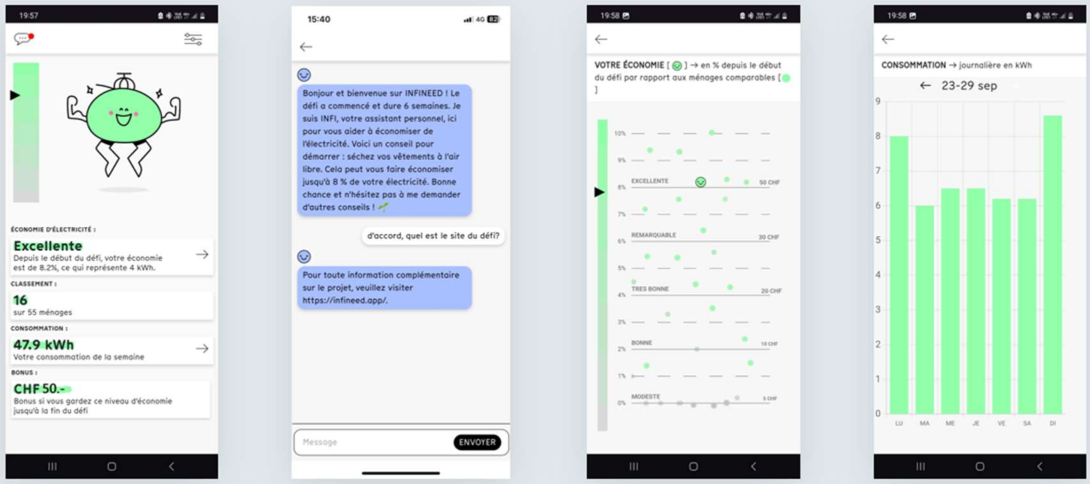
Group 1 - Control



Group 2 - Social



Group 4 – Financial + Social



Calculating electricity savings is less obvious than it might first seem. Indeed, because of seasonal factors and other external factors, it is meaningless to simply compare consumption from one week to the next. Electricity consumption is expected to naturally increase from August to September (and after), in particular because daylight is decreasing and external temperature is falling. Determining savings therefore requires a strategy whereby a counterfactual is estimated. Towards this end, we use the more than 4,000 households who are customers at La Goule but did not participate in the field experiment. These households compose what we call the “reference group” to distinguish them from the households in the control group. The difference between these two groups is that the former do not have access to the application and do not receive any information from us while the latter has access to the app and minimal information as discussed before. The reference group is used to estimate a counterfactual during the field experiment, while the control group will be used to estimate treatment effects in the econometric analysis.

As explained above, we use a DiD approach. Namely, using the reference group, we proceed as follows to construct counterfactual consumption for each participating household. For each segment, we compute the median (in FE1) or 3rd quartile (in FE2) change between two consecutive weeks: this is the expected evolution of electricity consumption in absence of any intervention. Assuming that changes in external conditions such as weather and temperature are the same for a given HH participating in the experiment and the counterpart HHs in the reference group, there is no need to further control for these variables. For each participating household, we thereafter compute savings as the raw savings achieved between two consecutive weeks by this specific household (this value is negative in case consumption increases) to which we *add* the median change from the reference households in the same segment. Finally, the savings reported in the app are the average weekly savings (in %) since the start of the experiment (mean savings). A measure of these savings is also reported in terms of kWh saved during the experiment.

The experiment ran for 6 weeks, from Monday August 19 to Sunday September 30. It was planned to update the information displayed in the app with data from the week before and to send an SMS to the participants to notify them of the update every Tuesday. However, during the first two weeks of the experiment, we encountered a few minor difficulties:

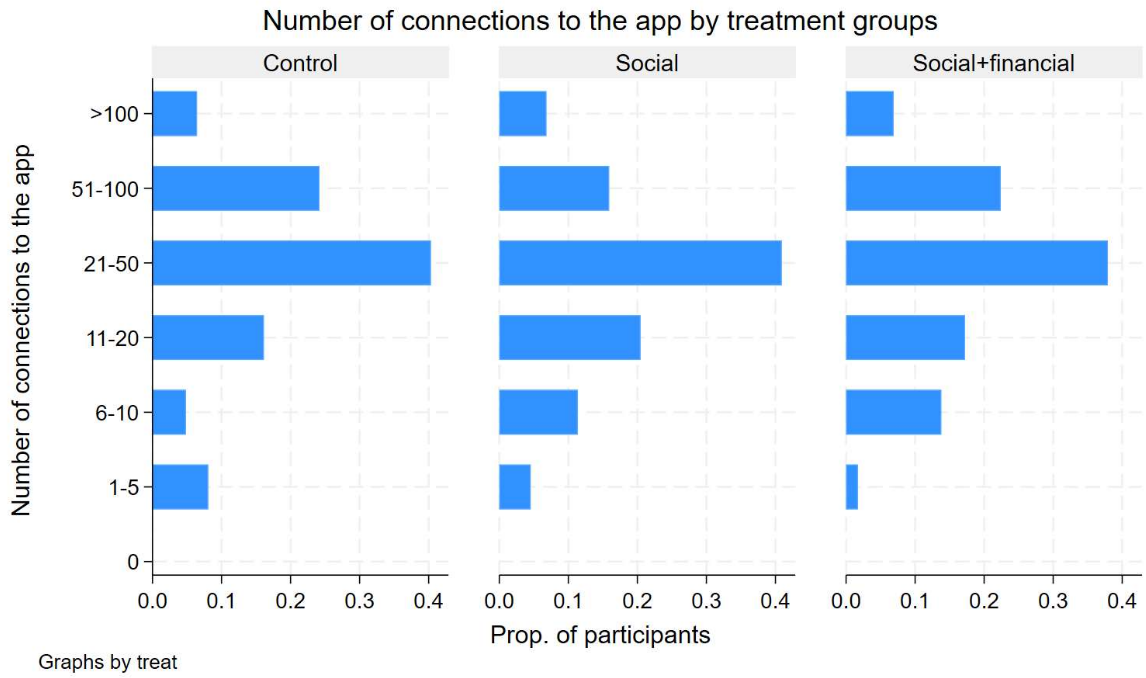
- The first feedback was released on Wednesday, not Tuesday, due to technical reasons.

- According to some of the owners' comments, the PV owners' consumption data appeared to be somewhat inaccurate. After a number of checks and exchanges with La Goule, Swiss Energy Park and HE-Arc, we understood that PV production was simply added to consumption and the data processing was corrected. Because of the time taken by these corrections, we could not update data during the second week.
- Fourteen participants were included only from the third week because they had registered late, were difficult for La Goule to identify, or had given an incorrect phone number at the time of registration.

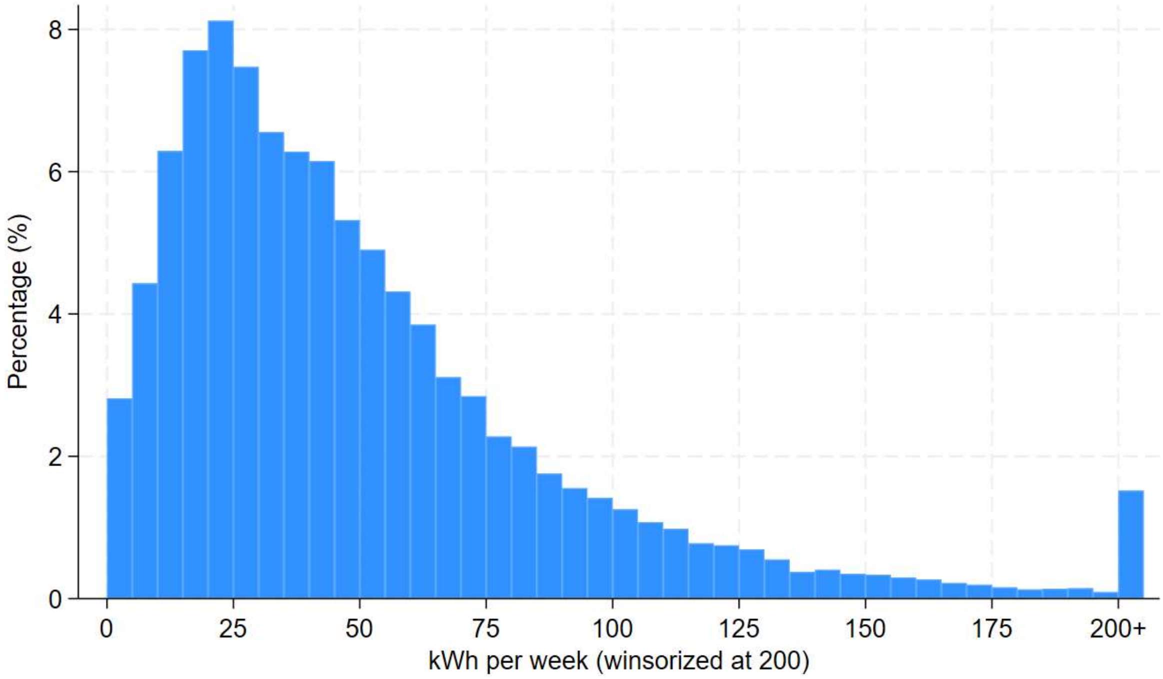
Since the third week, the data preparation process and the application have run as expected and very smoothly. Data updates and SMS have been distributed every Tuesday afternoon since then.

The graph below shows the number of times participants accessed the application during the experiment. The distribution indicates that around 70% of the participants (connected at least once, N = 164) visited the application more than 20 times over the six weeks of the experiment. There did not seem to be any significant difference between the treatment groups in terms of access to the application.

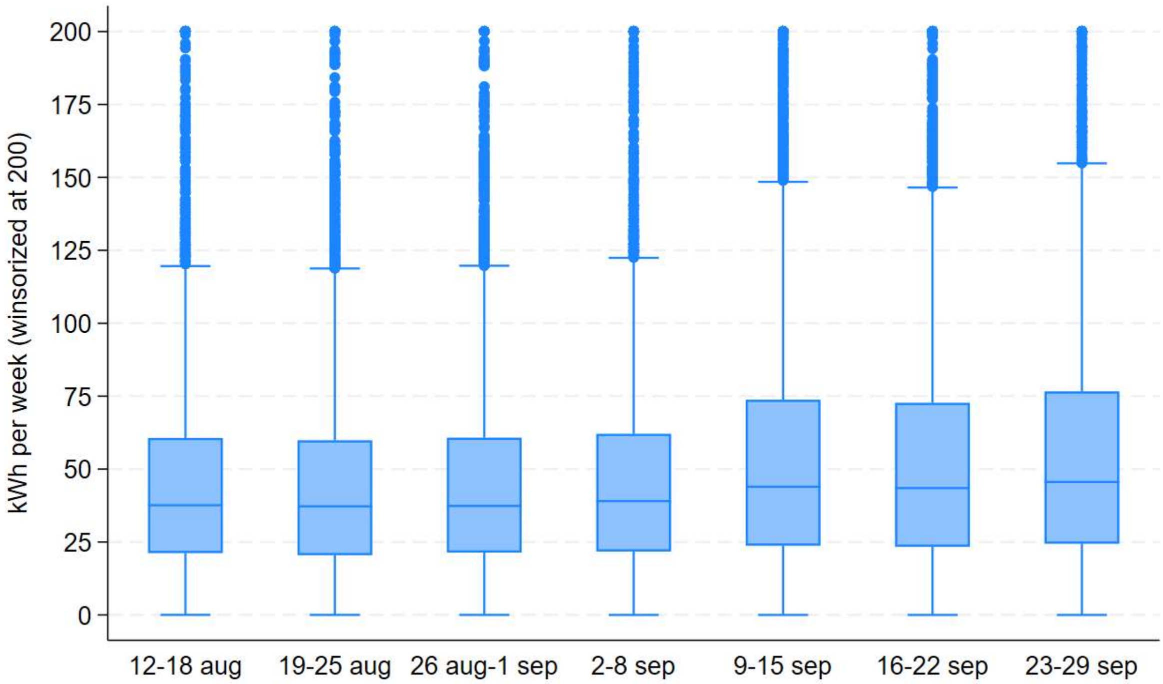
The following Figure shows the distribution of weekly electricity consumption among all households whose daily consumption for the entire six-week period of the experiment was provided by La Goule. These HHs include the FE participants as well as those in the reference group. Median consumption is around 40 kWh/week and mean consumption is 52 kWh/week. Note that this appears to be significantly lower than the Swiss national consumption averaged over the entire year. Given the strong variation of consumption with HH size, heating equipment and seasonal temperature, the relatively low average consumption might be related to any of these factors. This issue will be investigated further in the upcoming FE and discussed in the final report in Year 3.



The figure excludes a small percentage of weeks with one or more zero daily readings. However, there remain some extremely low-consumption days. These potentially erroneous outliers should not affect our saving estimations based on median values.



The next Figure splits the distribution of weekly consumption per week. Note that overall consumption is gradually increasing over the weeks, as expected because of seasonality, rendering the estimation of electricity savings a complex and indirect task as discussed above.



These consumption data and the associated electricity savings are still to be analyzed using econometric models such as difference-in-differences so that the treatment effects of social and financial incentives will be estimated by comparisons with the control group.

After the end of the field experiment, we have moreover taken the decision to re-conduct it a second time in an identical configuration. The rationale and the objectives of this second field experiment are the following:

- Take advantage of and leverage the experience gained during the first experiment, particularly regarding the process of collecting, transforming, and updating consumption data and savings.
- For households who already participated in the first experiment, the aim is to obtain information on consumption behavior and lasting effects, with the opportunity to observe two treatment periods separated by a five-week break.
- Recruit new participants to increase the sample size.
- Make a number of improvements (e.g., improve the precision of the chat and give more importance to the presence of photovoltaic panels during the segmentation analysis).
- Repeat the experiment during a winter period, which could enable households to achieve greater savings since electricity consumption is higher during this period.

Participants from the first experiment as well as new participants will be eligible to join this second field experiment which is planned from November 4 to and December 15, 2024. We have already launched a new promotion campaign.

At the end of the first experiment, participants were invited to complete a survey to obtain feedback on how they had perceived the experience. Two interesting outcomes are already worth mentioning: the response rate to the survey is high, with 129 complete answers (on October 17, out of 200 possible) and almost 70% of the respondents (87 out of the 129 respondents) expressed an interest in participating in the second field experiment. This figure is very encouraging, considering that the participants will be contacted a second time by mail to participate again. Interestingly, 35 respondents also stated they are open for individual phone interviews. We will contact around twenty of these participants to obtain detailed feedback that can be used to improve the second experiment.

3 Conclusions and outlook

The project’s results at the end of year 2 point to important conclusions. First, the missing values in SM readings do not represent any problem in daily estimates of consumption. 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, our study points to an important data limitation due to small-sample problems. The number of FE participants is not sufficient in order to establish saving potential for each individual HH based on a reasonable number of comparable HHs in each cluster. A realistic estimation of saving potential for each individual HH therefore remains an important challenge requiring a counterfactual “best-practice HH”, thus rejecting the feasibility of individual feedback on saving potentials. We instead use generic estimates of savings resulting from specific actions, letting respondents judge whether and to what extent a specific action is feasible in their HH.

The financial incentives and social comparisons embedded in our FE design require a reasonably accurate estimation of realized savings for each individual HH. Here again, we identify a similar trade-off between number of HHs (cluster size) and number of demand determinants (HH characteristics). Our analysis favors large clusters with a small number of determinants over small clusters with a large number of variables. Therefore, we use SM data from all HHs (about 6,000 private clients of La Goule) without any other HH characteristics such as household size, type of heating equipment and dwelling ownership.

The co-design workshops showed the importance of simplicity of intervention design. A tedious design with too much quantitative information could be counterproductive. The respondents are in general sensitive to the “fairness” of financial rewards. Moreover, if failing to achieve an ambitious saving goal would result in the loss of any reward, respondents might choose more modest goals. We plan to conduct interviews with a selection of the FE participants in order to improve our understanding of individual perspectives on possible savings and the behavioral effects of the experience.

The analysis of SP data from DCE 2023 points to significant moderating effects of social norms and environmental values on individuals’ preferences regarding sustainable actions. More importantly, social comparisons and monetary incentives could show some opposing effects, in particular on the trade-offs between different saving strategies. While suggesting a complex interplay of various interventions, these results highlight significant challenges for an adequate design of effective intervention schemes. In particular, there is no evidence that a simple intervention based on financial information or social comparison could be effective in changing consumers preferences toward electricity saving. However, our results suggest that social norms could be considered as a vector for behavioral change. We expect that DCE 2024 will provide further insight into how dynamic social norms could be used to promote electricity conservation.

In any case, conclusive results on the effectiveness of our interventions have to await a careful analysis of behavior observed during the field experiment. The project’s final year (Y3) starts with an intensive phase of data analysis of the FE as well as the post-experiment survey and DCE 2024. In the meantime, we expect to enhance the data via the experiments’ winter edition planned for November-December 2024.

4 National and international cooperation

We have developed two collaboration channels. The first one is a collaboration with a research team from the 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 also used the SHEDS data to elaborate the models for saving potentials. We will continue this cooperation in order to utilize the synergies between the two projects regarding behavioral change and energy conservation.

5 Publications and other communications

Three publications are under preparation at the end of Year 2. The first one (Berney et al., 2024) is on sustainable behaviors leveraged by design, which was presented to the CHI Conference on Human Factors in Computing Systems. The second publication (Giauque et al., 2024) documents the results of DCE 2023, and will appear as a working paper by the end of 2024. The third publication (Favre-Bulle and Weber, 2024) is on the clustering of load curves from residential consumers from La Goule. This paper has been presented at ENERDAY 2024 - 18th International Conference on Energy Economics and Technology, and will be published as a working paper by the end of 2024. In addition to these publications, the proposed model for missing SM data has been the topic of a Master thesis (John, 2023) that uses two LSTM models to estimate missing values based on historical data.

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