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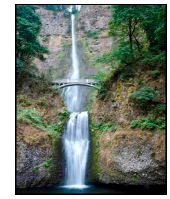

Feedback devices help only environmentally concerned people act pro-environmentally over time

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ABSTRACT

Technological advancements spawn products that tend to be useful when placed in the appropriate hands. Here we investigated whether potential benefits of owning a feedback device were driven by individual differences in environmental values (i.e. biospherism), or whether the device alone is sufficient to reduce energy over time. We examined a total of 276 households, 138 equipped with a feedback device formed our treatment group, and 138 control households selected from a wider pool of households (+2000) based on their similarity to the treatment households, according to a statistical matching procedure. The results indicated that individuals with low biospheric values fail to decrease their electricity expenditure when paired with a feedback device. Conversely, highly biospheric individuals do engage in more pro-environmental behaviour when they receive feedback, but only when they have owned the device for about three years or more. We obtained additional insights, by focusing on differences within the treatment group that suggest, once again, that only highly biospheric individuals who owned the device for over three years successfully implement changes in the household. Overall, these results indicate that feedback devices such as smart meters can be important tools in achieving energy reductions only when paired with environmentally concerned individuals. Given the current trend towards increased feedback technology, policy implications for decision makers are discussed.

1. Introduction

The world is becoming an increasingly digital environment, with millions of people interacting daily with interconnected devices. Entire neighbourhoods of connected homes equipped with feedback devices such as smart meters are being developed (see for instance “Desigo CC” in Siemens City Vienna) but further research is needed to investigate the conditions in which this technology is effective, for instance, the rebound effect is famously known to offset the positive effect of tech efficiency. It is thought that the technologies of the near-future can lead to stark energy consumption improvements, as is laid out in the Strategic Energy Technology Plan, formulated by the European Commission in 2015. Reliance upon feedback devices is also emphasized in the Energy RoadMap 2050 (second strategy: “High Energy Efficiency”). However, the rebound effect, for instance, is famously known to offset the positive effect of technology efficiency. Are there any specific circumstances under which technology and feedback devices in particular become more (or less) effective at curbing energy consumption? This research investigates the effect of feedback devices on energy consumption over time. Specifically, using a sample of owners and non-owners of feedback devices, this research provides a novel understanding of how the duration of the ownership of a smart meter interacts with biospheric values to affect energy consumption.

We start by reviewing the literature on the effect of feedback on pro-environmental behaviours over time. We then build on the habit literature and on the Elaboration Likelihood Model to develop our hypotheses. We then present the survey and the data analysis. Finally, we discuss our findings in light of the relevant literatures and detail the limitations of the research.

1.1. Effect of feedback on pro-environmental behaviours

Increased feedback information can prompt individuals to modify energy-related behaviours, according to the feedback they receive (Darby, 2006), which is important because it can be difficult to accurately gauge one's consumption (Weiss, Mattern, Graml, Staake, & Fleisch, 2009). The delivery of real-time feedback can produce important declines in residential electricity consumption (Ehrhardt-Martinez, 2012; Faruqui, Harris, & Hledik, 2010), with a number of studies observing a 5–15% reduction (Darby, 2006; Ehrhardt-Martinez, 2012; Houde, Todd, Sudarshan, Flora, & and Armel, 2013). Other researchers have reported larger benefits, of 20% electricity reduction

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(Gans, Alberini, & Longo, 2011) or even as high as 55% reduction of water consumption when receiving direct feedback from meters (Petersen, Shunturov, Janda, Platt, & Weinberger, 2007). Studies have also highlighted that it is the receiving of feedback itself which affects energy conservation, while the specific content of the feedback (i.e. emphasizing financial gains or environmental impact) is of lesser importance (Dogan, Bolderdijk, & Steg, 2014). Real-time feedback may be conveyed through a number of medium, however it seems that the most commonly employed methods are through water meters, and especially electricity smart meters. Consumption feedback can help the user to learn to distinguish between energy-heavy and energy-light behaviours (Fischer, 2008; Hargreaves, Nye, & Burgess, 2013) and, more generally, can help in the development of positive habits.

1.2. Long-run effectiveness of feedback devices

Feedback from devices such as smart meters can be powerful tools in aiding the reduction of energy consumption by providing consumption feedback to individuals, however, not all reports have been entirely positive. McCoy and Lyons (2017) found that exposure to energy consumption information provided by a feedback device may have the unintended effect of reducing investment in energy efficiency measures within the home. The authors found indeed that households who used a smart meter adopted less energy saving measures than those in a control group (23–28%), which casts doubts on the absolute effectiveness of feedback devices. However, the test phase of the study ran over a period of 12 months, and the treatment group who received the feedback from the device may have a) felt that by installing the device they had already performed an energy-saving measure, and b) required a greater time-frame within which to implement household changes. Tiefenbeck et al. (2018) investigated the effects of receiving real-time feedback on water consumption in the shower, by displaying both the number of litres consumed and also an animation of a polar bear standing on a block of ice that progressively shrunk, the more water was consumed. The device was located next to the shower and the authors found that it led to reductions of up to 22%, and 30% among those most environmentally concerned. However, the study lasted only 2 months, and while the benefits were consistent until the end of the tested period, it is difficult to know whether they may taper off. In fact, Snow, Buys, Roe, and Brereton (2013) interviewed a small group of long-term smart meter users and found that the device failed to maintain long-lasting engagement past an initial novelty phase, characterized by curiosity and engagement. Participants in the study did report an increase in energy awareness, which however was not followed by any concrete pro-environmental behaviour (PEB). When the effects of real-time feedback on electricity expenditure have been examined over longer periods lasting several years results have shown a stable reduction of 15–17% (Gans et al., 2011). It is yet unclear whether the reductions were experienced by all participants or just a subgroup driving the effect. Little is known about how possible reductions are achieved (e.g. modifying usage of the appliances or purchasing new energy efficient appliances). Darby (2006) states: “As a rule of thumb, a new type of behaviour formed over a three-month period or longer seems likely to persist – but continued feedback is needed to help maintain the change and, in time, encourage other changes”. Therefore, with some evidence in the literature showing that real-time feedback can lead to tangible reductions, we believe that given a sufficiently wide time period, the presence of a feedback device will give rise to reductions in expenditure. We formalize our hypothesis as follows:

H1. Households owning a feedback device will reduce their electricity expenditure over time

1.3. Environmental concern and feedback devices

When studying PEB, it is important to account for the values people harbour. Psychological values can be defined as “desirable goals, varying in importance, that serve as guiding principles in people's lives'” (Schwartz, 1992, p. 21). *Biospherism* is a particular psychological value that emphasizes a concern for the environment for its own sake, and not out of self-interest, therefore taking a collective and caring perspective towards life in all its forms (de Groot & Steg, 2008, 2009; Steg, Bolderdijk, Keizer, & Perlaviciute, 2014; Steg, de Groot, Dreijerink, Abrahamse, & Siero, 2011; Stern, Dietz, & Kalof, 1993). Biospheric values have often been found to be important predictors of PEB (e.g. Steg & De Groot, 2012), and specifically energy conservation efforts tend to be particularly associated with individuals adhering to biospheric values (Abrahamse & Steg, 2011).

Previous research supports the notion that environmental values and attitudes moderate the effect of feedback, with a limited number of studies showing that the effects of consumption feedback vary according to levels of environmental concern. Brandon and Lewis (1999) assigned participants to one of seven treatment conditions, one of which was a computer program that provided tailored feedback. Despite weak results due to methodological issues addressed by the authors, feedback from the computer showed some evidence of triggering PEB (i.e. no main effect of treatments, but effect on a post-hoc analysis) and this was especially true for those who held positive environmental attitudes. Tiefenbeck et al. (2018) also show that environmental attitude moderates the effect of feedback on conservation behaviour: people with higher environmental attitude save more water and energy when exposed to a feedback on their behaviour than people with lower environmental attitude.

1.4. Feedback effectiveness

A likely reason for why consumption feedback works better on environmental people is because feedback is more effective when coupled with a goal (Bandura & Cervone, 1983). Also, in order for a feedback to be relevant, it needs to draw the attention of the receiver to a goal that is self-relevant (Kluger & Denisi, 1996). For highly biospheric people, behaving pro-environmentally by reducing energy consumption will be a self-relevant goal that will hold over time. For lowly biospheric people, reducing energy consumption may be a more transient goal, decreasing the effectiveness of the feedback over time. This notion is consistent with Henn, Taube, and Kaiser (2019) who find that people with lower environmental attitude are less rigorous in taking action to conserve energy following a feedback.

Feedback effectiveness: biospheric values and habit building

In a meta-analysis, Karlin, Zinger, and Ford (2015) find that eco-feedback's effectiveness drops 3–6 months after it is initiated, but regains the initial effectiveness level when the feedback duration increases to more than 12 months. They suggest that after an initial period, users reduce their engagement with the feedback, explaining the drop in effectiveness. However, they hypothesize that a longer duration may stimulate the creation and reinforcement of habits. We suggest that highly biospheric people are more likely to form and develop energy-related habits that the feedback device stimulates. Habits are intentional; they form as people pursue goals (Ouellette & Wood, 1998; Wood & Rünger, 2016) and “develop as people repeat behaviours that (at least during habit development) meet valued goals” (Ouellette & Wood, 1998, p. 57). They can become less related to goals, because goals may evolve when habits have strengthened. In this sense, habits are the residue of past goal pursuit (Wood & Neal, 2009). Nonetheless, values such as biospherism, which are desirable *trans*-situational goals (Schwartz, 1994), are stable overtime (Rohan, 2000; Steg et al., 2014). Thus, highly biospheric individuals are more likely to create and develop energy-related habits that the smart meter encourages, in order to meet their environmental goals. One could claim that people could develop similar habits to meet other types of goals. In particular, individuals could use a smart meter to save money, thus appealing to more egoistical values. However, previous research shows that individuals who are motivated to use smart meters purely due to the potential money savings often remain disappointed, as savings may be small or negligible (Hargreaves, Nye, & Burgess, 2010). In this case, habits are less likely to strengthen since rewards are important in the strengthening process (Wood & Rünger, 2016).

Feedback effectiveness: biospheric values and Elaboration Likelihood Model

Communication is most effective at influencing behaviour when the nature of the message is aligned with an individual's disposition (Aaker & Lee, 2001; Avnet & Higgins, 2006). In line with this view is a central tenet of the Elaboration Likelihood Model (Petty & Cacioppo, 1986). ELM states that we process a message differently depending on our motivation and ability to process the information. Motivation is influenced by factors such as personal relevance of the message, whereas our ability to process the message is influenced by factors such as message comprehensibility or priori knowledge. The higher the motivation and ability of individuals to process a given message, the more these individuals will be cognitively invested in evaluating the message, and the more they will be persuaded by issue-relevant arguments, which is called the central route. The lower the motivation and ability, the more individuals will be persuaded by peripheral cues (peripheral route). ELM deals explicitly with exposure to persuasive communication but may be applied to other situations (Petty & Cacioppo, 1986). In particular, ELM has been used in various feedback contexts such as performance feedback in the workplace (O'Leary-Kelly & Newman, 2003) or hypothesized as the underlying theory explaining the effect of feedback on behaviour (e.g. for normative feedback, Schultz et al., 2014). We believe that highly biospheric individuals have a high likelihood of elaborating communication of an environmental nature and thus be persuaded by issue-relevant arguments, such as the number of kWh saved. On the other hand, individuals with lower biospheric values may be convinced by more peripheral cues (e.g. simplified color-coded feedback). According to ELM, the persuasion through the central route is more persistent and predictive of behaviour (Petty & Cacioppo, 1986). A change in attitude resulting from the peripheral route of persuasion is “relatively temporary, susceptible and unpredictive of behaviour” (Petty & Cacioppo, 1986, p. 4). Relating ELM in the context of smart meter to the habit literature, we would expect that lowly biospheric individuals will not likely form positive energy-related habits, because the change in attitude resulting from the peripheral route of persuasion will be short-lived. On the contrary, individuals with high biospheric values who will be persuaded by issue-relevant arguments, which, in the case of smart meter feedback, will be goal-relevant, are more likely to form and strengthen habits. We hypothesize therefore, that the change in behaviour of highly biospheric individuals will be stronger and more time-resistant.

Previous research could also be explained in light of habit development and ELM. For instance, Tiefenbeck et al., (2018) find that individuals with lower environmental attitudes also display positive conservation effects (albeit weaker than those with higher environmental attitudes). They explain that this may be due to these individuals being persuaded by the feedback message being so easily accessible. This explanation bears strong similarities with the ELM, and suggests that if the feedback message is particularly simple, unmotivated individuals may be persuaded through the peripheral route. Their study has a shorter time frame and our framework would predict that over time, habits may not necessarily be formed, which would attenuate the conservation behaviour of lowly biospheric individuals. Very similar conclusions can be drawn with regards to the Henn et al. (2019) study, as individuals with low environmental attitudes experienced some positive energy savings, possibly because a number of them may have owned the smart meter for more than a year, and the uncertain time frame of the study's intervention made ownership durations impossible to verify. This add doubt as to whether such savings would have continued into the future for these non-environmental people.

Accordingly, we hypothesize that:

H2a. Households owning a feedback device will reduce their electricity expenditure over time to a greater (vs lesser) extent when they hold higher (vs lower) biospheric values.

H2b. Below a certain threshold in biospheric values, owning a feedback device will not reduce electricity expenditure over time.

1.5. Our investigation

The current study will examine energy expenditure as a function of the duration the feedback device has been present in the household, in order to gauge the effects over time. We examine the most commonly available feedback device, the smart meter, in a naturalistic setting, focusing on a population of individuals who have acquired the device themselves. We first determined whether the device's presence in the household affected electricity expenditure, while accounting for differences in biospheric values. In order to overcome a selection bias among the studied smart meter population, we compare this group with a statistically matched group of non-smart meter users. Then the analysis moves onto examining whether electricity expenditure is affected by both biospheric values and the amount of time the device has between owned for. Lastly, we explored the impact that feedback devices had on household changes, by focusing first on number of changes, then of the magnitude of change.

2. Material and methods

2.1. Participants and procedure

The data was collected between April and June 2018 as part of the Swiss Household Energy Demand Survey (SHEDS), an investigation into the determinants of residential energy consumption. The survey was administered to a total of 3467 individuals, representative of Switzerland's population on age, gender and household size. Data from 276 individuals constituted our participant sample in the current study. Of this sample, 138 respondents formed our treatment group of smart meter users. This group included respondents who reported installing a smart meter device in their household, who knew when the device was installed, reported knowing their annual electricity expense and who reported being the head of the household. The 138 non-treatment respondents formed our control group, and comprised respondents who shared a set of key attributes with respondents from the treatment group (see section 2.4. “Matching Procedure” for details). New control groups were created for the temporal analyses conducted in Section 3.3, in order to pair the treatment groups with their matched control groups using the total participant pool, for better accuracy.

Using the statistical program G*Power 3.1 (Faul, Erdfelder, Buchner, & Lang, 2009), we estimated that a minimum sample size of 130 was necessary to predict a medium sized *effect* ($f^2 = 0.20$), given $\alpha = 0.05$ and 11 predictors included in our most complex model, considering also the interaction variables. Our samples of 276, in the main confirmatory analyses, and 138, when exploring effects within the treatment group, were sufficiently powered, with actual power always greater than 0.8.

All participants were recruited via a panel provider, answered the survey online, and were paid an amount equivalent to 6 CHF. While all participants were asked the same questions, only those owning a smart meter were asked questions related to their device. The survey was made available in three languages and the respondents could choose among the French, English or German version of the survey.

2.2. Measures

Values and demographics

Three items measured *biospheric* values (Cronbach's $\alpha = 0.88$), a scale originally used by de Groot and Steg (2008) and De Groot and Steg (2007), in turn based on a scale developed by Schwartz (1992). We also invited our participants to answer the following questions: 1) The year when their smart meter was installed, within a range from 2000 to 2018; 2) approximately how often they check the device, going from 1 (almost every day) to 7 (less than once every 2–3 months); 3) their age; 4) the size of their household surface in square meters; 5) their income in CHF, ranging from 1 (less than 3000) to 6 (more than 12,000); 6) the number of family members; 7) their plans to reduce their electricity consumption where we asked "in the next 12 months are you planning on reducing your electricity consumption …", going from 1 (very unlikely) to 5 (very likely); and 8) "privacy concern" where we asked participants "how important is having privacy to you", going from 1 (not important at all) to 5 (very important). The answer to the first question served as our independent variable, in order for us to assess changes in behaviour as a function of the extent the feedback device has been present in the household. The answers to questions two to six serve as covariates to the subsequent analyses, in order to control for confounds in the effects.

Energy expenditure

Next, the respondents were asked to report their annual energy expenditure by reporting a) how much they pay for electricity (including VAT) during a one-year period, and they were asked to report the monetary value in CHF. It was communicated to respondents that "it is extremely important for us to have accurate numbers in this area. Therefore, if possible, could you please find your last annual electricity bill before moving forward? Thank you very much". After reporting the expenditure values, participants stated the source of the information, by stating whether the information was obtained from the electricity bill or from a personal estimation. A 90% Winsorization of the expenditure data was then applied as a robust measure to reduce the effect of extreme values, thus setting all values above the 95th percentile to the value associated with the 95th percentile and doing the same for all values below the 5th percentile.

Household changes implemented

We also asked participant to "Please indicate if any changes occurred in your behaviour after the smart meter was installed". For this last question, the choice options offered to participants were the following: 1 (No change), 2 (Changes in the way electrical appliances are used), 3 (Changes in the type of electrical appliances purchased), 4 (Changes made to the lighting in the house), and 5 (Other: where participants were free to freely report their answer in text form). Based on this question, we created two operationalizations of changes made in the household: the number of changes and the magnitude of the change. These two measures of changes carried out in the household also acted as our dependent variables. For the first variable, we summed the number of changes that participants checked, thus creating a scale for Number of changes, from 0 change to three changes. We also aimed to capture the qualitative difference between the changes, based on the amount of financial resources invested. For this reason, we also created a scale for Magnitude of change, in order to glean additional insight from customer's reports. The scale first included the absence of change (coded as 0). Second, changes made in the way appliances are used, which is a behavioural change that does not require the investment of financial resources (coded as 1). Third, resource investments of a smaller cheaper nature, based on changes made to the lighting system in the household (coded as 2). Resource investments of a larger more expensive nature, comprising changes made to the household appliances purchased (coded as 3). When more than one change was made by the individual, we selected the one with the highest resource investment.

2.3. Exclusions and imputation

The participant sample of 276, comprising treatment and control groups, was reached after excluding all respondents who failed to report their annual electricity expenditure (26.1%). No further data was lost thanks to the imputation of the data, relying upon expectation maximization (EM) to estimate values for the reported income variable (13%) and for privacy concern (1.4%). These variables were entered into the estimation analysis along with age, accommodation size, household size, applying an inclusive strategy that makes use of more, rather than less, variables in order to obtain estimates from all available data (see Collins, Schafer, & Kam, 2001). Little's MCAR test proved non-significant (Chi-Square = 12.05, DF = 8, Sig. = 0.15), failing to reject the null hypothesis, therefore indicating a lack of biases in the missing data. Worth noting that the results reported in the following sections remain largely identical with or without the imputation procedure.

2.4. Matching procedure

Propensity score matching (Rosenbaum & Rubin, 1983) is a method for causal inference in non-randomized studies, that creates a control group that is considered "balanced" across a set of dimensions, with regard to a target group. We implemented the procedure in R using the MatchIt package (Ho, Imai, King, & Stuart, 2007, Ho et al., 2011). Our task was to match the groups across dimensions that would predict the propensity of owning a feedback device. We selected age as a matching variable because technology-based purchases have been shown to be driven by age (Czaja et al., 2006), and we therefore wanted to eliminate this possible bias in the data.

Income was also selected, as it is wealthier individuals who tend to make one-off environmental purchases of a relatively expensive kind (Lavelle, Rau, & Fahy, 2015). We also included the variable "plans to reduce electricity consumption", as those who purchase the device may do so with a clear intention to conserve energy, "privacy concern", which can refrain consumers from acquiring such devices (Cominola, Giuliani, Piga, Castelletti, & Rizzoli, 2015) and on biospherism, in order to match environmental values across groups. These used the "nearest neighbour" method to match all treatment units with their selected (i.e. matched) controls. This means that the matching procedure selects, and therefore selectively drops, cases from the control data depending on the specified requirements, and it does so without bias resulting in the data becoming balanced (see Appendix A). The method used to estimate the distance between treatment and control units was logistic regression, the default method within the MatchIt package. Sampling was carried out without replacement, which meant that each control unit was used only once.

3. Results

The following result section begins by presenting descriptive results, then examines the effect of feedback device presence on annual electricity expenditure moderated by biospherism, followed by an analysis into the joint effects of biospherism and feedback duration on electricity expenditure. This part is subdivided into an initial exploration only based on the treatment group and then group analysis over time using both treatment and control groups. Lastly, additional insights are derived by observing the changes that individuals make in their households, and assessing whether these are shaped by device duration and biospherism.

A summary of the descriptive results can be found in the table below (Table 1). Worth noting, the mean duration of the device's presence in the household was 3.8 years ($SD = 3.6$), where the minimum value was less than one year (i.e. device installed in 2018), and the maximum value was 17 years (i.e. device installed in 2001). Approximately 33% of the devices were installed in the two years prior to our study, whereas approx. 33% had been installed 17 to 5 years before the study

Table 1
Descriptive statistics of variables in treatment and control conditions.

	Treatment (x̄)	Treatment (*SD*)	Control (x̄)	Control (*SD*)	Total (x̄)	Total (*SD*)
Electricity expenditure (CHF)	890.0	657.3	803.2	580.4	774.1	587.3
Electricity expenditure source *	1.2	.4	1.3	.5	1.3	.5
Feedback duration (Years)	3.8	3.6	n.a.	n.a.	n.a.	n.a.
Change after feedback (N°)	.8	.9	n.a.	n.a.	n.a.	n.a.
Change after feedback (Magnitude)	1.0	1.2	n.a.	n.a.	n.a.	n.a.
Frequency of checking device *	5.3	2.1	n.a.	n.a.	n.a.	n.a.
Biospherism	4.2	.7	4.2	.7	4.0	.8
Age	48.6	14.5	46.7	14.6	49.1	14.9
Household surface area (m^2)	130.3	52.1	126.3	48.6	119.3	49.6
Income *	4.5	1.3	4.5	1.2	4.1	1.3
Household size (i.e. number of members)	2.5	1.3	2.5	1.2	2.3	1.2
Plans to reduce electricity consumption *	3.0	1.2	3.1	1.2	2.8	1.1
Privacy concern *	4.5	.6	4.5	.6	4.3	.7
Sample	138	138	138	138	2423	2423

Note: Mean values and Standard deviation are shown for descriptive variables, split between the treatment and condition conditions. N.A. signifies that the variable was Not Applicable to that condition, as it related only to the treatment group. * Electricity expenditure source is labelled 1 for Utility bill and 2 for personal estimate. Mean value of 1.2 in the treatment condition equates to 78% utility bill source, while 1.3 in the control condition equates to 72% utility bill source. * Frequency of checking device value of 5.3 is in between once a month (5) and once every two-three months (6). * Household income band of 4.5 indicates household gross income per month in between 6001–9000 (band 4) and 9001–12,000 (band 5). * Plans to reduce electricity consumption ranges from 1 to 5 on a Likert scale. * Privacy concern also ranges from 1 to 5 on a Likert scale.

(i.e. from 2001 to 2013). This skewness in the data (1.6) indicates the growing popularity of the device.

3.1. Presence of feedback device

First, we assessed the relationship between all the variables in the current study by examining bivariate correlations, which can be seen in Table 2 (Appendix B). Next, we sought to determine whether the presence of a feedback device in the household impacts the amount households spend on electricity. We compared electricity expenditure of the treatment and control groups by means of a Moderated Regression. We regressed the Winsorized annual electricity expenditure on treatment (smart meter owners or control), biospherism, and the treatment*biospherism interaction. We also regressed a set of control variables, which were age, income, household size and accommodation size. Interestingly, neither treatment ($b = 51.19$, $p = .432$, 95% CI [-77.35; 179.36]) biospherism ($b = -71.30$, $p = .122$, 95% CI [-163.41; 18.37]) nor their interaction ($b = -36.45$, $p = .692$, 95% CI [-217.71; 144.80]) proved to be significant predictors. On the other hand, the control variables all significantly predicted expenditure ($p < .05$). These initial results draw attention to the fact that the presence of a feedback device in the household appears not to be an effective means of reducing electricity expenditure, when examined in isolation. The results also failed to find differences in expenditure driven by differences in biospherism or the interaction between treatment and biospherism. This could be due to the matching procedure matching smart meter owners, who may have higher than average biospheric values, with equally biospheric control individuals, thus reducing variance within the data. Support for this comes from regressing biospherism on smart meter ownership, which comprised the 138 owners and the entire pool of 2423 non-owners who report their electricity expenditure. We added the same control variables as in the previous analysis. A logistic regression confirmed a small but significant effect of biospherism predicting smart meter ownership ($b = 0.01$, $p = .045$, 95% CI [0.00; 0.02]). This proved that the matching procedure selected non-smart meter users with relatively high levels of biospherim, in order to cancel out differences between the two groups on this dimension, thus reducing the possibility to observe a predictive effect of biospherism on expenditure. In fact, by repeating the moderated regression with the entire participant pool of 2561 (138 smart meter owners VS 2432 non-owners), biospherism emerges as a significant predictor of expenditure ($b = -36.12$, $p = .009$, 95% CI [-244.96; 810.91]), with treatment ($b = 282.97$, $p = .293$, 95% CI [-244.96; 810.91]), and treatment*biospherism interaction ($b = -54.43$, $p = .395$, 95% CI [-180.09; 71.21]) remaining non-significant.

Next, we will examine the role of feedback duration.

3.2. Electricity expenditure: treatment group exploration

We performed a robust linear regression (N = 138) using the regressed Winsorized annual electricity expenditure on the device's duration in the household (in years), and on the participant's biospheric values, including also the same control variables as in the previous analysis. The overall model was significant, $F(8, 129) = 6.68$, $p < .001$, $R^2 = 0.29$. Although device duration ($b = 2.83$, $p = .841$, 95% CI [-25.12; 30.79]) and biospherism ($b = -62.89$, $p = .394$, 95% CI [-208.51; 82.73]) were not significant predictors of electricity expenditure, the interaction between the two variables accounted for a significant portion of the variance, b = −42.71, $t(129) = -2.23$, $p = .027$, 95% CI [-80.54; −4.88]. These results are illustrated in Fig. 1. The impact of the control variables in the model can be seen in Appendix D. Analysis of the conditional effects of the focal predictor at values of the moderator set to 1 SD above or below the mean, highlighted no significant results for low levels of biospherism ($b = 30.72$, $p = .100$, 95% CI [-5.95; 67.39]), nor for high levels of biospherism ($b = -36.34$, $p = .098$, 95% CI [-79.52; 6.84]). When analysing the data only including those who reported obtaining their energy expenditure directly from the utility bill (107 out of 138 respondents), the interaction between feedback duration and biospheric values remains significant, b = −71.89, t(98) = −3.52, p < .001, 95% CI [-112.42; −31.37]. Post-hoc analyses on this interaction highlighted a statistically significant negative effect (indicating consumption reduction) of smart meter duration on energy expenditure when biospheric values were high, $b = -61.23$, $t(98) = -2.57$, $p = .012$, 95% CI [-108.48; −13.99], with a significant positive effect also emerging when biospheric values were low, $b = 46.60$, $t(98) = 2.41$, $p = .018$, 95% CI [8.28; 84.92].

Next, we aimed to unpack the interaction from the moderation analysis. We then we performed a floodlight analysis, sometimes referred to as the Johnson-Neyman procedure, to identify the region of significant effects (Spiller et al. 2013). This procedure highlighted a value of 3.4, representing the duration in years after which differences begin to emerge in consumption between highly environmental individuals and those less concerned with environmental issues. While this region of significant effects covers approximately 55% of the distribution, the differences in consumption are primarily driven by individuals high in biospherism reducing their consumption, as will become clearer in the following set of analyses, in Section 3.4.

Overall, this set of analyses highlighted that the feedback device was not able to generate significant reductions over time when considering the entire sample, therefore failing to confirm hypothesis 1a. On the other hand, the results confirmed hypothesis 2, showing that owning a real-time feedback device for longer, significantly reduced electricity expenditure for environmentally concerned households, while having no positive effects for those who do not share these values.

3.3. Electricity expenditure: analyses with control groups

Next, we test the effects observed in the previous section, this time comparing smart meter owners with non-owners. Since consumption differences between low and high biospheric individuals previously emerged after several years of owning the device, we sought to directly compare the electricity consumption of those who have owned the feedback device for longer durations with those who have owned it for shorter durations. In order to take a granular approach, we tested all possible temporal cut-offs around the suggested Johnson-Neyman value of 3.4, therefore testing the effects of owning the device for more or less than two, three or four years. Each treatment group, pertaining to a specific duration of smart meter presence in the household, was matched with its respective control group along the following dimensions: income, age, privacy concerns, electricity reduction intentions, and biospherism. All matchings led to statistical balance between the groups on all stated dimensions, with the mean values for each dimension becoming roughly numerically identical between groups. The outcome of the matching procedure, examining before and after averages for each variable of interest, is presented in Appendix C. The use of QQ plots, for visual observation, and a battery of t-tests testing for possible mean differences between treatment and control groups on each control dimensions (all $p > .2$) confirmed the between groups balance.

The following section discusses the three-year cut-off point, comparing groups of smart meter owners owing the device for more than three years, and for three years and less, each with their respecting control counterpart. We also performed the same procedure and analysis applying a cut-off point at two years and at four years, discussed in Appendix D.

Cut-off point: smart meter for > 3 years VS ≤ 3 years

We matched a group of smart meter owners owning the device for more than three years with their control group, then matched owners of smart meters of three years or less with their control group. We then ran a moderated moderation analysis (Hayes, 2013; model 3; 5000 bootstrap samples) testing the effects of the independent variable “treatment” (two levels: smart meter, & control), the 1st moderator “biospherism” (continuous variable), and the 2nd moderator “ShortLongDuration” (two levels: > 3 years, ≤3 years) on the dependent variable “annual electricity expenditure”. The main effects of treatment ($b = 23.37$, $p = .732$) and biospherism ($b = -14.90$, $p = .751$) were again not significant, as were the two-way interactions (all $p > .1$). Importantly, the three-way interaction between treatment*biospherism*ShortLongDuration was significant, $b = -396.21$, $t(264) = -2.13$, $p = .034$, 95% CI [-762.62; −29.80]. The test of conditional effects highlighted a significant negative effect of treatment on consumption at high levels of biospherism (1 *SD* above the mean) and long durations ($b = -362.20$, $p = .032$, 95% CI [-694.53; −29.89]), while there was no significant effect of the treatment when biospheric levels were low and the device was owned for short durations, ($b = 41.69$, $p = .727$, 95% CI [-193.56; 276.93]). The control variables age ($b = 7.66$, $p = .002$, 95% CI [2.80; 12.53]), income ($b = 63.79$, $p = .042$, 95% CI [2.21; 125.38]), household size ($b = 77.45$, $p = .016$, 95% CI [14.40; 140.52]) and accommodation size ($b = 3.30$, $p < .001$, 95% CI [1.61; 4.97]) were all statistically significant.

Observing that the key three-way interaction was statistically significant emphasizes that examining a treatment group, who have owned the smart meter for more than three years, can be an important time-stamp where one can distinguish between those who have experienced tangible benefits and those who have not. This temporal value also confirms the aforementioned Johnson-Neyman value of 3.4 year, previously observed in our analysis. These results are illustrated in Fig. 2 below.

Overall, the temporal analyses with control groups confirm that differences in consumption patterns emerge when the device is owned for more than three years (significant three-way interaction). As expected, we see the effect vanishes when considering longer or shorter durations, shown in Appendix D. For example, when considering the four-year cut-off, the group labelled as “short feedback durations” began to include longer ownership durations (i.e. less strict criteria), thus preventing a statistical interaction effect from emerging. These findings confirm that significant energy savings can be achieved by highly biospheric individuals after three years of owning the device, but not by lowly biospheric individuals. A summary of all the results can be found in Appendix E. Overall, H1 is not supported, hypothesizing an effect of feedback duration on expenditure, while H2a, expecting an

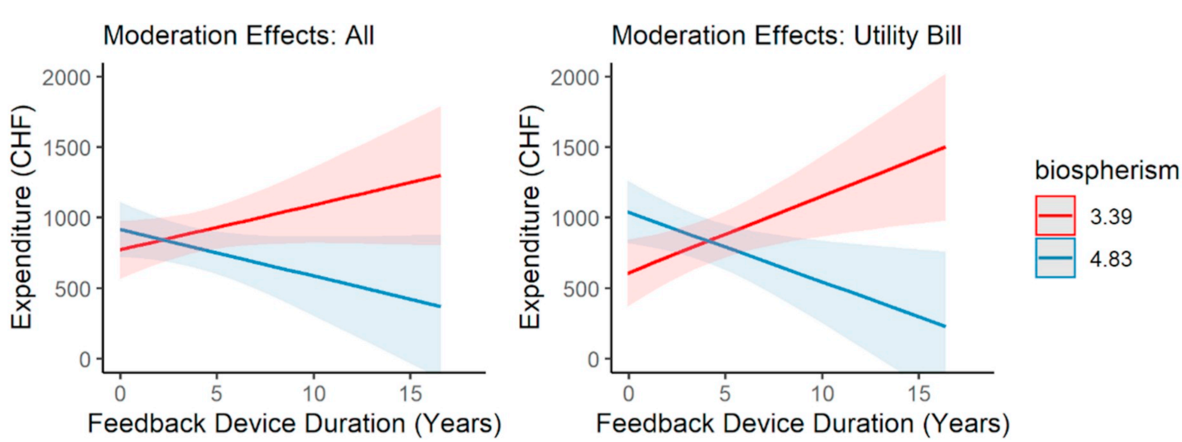

Fig. 1. Annual electricity expenditure for 2018 in CHF, on the Y axis, as a function of the amount of time the consumer has had the feedback device installed in the household, on the X axis. The moderating effect of the individual's biospheric values can be observed. The graphs represents data adjusted for age, income, accommodation size, household size and frequency of checks. Values for Biospherism were selected accordingly to 1 Standard Deviation above and below the mean. Left graph = annual electricity expenditure data obtained from utility bill or from personal estimates. Right graph = annual electricity expenditure data obtained only from utility bill. Coloured shaded areas represent the marginal effects of the regression models.

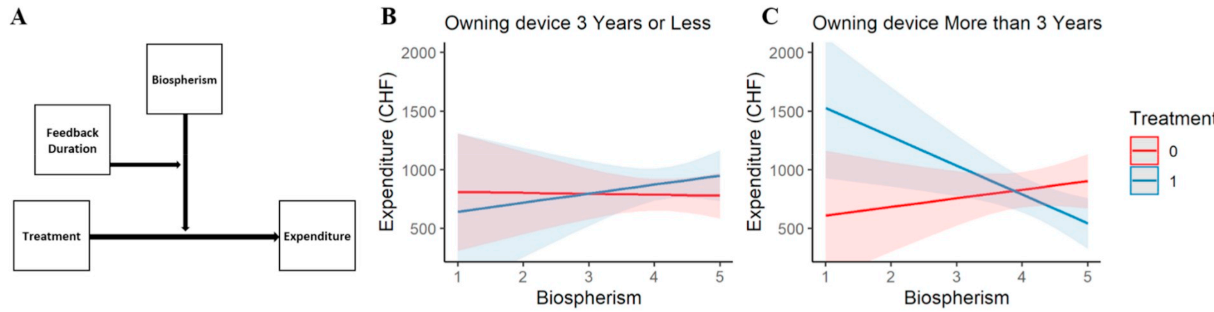

Fig. 2. The relationship between the tested variables can be seen in Panel A, in a moderated moderation model. The effect of treatment (owning a smart meter = 1; not owning a smart meter = 0) on annual electricity expenditure is moderated by biospheric values, which is moderated by the length of the feedback duration. Panel B illustrates lack of interaction effects between treatment and biospherism when the length of the feedback duration (i.e. length of smart meter ownership) is three years or less. Panel C illustrates the interaction effects between the variables when the length of the feedback duration is more than three years. The graphs represents data adjusted for age, income, accommodation size, household size. Coloured shaded areas represent the marginal effects of the regression models.

interaction between feedback duration and biospherism on expenditure, is supported. H2b is also supported as we observe no consumption reductions driven by smart meter ownership over time for lower levels of biospherism.

3.4. Additional insights: number of household changes & magnitude

In this final section of the results we sought to assess whether the changes made in the household, as a result of having installed a feedback device, are also determined by the interaction between the duration of the presence of the device in the house and biospheric values. This can be important to establish, since it has been shown that energy usage or expenditure might not always equate to pro-environmental behaviour (e.g. Gatersleben, Steg, & Vlek, 2002).

The three participants who did not know whether changes in the household had been made after the installation of the device (see Descriptives section) were not included in the analyses. First, we focused on the number of types of changes made in the household. We analyzed the data (N = 135) by employing the same statistical set-up described in the original analysis in the Expenditure section which shows that the overall model was significant, $F(8, 126) = 3.92$, $p < .001$, $R^2 = 0.20$. Device duration was a significant predictor of changes made in the household, supporting H1b, $b = 0.05$, $p = .036$, 95% CI [0.00; 0.09]. A statistically significant interaction also emerged between device duration and biospherism, $b = 0.07$, $t(126) = 2.24$, $p = .027$, 95% CI [0.01; 0.12]. This showed that there was an effect of device duration on the number of types of changes made in the household, at differing levels of the biospheric values (see Appendix F). Analysis of the interaction's conditional effects showed that there was no significant relationship between device duration and number of changes made when examining low biospheric values ($b < .01$, $p = .907$, 95% CI [-0.05; 0.06]). The relationship between device duration and number of changes was instead significant at high biospheric values, $b = .10$, $t(126) = 3.05$, $p = .003$, 95% CI [0.03; 0.17]. The complete list of results for this analysis is presented in Appendix E. The results show that when biospheric values are high, every additional year of owning a smart meter is associated with increased change made within the household, adding further weight to hypothesis 2 and confirming the pattern of results seen for expenditure.

As stated in the Methodology section, we aimed to also assess differences in magnitude of change based on resource investment. We therefore repeated the analyses by investigating the effect of device duration and biospheric values on the second operationalization of the implementation of changes in the household, the magnitude of household change, which distinguishes between small, medium and large resource investments. A total of 135 participants were included in the analysis. The overall model was significant: $F(8, 126) = 3.75$, $p < .001$, $R^2 = 0.19$., and the analysis highlighted a significant effect on the key interaction between device duration and biospheric values that predicts magnitude of change, $b = 0.07$, $t(126) = 2.03$, 95% CI [0.00; 0.15]. These results are largely identical to those documenting the number of types of household changes, as a significant relationship between device duration and magnitude of change emerged only for high biospheric values, $b = .11$, $t(126) = 2.59$, $p = .011$, 95% CI [0.02; 0.19]. The results show that when environmental concern is high, every additional year of owning a smart meter is associated with greater magnitude of household change (see Appendix F for illustration).

These results show that on average, feedback devices have limited effect on PEB over time. However, when looking at more environmentally concerned households, significant positive effects emerge.

4. Discussion

This study examined the effect that owning a feedback device has on pro-environmental behaviour. The findings consistently showed that it is only those individuals who are concerned with environmental issues who engage in pro-environmental behaviours when a feedback device is present in their household for extended periods of time. On the contrary, when individuals less concerned with environmental issues were paired with a feedback device for longer periods of time they consistently failed to act pro-environmentally, failing to reduce their electricity expenditure and to implement household changes. The results showed that pairing such devices with environmental individuals yields tangible impactful results, in terms of electricity reduction and energy-related changes in the household. The results also highlighted that aiming to reach challenging environmental goals by relying on feedback devices alone may not be a wise solution. In fact, when collapsing individual differences, the effects of feedback devices over time on pro-environmental behaviour appeared weak and inconsistent.

Motivation has been shown to be an important factor in driving behaviour, and Hargreaves et al. (2010) document that the motivation to use feedback devices determine their success. The current results report pro-environmental behaviour induced by a lengthy feedback period from smart meters, in the context of intrinsic motivation, where the devices were self-acquired. Other similar studies that have also reported long term benefits of feedback from smart meters on consumption, in conditions where the device was not experimentally assigned to individuals, are those by Gans et al. (2011) and Darby (2006). However, it was only when distinguishing between differing levels of environmental concern that benefits could be seen over time, in the current study. In fact, completely different trends emerged depending on whether the head of the household scored higher or lower in biospherism. A possible explanation of the divergence of findings, is that both Gans et al. (2011) and Darby (2006) studies ran over a decade ago, when feedback devices were niche products likely owned by particular subsets of the population. This point is particularly relevant when considering the impressive reductions reported by Darby (2006).

4.1. Importance of examining biospheric values and time

Despite highlighting no main effects of biospherism on our dependent variables, which was likely due to methodological reasons discussed in the results section 3.2, our results specifically show highly biospheric people to be more susceptible to feedback from consumption and that ample time is needed for these people to start observing tangible benefits. This could help explain why Houde, Todd, Sudarshan, Flora, and Armel (2013), McCoy and Lyons (2017) and Snow et al. (2013) failed to find comprehensively positive effects of owning a feedback device, given their undifferentiated participant sample who were assigned the device (e.g. extrinsically motivated participants). In addition, the test phase in these three studies was two months, one year and three years, which the current results show may not have been sufficient to properly gauge the benefits. Contrary to Tiefenbeck et al. (2018), who found consumption feedback effective at inducing consumption reductions even in those individuals less concerned with environmental issues (even if the effect was weaker for this group), we only observe positive change among the most environmental individuals. The difference between the findings may be due to the specificities of the behaviours: the feedback on showering used in Tiefenbeck et al. study requires minimal elaboration (i.e. low cognitive effort), contrary to the aggregated electricity feedback, investigated in the current study, which is driven by a whole plethora of behaviours. It also may be explained by the relatively short duration of the study (< 1 year) which may have maintained the interest of environmentally disinterested individuals.

We focused on the ELM, as this theory offers a parsimonious explanation about why those most concerned with environmental issues experience substantial reductions in electricity expenditure over time, also performing positive energy-related changes in the household. People clearly hold the ability to develop repeated behaviours that consolidate into habits (Ouellette & Wood, 1998; Wood & Rünger, 2016). Nevertheless, the value the person holds seems to be a fundamental aspect in determining how feedback will be elaborated and ultimately enacted into daily behaviours. The ease of elaboration of the shower feedback device in the Tiefenbeck et al. (2018) study meant that the most environmental individuals were likely driven to save water by the numerical information about the number of litres consumed, corresponding to the central route, while the animation of the polar bear standing on the block of progressively shrinking ice would have been elaborated peripherally by those least concerned with the environment. This would thus explain why both sets of individuals enjoyed consumption savings. The Brandon and Lewis (1999) study on the other hand offered consumption feedback through a computer program that would have required more cognitive effort to elaborate, since it displayed graphs comparing consumption at two time points along with a directory containing advice on a computer screen. Despite the substantial differences between that and the current study, our framework could help make sense of the shortcomings of the Brandon and Lewis (1999) study, predicting that only those highly biospheric individuals would derive practical use from such feedback over time, while lowly biospheric people may benefit only initially from being introduced to the program. In fact, simply adhering to the program and receiving reminders may well influence them initially (i.e. peripheral route), but these initial positive effects are unlikely to be long-lasting. Henn et al. (2019) demonstrate that only those who care strongly about environmental issues demonstrate the behavioural resilience to rigorously act upon the smart meter feedback they receive. The authors stress that what distinguishes highly environmentally concerned individuals from those less concerned is their relentlessness in behaving pro-environmentally when given feedback. The similarities with our ELM interpretation where highly environmental individuals elaborate the message through the central route leading to the development and maintenance of environmental habits, is uncanny. Furthermore, the current findings appear entirely complementary to those by Henn et al. (2019). While the authors identify a link between environmental attitudes and effectiveness of smart meter feedback, they did not investigate when the smart meters in their study were installed, knowing simply that it occurred sometime within a three-year period, and speculated that this may have led to considerable noise in their data. Given our current findings, it is likely this omission had a large impact on their data, as longer feedback durations are associated with higher energy reductions and more household changes among those who care the most about environmental issues.

Lastly, we observed that those who were less concerned with environmental issues failed to reduce their electricity expenditure or to implement household changes. We can only speculate that these individuals may have acquired the devices as a novelty gadget, an approach to the product that has been previously reported (Hargreaves et al., 2010; Hargreaves et al., 2013). Given that customers do not value smart metering equally (Kaufmann, Künzel, & Loock, 2013) it seems essential to also focus on those instances where the device was not of value to its host, as advocated by Snow et al. (2013).

4.2. Limitations

The current study has several limitations. First, there are at least three main kinds of smart meter available on the international market (Hargreaves et al., 2013), plus a number of devices that can be acquired directly within Switzerland. While all models communicate consumption and expenditure feedback, they differ in the ways this information is displayed and in how the user interacts with the device (e.g. goal setting). The current study does not discern between types of installed devices and how the subsequent feedback is offered. Future research would best distinguish between the subtle ways in which the feedback is communicated in order to glean further insights and better control for differences among devices. Second, feedback device effects on behaviour are difficult to study because they require careful consideration of many variables in order to isolate behavioural effects and such effects may take time, as we have just shown. In our study, we analyse current consumption depending on the duration of owning the device, while controlling for the most relevant factors. A longitudinal study would give us more information on identifying the drivers of the change. However, that would require keeping track of people over 5–10 years, which leads to other difficulties such as sample size and attrition rate. Third, we highly emphasized that it was important to us that participants find their last annual electricity bill, then asked them whether the source of their expenditure data came from their electricity bill or their own estimation. This might have led to an overestimation of the number of participants who answered that their data comes from the electricity bill, because some participants may have wanted to fit our expectations even if they did not find or look for their electricity bill. However, for this to have affected our results, an unlikely sequence of response would have been required. For example, these same smart meter owners who untruthfully claimed to have used a utility bill, would have also had to claim that their consumption was low, and also claim to have owned the device for long periods of time. The chances that many participants acted in such a way, systematically exaggerating and downplaying these answers, to such an extent that leads to the rejection of a null hypothesis appears unlikely. Another such bias may derive from self-reports of changes implemented, which could be systematically more biased for participants with stronger biospheric value orientation. If that were the case, we would find biospherism to predict changes implemented. However, the data do not show this pattern. We only find that highly biospheric individuals implement more changes *over time*. Fourth, the categories used to measure the changes implemented in the household are an estimate of this dependent variable. A more complete assessment of this aspect could be accomplished with a more qualitative approach. Fifth, a self-selection bias within the tested feedback device population likely remained partly uncontrolled for even after the matching procedure. For instance, an openness to innovation likely characterized those who installed the smart meter years before most people had even heard of them. This argument would only apply to a small fraction of our sample and is unlikely to impact the overall interaction observed. Lastly, the overall survey carried out is representative of Switzerland on gender, age and household size. We also know that smart meter owners in our sample have different characteristics than the Swiss population (e.g. older). However, we can only assume that our sample of smart meter owners is representative of the population of smart meter owners in Switzerland as we do not know their real socio-demographic characteristics.

4.3. Conclusion

Previous studies that have addressed the effects of consumption feedback from smart meters have not distinguished between levels of environmental concern (e.g. Abrahamse, Steg, Vlek, & Rothengatter, 2007), while those that have investigated differences in environmental concern have not directly examined the effect of smart meters on pro-environmental behaviour (Brandon & Lewis, 1999) or have investigated them over a limited period of time (Tiefenbeck et al., 2018). Here we show that fundamentally different trends of electricity expenditure and implementation of household changes emerged when jointly considering differences in biospheric values between feedback device owners and the different lengths of time these devices were owned. We also show that these trends need an ample time-frame to consolidate themselves, as it was specifically highly biospheric individuals who owned the device for over three years who derived tangible reductions. Importantly, we show that energy reductions and household improvements can be expected by providing feedback devices to the individuals most likely to cognitively elaborate that feedback and by measuring those improvements over an extended period of time. It has been stated that smart meters will make smart consumers (Venables, 2007). The current findings suggest this may be the case for some consumers only.

A great deal of weight is being placed upon the effectiveness that feedback devices will have in the years to come (please see "Energy Roadmap 2050, 2012"; pp 27). The technologies of the near future can lead to stark energy consumption improvements, as is laid out in the "Strategic Energy Technology Plan" (European Commission, 2015, pp. 11–12), however a sober approach is warranted, acknowledging that in their current form these devices may not work for everyone, and that their beneficial effect may take years to appreciate. It seems that simply motivating people to acquire smart meters may not be enough to conserve energy over time. More profound changes in individual values appear warranted in order for feedback devices to have a positive impact over time. By understanding how savings from feedback devices are achieved it becomes possible to create the conditions that encourage individuals to make those high-resource investments, which have particularly important energy-related consequences.

Ethics

Ethical approval for the research was granted by the ethics committee of the institution.

Funding

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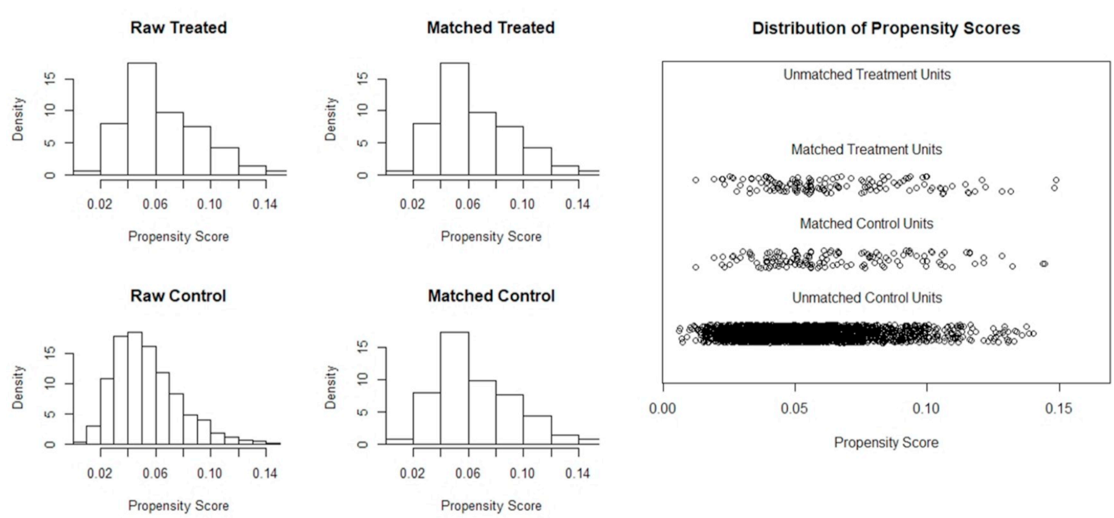
Declaration of competing interest

None.

Appendix G. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvp.2020.101459.

Appendix A. Outcome of the Matching Procedure



Output of the propensity score matching procedure, where the 138 treatment units were matched with 138 control units selected out of a pool of 2423 non-owners. The treatment group remained untouched by the procedure (Raw versus Matched) while the control group's density changed after the procedure, becoming matched to the treatment group (i.e. achieving statistical "balance"). Using the nearest neighbour method all respondents in the treatment consition were matched with similar resondents in the matched control group, as shown in the Distribution of Propensity scores graph.

Appendix B

Pattern of Correlations between all variables employed in the study

	Expendit	Expenditsource	Feedback duration	Number of Changes	Magn. Of change	Check. Freq.	Bios.	Age	Surface	Income	Househ. size	Reduct. Plans	Privacy concern
Expenditure		-.010	-.009	.049	.037	-.243**	-.111	.201*	.409**	.343**	.302**	.068	.019
Expenditure source			-.224**	-.134	-.110	-.042	.092	-.055	.049	-.101	-.090	.074	.109
Feedback duration				.115	.086	.179*	-.038	.189*	-.112	-.091	-.071	-.054	-.005
Number of Changes					.946**	-.320**	.088	.092	.062	.145	.090	.291**	.034
Magnitude of change						-.318**	.100	.120	.040	.141	.051	.280**	-.015
Checking Frequency							.082	-.003	-.311**	-.237**	-.220**	-.133	-.131
Biospherism								.116	-.024	-.116	-.113	.179*	.269**
Age									.109	-.056	-.125	-.023	-.023
Surface										.459**	.514**	.100	-.082
Income											.357**	.107	-.050
Household size												-.025	-.080
Reduction Plans													-.014
Privacy concern													

Note: **Correlation significance at the 0.01 level (2-tailed). *Correlation significance at the 0.05 level (2-tailed).

Appendix C

Descriptive Statistics Comparing Variables in the Treatment and Control Conditions

			Matching Variables				
Feedback Device Duration	Group	*S*	Age	Income	Biospherism	Reduction Plans	Privacy Concern
	Total Pool	2423	49.1	4.1	4.0	2.8	4.3
> 2 years	Treatment	64	49.1	4.5	4.1	2.9	4.4
	Matched Control	64	47.6	4.5	4.0	2.9	4.5
≤2 years	Treatment	74	48.2	4.6	4.2	3.1	4.5
	Matched Control	74	48.8	4.5	4.2	2.9	4.6
> 3 years	Treatment	55	49.5	4.5	4.1	3.0	4.5
	Matched Control	55	47.5	4.4	4.0	3.1	4.5
≤3 years	Treatment	83	48.0	4.5	4.2	3.0	4.5
	Matched Control	83	46.2	4.6	4.1	3.0	4.5
> 4 years	Treatment	45	50.5	4.5	4.1	3.0	4.4
	Matched Control	45	48.0	4.6	4.2	3.0	4.3
≤4 years	Treatment	93	47.7	4.6	4.2	3.0	4.5
	Matched Control	93	46.9	4.5	4.1	2.9	4.5

Note: Mean values are presented for each control variable employed in the matching procedure, matching specific groups of smart meter, owners based on the length of time they have owned the device, with their control counterparts. Each matching procedure began with the total pool of non-smart meter owners (i.e. before) and extracted a sub-sample that was matched on the control variables (i.e. after). S = sample size. Independent *t*-test statistics comparing treatment and control conditions on each variable found no statistical difference.

Appendix D. Comparing differences in feedback effectiveness at different ownership durations

Cut-off Point: Smart Meter for > 2 years VS ≤ 2 years

We matched two groups of smart meter owners, one owning the device for more than two years and one owing the device for two years or less, each with their control group counterparts. We then ran a moderated moderation analysis (Hayes, 2013; model 3; 5000 bootstrap samples) testing the effects of the independent variable "treatment" (two levels: smart meter, & control), the 1st moderator "biospherism" (continuous variable), and the 2nd moderator "ShortLongDuration" (two levels: > 2 years, ≤2 years) on the dependent variable "annual electricity expenditure". The control variables age, income, household size and accommodation size were included in the analysis. The main effects of treatment (b = 51.24, p = .439) biospherism (b = −94.25, p = .060) on expenditure were not significant. The interactions between treatment and biospherism (b = 35.70, p = .717), treatment and ShortLongDuration (b = −28.93, p = .827), biospherism and ShortLongDuration (b = −129.84, p = .178) and the three-way interaction between treatment*biospherism*ShortLongDuration (b = −340.32, p = .080) were all not statistically significant. The control variables of age (b = 12.09, p < .001), income (b = 80.35, p = .012) and accommodation size (b = 3.48, p < .001) had significant effects on the model, while household size was not statistically significant (b = 60.61, p = .057).

The lack of a statistically significant three-way interaction could be, to some extent, expected, given that the group of long-term smart meter users in this analysis contained all individuals who owned the meter for more than two years. With the time required to see highly biospheric people experience significant expenditure reductions was seen to be approximated after three and a half years of owning the device (i.e. the Johnson-Neyman value), we might expect the three-way interaction to yield significant results in the next analysis, when considering owners of more than three years.

Cut-off Point: Smart Meter for > 4 years VS ≤ 4 years

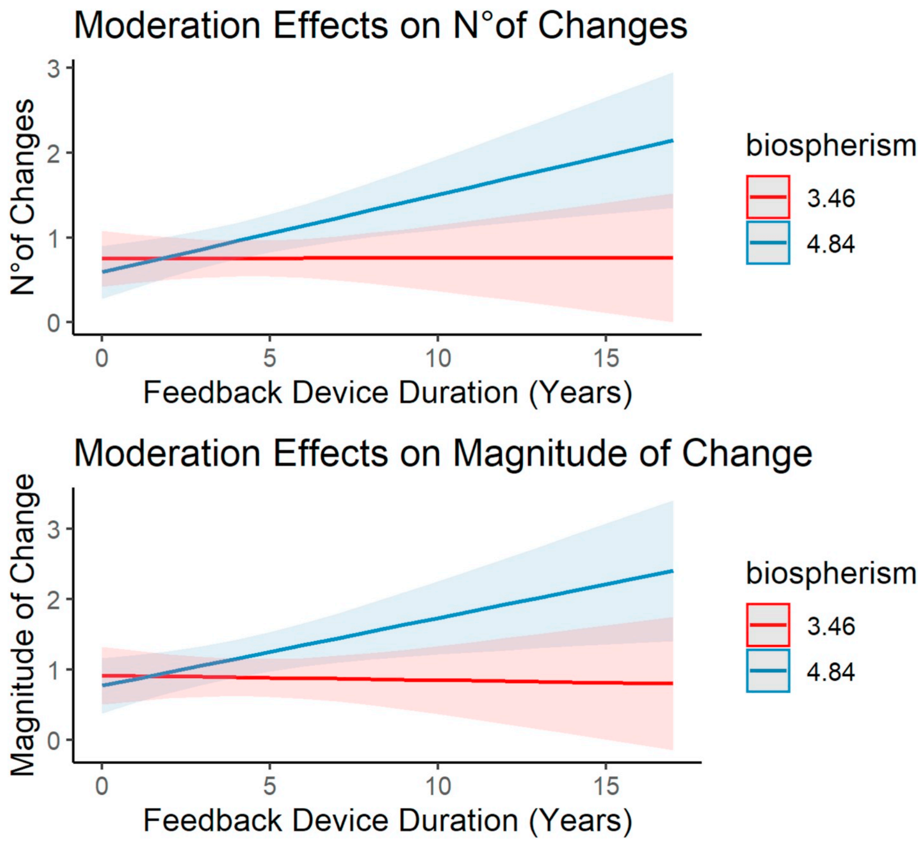
We ran the moderated moderation analysis on this new cut-off point. All variables in the analysis where maintained unaltered, while we updated the 2nd moderator "ShortLongDuration" (> 4 years, ≤ 4 years). None of the interactions were statistically significant, with the exception of biospherism*ShortLongDuration, b = −204.22, t(264) = −2.01, p = .045, 95% CI [-403.70; −4.74]. The control variables age (b = 9.10, p < .001), household size (b = 119.96, p < .001) and accommodation size (b = 3.15, p < .001) were all statistically significant, while income had no significant effect (b = 54.70, p = .072).

Appendix E

Main Effects and Interaction Effects on Electricity Expenditure and Household Changes

	Smart Meter Owners and Matched Controls					Smart Meter Owners														
	> 3 Years VS ≤ 3 Years					Expenditure: All Owners					Expenditure: Utility Bill					N° of Changes				
	b	95% CI		*t*	*p*	b	95% CI		*t*	*p*	b	95% CI		*t*	*p*	b	95% CI		*t*	*p*
Treatment	23.37	−110.97	157.70	.34	.733	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Biospherism	−14.90	−107.24	77.45	-.31	.751	−62.89	−208.51	82.73	-.85	.394	36.50	−116.87	189.86	.47	.638	.13	-.09	.36	1.17	.243
Duration	38.06	−102.30	178.42	.534	.594	2.83	−25.12	30.79	.20	.841	2.42	−27.37	32.23	.16	.872	.05	.00	.09	2.12	.036
Treatment* Biospherism	−69.90	−254.12	178.42	-.74	.456	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Treatment* Duration	−177.38	−451.85	97.09	−1.27	.204	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Biospherism* Duration	−126.12	−309.03	56.80	−1.36	.176	−42.71	−80.54	−4.88	−2.23	.027	−71.89	−112.40	−31.37	−3.52	< .001	.07	.01	.12	2.24	.027
Treatment*Bios.* Duration	−396.21	−762.62	−29.81	−2.13	.034	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Conditional Effects: Low Bios.	41.69	−193.56	276.93	.35	.727	30.53	−6.11	67.18	1.65	.102	46.60	8.28	84.92	2.41	.018	< .01	-.05	.06	.12	.907
Conditional Effects: High Bios.	−362.20	−6694.52	−29.89	−2.15	.032	−33.52	−76.81	9.75	−1.53	.128	−61.23	−108.48	−13.99	−2.57	.012	.102	.04	.17	3.05	.003
Age	7.66	2.80	12.53	3.10	.002	10.24	3.19	17.29	2.87	.005	14.85	7.07	22.62	3.79	< .001	< .01	-.01	.01	.64	.521
Income	63.79	2.21	125.38	2.04	.042	92.12	5.08	179.17	2.09	.038	71.19	−26.54	168.91	1.44	.151	.11	-.02	.25	1.65	.102
Accommodation size	3.30	1.61	4.97	3.86	< .001	2.11	.26	3.97	2.26	.026	2.83	.11	5.54	2.07	.041	< -.01	−01	.01	−1.29	.198
Household size	77.45	14.40	140.51	2.42	.016	55.28	−36.68	147.24	1.19	.236	73.96	−19.47	167.39	1.57	.119	.05	-.09	.19	.75	.457
Frequency of Checks	–	–	–	–	–	−29.36	−78.23	19.52	−1.19	.237	−2.54	−60.13	55.04	-.087	.930	-.17	-.24	-.09	−4.35	< .001
Observations	276					138					107					.200				
$\mathbf{R^2}$	0.251					0.293					.364					135				

Note: Results are reported for the three investigated dependent variables: electricity expenditure, number of household changes and magnitude of change. The effect on each dependent variable was tested in a main moderation analysis and in a follow-up robustness check. The main analysis employed the raw independent variable (duration of feedback device presence in years). * and ** denote statistical significance at 5% and 1% levels respectively.



Appendix F. Implementation of Household Changes over time

Top graph = moderation effects on the number of types of changes implemented in the household after the installantion of the feedback device, thefore gauging quantity of change. Bottom graph = moderation effects on the magnitude of change implemented in the household after the installantion of the feedback device, gauging change qualitatively. Feedback device duration (IV) predicting the number of changes made after the smart meter was installed (DV) at different levels of biospheric value (M). All reported covariates were included. Values for Biospherism were selected accordingly to 1 Standard Deviation above and below the mean. Coloured shaded areas represent the marginal effects of the regression models.

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