New Clean Energy Communities in a Changing European Energy System (NEWCOMERS)

Deliverable 5.2

Success of interventions to stimulate conservation behaviour and load shifting in new clean energy communities

Version: 2.0

WP5: Potential to stimulate conservation behaviour and demand response

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Summary of NEWCOMERS

In its most recent Energy Union package, the European Union puts citizens at the core of the clean energy transitions. Beyond policy, disruptive innovations in energy sectors are challenging the traditional business model of large energy utilities. One such disruptive, social innovation is the emergence of new clean energy communities ("NEWCOMERS").

The possible benefits of these "NEWCOMERS" for their members and for society at large are still emerging and their potential to support the goals of the Energy Union is unclear. Using a highly innovative holistic approach – drawing on cutting edge theories and methods from a broad range of social sciences coupled with strong technical knowledge and industry insight – the NEWCOMERS consortium will analyse European energy communities from various angles. By taking an interdisciplinary approach and through employing co-creation strategies, in which research participants are actively involved in the design and implementation of the research, the NEWCOMERS project will deliver practical recommendations about how the European Union as well as national and local governments can support new clean energy communities to help them flourish and unfold their potential benefits for citizens and the Energy Union.

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Summary of NEWCOMERS's Objectives

As subsidiary objectives, the NEWCOMERS project aims to

- provide **a novel theoretical framework based on polycentric governance theory**, combined with elements from social practice theory, innovation theory and value theory, in which the emergence and diffusion of new clean energy communities can be analysed and opportunities for learning in different national and local polycentric settings can be explored;

- develop a **typology of new clean energy community business models** which allows to assess the different types of value creation of "newcomers" as well as their economic viability and potential to be scaled up under various conditions;

- identify the **types of clean energy communities that perform best along a variety of dimensions**, such as citizen engagement, value creation, and learning, and their potential to address energy poverty, while being based on sustainable business models;

- investigate the **regulatory, institutional and social conditions**, at the national and local level which are favourable for the emergence, operation and further diffusion of new clean energy communities and enable them to unfold their benefits in the best possible way;

- explore **how new clean energy communities are co-designed with their members' (i.e. citizens' and consumers') needs**, in particular whether new clean energy communities have the potential to increase the affordability of energy, their members' energy literacy and efficiency in the use of energy, as well as their members' and society's participation in clean energy transition in Europe;

- deliver **practical recommendations based on stakeholder dialogue** how the EU as well as national and local governments can support new clean energy communities to make them flourish and unfold their benefits in the best possible way;

- offer citizens and members of new clean energy communities a **new online platform 'Our-energy.eu'** on which new clean energy communities can connect and share best practices and interested citizens can learn about the concept of energy communities and find opportunities to join an energy community in their vicinity.

Find out more about NEWCOMERS at: https://www.newcomersh2020.eu/

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NEWCOMERS Consortium Partners

Logo	Organisation	Type	Country
	Institute for Environmental Studies (IVM), Vrije Universiteit Amsterdam (VUA)	University	The Netherlands
	International Institute for Industrial Environmental Economics (IIIEE) at Lund University (LU)	University	Sweden
	Environmental Change Institute (ECI), University of Oxford (UOXF)	University	United Kingdom
	Institute of Social Sciences, University of Ljubljana (UL)	University	Slovenia
	Institute for Advanced Energy Technologies "Nicola Giordano" (ITAE), National Research Council (CNR)	Research organisation	Italy
	RWI – Leibniz Institute for Economic Research (RWI)	Research organisation	Germany
	Consensus Communications (CONS)	Private for Profit (SME)	Slovenia
	GEN-I	Private for Profit (Large company)	Slovenia

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1 EXECUTIVE SUMMARY

Clean energy communities aim to promote renewable energy as well as energy efficiency (Gui and MacGill, 2018; Mlinarič et al., 2019). They are social networks that could create a new social identity among their members, enable social learning about energy conservation and create collective efficacy beliefs. These factors could thereby lead to new environmentally friendly behaviours among energy community members. Initial qualitative evidence suggests that involvement in energy communities may indeed encourage sustainable energy behaviours (Andor et al., 2022; Biddau et al., 2016; Middlemiss, 2011)

In this report, we investigate whether energy communities can (i) increase the impact of behavioural interventions to reduce energy consumption and (ii) change energy consumption patterns in private households. Specifically, we conducted two field experiments in a virtual energy saving community founded by GEN-I, the largest Slovenian electricity utility. The experiments took place subsequent to the rollout of this newly created GEN-I Energy Community, the effect of which on overall electricity use is analysed in Deliverable 5.1 (Andor et al., 2021).

The GEN-I Energy Community consisted of 150 exogenously selected GEN-I customers that were interconnected via an online platform. They were enabled and encouraged to communicate with each other via the platform where they also received energy saving tips, detailed information about their own and the community's energy consumption and were encouraged to find ways to save energy together as a group. A control group of 150 additional customers, selected according to the same procedure as the members of the energy community, got access to a similar platform, which did not contain the specific community-related features that the energy community had. For example, there was no possibility to communicate, no group-level information, and no community framing. Thus, the isolated effect of the energy community can be identified through the comparison of the treatment group, the GEN-I Energy Community, and the control group.

Besides these 300 core study participants, we also obtained electricity consumption data from more than 700 further GEN-I customers. We do not consider these customers as core study participants, as we did not further interact with them during the study and solely analyse their electricity consumption data as additional control group data in parts of the analyses.

In the first experiment, we investigate whether the effect of real-time feedback while showering is enhanced by membership in the GEN-I Energy Community. Showering is a highly relevant subject of study, as it is an everyday activity that involves high energy consumption due to the need to heat up large amounts of water. Real-time feedback is a behavioural intervention that is, in the context of our experiment, provided by shower heads that are able to indicate the water use while showering via coloured LED lights.

The results provide evidence that real-time feedback is highly effective in reducing water and energy use while showering. Our results thus confirm previous findings (for example Tiefenbeck et al., 2018) and extend them, among others, by demonstrating this effectiveness for the first time in an Eastern European country, thus contributing to the knowledge on the generalisability of the effects. Yet, we do

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not find differential treatment effects across energy community members compared to other study participants.

In the second experiment, we examine whether membership in the GEN-I Energy Community results in community members responding better to an incentivised group-level goal to reduce peak electricity consumption than those who were not part of the community. All 300 core study participants were challenged to reduce their peak-time electricity consumption (between 5:00 pm and 9:00 pm) by 10 per cent for one month. If the goal was met in the group average, GEN-I pledged to make a donation for each study participant or energy community member to a charity chosen by the participants themselves by vote on the virtual platform. The goal had to be achieved collectively rather than individually. Thus, for energy community members, the goal was described as a goal of the energy community, while for the other study participants, it was described as a goal for all participants in the study.

The results indicate that the energy community group was able to reduce its electricity use in peak hours on average by 4 per cent, while the other study participants did not reach a comparable reduction. Deeper analysis shows that this effect is mainly driven by the half of the energy community that previously experienced real-time feedback and still did during the challenge. This group reduced its electricity use in peak hours on average by 7.2 per cent, while none of the other groups exhibited a comparable reduction. This suggests that the experience of real-time feedback and membership in the energy community combined lead to these participants also being willing to change their electricity consumption behaviour over the course of the day.

2 INTRODUCTION

The NEWCOMERS project aims to systematically investigate several aspects of energy communities, such as the benefits for their members, the benefits for society as a whole, their governance structure, the different forms that they can take, and their different business models. To this end, research is carried out in six European countries (NL, SE, UK, DE, IT, SI) using a variety of methodologies.

In this report, we analyse whether energy communities can enhance the effects of behavioural interventions aimed at reducing energy consumption or altering energy consumption patterns in private households. Specifically, we analyse whether (i) real-time, appliance-level feedback during showering, which is an energy-intensive everyday behaviour, and (ii) group-level incentives to reduce electricity use at times of day when total electricity consumption is high, do differentially affect energy community members compared to regular households.

An extensive literature has considered the effect of behavioural interventions on stimulating conservation (see Andor and Fels, 2018, and Buckley, 2020, for systematic reviews). While these interventions usually focus on regular customers of energy suppliers, to the best of our knowledge, they have not been applied in the context of energy communities so far. Yet, energy communities have distinct features that make the application of behavioural interventions to stimulate conservation behaviour and demand response very promising. Being part of an

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energy community provides new opportunities to interact with other energy community members, which may contribute to social learning, where people acquire new behaviours through observing and learning from their social environment (Bandura, 1977). Moreover, energy communities allow for testing the combination of new information and communication technologies with interventions that harness the potential of the new social network. Furthermore, framing energy conservation as a group task can lead to a motivational boost to conserve energy, which could also enhance the effectiveness of behavioural interventions. De Ridder et al. (2021) argue for example, that behavioural interventions work best if they are aligned with the pre-existing preferences of the treated persons. Thus, the potential motivational boost that might arise from being part of an energy-saving community could give more weight to the participants' pro-environmental preferences, making them more susceptible to behavioural interventions aimed at energy conservation. One mechanism for such a motivational boost could be that the energy community creates collective efficacy beliefs (cf. Bandura, 2000): Some people may not believe that they can effectively conserve substantial amounts of energy on their own, but they could do so on the group level.

In Deliverable 5.1 (Andor et al., 2021), we analysed in a field experimental setting, how the introduction of a new energy community affected aggregate electricity consumption in private households. Yet, we did not find any considerable effect of energy community membership on electricity conservation. There may be several reasons for this result, some of which could be overcome by the behavioural interventions analysed in this report, so that the energy community could yield energy savings given the presence of these interventions. For example, it could be that total household electricity consumption, which is the outcome variable in Deliverable 5.1, is seen by consumers as very difficult to change unless they get more granular information on their electricity use, such as appliance-level feedback (Brülisauer et al., 2020; Gerster et al., 2021). This more granular appliance-level information is provided by the real-time feedback intervention studied in this report.

Furthermore, it could be that the participants were missing a stronger incentive to reduce their consumption beyond just the potential of monetary savings from reducing electricity consumption, which is small in many cases (Asensio and Delmas, 2015). In addition, it may be more feasible for consumers to reduce their electricity use only during certain hours and, for example, shift some of their electricity demand throughout the day rather than reducing it completely. Such shifts in electricity use can have a strong positive impact on the environment, as hours of pronounced high demand are particularly challenging to meet using energy from renewable sources only. The second intervention studied in this report therefore aims at reducing electricity consumption during peak hours, rather than overall electricity consumption, and introduces an additional incentive at the group level.

Finally, the lack of a discernible effect of energy community membership on electricity consumption in Deliverable 5.1 could indicate a generally high level of efficiency in Slovenian households' electricity consumption behaviour and thus

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limited scope for energy savings through behavioural change. In this case, we would also expect only a weak effect of the behavioural interventions studied in this report. A pronounced effect of these behavioural internals would, in turn, indicate a potential for improvement in energy efficiency in Slovenian households. The presence of such potentials is for example also suggested for German households by the results in Andor et al. (2021).

2.1 Role of this deliverable in the project

Based on a randomised controlled trial and using econometric methods, this deliverable analyses whether membership in an energy community, namely the GEN-I Energy Community, can enhance the effectiveness of behavioural interventions aimed at reducing energy consumption or altering energy consumption patterns in private households. Specifically, we focus on two experiments implemented in our setting of a newly created energy community (see Deliverable 5.1 for more details on the results concerning the effect of energy community membership on overall electricity use). The main aim of these experiments is to deepen our knowledge on the potential of utility founded energy communities to reduce energy consumption and to trigger electricity demand response by private households. Overall, the results from this deliverable complement the findings of Deliverable 5.1.

Furthermore, the additional experiments yield valuable general insights on the potential of behavioural interventions to stimulate resource conservation and load shifting behaviour. In addition, the experiments allow us to investigate potential unintended consequences of such nudges that could, for example, result from moral licensing effects (Tiefenbeck et al., 2013).

2.2 Approach

The experiments analysed in this report are based on a field experimental approach. The study population for these experiments is the same as in Deliverable 5.1. More precisely, the experiments took place subsequent to the rollout of the GEN-I Energy Community, the effect of which is analysed in Deliverable 5.1.

In March 2021, the treatment phase for the first experiment embedded in the setting of the GEN-I Energy Community took place. In this experiment, half of the members of the control group and half of the members of the energy community henceforth received real-time feedback while showering, delivered by smart shower heads that were installed at the outset of the study.

The treatment phase of the second experiment took place in April 2021. All 300 participants in the core study were given the task of reducing their electricity consumption at times of day when overall electricity consumption is high. Specifically, they were asked to reduce their electricity consumption by an average of 10 per cent over a period of one month during the daily peak hours between 5:00 pm and 9:00 pm. The participants were furthermore told that this goal had to be achieved collectively rather than individually. Thus, for energy community members, the goal was described as a goal of the energy community, while for the others it was described as a goal for all participants in the study. If the goal was met, GEN-I pledged to make a donation for each study participant or energy community member, respectively, to a charity chosen by the participants by vote on the virtual

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platform. The participants had the choice between three charities that provide support for critically ill or disabled people.

In this report, the participants' behaviour in both experiments is examined with particular focus on potential behavioural differences between energy community members compared to the other study participants using difference-in-differences approaches.

2.3 Structure of the document

The remainder of this document is structured as follows: The next section provides more detail on the background of the experiments analysed in this report. Section 4 provides a short recapitulation of Deliverable 5.1. The first new experiment is described in Section 5, where the main technology used in this experiment is described (5.1), the experimental design and the data set are introduced (5.2), and subsequently the results are presented (5.3). The second experiment is described in Section 6, where the experimental design and the data set are introduced (6.1) and the results are presented (6.2). Section 7 reports additional survey results on the participants' evaluation of the study and of the energy community. Section 8 concludes.

3 Background

The 2030 goals of the European Union do not only target considerable reductions in greenhouse gas emissions but also aim to increase the shares of renewable energy sources on both supply and demand sides. Additionally, energy efficiency throughout the entire energy chain is set as one of the main goals (European Commission, 2015). This also includes improvements in energy end-use by consumers. However, knowledge about effective actions that policymakers and utilities can take to improve consumers' end use of energy is still incomplete, and more evidence on the topic is still needed. A newer strand of research addresses the question of whether the creation and/or promotion of clean energy communities can potentially trigger large energy saving potentials by creating group level energy saving motivations and enabling social learning about effective energy conservation measures.

In general, clean energy communities are characterised by their aim to promote renewable energy as well as energy efficiency (Gui and MacGill, 2018; Mlinarič et al., 2019). Initial qualitative evidence suggests that involvement in energy communities may encourage sustainable energy behaviours (Biddau et al., 2016; Middlemiss, 2011). Hoppe et al. (2019) document that a non-negligible share of energy community members state that their energy communities contributed to enabling energy savings in their household and that they reduced their energy use since they entered the community. Furthermore, Sloot et al. (2018) find a positive relationship between energy community membership and self-reported sustainable energy behaviours, e. g. energy saving measures, thermostat setting, efficiency of appliances.

However, Sloot et al. (2018) point out that energy community membership is strongly related to pre-existing pro-environmental motivations, which means that the measured relationship between community membership and energy-saving

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behaviour could be biased by unobservable confounders. To avoid such biases, we follow an experimental approach by creating an energy community in cooperation with the Slovenian energy utility GEN-I and by randomly assigning community membership. The effect of this exogenously created energy community on aggregate household electricity consumption is presented in Deliverable 5.1, where the results show that there is no discernible effect of energy community membership on electricity consumption.

3.1 Background on Experiment 1: Real-time Feedback

One explanation for the lack of a discernible effect of energy community membership on electricity consumption could be that total household electricity consumption is seen by consumers as very difficult to change. One potential way to overcome such obstacles is the provision of more granular, immediate, and actionable information about energy use in the household. Gerster et al. (2021) show that, compared to aggregate feedback about household electricity use, continuous appliance level feedback, which allows the household members to identify and monitor the most effective energy conservation measures, leads to additional reductions in electricity use by 5 per cent. Furthermore, Tiefenbeck et al. (2018) show that real-time feedback about the water and energy use while showering could yield energy savings of 22 per cent per shower, which is a massive reduction compared to the effects of other behavioural interventions and which is the reason we chose to apply this intervention in this experiment. The high potential of real-time feedback as a behavioural intervention to reduce resource consumption has been corroborated by various studies, for example Houde et al. (2013) and Tiefenbeck et al. (2019).

Thus, in the first experiment documented in this report, we test whether the energy saving potential of energy community membership, through e. g. additional pro-environmental motivation at the group level or social learning, can be unlocked by providing a provably effective energy saving tool, namely real-time feedback while showering.

3.2 Background on Experiment 2: Load shifting

Given the growing share of electricity from renewable energy sources, total household electricity consumption could potentially become increasingly unproblematic if emission-free electricity is available in abundance. However, one challenge of electricity generated by renewable energy sources is their fluctuation in generation. This usually implies the need for reserve generation plants, which are expensive and often carbon intensive, to ensure the security of power supply in times where renewable energy sources do not provide enough energy to meet demand (O'Connell et al., 2014). This is particularly important during pronounced electricity demand peaks in the evening hours. One solution to this problem are demand response measures – not only by industrial customers but also households. By shifting away electricity demand from peak times, power demand in general can be smoothed (cf. Albadi and El-Saadany, 2008; Kim and Shcherbakova, 2011; O'Connell et al., 2014; Gyamfi and Krumdieck, 2011). Potential benefits of demand response include lower electricity costs as expensive reserves are less needed, higher grid stability and security of supply, as well as environmental benefits such as better land utilisation, improved air and water

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quality and reduced depletion of natural resources (Albadi and El-Saadany, 2008). Although demand response programmes mostly involve financial incentives such as Time-of-Use pricing, voluntary measures can also be implemented. Gyamfi and Krumdieck (2011), for example, conducted a case study in Christchurch, New Zealand, to assess the potential of voluntary residential demand response. To this end, a mail-back survey was sent out, including basic information about the local power supply network. The researchers aimed for information about the household's electricity use during peak hours (activities and appliances), their awareness with regard to the three main issues in power provision (possible outage due to grid congestion, higher pollution by local peak diesel generation and price increase during times of peak demand) as well as their stated willingness to voluntarily shift away demand from peak hours to avoid these issues. Based on this information, Gyamfi and Krumdieck (2011) estimate a potential of 10 per cent reduction for aggregate critical peak demand by voluntary measures. Gyamfi et al. (2013) highlight possible issues of price-based incentives (e.g. Time-of-Use pricing), that could be mitigated using voluntary peak reduction: consumer non-responsiveness to prices, discrimination against households with lower income, and high associated cost for the provision of necessary infrastructure such as in-home-displays and smart meters.

Regardless of which approach is chosen, consumer education is central. Kim and Shcherbakova (2011) state that there is still a large share of people all over the world, who have only very little knowledge about their own electricity consumption patterns and the functioning of electricity markets in general. To alter consumer behaviour, it is first necessary to increase their level of knowledge about the status quo. This could not only be done by governmental initiatives, but also by energy providers who do not advertise these programmes and their potential benefits as much as needed (Kim and Shcherbakova, 2011). Again, energy communities can be an interesting subject to study in this context as community members have the opportunity to learn from each other, are interconnected such that they can coordinate their efforts, and may have a generally larger motivation to engage in efforts that are beneficial for the whole group.

Even if membership in the exogenously created energy community had no effect on aggregate electricity consumption, load-shifting may be a different case as load shifting is a simpler task, because electricity consumption does not need to be reduced but can instead be shifted to other times of the day. Therefore, in the second additional experiment, we test whether energy communities can facilitate the shifting of electricity consumption patterns of their members.

This experiment had another additional feature: A group-level prosocial incentive. If the community members as a whole were able to effectively shift their consumption patterns over a time period of one month, a donation was made for each community member to a charity chosen by the members. Imas (2014) shows in a laboratory experiment that, depending on the height of the financial incentive, people are willing to work harder if the gain is intended for charity instead of themselves. Thus, in some circumstances, the utility derived from the warm glow of giving to charity could be higher than the utility that derived from earning the

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same amount for oneself. Moreover, the connection between community members could lead to a stronger motivational effect of such an incentive.

3.3 Background on the combination of behavioural interventions

As the two experiments were conducted subsequently to each other on the same study population, it is conceivable that the behavioural interventions from both experiments interact. It could be that the experience of the first intervention, i.e., real-time feedback, leads participants to respond even more strongly to the load shifting intervention (crowding in/complementarity). On the other hand, it could also reduce the effect of the load shifting intervention, e. g. because the participants' motivation is increasingly strained (crowding out).

Such interactions are becoming increasingly investigated in the scientific literature. Brandon et al. (2019), for example, investigate the interaction between home energy reports aimed at reducing overall household electricity use and peak energy reports aimed at reducing electricity use in specific peak hours only. They find that the combination of the two nudges leads to a slightly larger effect than the sum of the two interventions in isolation. This suggests that the combination of nudges leads to crowding in rather than crowding out. Similarly, Fang et al. (2020) analyse the effect of combining real-time feedback while showering and home energy reports about showering behaviour. While they find that home energy reports alone do not decrease water use while showering whereas real-time feedback exhibits a strong conservation effect, the combination of the two results in an increase in the effect of the real-time feedback by over 50 per cent, also suggesting crowding in rather than crowding out.

Moreover, this strand of research is not limited to the combination of behavioural interventions alone, but also covers the combination of behavioural interventions with price-based policy measures. Osman et al. (2021) find a complementary effect of behavioural interventions and carbon prices on food choice, where the effect of the combination of the two leads to larger effects than the sum of the two effects in isolation.

4 The GEN-I Energy Community: Recap from Deliverable 5.1

To assess the effect of energy community membership on energy conservation, we cooperated with GEN-I, the largest electricity utility located in Slovenia, to implement a field experiment among their customers. In 2020, GEN-I supplied around 380,000 customers in Slovenia, Croatia and Austria with electricity and natural gas (GEN-I, d.o.o, 2021).

Out of GEN-I's customer base, a sample of around 10,000 Slovenian households, who are equipped with smart electricity meters, were randomly selected and invited by email in June and July 2020 to participate in the study. As a requirement for participation, customers needed to fill in an online survey and agree to share their electricity use data for the duration of the study. For the purpose of the project, only customers located in the region around the capital Ljubljana were selected.

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In total, around 1,000 customers submitted the survey and agreed to share their smart meter electricity use data. We selected 300 out of these 1,000 customers to become part of the core study and to receive so-called smart shower heads at the outset of the study. We selected these 300 core study participants firstly based on their stated willingness to participate in the real-time feedback experiment and their stated fulfilment of the technical requirements needed to install the smart shower heads (384 households). Out of these 384 households, the final sample selection was conducted by excluding households with more than 5 members and 2 showers in order to increase the homogeneity of the sample. The remaining group of 782 households, who gave consent to share their electricity use data but were not selected as core study participants, is studied as an additional control group.

In addition to this observational data, we collected sociodemographic characteristics, such as age, gender, and the educational attainments of the respondents. In the pre-intervention survey, we also asked for dwelling characteristics, energy sources, the electric appliance stock, and energy literacy.

Furthermore, personal attitudes towards the environment, energy use and social influence were measured. A special focus in our study is on measures that we refer to as environmental concern (adopted from Tiefenbeck et al., 2018), social concern (adopted from Czibere et al., 2020) and social identity (adopted from Allcott and Taubinsky, 2015). The wording of the items used to elicit these measures is shown in Table A1 in the appendix. The measure environmental concern is used to represent the participants' general willingness to behave in an environmentally friendly way. The measure social concern is used to elicit the perceived environmental concern of people that are important to the participants and thus the participants' perceived social pressure to behave in an environmentally friendly way. Third, the measure social identity is collected to represent the participants' general tendencies to behave according to social demand or pressure. We collected these measures because we believe they may predict how responsive a person is to being a member of an energy community.

At the end of the study, in June 2021, an endline survey was conducted to determine, for example, whether participants had a positive or negative experience with the study. In addition, indicators of the interaction with the newly designed virtual platform, which is an essential part of the study, such as the number of logins, was recorded.

In Deliverable 5.1, we examined the representativeness of the sample by comparing summary statistics of the sample to national statistics from Slovenia 2019 and found that larger households, older person, and males are slightly overrepresented in our study sample (see Table A2 in the Appendix for more details on this comparison).

All core participants were provided with nudges aiming at reducing the participants' electricity consumption, in particular social comparisons, information provision and norm-based messages, which were implemented via monthly energy reports and the newly designed virtual platform. On top of these nudges, the randomly selected group that became part of the energy community received augmented versions of the energy reports and of the virtual platform. These

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augmented versions consisted of elements that were intended to increase the motivation to reduce electricity consumption by framing energy conservation as a community effort and to enable social learning by granting the opportunity of communication between the energy community members. These augmentations, which are described in more detail in Section B in the Appendix, represented the main treatment. Originally, it was furthermore planned to organize physical meetings among the members of the energy community who all live near or in Ljubljana. Due to the COVID-19 pandemic, physical meetings were not possible during the study period. The community can therefore be characterized as a virtual energy community, in which virtual interactions were possible and stimulated.

5 Experiment 1: Real-time Feedback

5.1 The smart shower head

For the purpose of the first experiment, the core study participants were equipped with so called "smart shower heads" at the outset of the study in October 2020. We sent a package to each core participant containing the smart shower head, as well as a Wi-Fi gateway. In parallel, participants received the installation instructions in digital form via email. Upon request, a printed version of the instructions was enclosed in the package.

The installation of the smart shower heads and the infrastructure for data transmission took place in the following steps:

1. The existing shower head had to be unscrewed from the shower hose and the smart shower head, which in its deactivated form also has the form and function of an ordinary shower head, had to be screwed on.
2. The proper function of the shower head could be tested by the shower head lighting up briefly after the water is turned on. Apart from this short signal, the shower head had no other special properties in the baseline phase.
3. The Wi-Fi gateway had to be plugged into a power outlet near the shower head. Participants then had to download an app to connect the Wi-Fi gateway to their home network. This was done selecting the correct Wi-Fi network and entering the network key. The gateway signalled visibly when it was correctly connected.
4. If problems arose, participants could reach the project team at GEN-I by e-mail. The problems were then solved either by e-mail, phone call or personal visit. Only for a minority of the study participants the problems were not solvable. In most cases, there were problems with the configuration of the Wi-Fi network or the distance between the Wi-Fi gateway and the smart shower head, which could be easily solved.

After successful installation, the shower head transmitted the information per shower (time stamp, amount of water used, average water temperature, water flow, length of shower breaks) via Bluetooth to the Wi-Fi gateway, which then transmitted the information to the research team via the Internet. Participants had no way to access this information during the study.

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If the Wi-Fi gateway was not plugged in or had no internet connection during a shower, the data from that shower was stored in the shower head (up to 200 showers can be stored) and transmitted with the next successful connection. Interruptions of showers of less than 3 minutes were interpreted by the smart shower head as shower breaks, while an interruption of more than 3 minutes signalled the start of a new shower.

The smart shower heads do not only record and transmit shower data but are also able to provide real-time feedback while showering: The special feature of these shower heads is their ability to display water consumption in real time through a coloured LED system. For this purpose, LEDs are embedded in the shower head, which can be seen during the shower by the person taking the shower.

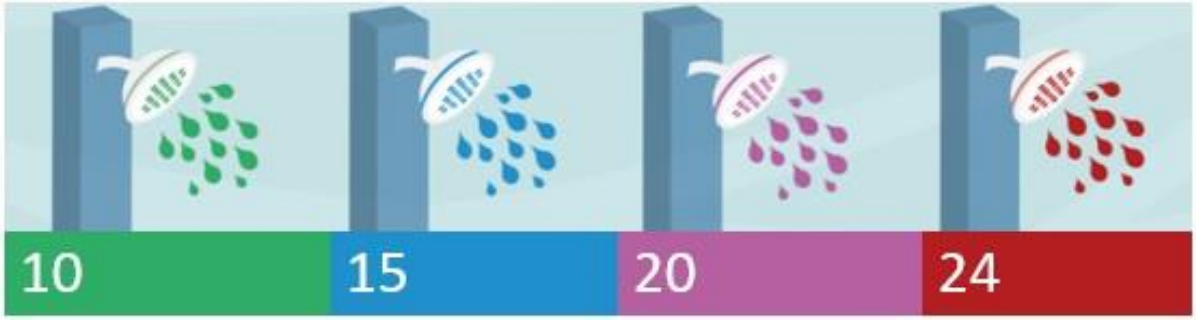

Figure 1: Visualisation of real-time feedback

These LEDs can change their colours during the shower depending on the water consumption. This provides direct feedback to the persons showering on their actual water consumption in real-time and allows them to see when they have reached certain thresholds (see Figure 1). In the present study, the shower head was configured to glow green for the first 10 litres, glow blue between 10 and 15 litres, glow purple between 15 and 20 litres, glow red between 20 and 24 litres, and flash red after 24 litres. The highest threshold was chosen because it represents the average water consumption per shower of the study participants in the baseline phase.

Note that the real-time feedback function of the shower head could be turned on and off remotely by the research team. When it is off, the shower head acts as a normal shower head and the LED lights are off, so there is no feedback at all. At the beginning of the study, until the start of the experiment in March 2021, the real-time feedback function was turned off for all shower heads. Thus, the usual water use per shower was measured over a longer period of time, which is later referred to as baseline water use.

5.2 Experimental Design and Data

In December 2020, before the start of the energy community, the study sample was divided into four different equally sized treatment groups. This division was conducted randomly, with stratification ensuring that the groups differed as little as possible in terms of their electricity consumption, household size, type of water heating, water use per shower, as well as their environmental attitudes and their tendency to be influenced by their social environment.

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The following experimental interventions were designated for the four different treatment groups: The first group was neither to become part in the energy community nor to receive real-time feedback (Control group). The second group was to become part of the energy community but not receive real-time feedback (EC group). The third group was to receive real-time feedback but not become part of the energy community (RTF group), and the last group was to both become part of the energy community and receive real-time feedback (EC+RTF group).[1] Table 1 provides an overview of the experimental design.

Table 1: Design of Experiment 1

		Energy Community	
		No	Yes
Real-time feedback	No	Control	EC
	Yes	RTF	EC+RTF

As neither the Control group nor the EC group received real-time feedback and there is no difference in the reaction to the start of the treatment period among these two groups, which is also shown by regression analyses in Appendix F. We pool the Control group and the EC group to one larger control group in order to maximize statistical power, for the course of the further analysis.

In Table 2, we provide a detailed comparison of the three groups, which provides evidence that the groups are well balanced on all pre-treatment covariates, with a minor exception regarding the social concern scale, overall indicating that the stratified randomisation was successful.

On 8 March 2021, the treatment period began. As part of the energy report for the month of March, which the participants received as part of the overall study, members of the RTF and EC+RTF groups were informed that their shower heads now light up with the previously described threshold settings to give them more control over their showering behaviour (see Appendix C).

In addition, participants in all groups were informed about the high energy intensity and environmental impact of showering. This ensured that all participants paid similar attention to the issue of water and energy consumption while showering, so the only difference between the groups is that besides the ongoing membership in the energy community for the EC group and the EC+RTF group, the RTF group and the EC+RTF group began to receive real-time feedback to help them reduce their water use in the shower. Once turned on, real-time feedback remained activated until the end of the study period.

[1] Note that we pooled the Control group and the RTF group as well as the EC group and the EC+RTF group in Deliverable 5.1 because real-time feedback was not relevant and was turned off during the study period reported in Deliverable 5.1. It should also be noted that the energy community characteristics were identical for the EC and EC+RTF groups, but to avoid spillover effects, these two subgroups constituted separate energy communities. That is, there was no possibility of communication between these subgroups, and social comparisons were also calculated separately for all subgroups.

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Table 2: Summary statistics by experimental group (Experiment 1)

Variable	Unit	Control	RTF	EC+RTF
Baseline water use	Litres per shower	24.029	24.026 (-0.002)	23.692 (-0.178)
Control variables				
Avg. outdoor temperature	°C	3.585	4.104 (1.867)	3.808 (0.762)
Age	Years	53.193	52.841 (-0.182)	52.277 (-0.486)
Household size	Number of persons	3.130	3.200 (0.380)	3.211 (0.422)
Female	Percentage	0.348	0.257 (-1.327)	0.338 (-0.141)
University degree	Percentage	0.355	0.314 (-0.584)	0.310 (-0.651)
Retired	Percentage	0.290	0.271 (-0.277)	0.254 (-0.553)
High income (household monthly net income > 3.500 Euro)	Percentage	0.145	0.086 (-1.219)	0.113 (-0.646)
Decentral heating of shower water	Percentage	0.261	0.271 (0.162)	0.282 (0.320)
Showers in household	Number of showers installed in the household	1.472	1.493 (0.265)	1.431 (-0.546)
Bathtub in household	Percentage	0.703	0.643 (-0.877)	0.718 (0.231)
Environmental concern	Sum of responses (on four 5-point scales; see Table A1 for the wording)	16.478	16.243 (-0.791)	16.859 (1.421)
Social concern	Sum of responses (on three 5-point scales; see Table A1 for the wording)	11.080	10.686 (-1.451)	10.507 (-2.044*)
Social identity	Sum of responses (on three 5-point scales; see Table A1 for the wording)	9.022	8.914 (-0.401)	9.183 (0.604)
No. of households		138	70	71

Note: t-statistics for comparison to the control group are reported in parentheses. ** and * denote statistical significance at the 1% and 5%, level, respectively. Here, the Control group is pooled together with the EC group as described in Table 1.

The main outcome of our analysis is water use per shower. We focus on water use per shower instead of energy use per shower as the main outcome because this value is directly reported by the smart shower head and does not require any assumptions about the efficiency of the water heating appliances in Slovenia. For a rough estimate, the available data from Switzerland can be consulted, where Tiefenbeck et al. (2018) calculate an average electricity consumption of 58 Wh (i.e., 0.058 kWh) per litre of shower water. Throughout the analyses, we trim the sample by excluding showers that consumed less than 5 litres and more than 200 litres. This is done to reduce the influence of measurement failures and of water withdrawals from the shower head that do not constitute showers (e.g.,

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small water withdrawals to fill cleaning buckets or large water withdrawals to fill the bathtub). An alternative approach would be not to trim the large water withdrawals, but to censor them by assigning them a maximum value of 200 litres. The results, however, are largely robust to such changes in the data cleaning procedures. We define a baseline period that spans from 15 October 2020 to the beginning of March 2021.[2]

5.3 Results

5.3.1 Average treatment effect

Figure 2 depicts weekly averages of the water use per shower for the three different treatment groups over the study period. The date at which the real-time feedback intervention was activated for the RTF group and the EC+RTF group is marked by the vertical line in week 0.

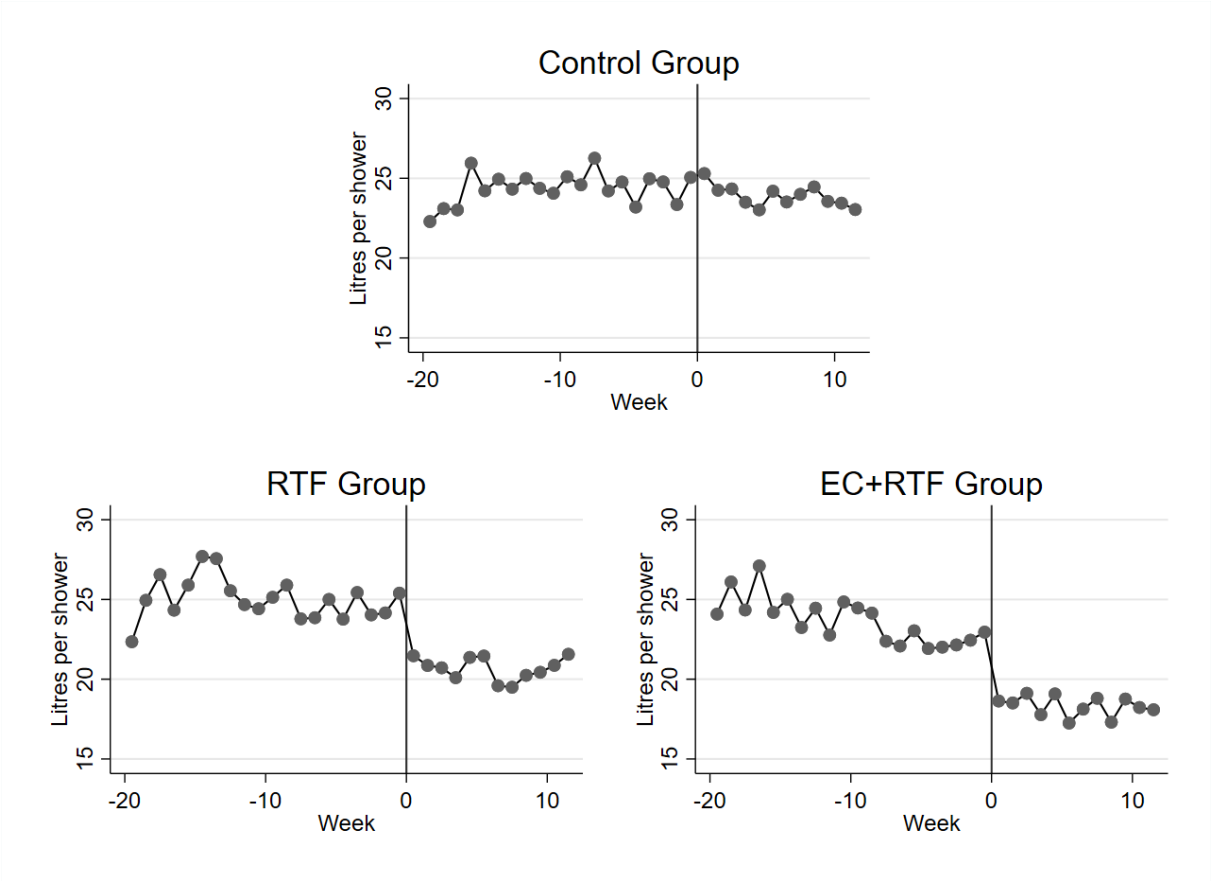

Figure 2: Water use per shower (weekly averages) over time per treatment group.
The vertical line marks the date at which the real-time feedback intervention was activated for the RTF group and the EC+RTF group.

It is clearly visible that the water use per shower drops sharply for the groups that start to receive real-time feedback during the treatment period, while there is no

[2] Note: The start date of the study was 1 October 2020, yet we exclude the shower data of the first 15 days, because the installation of the shower heads was associated with some test runs, which generated uninformative variation and should therefore not be part of the estimation sample. Moreover, the baseline period before the start of the real-time feedback period is considerably long compared to other studies anyway (cf. Tiefenbeck et al., 2018). Furthermore, the baseline period includes the start date of the energy community. Yet, as shown in Appendix E, the introduction of the energy community had no effect on water use per shower.

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comparable change for the control group. This pattern of an immediate, strong, and long-lasting decline in water use per shower once the real-time feedback is activated is characteristic for real-time feedback interventions (see e.g. Tiefenbeck et al., 2018) and proves the effectiveness of real-time feedback in stimulating resource conservation.

To analyse the treatment effects quantitatively, we estimate the following difference-in-differences regression model:

$$Y_{it} = \alpha_i + \beta_0 Post_t + \beta_1 RTF_i \times Post_t + \beta_2 (EC_i + RTF_i) \times Post_t + \tau_t + \epsilon_{it},$$

where Y_{it} represents water use per shower at time t in terms of differences from the control group's average water use per shower in the treatment period ($\bar{C}_w^c$), i. e. $Y_{it} = \frac{C_{it} - \bar{C}_w^c}{C_w^c}$. Thereby, the treatment effects can be interpreted as percentage deviations from the control group's water use per shower. $Post_t$ is 0 if an observation is in the baseline period and 1 if it is in the treatment period. RTF_i and (EC_i + RTF_i) indicate membership in the respective experimental groups, as described in Table 1. α_i represents individual fixed effects, while τ_t represents daily fixed effects. Our main interests are the interaction terms $RTF_i \times Post_t$ and $(EC_i + RTF_i) \times Post_t$. We cluster the standard errors at the household level (Bertrand et al., 2004).

Our main results are reported in Table 3, where the empirical estimation sustains the graphical illustration from Figure 2 that water consumption per shower dropped sharply in the RTF and EC+RTF group after the real-time feedback was activated. The interaction terms $RTF_i \times Post_t$ and $(EC_i + RTF_i) \times Post_t$ are both large in magnitude and statistically significantly different from zero. The results indicate that real-time feedback causally reduces water use per shower by 16.2 per cent in the RTF group and by 17.1 per cent in the EC+RTF group. While the effect in the EC+RTF group is one percentage point larger than the effect in the RTF group, this difference is not statistically significant.

The fixed-effects estimator controls for all largely time-invariant characteristics, such as a household's sociodemographic status. In addition, the day-specific fixed effect controls for time varying variables that affect all participants uniformly. One example is outdoor temperature, which exhibits little cross-sectional variation among the study participants because of their regional proximity. To examine the robustness of the results from Column (1), we omit the day-specific fixed effects in Column (2) and instead control for the daily outdoor temperature. The resulting estimates of the treatment effects, i.e., the interaction terms $RTF_i \times Post_t$ and $(EC_i + RTF_i) \times Post_t$, remain virtually unchanged compared to Column (1). On the other hand, a strongly negative effect of an increase in the outside temperature on water use per shower emerges, indicating that a one-degree Celsius increase in the average outdoor temperature is on average associated with a decrease in the water use per shower by 0.3 per cent. This shows that the outside temperature is a predictor of water use per shower over time.

To further investigate the sensitivity of the results and to identify other factors influencing water consumption per shower, we omit the individual fixed effects

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in Column (3) and instead control for observable characteristics and binary dummy variables that indicate treatment group membership (RTF_i and $EC_i + RTF_i$). This specification shows that difference in the baseline water consumption per shower between the control group and the treatment groups is not significantly different from zero, corroborating the graphical results from Figure 2. The point estimate of the interaction term $RTF_i \times Post_t$ is virtually unchanged compared to Columns (1) and (2). However, the point estimate of the interaction term $(EC_i + RTF_i) \times Post_t$ decreases by more than two percentage points compared to specifications (1) and (2). Although this decrease is not statistically significant, it suggests that there may be unobserved differences between the treatment groups that are controlled by the fixed effects in specifications (1) and (2) but not by the control variables in specification (3).

Table 3: Difference-in-differences estimation results - Outcome variable: Water use per shower

	(1)		(2)		(3)		(4)	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
RTF	–	–	–	–	0.091	(0.079)	0.007	(0.008)
EC+RTF	–	–	–	–	0.005	(0.077)	-0.002	(0.008)
Post	0.158	(0.095)	-0.018	(0.021)	-0.015	(0.026)	-0.031	(0.020)
RTF × Post	-0.162**	(0.037)	-0.161**	(0.037)	-0.163**	(0.042)	-0.139**	(0.035)
(EC+RTF) × Post	-0.171**	(0.040)	-0.172**	(0.040)	-0.198**	(0.052)	-0.155**	(0.042)
Average temperature	–	–	-0.003**	(0.001)	-0.001	(0.002)	-0.002**	(0.001)
Age	–	–	–	–	-0.006	(0.004)	0.000	(0.000)
Household size=2	–	–	–	–	0.124	(0.111)	-0.001	(0.017)
Household size=3	–	–	–	–	0.103	(0.102)	0.045**	(0.016)
Household size=4	–	–	–	–	0.159	(0.101)	0.005	(0.015)
Household size=5	–	–	–	–	-0.058	(0.120)	0.016	(0.016)
Female	–	–	–	–	-0.026	(0.069)	0.005	(0.009)
University	–	–	–	–	0.034	(0.066)	0.007	(0.008)
Retired	–	–	–	–	0.022	(0.119)	0.013	(0.014)
High income	–	–	–	–	0.116	(0.098)	-0.012	(0.015)
Decentral water heating	–	–	–	–	-0.230**	(0.064)	-0.017*	(0.008)
Number of showers=2	–	–	–	–	-0.004	(0.064)	-0.022*	(0.010)
Bathtub	–	–	–	–	-0.076	(0.063)	0.003	(0.010)
Baseline consumption	–	–	–	–	–	–	0.040**	(0.001)
Constant	-0.166*	(0.081)	0.057**	(0.007)	0.328	(0.253)	-0.936**	(0.033)
Day fixed effects	Yes		No		No		No	
Individual fixed effects	Yes		Yes		No		No	
No. of observations	90358		90358		81737		81737	
No. of households	279		279		244		244	

Note: Standard errors are clustered at the household level and reported in parentheses. For the analysis, we drop showers below 5 litres and above 200 litres. ** and * denote statistical significance at the 1% and 5%, level, respectively. The outcome variable (Y_{it}) is defined as the percentage deviation of water use per shower (C_{it}) from the average water use per shower of the control group in the treatment period ($\bar{C}_w^c$ = 23.29 litres), i.e. $Y_{it} = \frac{C_{it} - \bar{C}_w^c}{C_w^c}$.

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The vast majority of control variables in Column (3) do not appear to have a statistically significant effect on water use per shower. Only households where hot water for the shower is heated decentrally, e. g. with an electric boiler or instantaneous water heater, show an average of 23 per cent lower water use per shower compared to households where the shower water is heated by the central heating system. One reason for this could be that electric water heating, which is mostly used in decentralised systems, is more expensive per litre than water heating by gas or oil combustion. Another reason could be that decentralised heating systems are often somewhat less convenient than central heating systems, e.g., some devices have certain requirements regarding the water pressure and with older devices the water temperature cannot always be comfortably regulated. In addition, some devices can only heat a limited amount of water for a certain period of time, so the amount of water per shower is limited for technical reasons.

In Column (4), we add the average water use per shower in the baseline period as a control variable. We find a strong correlation between water use per shower in the baseline and treatment phases, which is to be expected due to the stability of habits. Furthermore, we find that nearly all coefficients of the other control variables shrink substantially compared to Column (3), which is likely due to the high collinearity between these characteristics and the water use in the baseline period. Some coefficients gain significance in Column (4) compared to Column (3), which is primarily due to the reduction in standard errors after the inclusion of the baseline consumption.

5.3.2 Heterogenous treatment effects

Next, we investigate whether the treatment effects differ across different time periods or are heterogeneous with respect to some participant characteristics. For the first investigation, we consider the two treatment months, March and April, separately. For the heterogeneity analysis, we extend our empirical model to include interaction terms between the participant characteristics, the *Post* dummy, and additional interaction terms with the treatment group indicators.

As reported in Table 4, the effects of real-time feedback decrease slightly in April compared to March. This could indicate a slight backsliding effect, as for example documented in Allcott and Rogers (2014) for home energy reports or is due to the lower general water consumption per shower in April. Yet, the treatment effects remain substantial in April, and the ratio of the effect in the RTF group to the effect in the RTF+EC group remains roughly constant.

To analyse whether the treatment effects vary with respect to the participants' personal attitudes, we focus on three measures elicited in the pre-intervention survey and described in Section 4: *Environmental concern*, *social concern* and *social identity*. To facilitate interpretation, we standardise these variables by subtracting the means and dividing through the standard deviations. As depicted in Table 5, we do not find significant differences in the treatment effects according to these attitudinal variables.

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Table 4: Difference-in-differences estimation results for different time periods - Outcome variable: Water use per shower

	March		April	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Post	0.214*	(0.095)	0.123	(0.090)
RTF × Post	-0.194**	(0.038)	-0.153**	(0.035)
(EC+RTF) × Post	-0.200**	(0.048)	-0.163**	(0.042)
Constant	-0.174*	(0.083)	-0.171*	(0.083)
Day fixed effects	Yes		Yes	
Individual fixed effects	Yes		Yes	
No. of observations	68244		70108	
No. of households	279		279	

Note: Standard errors are clustered at the household level and reported in parentheses. For the analysis, we drop showers below 5 litres and above 200 litres. ** and * denote statistical significance at the 1% and 5%, level, respectively. The outcome variable (Yit) is defined as the percentage deviation of water use per shower (Cit) from the average water use per shower of the control group in the treatment period ($\bar{C}_w^c$ = 23.29 litres), i.e. $Y_{it} = \frac{C_{it} - \bar{C}_w^c}{C_w^c}$.

Table 5: Heterogeneous treatment effects - Outcome variable: Water use per shower

	(1)		(2)		(3)		(4)	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Post	0.156	(0.094)	0.156	(0.096)	0.158	(0.095)	0.250*	(0.113)
RTF × Post	-0.161**	(0.036)	-0.158**	(0.036)	-0.161**	(0.037)	-0.013	(0.087)
(EC+RTF) × Post	-0.164**	(0.037)	-0.169**	(0.041)	-0.172**	(0.040)	0.079	(0.101)
Post × Env. concern	-0.008	(0.023)	–	–	–	–	–	–
RTF × Post × Env. concern	0.001	(0.034)	–	–	–	–	–	–
(EC+RTF) × Post × Env. concern	-0.016	(0.038)	–	–	–	–	–	–
Post × Soc. concern	–	–	0.015	(0.030)	–	–	–	–
RTF × Post × Soc. concern	–	–	0.003	(0.041)	–	–	–	–
(EC+RTF) × Post × Soc. concern	–	–	-0.009	(0.041)	–	–	–	–
Post × Soc. identity	–	–	–	–	0.017	(0.014)	–	–
RTF × Post × Soc. identity	–	–	–	–	0.002	(0.036)	–	–
(EC+RTF) × Post × Soc. identity	–	–	–	–	-0.012	(0.028)	–	–
Post × Baseline water use	–	–	–	–	–	–	-0.003	(0.004)
RTF × Post × Baseline water use	–	–	–	–	–	–	-0.005	(0.004)
(EC+RTF) × Post × Baseline water use	–	–	–	–	–	–	-0.011*	(0.005)
Constant	-0.165*	(0.081)	-0.166*	(0.081)	-0.165*	(0.081)	-0.173*	(0.084)
Day fixed effects	Yes		Yes		Yes		Yes	
Individual fixed effects	Yes		Yes		Yes		Yes	
No. of observations	90358		90358		90358		90358	
No. of households	279		279		279		279	

Note: Standard errors are clustered at the household level and reported in parentheses. For the analysis, we drop showers below 5 litres and above 200 litres. ** and * denote statistical significance at the 1% and 5%, level, respectively. The outcome variable (Y_{it}) is defined as the percentage deviation of water use per shower (C_{it}) from the average water use per shower of the control group in the treatment period ($\bar{C}_w^c$ = 23.29 litres), i.e. $Y_{it} = \frac{C_{it} - \bar{C}_w^c}{C_w^c}$.

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Furthermore, we investigate whether real-time feedback does differentially affect the participants according to their baseline water use per shower (Column 4 of Table 5), which is a typical result found for real-time feedback (Tiefenbeck et al., 2018) and also for other behavioural interventions on energy use (Allcott, 2011; Andor et al., 2020). In the EC+RTF group, we find a significant interaction effect with respect to baseline water use. For each additional litre used per shower in the baseline period, the RTF+EC group reduced water use per shower compared to the control group by 1.1 per cent. The interaction effect for the RTF group is smaller and amounts to 0.5 per cent per litre. This interaction effect is not significantly different from zero but also not significantly different from the interaction effect in the EC+RTF group.

5.3.3 Cross-domain spillover effects

There is a growing focus in the scientific literature on unintended side effects of behavioural economic interventions. One example of such an effect are cross-domain spillovers, for example documented in Tiefenbeck et al. (2013). In their study placed at multifamily residence in the U.S., the authors found that frequent feedback on water use led to a reduction in water use, but also to an increase in electricity use. The authors argue that this result is consistent with a "moral licensing" effect, which is a concept from social psychology, stating that a person's moral action in one domain or at one point in time could subjectively justify an immoral action in another domain or at another time. In this example, it means that water conservation efforts could have justified a more relaxed use of electricity.

Table 6: Difference-in-differences estimation results – Outcome variable: Daily electricity use

	Coeff.	Std. Err.
Post	-0.012	(0.033)
RTF × Post	-0.008	(0.035)
(EC+RTF) × Post	-0.012	(0.035)
Constant	-0.037	(0.027)
Day fixed effects	Yes	
Individual fixed effects	Yes	
No. of observations	49,778	
No. of households	274	

Note: Standard errors are clustered at the household level and reported in parentheses. For the analysis, we drop the 1% and 99% percentile of our dependent variable. ** and * denote statistical significance at the 1% and 5%, level, respectively. The outcome variable (Y_{it}) is defined as the percentage deviation of electricity consumption (C_{it}) from the average electricity consumption of the control group in the treatment period ($\bar{C}_e^c$ = 15.60 kWh), i.e. $Y_{it} = \frac{C_{it} - \bar{C}_e^c}{C_e^c}$.

A similar effect is conceivable with respect to the real-time feedback intervention in the present experiment. Therefore, we check whether the reduction of water

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use per shower due to the real-time feedback had an effect on electricity use. To this end, we re-run the analysis displayed in Column I of Table 3, replacing the outcome variable by daily electricity use instead of water use per shower.

As the interaction terms $RTF_i \times Post_t$ and $(EC + RTF)_i \times Post_t$ in Table 6 are small in magnitude and statistically insignificantly different from zero, our results suggest that real-time feedback in the shower did not substantially affect household electricity use. These results thus indicate that there were no noticeable moral licensing effects leading to higher electricity use.

6 Experiment 2: Load shifting

6.1 Experimental Design and Data

In this experiment, we investigate whether energy community membership can help convince households to shift their electricity consumption away from peak hours to other times of the day. Therefore, in April 2021, all core study participants received an email by GEN-I posing the "load-shifting challenge". In this context, it was explained why pronounced electricity consumption peaks, especially in the evening hours, pose problems for electricity supply security and that these problems can end up being an electricity cost driver (see Appendix D for the wording). Therefore, the study participants were asked to reduce their electricity consumption by 10 per cent during the evening hours from 5:00 pm to 9:00 pm in the month of April compared to the previous month.[3] If the study participants succeeded in reaching this target on a group average, GEN-I committed to make a donation of 10 Euros per study participant to a charitable organisation selected by a vote of the participants. The participants had the choice between three charities that provide support for critically ill or disabled people. Two weeks after the challenge started, the participants received an initial update showing their peak load reduction to date at the individual and group levels. After the challenge ended, the participants received a final evaluation.

In more detail, the challenge was posed differently for the energy community members compared to the non-community members as follows. While the non-community members (Non-EC Group) were told that the reduction target of peak consumption had to be achieved as an average of all "study participants", the energy community members (EC Group) were told that the reduction of the peak consumption had to be achieved as an average of all "energy community members" and therefore it is a group task for the community. This design ensures that we can identify the exclusive effect of the energy community features.

For the analysis of the effect of the community features on load shifting, we initially pool the groups that received real-time feedback in the context of the first experiment with those who did not, in order to make the analysis of the load-shifting challenge more concise and to increase the size of the experimental groups. Yet, in Section 6.2.3 we also analyse whether being treated with real-time feedback leads to differential reactions to the load shifting challenge.

[3] Note that while this reduction may seem large, the challenge fell into a seasonal period when electricity consumption is decreasing anyway due to warmer weather. This was intentional to keep participant/customer motivation high and allow for a sense of accomplishment.

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The data analysed in this experiment consists of smart meter electricity data measured at quarter-hourly intervals. We aggregate the daily electricity consumption data in the period from 5:00 pm to 9:00 pm, while we omit the data outside this period.

Table 7: Summary statistics by experimental group (Experiment 2)

Variable	Unit	Control	Non-EC	EC
Baseline peak hour consumption	kWh per day (sum of kWh used between 5:00 pm and 9:00 pm)	3.391	3.346 (-0.214)	3.506 (0.543)
Control variables				
Avg. outdoor temperature	°C	5.432	5.239 (-0.782)	5.404 (-0.114)
Age	Years	53.107	53.402 (0.231)	52.472 (-0.513)
Household size	Number of persons	3.087	3.144 (0.451)	3.123 (0.285)
Female	Percentage	0.387	0.311 (-1.664)	0.346 (-0.877)
University degree	Percentage	0.330	0.295 (-0.774)	0.338 (0.195)
Retired	Percentage	0.304	0.311 (0.153)	0.269 (-0.796)
High income (household monthly net income > 3.500 EUR)	Percentage	0.138	0.114 (-0.767)	0.138 (0.002)
Equipment with a heat pump	Percentage	0.313	0.341 (0.624)	0.346 (0.738)
Environmental concern	Sum of responses (on four 5-point scales)	16.233	16.326 (0.480)	16.692 (2.394*)
Social concern	Sum of responses (on three 5-point scales)	10.765	10.924 (0.853)	10.877 (0.588)
Social identity	Sum of responses (on three 5-point scales)	9.031	9.030 (-0.005)	9.046 (0.088)
No. of households		741	133	130

Note: t-statistics for comparison to the control group are reported in parentheses. ** and * denote statistical significance at the 1% and 5%, level, respectively. The control group consists of the 741 participants that were not part of the core study. The Non-EC group consists of the group of core study participants that were not part of the energy community. The EC group consists of the group of core study participants that were part of the energy community. No distinction is made regarding the experience of real-time feedback in the first experiment.

Smart meter electricity data is available from 1,004 households for the relevant time period. Besides the core study participants, we also include the 741 additional households that were not part of the core study in the analysis of this experiment. The reason is that all core study participants were treated, i.e. posed

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the load shifting challenge with different framings among the EC vs. the Non-EC participants. Therefore, we analyse the non-core study participants as a control group for this experiment. Even though these additional participants were not randomly allocated, Table 7 as well as Figure 3 do not indicate substantial pre-treatment differences of this group compared to the core study participants. Furthermore, the applied difference-in-differences approach does inherently control for time-invariant pre-treatment differences between the groups.

To minimise the influence of outliers due to data transmission errors, we drop observations that are below the 1st percentile or above the 99th percentile of the distribution of aggregated electricity consumption from 5:00 pm to 9:00 pm.

6.2 Results

6.2.1 Average treatment effect

We define the baseline period as the month of March 2021, since the load shifting challenge is based on the comparison to this month. The treatment period begins on 2 April 2021, the date the first email posing the challenge was sent and ends one month later on 2 May 2021.

Figure 3 depicts weekly averages of peak electricity use for the different treatment groups between 2 March 2021 and 2 May 2021. The date at which the treatment period starts is marked by the vertical line in week 0. For the baseline period, it is clearly visible that the EC group used slightly more electricity in peak hours than the Non-EC and the control group. Yet, after the treatment started, the curves align, indicating a reduction in peak electricity use for the EC group.

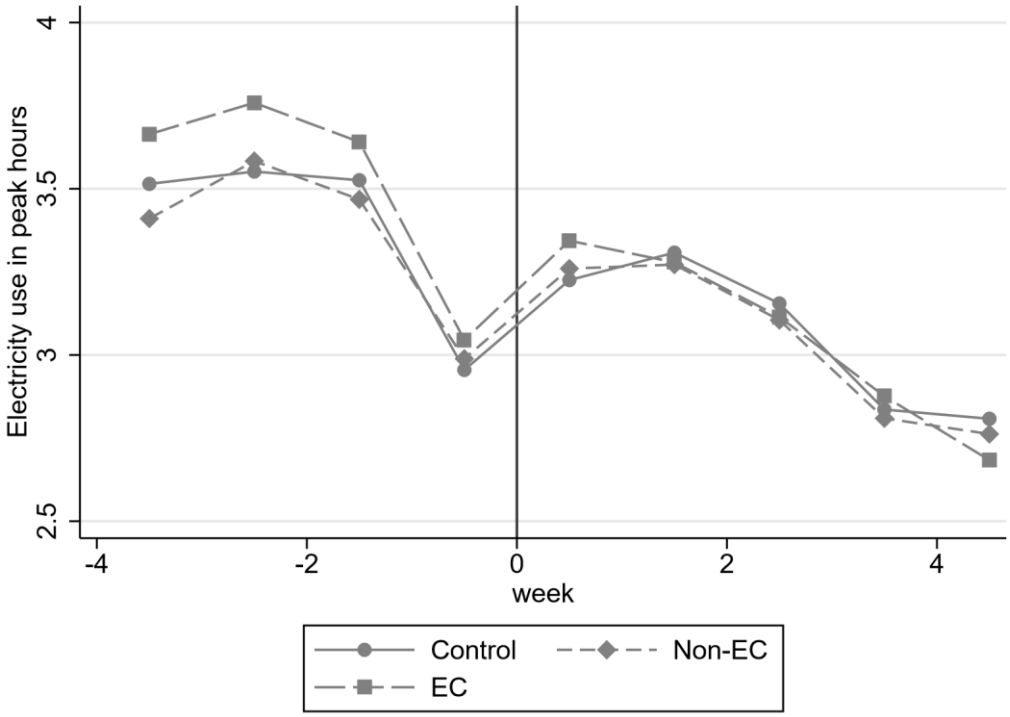

Figure 3: Peak hour electricity use over time per treatment group
The vertical line marks the date at which the load shifting challenge was posed for the Non-EC group and the EC group.

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To analyse the treatment effects quantitatively, we estimate the following difference-in-differences regression model:

$$Y_{it} = \alpha_i + \beta_0 Post_t + \beta_1 Non - EC_i \times Post_t + \beta_2 EC_i \times Post_t + \tau_t + \epsilon_{it},$$

where Y_{it} represents the electricity use in peak hours at day t in terms of differences from the control group's average electricity use in peak hours in the treatment period ($\bar{c}_e^c$), i.e. $Y_{it} = \frac{c_{it} - \bar{c}_e^c}{c_e^c}$. Thereby, the treatment effects can be interpreted as percentage deviations from the control group's peak hour electricity use. $Post_t$ is 0 if an observation is in the baseline period and 1 if it is in the treatment period. $Non\text{-}EC_i$ is 1 if individual i is part of the core study participants, but not in the energy community, and 0 otherwise, while EC_i is 1 if individual i is member in the energy community and 0 otherwise. The base group consists of those participants who are not part of the core study. α_i represents individual fixed effects, while τ_t represents daily fixed effects. Our main interest are the interaction terms $Non\text{-}EC_i \times Post_t$ and $EC_i \times Post_t$. We cluster the standard errors at the household level (Bertrand et al., 2004).

Our main results are reported in Table 8. The interaction term $Non\text{-}EC_i \times Post_t$ is near zero and not significantly different from zero. In contrast, the $EC_i \times Post_t$ interaction term, is statistically significant on the 5 per cent level and indicates that the energy community members reduce their peak hour electricity consumption by 4 per cent compared to the control group in response to the load shifting challenge.

As a robustness check, we estimate an alternative specification that omits the day-specific fixed effects but instead controls for the daily outdoor temperature, which can be expected to be an important time-varying influence on electricity use. As displayed in Column (2) in Table 8, the estimate of the treatment effects, i.e., the interaction terms $Non\text{-}EC_i \times Post_t$ and $EC_i \times Post_t$, remain virtually unchanged in this specification compared to Column (1). The coefficient of the outside temperature indicates that a 1-degree Celsius increase in the average outdoor temperature is on average associated with a reduction of electricity use in the peak hours by 2 per cent.

We further investigate the sensitivity of our results by adding another specification that omits also the individual fixed-effects and instead controls additionally for observable characteristics and binary dummy variables that indicate treatment group membership ($Non\text{-}EC_i$ and EC_i). Column (3) in Table 8 shows that the differences in baseline peak hour consumption between the control group and the treatment groups are not statistically significant from zero. The point estimates of the interaction terms $Non\text{-}EC_i \times Post_t$ and $EC_i \times Post_t$ are virtually unchanged. Moreover, this model shows that, in addition to the outdoor temperature, the household size and the equipment with a heat pump are predictive of electricity consumption in peak hours.

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Table 8: Difference-in-differences estimation results - Outcome variable: Peak hour electricity use

	(1)		(2)		(3)		(4)	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Non-EC	–	–	–	–	-0.029	(0.055)	-0.002	(0.007)
EC	–	–	–	–	0.011	(0.053)	0.003	(0.007)
Post	-0.032	(0.022)	-0.059**	(0.008)	-0.058**	(0.009)	-0.069**	(0.008)
Non-EC × Post	0.005	(0.022)	0.005	(0.022)	0.001	(0.024)	0.002	(0.024)
EC × Post	-0.040*	(0.019)	-0.041*	(0.019)	-0.044*	(0.020)	-0.043*	(0.019)
Average temperature	–	–	-0.020**	(0.001)	-0.019**	(0.002)	-0.015**	(0.001)
Age	–	–	–	–	0.001	(0.002)	0.000	(0.000)
Household size=2	–	–	–	–	0.225**	(0.046)	0.012	(0.010)
Household size=3	–	–	–	–	0.471**	(0.054)	0.028*	(0.012)
Household size=4	–	–	–	–	0.538**	(0.057)	0.026*	(0.012)
Household size=5	–	–	–	–	0.784**	(0.065)	0.047**	(0.012)
Female	–	–	–	–	0.021	(0.038)	0.001	(0.008)
University	–	–	–	–	-0.005	(0.038)	0.001	(0.007)
Retired	–	–	–	–	-0.068	(0.062)	-0.000	(0.011)
High income	–	–	–	–	-0.050	(0.058)	-0.006	(0.010)
Heat pump	–	–	–	–	0.566**	(0.045)	0.001	(0.011)
Baseline consumption	–	–	–	–	–	–	0.292**	(0.002)
Constant	0.096**	(0.013)	0.212**	(0.008)	-0.444**	(0.115)	-0.860**	(0.024)
Day fixed effects	Yes		No		No		No	
Individual fixed effects	Yes		Yes		No		No	
No. of observations	60705		60705		54642		54642	
No. of households	1004		1004		900		900	

Note: Standard errors are clustered at the household level and reported in parentheses. For the analysis, we drop the 1% and 99% percentile of our dependent variable. ** and * denote statistical significance at the 1% and 5%, level, respectively. The outcome variable (Y_{it}) is defined as the percentage deviation of peak hour electricity consumption (C_{it}) from the average electricity consumption in peak hours of the control group in the treatment period ($\bar{C}_e^c$ = 3.414 kWh), i.e. $Y_{it} = \frac{C_{it} - \bar{C}_e^c}{C_e^c}$.

In Column (4), we furthermore control for the average peak hour electricity use in the baseline period. We find that the coefficients on household size and the equipment with a heat pump shrink substantially compared to Column (3) and peak hour electricity consumption in the baseline period becomes a significant predictor of current peak hour consumption. The interaction terms $Non\text{-}EC_i \times Post_t$ and $EC_i \times Post_t$ remain virtually unchanged.

6.2.2 Heterogeneous treatment effects

In the following, we investigate the heterogeneity of the treatment effects. First, we separately analyse the first two weeks of April, before the update report was sent, and the last two weeks of April, after the update report was sent. Second, we conduct several heterogeneity analyses in which we extend our empirical model to include interaction terms between the sources of heterogeneity, the

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Post dummy, and additional interaction terms with the treatment group indicators.

In Table 9, we find that the *Non-EC*$_i$ × *Post*$_t$ interaction is small and insignificant in both halves of April. In contrast, the *EC*$_i$ × *Post*$_t$ interaction indicates a 3.5 per cent average reduction of peak electricity use in weeks 1 and 2 and a 4.5 per cent reduction in weeks 3 and 4, suggesting that the effect does not decrease and even seems to increase over time. Yet, the standard errors in weeks 3 and 4 are larger than in the previous weeks, which is why the *EC*$_i$ × *Post*$_t$ interaction is not statistically significant anymore despite its slightly larger size compared to weeks 1 and 2. Overall, the two interaction effects do not significantly differ from each other across the different time frames.

Table 9: Difference-in-differences estimation results for different time periods - Outcome variable: Peak hour electricity use

	Weeks 1/2		Weeks 3/4	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Post	-0.084**	(0.019)	-0.032	(0.022)
Non-EC × Post	0.006	(0.020)	0.006	(0.027)
EC × Post	-0.035*	(0.018)	-0.045	(0.025)
Constant	0.094**	(0.013)	0.096**	(0.013)
Day fixed effects	Yes		Yes	
Individual fixed effects	Yes		Yes	
No. of observations	44270		47184	
No. of households	999		1004	

Note: Standard errors are clustered at the household level and reported in parentheses. For the analysis, we drop the 1% and 99% percentile of our dependent variable. ** and * denote statistical significance at the 1% and 5%, level, respectively. The outcome variable (Y_{it}) is defined as the percentage deviation of peak hour electricity consumption (C_{it}) from the average electricity consumption in peak hours of the control group in the treatment period ($\bar{C}_e^c$ = 3.414 kWh), i.e. $Y_{it} = \frac{C_{it} - \bar{C}_e^c}{C_e^c}$.

To analyse whether the treatment effect differs according to the participants' personal attitudes, we focus on three measures elicited in the pre-intervention survey and described in Section 4: *Environmental concern*, *social concern* and *social identity*. Again, we standardise these variables by subtracting the means and dividing through the standard deviations. As depicted in Table 10, we do only find one significant difference in the treatment effects according to these attitudinal variables: A higher environmental concern, is associated with an increase in peak electricity use in the treatment period for the group of study participants who are not part of the energy community. Since we have not pre-specified the heterogeneity analyses of the load shifting treatment and see no clear theoretical reason for this explorative result, it should not be overinterpreted.

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In column (4) of Table 10, we furthermore investigate whether the treatment effects vary according to the participants' baseline peak electricity use but find no such variation.

Table 10: Heterogeneous treatment effects – Outcome variable: Peak hour electricity use

	(1)		(2)		(3)		(4)	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Post	-0.032	(0.022)	-0.032	(0.022)	-0.032	(0.022)	0.147**	(0.022)
Non-EC × Post	0.004	(0.022)	0.005	(0.022)	0.005	(0.022)	0.023	(0.032)
EC × Post	-0.042*	(0.019)	-0.040*	(0.019)	-0.040*	(0.019)	-0.037	(0.025)
Post × Env. Concern	-0.002	(0.009)	–	–	–	–	–	–
Non-EC × Post × Env. Concern	0.060**	(0.018)	–	–	–	–	–	–
EC × Post × Env. Concern	0.013	(0.019)	–	–	–	–	–	–
Post × Soc. Concern	–	–	0.000	(0.009)	–	–	–	–
Non-EC × Post × Soc. Concern	–	–	0.011	(0.016)	–	–	–	–
EC × Post × Soc. Concern	–	–	0.005	(0.017)	–	–	–	–
Post × Soc. Identity	–	–	–	–	-0.002	(0.009)	–	–
Non-EC × Post × Soc. Identity	–	–	–	–	0.029	(0.025)	–	–
EC × Post × Soc. Identity	–	–	–	–	-0.022	(0.016)	–	–
Post × Baseline con.	-	–	–	–	–	–	-0.052**	(0.004)
Non-EC × Post × Baseline cons.	-	–	–	–	–	–	-0.006	(0.011)
EC × Post × Baseline cons.	–	–	–	–	–	–	0.001	(0.009)
Constant	0.096**	(0.013)	0.096**	(0.013)	0.096**	(0.013)	0.095**	(0.013)
Day fixed effects	Yes		Yes		Yes		Yes	
Individual fixed effects	Yes		Yes		Yes		Yes	
No. Of observations	60705		60705		60705		60655	
No. Of households	1004		1004		1004		999	

Note: Standard errors are clustered at the household level and reported in parentheses. For the analysis, we drop the 1% and 99% percentile of our dependent variable. ** and * denote statistical significance at the 1% and 5%, level, respectively. The outcome variable (Y_{it}) is defined as the percentage deviation of peak hour electricity consumption (C_{it}) from the average electricity consumption in peak hours of the control group in the treatment period ($\bar{C}_e^c$ = 3.414 kWh), i.e. $Y_{it} = \frac{C_{it} - \bar{C}_e^c}{C_e^c}$.

6.2.3 Heterogeneity with respect to experience with real-time feedback

In the preceding analyses, three experimental groups were distinguished: The 741 participants that were not selected for the core study, served as a control group, the 133 participants of the core study, who were not part of the energy community, were the first treatment group (Non-EC), and the 130 participants of the core study, who were part of the energy community, were the second treatment group (EC). Yet, as visualised in Table 1, the design of the real-time feedback experiment, which took place before the load-shifting challenge, implied that the Non-EC group and the EC group were subdivided. One half of the Non-EC group and one half of the EC group received real-time feedback. While we initially pooled these subsamples to make the analysis of the load-

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shifting challenge more concise and to increase the size of the experimental groups, we now test the sensitivity of the effect of the load-shifting challenge with regard to prior and ongoing experience with real-time feedback. This also provides insights into potential interactions between the nudges, as discussed in Section 3.3. Thus, we can investigate whether the two interventions tend to reinforce each other, attenuate each other, or operate independently.

Table 11: Difference-in-differences estimation results - Outcome variable: Peak hour electricity use

	Coeff.	Std. Err.
Post	-0.032	(0.143)
Non-EC × Post	0.024	(0.032)
(Non-EC+RTF) × Post	-0.013	(0.027)
EC × Post	-0.009	(0.023)
(EC+RTF) × Post	-0.072**	(0.026)
Constant	0.096**	0.0132
Household FE	Yes	
Daily FE	Yes	
No. of observations	60,705	
No. of households	1,004	

Note: Standard errors are clustered at the household level and reported in parentheses. For the analysis, we drop the 1% and 99% percentile of our dependent variable. ** and * denote statistical significance at the 1% and 5%, level, respectively. The outcome variable (Y_{it}) is defined as the percentage deviation of daily electricity consumption (C_{it}) from the average electricity consumption of the control group in the treatment period ($\bar{C}_e^c$ = 3.414 kWh), i.e. $Y_{it} = \frac{C_{it} - \bar{C}_e^c}{C_e^c}$.

The results presented in Table 11 reveal that the reduction In peak electricity use due to the load-shifting challenge in the EC group is fully driven by the subgroup of the energy community that also experienced real-time feedback: The $(EC_i + RTF_i) \times Post_t$ interaction indicates that the load shifting challenge lead to a significant 7.2 per cent reduction in peak hour electricity use in this group. In contrast, the effects for all other groups are smaller and statistically indistinguishable from zero.

Based on the experimental design, we can rule out that it was a pure change in showering behaviour in response to the real-time feedback that contributed to the reduction in peak load power consumption, as we would have seen a similar effect in the Non-EC+RTF group in this case. Furthermore, it can be concluded that the effect must arise from the combination of real-time feedback and community membership, since the effect of the load shifting challenge on the part of the EC group that did not receive real-time feedback is very close to zero. This explorative result therefore suggests that real-time feedback and the load shifting challenge act as complements to each other, pointing in the same direction as other studies examining the combination of behavioural interventions (Brandon et al., 2019; Fang et al., 2021)).

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7 Analysis of platform use and survey data

In this final section of results, we investigate how treatment group membership affected the number of logins on the virtual platform as well as the responses to the endline survey, which was administered after the end of the load-shifting challenge. The endline survey was send to all core study participants but not to the members of the additional control group.

7.1 Effects on study engagement and study experience

First, we investigate how two indicators of study engagement and study experience vary with treatment group membership. Study engagement is measured by the number of logins on the virtual platform throughout the study. Study experience is measured by a survey question in the endline survey that was elicited at the end of the study. The question read "What is your overall experience in our research study?" and could be answered on a five-point Likert scale, where the items were labelled "Poor" (1), "Fair" (2), "Good" (3), "Very good" (4), "Excellent" (5). The data on the number of logins on the platform is available from 279 participants. The responses to the question about the overall study experience is available from the 219 participants who filled out the endline survey. Figure 4 presents the respective histograms of the data.

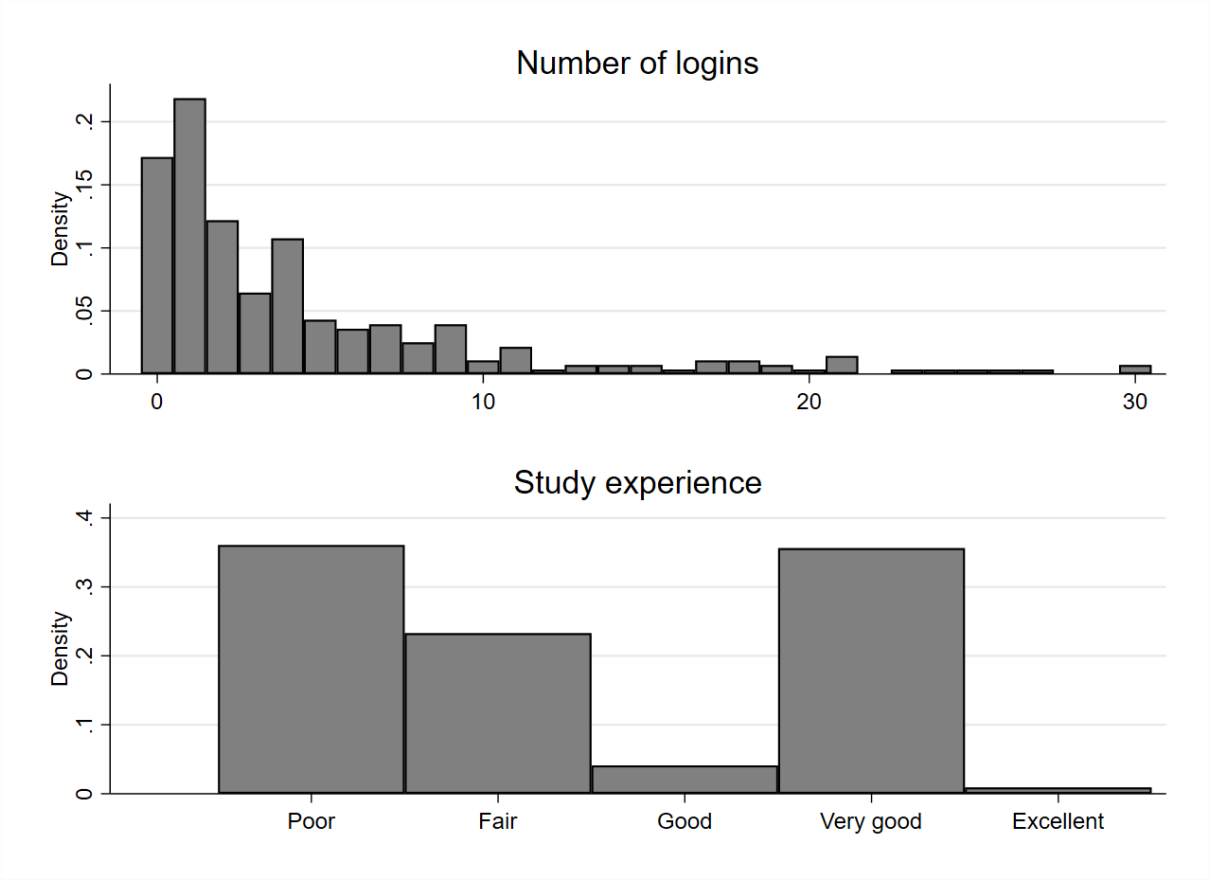

Figure 4: Histograms of the number of logins on the virtual platform and overall study experience

In Columns 1 and 2 of Table 12, we depict the effects of treatment group membership on the number of logins on the virtual platform. We use a negative binomial regression model, as the number of logins represents count data that

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exhibits overdispersion. Here we present the mean marginal effects, while the regression coefficients are depicted in Table A3 in the Appendix. Overall, the results indicate that, compared to being part of the control group, the experience of real-time feedback (RTF and EC+RTF) increased the number of logins on the virtual platform on average by around 2 to 2.5 logins, while there are no similar significant effects for the group of participants that were part of the energy community but did not experience real-time feedback (EC). Furthermore, there is no significant difference in the effects of the experience of real-time feedback between the group that was also part of the energy community (RTF+EC) compared to those who solely received real-time feedback (RTF).

This holds also when we control for covariates (Column 2). We further investigate the sensitivity of our results by adding another specification that omits also the individual fixed-effects and instead controls additionally for observable characteristics and binary dummy variables that indicate treatment group membership ($Non\text{-}EC_i$ and EC_i).

Column (3) in Table 8 shows that the differences in baseline peak hour consumption between the control group and the treatment groups are not statistically significant from zero. The point estimates of the interaction terms $Non\text{-}EC_i \times Post_t$ and $EC_i \times Post_t$ are virtually unchanged. Moreover, this model shows that, in addition to the outdoor temperature, the household size and the equipment with a heat pump are predictive of electricity consumption in peak hours.

Table 12: Negative binomial regression analyses of treatment group membership on the number of logins on the virtual platform and ordered logit regression analyses of treatment group membership on the overall study experience – marginal effects

	No. of Logins (negative binomial model)				Study experience (ordered logit model)			
	(1)		(2)		(3)		(4)	
	Marg. Eff.	Std. Err.	Marg. Eff.	Std. Err.	Marg. Eff.	Std. Err.	Marg. Eff.	Std. Err.
Marginal effects on the number of logins								
EC	0.903	(0.752)	0.909	(0.769)				
RTF	2.255*	(0.893)	2.352*	(0.926)				
EC+RTF	2.448**	(0.919)	1.918*	(0.893)				
Marginal effect of EC on								
“Poor”					0.014	(0.086)	-0.019	(0.084)
“Fair“					-0.002	(0.012)	0.003	(0.011)
“Good”					-0.001	(0.005)	0.001	(0.005)
“Very good”					-0.011	(0.067)	0.015	(0.066)
“Excellent”					-0.000	(0.002)	0.001	(0.002)
Marginal effect of RTF on								
“Poor”					-0.184*	(0.078)	-0.177*	(0.080)

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"Fair"	-0.012	(0.016)	0.004	(0.015)
"Good"	0.007	(0.005)	0.008	(0.005)
"Very good"	0.181*	(0.077)	0.166*	(0.075)
"Excellent"	0.007	(0.006)	0.007	(0.006)
Marginal effect of EC+RTF on				
"Poor"	-0.180*	(0.079)	-0.176*	(0.081)
"Fair"	-0.011	(0.016)	-0.003	(0.015)
"Good"	0.007	(0.005)	0.008	(0.005)
"Very good"	0.176*	(0.078)	0.164*	(0.077)
"Excellent"	0.007	(0.006)	0.007	(0.006)
Control variables	No	Yes	No	Yes
No. Of observations	279	263	219	207

Note: Delta-method standard errors are reported in parentheses. ** and * denote statistical significance at the 1% and 5%, level, respectively. The control variables include age, gender, household size, education, income and retirement status.

7.2 Attitudes towards the energy community

Second, we examine three measures of the participants' attitudes towards the GEN-I Energy Community. To do this, we analyse the community members' agreement with three sets of statements elicited in the endline survey. These statements were exclusively shown to the energy community members:

Solidarity with the energy community:

- "I feel a bond with my GEN-I Energy Community."
- "I feel solidarity with my GEN-I Energy Community."
- "I feel committed to my GEN-I Energy Community."

Satisfaction with the energy community:

- "I am glad to be a member of my GEN-I Energy Community."
- "It is pleasant to be a member of my GEN-I Energy Community."
- "Being a member of my GEN-I Energy Community gives me a good feeling."

Centrality of the energy community:

- "I often think about the fact that I am a member of the Energy Community."

All items could be rated on a 5-point Likert Scale with the following options: "strongly agree (1)", "agree (2)", "neither agree nor disagree (3)", "disagree (4)", "strongly disagree (5)". Per set of questions, we calculate a composite index by computing the respective average responses.

Figure 5 depicts these indices. The results indicate that around 40 per cent of the community members agreed or strongly agreed on the items of the solidarity with the energy community category. This is roughly as large as the share that

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indiciated "neither agree nor disagree", while only a minority of less than a quarter disagreed on average.

Turning to the mean responses to the questions about the satisfaction with the energy community, we find that a majority of slightly above 50 per cent indicated "agree" or "strongly agree", on average. 27.8 per cent of the community members neither agreed nor disagreed and roughly 20 per cent disagreed.

When asked whether participants often thought about being part of the energy community (Centrality), the picture is somewhat different. The large majority of almost 70 per cent stated "disagree" or "strongly disagree" here. The second largest group was undecided, while only around 10 per cent of the participants indicated "agree" or "strongly" agree. Since the issue of energy plays only a minor role in most people's everyday lives, though, this does not appear to be a surprising result.

In Table A4 in the Appendix, we present the coefficients of ordered logit models estimating the effect of being part of the EC+RTF group compared to the EC-only group on these three indices. Yet, we do not find significant differences.

Figure 5: Attitudes towards the energy community – Numbers of observations: Solidarity (107), Satisfaction (108), Centrality (111).

7.3 Perceived environmental norms

Finally, we analyse two further questions from the endline survey, intended to elicit the perception of environmental norms in the energy community or in the general Slovenian population. These questions were again posed to the energy

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community members (EC) but also, in modified form, to the core study participants that were not part of the energy community (Non-EC).

Specifically, the participants were asked to indicate their agreement with the following statements:

- "Energy community members try to behave climate-friendly" (EC) / "Slovenian households try to behave climate-friendly" (Non-EC)
- "It is important to energy community members to fight climate change" (EC) / "It is important to Slovenian households to fight climate change" (Non-EC)

Again, the agreement to these items could be indicated on a 5-point Likert Scale with the following options: "strongly agree (1)", "agree (2)", "neither agree nor disagree (3)", "disagree (4)", "strongly disagree (5)".

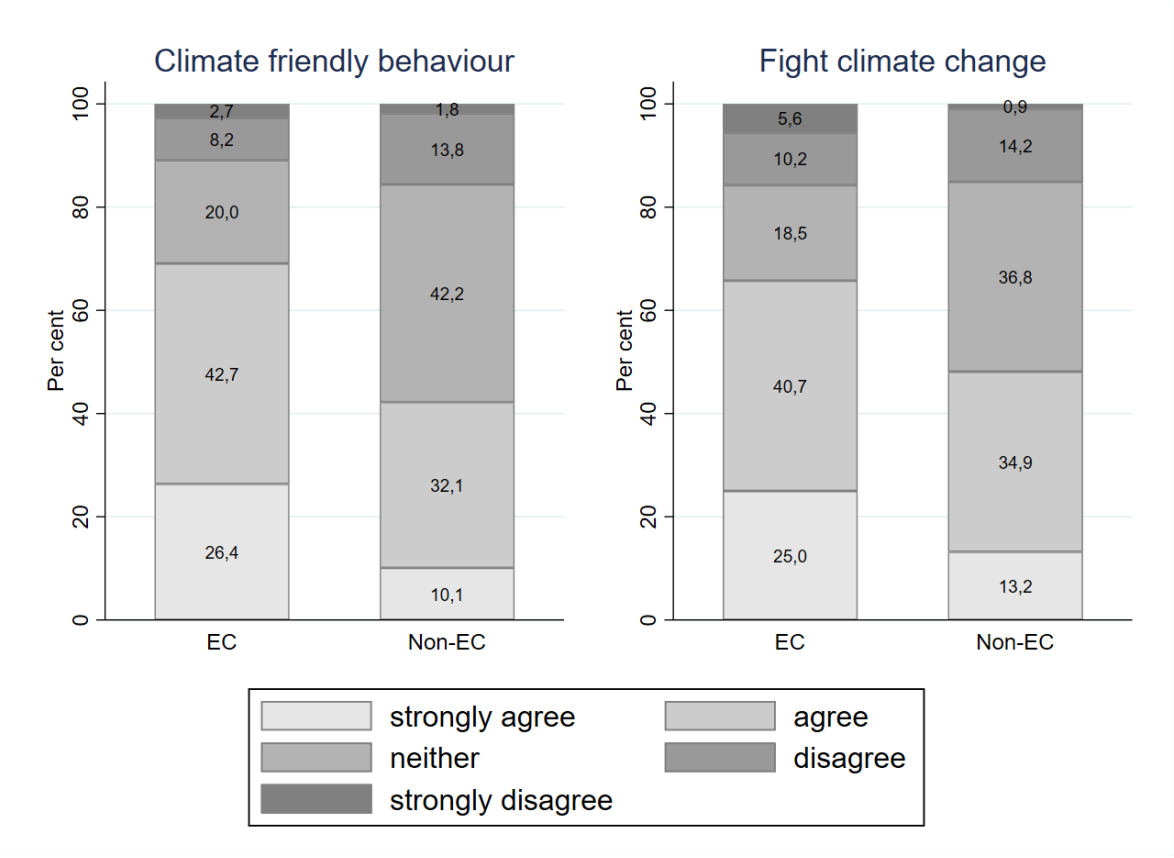

Figure 6: Perception of the environmental norms in the energy community / Slovenian population – Numbers of observations: Climate friendly behaviour (219), fight climate change (214).

The results in Figure 6 indicate that the EC members perceived the other members of the community as significantly more environmentally concerned than the Non-EC participants assessed the general Slovenian population. This holds for both items. In detail, more than 60 per cent of the EC members agreed or strongly agreed that the other energy community members try to behave climate-friendly or deem the fight against climate change important. In contrast, the Non-EC members assessed this proportion to be well below 50 per cent in the general Slovenian population.

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As shown by the coefficients of ordered logit models in Table A5 in the Appendix, these differences are also statistically significant. Yet again, there is not evident significant difference between participants that received real-time feedback compared to those who did not.

8 Conclusions

The aim of this study was to analyse whether membership in an energy community amplifies the effect of behavioural interventions aimed at reducing resource consumption. The study was set in the context of a top-down exogenously created energy community that was co-created in collaboration with the largest Slovenian electricity supplier, GEN-I. The results from Deliverable 5.1 showed that membership in this energy community did not have a considerable conservation effect on aggregate electricity use in the first three months of the study.

In this report, we analysed two additional experiments that were conducted within this energy community: First, we investigated whether the effect of the provision of real-time feedback while showering is amplified by membership in the energy community. Second, we investigated whether the energy community members were more successful in coordinating on a joint reduction of electricity use in hours where aggregate electricity demand is high than the other study participants, given a prosocial incentive in form of a charitable donation made by GEN-I per group member if a certain reduction goal is met throughout one month. We conclude that real-time feedback proves to be a highly effective behavioural intervention for reducing resource use, and we extend the existing body of research on the topic, which is largely focused on Central European countries, by showing that this effect is also transferable to a Slovenian study population. While the reduction effect of 16-17 per cent of water use per shower is somewhat smaller compared to the 22 per cent reduction found in Tiefenbeck et al. (2018). This could be explained by the substantially smaller baseline water use per shower in Slovenia (24 litres) compared to Switzerland (45 litres). We do not find a considerable difference in the effect of real-time feedback between the energy community members and the other study participants. Furthermore, we do not observe noticeable effects of real-time feedback on overall household electricity use, as could for example be expected if moral licensing effects were present (Tiefenbeck et al. 2013)

Concluding, the average treatment effects from the first experiment substantiate the findings from Deliverable 5.1. This means that there seems to be limited potential of the newly created energy community to stimulate more resource conservation than can be achieved with already established behavioural interventions.

The results of the second experiment suggest that the energy community group was able to reduce its electricity use in peak hours on average by 4 per cent, while the other study participants did not reach a comparable reduction. Deeper analysis shows that this effect is mainly driven by the half of the energy community that experiences real-time feedback. This group reduced its electricity use in peak hours on average by 7.2 per cent, while none of the other

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groups exhibited a comparable reduction. This leads to the conclusion that the experience of real-time feedback and membership in the energy community combined lead to these participants also being willing to change their electricity consumption behaviour over the course of the day.

Possible explanations are: (i) Real-time feedback might have become a very present part of everyday life, increasing attention to one's own resource use and to one's own membership in the energy community. (ii) Because real-time feedback resulted in high water and energy savings, which the participants were able to track on the virtual platform, there may have been a collective sense of accomplishment that led to a willingness to invest more effort within the energy community to achieve further accomplishments, thus making the participants more susceptible to the load-shifting challenge. (iii) On a similar note, we have found that the experience with real-time feedback is associated with more logins on the virtual platform and a higher overall satisfaction with participation in the study. Perhaps this boost in attention to and satisfaction with the study, which might have been lacking in the first study phase analysed in Deliverable 5.1, was necessary for people to engage with the feeling of being part of an energy community.

Analyses of the endline survey revealed that a large proportion of energy community members had a positive attitude towards their energy community. About 50 per cent of the community members indicated that they drew a positive feeling from their membership, while only less than a quarter disagreed; the remainder was undecided. Likewise, 40 per cent of the members experienced a sense of solidarity or commitment to the energy community, while only about 20 per cent disagreed. These results corroborate findings from the citizen survey (Deliverable 6.3) suggesting that new forms of virtual energy communities can in fact be appealing to a wide range of people.

Taken together, the results from the two experiments analysed in this report provide mixed evidence: The first experiment seems to support the conclusion from Deliverable 5.1 as the newly created GEN-I energy community did not enhance the effect of the applied behavioural intervention to reduce resource use, namely real-time feedback. The results of the second experiment suggest that solely the energy community members, who also experienced real-time feedback, were successful in reducing their electricity use in hours with high aggregate electricity demand, while none of the other group exhibited a similar reduction.

Thus, the conclusion of Deliverable 5.1 is not entirely corroborated in this report. Rather, it shows that the experience of real-time feedback while showering, which is a behavioural intervention that is very present in everyday life and led to high water and energy savings, was apparently necessary for membership in the energy community to develop an effect. For future research, this means that more attention should be paid to combining different behavioural interventions, since, for example, large energy saving successes in one area could also trigger efforts in other areas.

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9 Appendix

A Tables and Figures

Table A1: Scales used to measure Environmental concern, Social concern, and Social identity

Question	Scaling adjustments
Environmental concern • I am willing to act environmentally responsible, even if this is associated with higher costs and efforts. (Tiefenbeck et al., 2018) • I am willing to act environmentally responsible only if others do the same. • I would act according to my principles if I save energy. (Czibere et al., 2020) • I feel personally responsible for trying to save energy. (Czibere et al., 2020)	Reverse coding
Social concern (Czibere et al., 2020) • Most of the people who are important to me think I should try to use as little energy as possible. • Most of the people who are important to me will approve of when I try to use as little energy as possible. • Most people who are important to me try to use as little energy as possible.	
Social identity (Allcott and Taubinsky, 2015) • It's important to me to fit in with the group I'm with. • My behaviour often depends on how I feel others wish me to behave. • I would NOT change my opinions (or the way I do things) in order to please someone else or win their favour.	Reverse coding

Environmental concern, Social concern, Social identity: Respondents could answer these questions on a five-point Likert scale, ranging from 'I strongly disagree' to 'I strongly agree'. The nature of some questions made it necessary to rescale the answers before combining them into one measure to ensure coherence. This is indicated by 'reverse coding'.

Table A2: Comparison of the study sample to the Slovenian population

	Study sample	Slovenian population
Household size in number of persons	3.1	2.5
Age in years	35.1	44.5
University degree in per cent	0.33	0.33
Female in per cent	0.369	0.513
Net monthly household income in €	1,500 – 2,500	2,060

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Table A3: Negative binomial regression analyses of treatment group membership on the number of logins on the virtual platform and ordered logit regression analyses of treatment group membership on the overall study experience - regression coefficients

	No. of Logins (negative binomial model)				Study experience (ordered logit model)			
	(1)		(2)		(3)		(4)	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
EC	0.247	(0.222)	0.237	(0.199)	-0.058	(0.348)	0.082	(0.364)
RTF	0.530**	(0.205)	0.526**	(0.199)	0.817*	(0.355)	0.819*	(0.377)
EC+RTF	0.565**	(0.210)	0.447*	(0.202)	0.797*	(0.359)	0.813*	(0.387)
Age	–	–	0.001	(0.008)	–	–	-0.055**	(0.017)
Household size=2	–	–	0.601*	(0.284)	–	–	-0.271	(0.515)
Household size=3	–	–	0.076	(0.289)	–	–	-0.522	(0.529)
Household size=4	–	–	0.481	(0.274)	–	–	-0.670	(0.519)
Household size=5	–	–	0.376	(0.291)	–	–	-0.075	(0.550)
Female	–	–	0.679**	(0.164)	–	–	0.123	(0.292)
University	–	–	0.028	(0.151)	–	–	-0.375	(0.296)
Retired	–	–	-0.304	(0.241)	–	–	1.024*	(0.486)
High income	–	–	-0.145	(0.222)	–	–	0.066	(0.435)
Constant	1.171**	(0.153)	1.065*	(0.499)	–	–	–	–
Cut 1	–	–	–	–	-0.225	(0.266)	-3.255**	(0.989)
Cut 2	–	–	–	–	0.763**	(0.271)	-2.163*	(0.975)
Cut 3	–	–	–	–	0.947**	(0.274)	-1.982*	(0.974)
Cut 4	–	–	–	–	5.160**	(0.755)	2.176	(1.172)
No. of observations	279		263		219		207	

Robust standard errors are reported in parentheses. ** and * denote statistical significance at the 1% and 5%, level, respectively.

Table A4: Ordered logit regression analyses of treatment group membership on indicators of attitudes towards the energy community - regression coefficients (Base group: EC group; Categories: Fully agree (1) to fully disagree (5))

	Solidarity				Satisfaction				Centrality			
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
EC+RTF	0.358	(0.358)	0.471	(0.391)	0.045	(0.351)	0.032	(0.374)	0.101	(0.358)	0.252	(0.388)
Age	–	–	-0.021	(0.025)	–	–	-0.013	(0.024)	–	–	-0.039	(0.027)
Household size=2	–	–	-0.411	(0.627)	–	–	-0.582	(0.640)	–	–	-0.406	(0.589)
Household size=3	–	–	-0.365	(0.742)	–	–	-1.005	(0.677)	–	–	-0.092	(0.769)
Household size=4	–	–	-0.517	(0.504)	–	–	-0.768	(0.581)	–	–	-0.553	(0.609)
Household size=5	–	–	-0.841	(0.630)	–	–	-1.236	(0.717)	–	–	-0.833	(0.623)
Female	–	–	-0.450	(0.509)	–	–	-1.105*	(0.496)	–	–	-0.636	(0.490)
University	–	–	0.562	(0.425)	–	–	0.623	(0.399)	–	–	0.566	(0.427)
Retired	–	–	-0.124	(0.646)	–	–	0.169	(0.673)	–	–	-0.297	(0.784)
High income	–	–	1.023*	(0.503)	–	–	1.111*	(0.515)	–	–	1.040	(0.547)
Cut 1	-1.492**	(0.311)	-2.938*	(1.344)	-1.176**	(0.293)	-2.769*	(1.211)	-3.001**	(0.534)	-5.585**	(1.489)
Cut 2	-0.291	(0.275)	-1.680	(1.333)	0.099	(0.276)	-1.273	(1.184)	-1.965**	(0.394)	-4.585**	(1.476)
Cut 3	1.340**	(0.320)	0.022	(1.309)	1.389**	(0.327)	0.087	(1.135)	-0.718*	(0.316)	-3.158*	(1.467)
Cut 4	3.030**	(0.518)	1.770	(1.302)	3.580**	(0.676)	2.333	(1.335)	0.631*	(0.306)	-1.564	(1.446)
No. of observations	107		104		108		105		111		107	

Robust standard errors are reported in parentheses. ** and * denote statistical significance at the 1% and 5%, level, respectively.

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Table A5: Ordered logit regression analyses of treatment group membership perceptions of environmental norms in the energy community / Slovenian population - regression coefficients (Base group: core study control group; Categories: Fully agree (1) to fully disagree (5))

	Climate friendly behaviour				Fight Climate change			
	(1)		(2)		(3)		(4)	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
EC	-1.149**	(0.385)	-1.091**	(0.392)	-0.633	(0.365)	-0.696	(0.369)
EC+RTF	-0.858*	(0.341)	-0.960**	(0.362)	-0.349	(0.359)	-0.551	(0.384)
RTF	0.032	(0.320)	0.053	(0.351)	0.186	(0.312)	0.063	(0.336)
Age	–	–	-0.006	(0.014)	–	–	-0.012	(0.016)
Household size=2	–	–	-0.050	(0.412)	–	–	-0.526	(0.524)
Household size=3	–	–	-0.612	(0.514)	–	–	-1.652**	(0.544)
Household size=4	–	–	-0.231	(0.385)	–	–	-0.907*	(0.452)
Household size=5	–	–	-0.447	(0.376)	–	–	-1.384**	(0.476)
Female	–	–	-0.559	(0.313)	–	–	-0.519	(0.302)
University	–	–	-0.159	(0.282)	–	–	0.108	(0.288)
Retired	–	–	-0.142	(0.417)	–	–	-0.122	(0.524)
High income	–	–	0.763*	(0.311)	–	–	0.618*	(0.308)
Cut 1	-2.068**	(0.285)	-2.891**	(0.939)	-1.662**	(0.273)	-3.519**	(0.954)
Cut 2	-0.222	(0.239)	-0.919	(0.907)	0.110	(0.239)	-1.545	(0.921)
Cut 3	1.505**	(0.266)	0.792	(0.896)	1.558**	(0.260)	-0.101	(0.904)
Cut 4	3.391**	(0.476)	2.842**	(0.898)	3.242**	(0.396)	1.710	(0.951)
No. of observations	219		207		214		202	

Robust standard errors are reported in parentheses. ** and * denote statistical significance at the 1% and 5%, level, respectively.

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B Background on the experiment

Features that were accessible to all study participants (treatment and control group) via the virtual platform and the monthly energy reports:

- A graphical representation of high-resolution household electricity consumption data over time in 15-minute intervals (see Figure A1).
- A graphical representation of water and energy consumption per shower over time (see Figure A2).
- Messages providing tips on how to effectively conserve energy in the household (see Figure A3).
- A comparison of the weekly average electricity use of the participant's household to the average weekly electricity use of the other study members (calculated based on the control group data). This comparison was accompanied by an injunctive norm message (see for example Schultz et al., 2007) in form of a happy or frowny face that indicates whether the own electricity use was below or above the average electricity use of other study participants.
- The same comparison was provided with regard to water use per shower.

Additional features that were accessible only to the energy community:

- A message informing that the participant is now a member of a newly created energy community with the common goal to contribute to more sustainable future by reducing electricity use and thereby lowering one's own electricity bill.
- A comparison of the weekly average electricity use of the treatment group members (referred to as the participant's *energy community*) to the average weekly electricity use of the control group members (referred to as the *other study participants*). Again, this comparison was accompanied by an injunctive norm message (Schultz et al., 2007) in form of a happy or frowny face that indicates whether the treatment group's electricity use was below or above the control group's electricity use (see Figure A4).
- The same comparison was provided with regard to water use per shower.
- A moderated interactive discussion forum where participants could share advice on saving energy at home, motivate each other to increase conservation efforts, and also discuss off-topic content. GEN-I moderated this forum by posting public polls on various energy-related topics, asking general questions to stimulate discussion among participants, and providing opportunities to comment on the energy saving tips (see Figure A5).
- A map displaying the location of the other treatment group members, intended to emphasize that the participants are connected by being from a similar area (see Figure A4).

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Table A6: Overview: Differences between the treatment and the control group

	EC (treatment)	Non EC (control)
Portal access	✓	✓
Data on own electricity & water consumption	✓	✓
Energy saving tips	✓	✓
Monthly comparison of own water and electricity with other study participants	✓	✓
View location of other EC members	✓	X
Interactive discussion forum	✓	X
Average electricity consumption of avg EC members compared to avg study participants	✓	X
Info about the purpose of the platform	EC members have common goal to contribute to more sustainable future by reducing electricity use and thereby lowering electricity bill	platform access to track own energy use

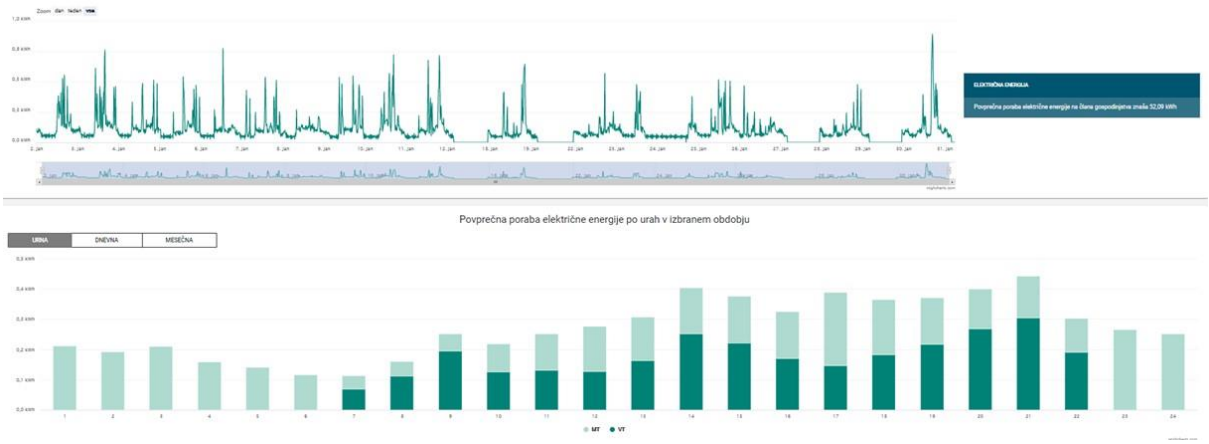

Figure A1: Electricity consumption shown on the virtual platform to all study participants.

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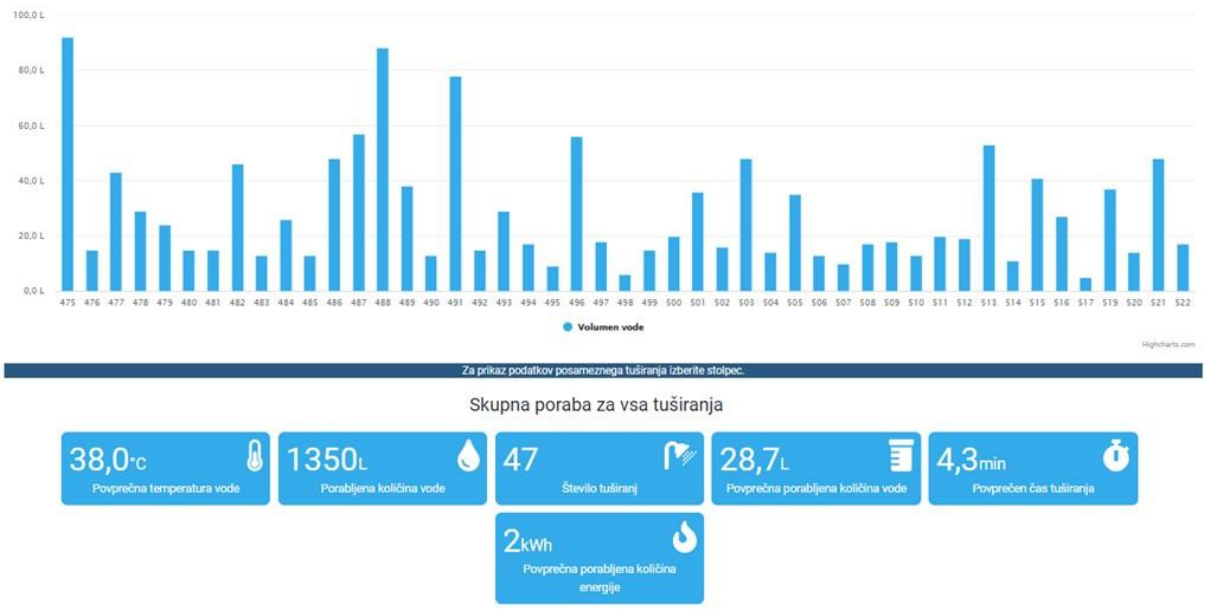

Figure A2: Water consumption shown on the virtual platform to all study participants.

Practical tips for saving energy in January

We have entered the new year 2021, which we all wish will be positive. In the winter months, when the temperatures outside are not at all tempting, we will spend more time indoors, in the warmth. But the comfort of warm radiators can quickly be overshadowed by high heating costs, which we often have, whether we admit it or not. At least in part. We want to share some practical tips on how to ensure a comfortable stay and at the same time save on energy consumption.

✔Lower the temperature of your heating by one degree. By doing so, your heating costs will be up to 6 percent lower. Plus, you'll have a great excuse to re-wear your Christmas sweater.

✔Lower the room temperature to 15 ° C at night. You can do this on the eve of bedtime.

✔Your appliances (washing machine, dishwasher, dryer) should operate during the time of lower electricity tariffs, between 10 pm and 6 am By using the devices at night, you will help to reduce the load on the electricity network during higher daily tariff items, which are charged every working day between 6 am and 10 pm.

Comments (0) Like (1)

Figure A3: Energy saving tips shown on the virtual platform to all study participants (example).

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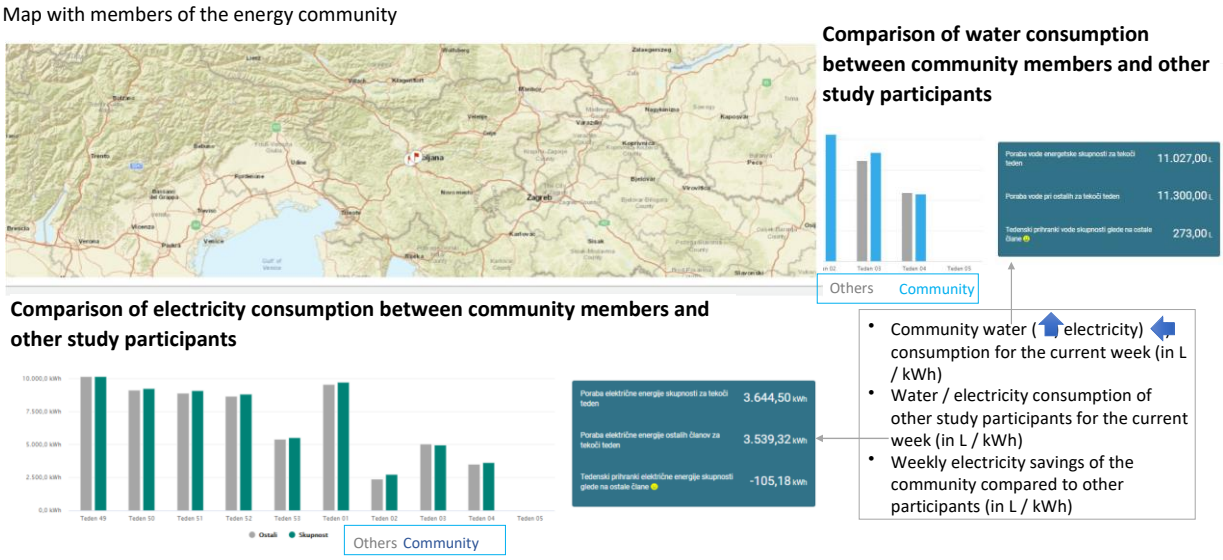

Figure A4: Features of the virtual platform for Energy Community members only.

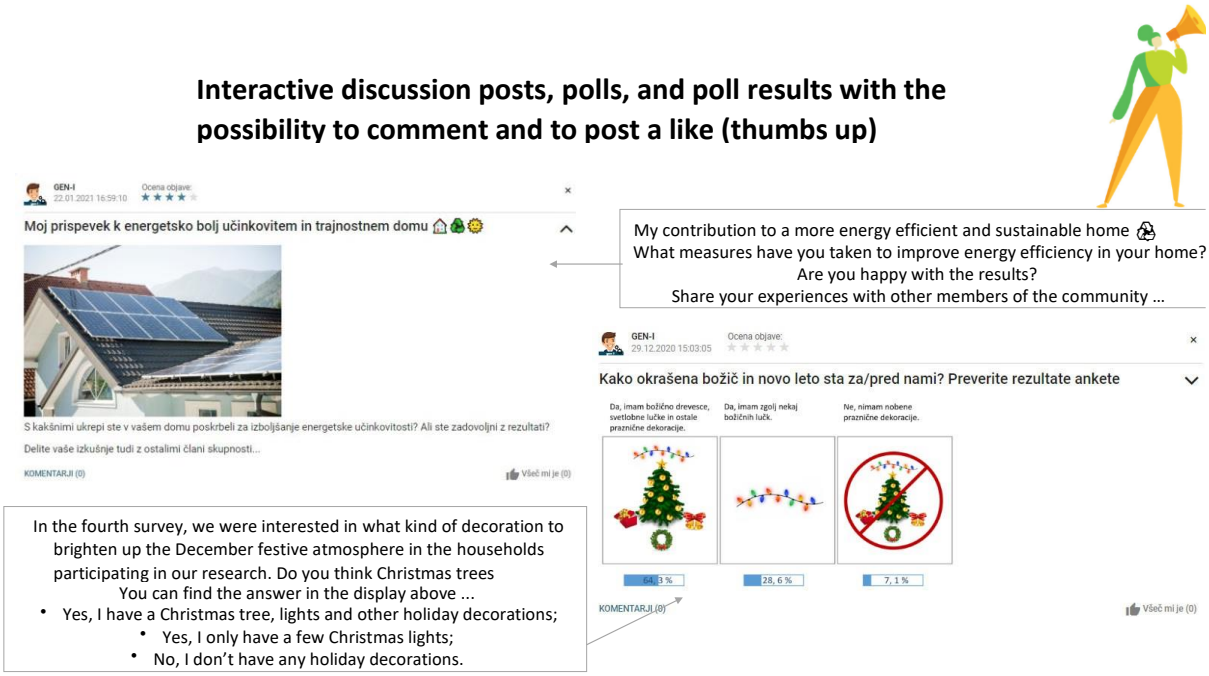

Figure A5: Screenshot of the interactive discussion forum on the virtual platform for Energy Community members only.

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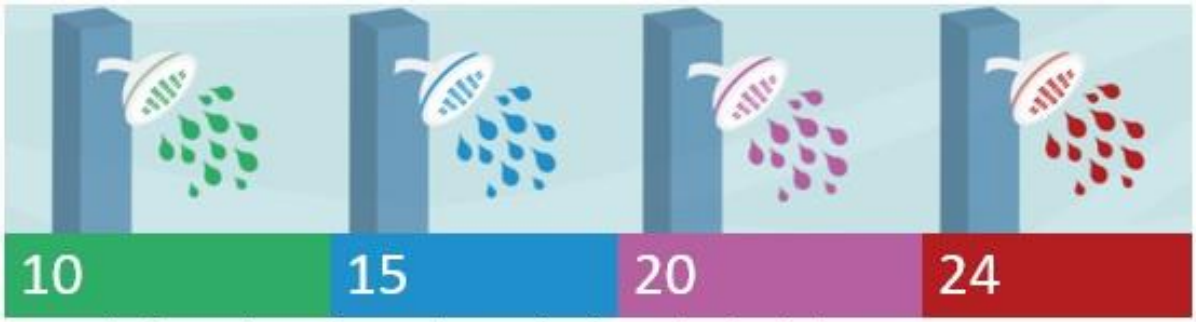
C Introduction of real-time feedback on the virtual platform and in the monthly energy report on 3 March 2021

For the purpose of this study, you have all installed a smart shower head. We would like to give you a few tips to save on water and energy used by showering.

- Try to shower for no longer than 3 minutes. You'll save time, money and the environment! On average, every person is in the shower for 120 days in his or her life. That is 1.5 days per year. If you take a more conscious shower and turn off the tap after 3 minutes, you will save 1350 minutes every year that you can use for walks, watching football, playing with the kids or whatever you like to do!
- Take a shower instead of a bath. An average bath of 120 litres uses five times as much water and therefore energy as a 3-minute shower.
- Play your favourite shower songs which last in total a maximum of 3 minutes, to remind yourself to turn off the shower in time.
- Turn off the shower while you are shampooing. This will strongly reduce the water use per shower.

Extra-Info for the RTF Group and the EC+RTF Group:

From now on, your shower head will help you keep an eye on your water consumption while showering. It will light up in colour and as your water consumption increases, the colour will change. Finally, once your water consumption exceeds 24 litres, it will start flashing red. The exact colour pattern is as follows:



During the first **10** liters of your shower, the shower head will glow green.
After **10** liters, your shower head will begin to glow blue.
After **15** liters, your shower head will begin to glow purple.
After **20** liters, your shower head will begin to glow red.
Finally, after **24** liters, your shower head will begin to flash red.

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D Load shifting challenge – sent via email on 2 April 2021

green: text only shown to the EC group
blue: text only shown to the non-EC group

Hello NAME!

We have a challenge for you, which you can read more about below.

First of all, can you imagine the electricity grid as a highway? What is it about?

Imagine a three-lane highway. If you were to drive on it on a Sunday morning when the highway is almost empty, six empty lanes would most likely seem completely redundant to you. However, if you were to drive along this same highway on Friday afternoon in crowds or even congestion, you would definitely think that an extra lane would be more than welcome.

What are daily peaks?

In the same way as roads at rush hour, the electrical network perceives a period of increased traffic or. electricity demand. Periods of maximum network loads are called daily peaks. In the case of electricity, these peaks do not slow down the flow of electricity, as is the case with road congestion, but contribute to increasing network costs. Taking into account the theory of supply and demand, the price of electricity is the most expensive at the time of the greatest demand for electricity.

By reducing electricity consumption during peak hours, we help balance its supply and demand, contribute to ensuring greater stability of the electricity network and lower network costs, which can also affect the possibility of lowering the price of electricity.

Redistribute electricity consumption outside the peaks. Every individual counts!

Redistributing electricity consumption in your household throughout the day has minor, but by no means negligible, effects on relieving the grid during times of increased consumption. If a larger number of users commit to a single goal of redistributing electricity consumption, we can contribute to even better end results through joint steps.

Join the challenge, be charitable.

Join us and take part in a one-month challenge with the common goal of redistributing electricity consumption outside the peak hours. We encourage you and other members of your household to reschedule your daily tasks (such as heating with electricity, ironing, using a washing machine or dishwasher, cooking on an electric hob, etc.) from the peak hours to the time of day when electricity consumption is lower. You can also contribute to lower electricity consumption during peak hours by turning off some larger electricity consumers

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for a shorter period of time. by not turning on the latter during peak hours. The challenge runs for one month, until May 3, 2021. All you have to do is try to minimize your household's electricity consumption during peak hours, that is, between 5pm and 9pm. The goal of the common challenge is to balance the daily electricity consumption curve.

If the members of the energy community as a whole reduce electricity consumption during the daily peaks by 10 percent next month, we will donate the collected funds (in the amount of EUR 10 per individual member of the energy community) to the selected charity.

If the members of the research study as a whole reduce electricity consumption during the peak hours by 10 percent in the next month, we will donate the collected funds (in the amount of EUR 10 per member of the research study) to the selected charity.

Since we want to offer you the possibility of choosing a charity that will receive funds (donation), we invite you to vote on the user portal (URL). On the portal, you can choose your favourite from the proposed charities. Cast your vote and show that you care. The decision is yours.

Below you can find a graph that depicts your average electricity consumption as well as your energy community's average electricity consumption / the average electricity consumption of all study participants in each hour of the day (since the start of the study).

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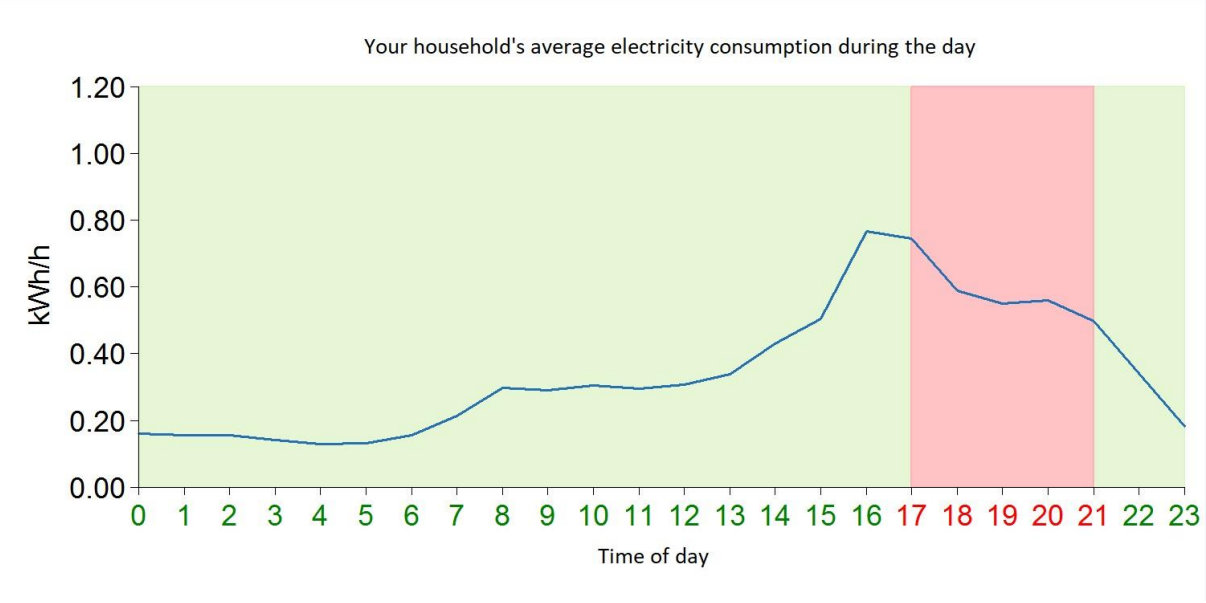

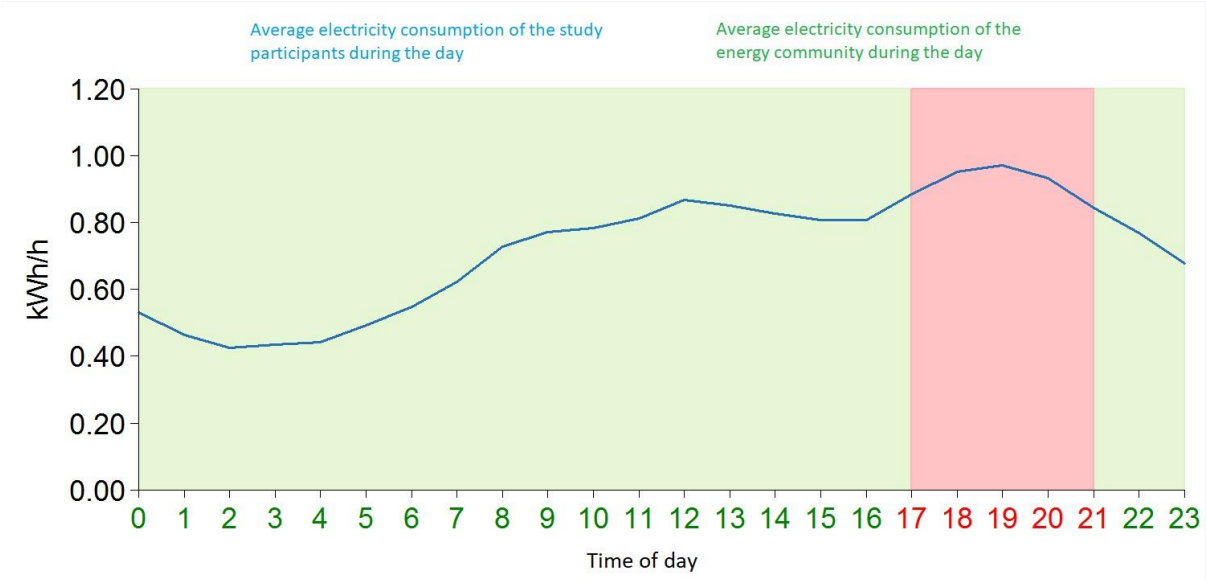

Remember: The common goal is to reduce electricity consumption during the daily peak hours (red colour in the graph).

Are you willing to take part in the challenge and contribute to the common goal? If the common goal is reached next month, GEN-I, together with research project partners, RWI - Leibniz Institute for Economic Research, Germany, and the University of Amsterdam, will support a charity of your choice of 10 Euros per individual community member / study participant.

Every individual can contribute to achieving the goal. Together, as an energy community, we can achieve even greater results! / Every individual can contribute to achieving the goal!

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E Did the introduction of the energy community have an effect on water use per shower?

To check whether the mere introduction of the energy community in December 2020, in the absence of any real-time feedback intervention, had an effect on the participants' water use while showering, we run a difference-in-difference model based on a sample that starts at the beginning of the baseline period and ends before the introduction of the real-time feedback. The beginning of the energy community treatment is dated on December 11, 2020, which marks the start date of the treatment period in the following estimations. To maximize statistical power, we pool the experimental groups to one control group and one energy community group. This pooling is uncritical because the other distinguishing feature between the sub-groups, real-time feedback, did not play a role at this point in the experiment.

Table A7: Difference-in-differences estimation results - introduction of the energy community
Outcome variable: Water use per shower

	Coeff.	Std. Err.
Post	0.269**	(0.095)
EC × Post	0.001	(0.023)
Day fixed effects	Yes	
Individual fixed effects	Yes	
No. of observations	59,079	
No. of households	279	

Note: Standard errors are clustered at the household level and reported in parentheses. For the analysis, we drop showers below 5 litres and above 200 litres. ** and * denote statistical significance at the 1% and 5%, level, respectively. The outcome variable (Y_{it}) is defined as the percentage deviation of water use per shower (C_{it}) from the average water use per shower of the control group in the treatment period ($\bar{C}_w^c$ = 23.29 litres), i.e. $Y_{it} = \frac{C_{it} - \bar{C}_w^c}{C_w^c}$.

As the interaction term $EC_i \times Post_t$ is small in magnitude and statistically insignificantly different from zero, the results presented in Table A7 provide evidence that the introduction of the energy community itself had no effect on the participants' water use per shower. Therefore, we will consider the phase in which the energy community already existed, but real-time feedback was not yet activated to be part of the baseline phase in order to maximize our sample size.

F Did the start of the real-time feedback treatment period have differential effects on the energy community group compared to the control group?

To check whether the start of the real-time feedback treatment period on 8 March 2021 did differentially affect the two groups that did not receive real-time feedback, i.e. the groups "Control" and "EC", we replicate Figure 2 and re-run the analysis displayed in Column I of Table 3 differentiating the pooled control group with regard to the participants' membership in the energy community.

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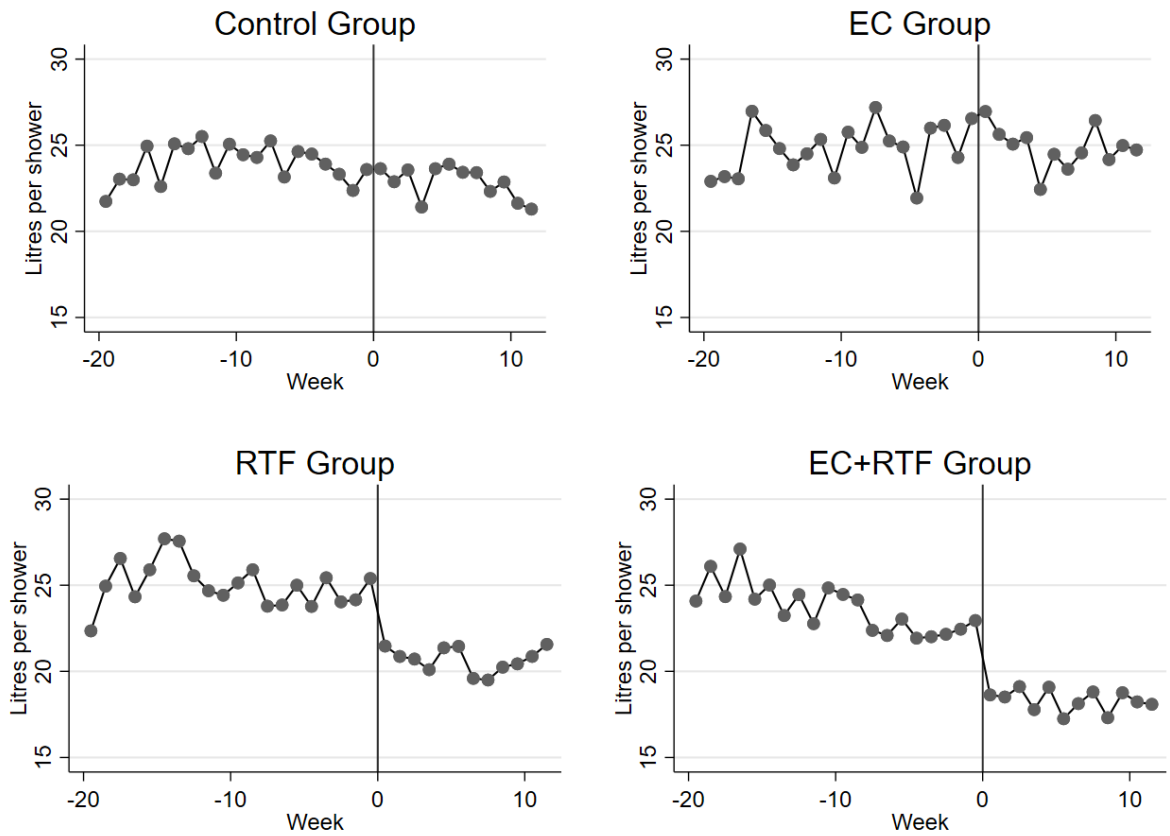

Figure A6: Water use per shower (weekly averages) over time per treatment group

Table A8: Difference-in-differences estimation results - differentiated control group
Outcome variable: Water use per shower

	Coeff.	Std. Err.
Post	-0.074	(0.088)
EC × Post	0.059	(0.044)
RTF × Post	-0.139**	(0.048)
(EC+RTF) × Post	0.130**	(0.045)
Day fixed effects	Yes	
Individual fixed effects	Yes	
No. of observations	90,358	
No. of households	279	

Note: Standard errors are clustered at the household level and reported in parentheses. For the analysis, we drop showers below 5 litres and above 200 litres. ** and * denote statistical significance at the 1% and 5%, level, respectively. The outcome variable (Y_{it}) is defined as the percentage deviation of water use per shower (C_{it}) from the average water use per shower of the control group in the treatment period ($\bar{C}_w^c$ = 23.29 litres), i.e. $Y_{it} = \frac{C_{it} - \bar{C}_w^c}{C_w^c}$.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 837752.

As the interaction term $EC_i \times Post_t$ in Table A8 is small in magnitude and statistically insignificantly different from zero and also the graphical illustration does not reveal a noticeably different pattern between the Control group and the EC group, the results provide evidence that the start of the real-time feedback treatment period did not differentially affect these groups. Therefore, we pool these two groups for the main analyses.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 837752.

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