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THE ROLE OF ENVIRONMENTAL ATTITUDE IN THE EFFICACY OF SMART-METER-BASED FEEDBACK INTERVENTIONS

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Abstract

When implemented in the field, smart-meter-based feedback interventions typically lag behind the presumed energy-saving potential of the technology. As we and others argue, part of the problem is that such interventions do not work equally well for everyone. The significance of a feedback intervention for actual energy savings depends on the rigor with which people make use of smart-meter-based information. In a quasi-experiment (N = 186), we expectedly found that registering for a web portal that provided smart-meter-based feedback led to moderate energy savings conditional on a person's environmental attitude level. Apparently, a person's attitude discloses itself in the rigor with which this person makes use of an energy-saving opportunity. Hence, to effectively restrain consumption and save energy, environmental attitude is essential because, not only must people make appropriate behavioral choices, but they must also rigorously implement these choices.

Keywords: environmental attitudes, feedback intervention, conservation (ecological behavior), energy savings

1. Introduction

Feedback on energy consumption has been recognized in several reviews and meta-analyses as an effective way to help private households save energy (Abrahamse, Steg, Vlek, & Rothengatter, 2005; Delmas, Fischlein, & Asensio, 2013; Karlin, Zinger, & Ford, 2015). Concomitantly, several countries have implemented policies that have made smart meters mandatory with the goal of reducing the overall energy consumption of households (see, e.g., European Union, 2012). Smart meters record energy consumption data and can thus provide feedback for households. Unfortunately and despite some anticipation that such feedback would generate an average savings of about 5% to 15% (e.g., Darby, 2006; Farhar & Fitzpatrick, 1989; Fischer, 2008), actual recordings of energy savings in field tests have bred an average of only 1.5% to 4% (see e.g., Commission for Energy Regulation, 2011; Gleerup, Larsen, Leth-Petersen, & Togeby, 2010; Schleich, Klobasa, Brunner, Gölz, & Götz, 2011). This is a three to four times smaller reduction in consumption than had originally been anticipated (Gölz, 2017). In this article, we argue that actual savings were not as high as expected because the predictions did not take into account people’s environmental attitude (i.e., people’s esteem for environmental protection, their inclination to protect the environment; for a detailed discussion of the concept, see Kaiser, Hartig, Brügger, & Duvier, 2013).

Measures (e.g., smart-meter-based feedback interventions) that are meant to reduce people’s negative impact on the environment (e.g., energy consumption) necessarily depend on behavior. For example, before information about a person’s actual consumption leads to a reduction in the amount of energy this person consumes, he or she must continuously engage in various activities, such as registering to receive feedback, consulting the feedback device, switching off appliances, or using some of them less frequently (e.g., dishwashers). Accordingly, measures such as smart-meter-based feedback interventions do not work equally well for everyone because behavior and behavioral goals can be implemented in more or less rigorous ways because a multitude of behaviors have to be—ideally, in their entirety—meticulously and relentlessly implemented to actually achieve some impact. The rigor with which a person strives to attain a behavioral goal likely depends on this person's esteem for the attitude object (e.g., environmental protection, frugal use of energy) associated with the corresponding behavioral inclination (i.e., to protect the environment, to save energy). In other words, a person's environmental attitude as a proxy for this person's inclination or motivation to protect the environment or to save energy (Kaiser et al., 2013) is anticipated to account for the rigor with which the person will make use of smart-meter-based information to save energy. In this research, we thus expected that the influence of smart-meter-based feedback on a person's energy consumption would be moderated by the person's level of environmental attitude.

In the following, we present an overview of the literature on how smart-meter-based feedback is theoretically postulated to lead to energy savings. Subsequently, grounded in our previous research, we explain why we believe environmental attitude plays a crucial role in the efficacy of smart-meter-based feedback.

1.1 Saving Energy with Feedback Interventions

Smart-meter-based feedback provides information about a consumer's otherwise hardly perceptible energy consumption. However, registering to receive feedback, albeit an obvious and necessary requirement for feedback to become effective, is not sufficient for saving energy directly because it is what Schultz (2014) calls non-end-state behavior: The registration itself does not reduce energy consumption unless it is mediated by other behaviors (e.g., consulting the feedback portal, reducing laundry temperature, turning off unused appliances). Thus, there is an expectedly complex process that converts the information gained from smart-meter-based feedback into energy savings. Several attempts have been made to explain this process (e.g., Abrahamse et al., 2005; Costa & Kahn, 2013;

Ehrhardt-Martinez, Donnelly, & Laitner, 2010; Karlin et al., 2015; Wallenborn, Orsini, & Vanhaverbeke, 2011).

Feedback is often presumed to increase motivation either directly or indirectly via knowledge (Gölz, 2017). For example, feedback is thought to raise or expand people's concern for the environment or concerns about unnecessary expenditures of money. Alternatively, information about people's energy consumption is meant to remove a deficit in knowledge, thus providing an opportunity to learn about the controllability of a household's energy consumption (Darby, 2006; Wilhite & Ling, 1995). Either way, people's motivation to reduce their energy consumption should increase. Before we argue for an alternative view, we present how feedback is expected to become effective according to feedback intervention theory (Kluger & DeNisi, 1996), a comprehensive model that integrates the factors of knowledge and motivation.

According to feedback intervention theory, information about a person's actual energy consumption will prompt or raise this person's motivation to save energy, but *only* if the person was surprised that the feedback had identified his or her consumption level as considerably higher than what the person had expected it to be (see Karlin et al., 2015; Kluger & DeNisi, 1996). In other words, feedback is thought to create or fuel the necessary motivation to change behavior by making salient the *negative* consequences of a person's behavior in terms of energy consumption (see also Abrahamse et al., 2005; Gölz, 2017).

With regard to an explanation for the smaller-than-anticipated energy saving effects of feedback (see, e.g., Gölz, 2017), feedback intervention theory hence implies that most people view their consumption levels as unremarkable after receiving the feedback (see Karlin et al., 2015). However, to our knowledge, this idea has yet to be tested. In the upcoming sections, we will offer an alternative explanation.

1.2 Attitude-Dependent Efficacy of Feedback

Even if smart-meter installation is mandatory, reading and processing information about one's energy consumption remains voluntary—no matter whether a bill states the amount of energy consumed once per year, or a multifunctional web portal continuously offers high-resolution consumption data. Effective use of feedback includes understanding the consequences that are likely to arise from the presented information and implementing various energy-saving behaviors, which may need to be applied continuously over time. Thus, the required behavior changes do not follow automatically from only registering to receive feedback but require some degree of dedication if a person is going to be successful at saving energy.

Expectedly, people who aim to protect the environment (i.e., people with high levels of environmental attitude) will be motivated to reduce their energy consumption. They will thus make use of the feedback more rigorously by implementing the necessary behavioral changes, which will ultimately become apparent in energy savings, compared with people with lower levels of environmental attitude.

Other goals (e.g., to save money) can also motivate people to save energy. Accordingly, different types of feedback (e.g., kWh or money) should target different motivations. Feedback in the form of how much energy is saved in kilowatt hours (kWh) or in kg of CO_2 emissions expectedly addresses people's environmental concern or attitude. Feedback in the form of amount of money spent (e.g., in Euro, €), by contrast, expectedly addresses a person's economic motivation not to waste money.

Whereas both types of feedback are typically provided in most studies (i.e., kWh and money; see, e.g., Darby, 2006; Gölz, 2017), some have used one or the other type separately, allowing researchers to test differential effects (see, e.g., Fischer, 2008). Interestingly, the efficacy of feedback does *not* seem to depend on the type of feedback (Karlin et al., 2015). Thus, we can assume that both goals (i.e., saving money and protecting the environment) can motivate people to save energy. In this research, we focus on environmental attitude, notwithstanding the fact that other motives can encourage energy saving as well.

Because not everyone is equally dedicated to saving energy when given the opportunity to do so, several authors have raised the question (see, e.g., Gölz, 2017; Nilsson et al., 2014; Webb, Benn, & Chang, 2014): For whom does feedback work best? In contrast to feedback intervention theory, we argue that motivation will not be created or advanced by feedback. Rather, we expect that a certain level of motivation apparent in a person's environmental attitude is required for feedback to become effective.

Whereas several reviews have concluded that it is primarily environmentally engaged people who will participate in feedback interventions (Abrahamse et al., 2005; Darby, 2006; Fischer, 2008), we expect to find that environmental attitude will moderate the effect of registering to receive smart-meter-based feedback on energy consumption. To our knowledge, no other research has before predicted and corroborated such an attitude-dependent efficacy of feedback. Previously, only a specific moderating effect of environmental attitude for real-time feedback on water consumption in showers was reported (Tiefenbeck et al., 2016).

1.3 Environmental Attitude's Role in Feedback Use and Energy Saving

For feedback to become effective in terms of saving energy, a multitude of behaviors must be implemented in their entirety both meticulously and relentlessly (i.e., rigorously). For example, feedback must be repeatedly accessed (e.g., one has to log in to a web portal where individual feedback is provided); valid knowledge about actions that are effective for reducing energy consumption has to be acquired (e.g., reducing the water temperature for laundry saves more energy than turning off devices in stand-by mode); and specific energy-saving behaviors must constantly be remembered in appropriate situations (e.g., when leaving a room or doing one's laundry) and must in turn be implemented. Only with a pronounced level of environmental attitude can a person be expected to engage in all of these activities (Otto, Kaiser, & Arnold, 2014; Urban & Ščasný, 2014).

According to this logic, a person's esteem for an object (e.g., environmental protection, frugal use of energy) or goal (e.g., to protect the environment, to save energy) is expected to lead to various behaviors a person engages in or avoids. Predictably, the more pronounced a person's attitude is, the less energy he or she will consume because the person will engage in more—and also in more demanding—attitude-relevant behaviors (Campbell, 1963; Kaiser, Byrka, & Hartig, 2010). Behaviors are demanding when they are time-consuming or inconvenient, receive no social support, cost money, or require physical effort. Expectedly, such behavioral impediments or—figuratively speaking—costs are more likely to be overcome when a person embodies a corresponding level of environmental attitude. In various experiments and quasi-experiments, we were able to corroborate this prediction (References blinded for review). In these previous studies, we found that a person's attitude level and the costs of a behavior jointly determined whether a behavior was performed (e.g., washing laundry at low water temperatures: see grey arrows in Figure 1).

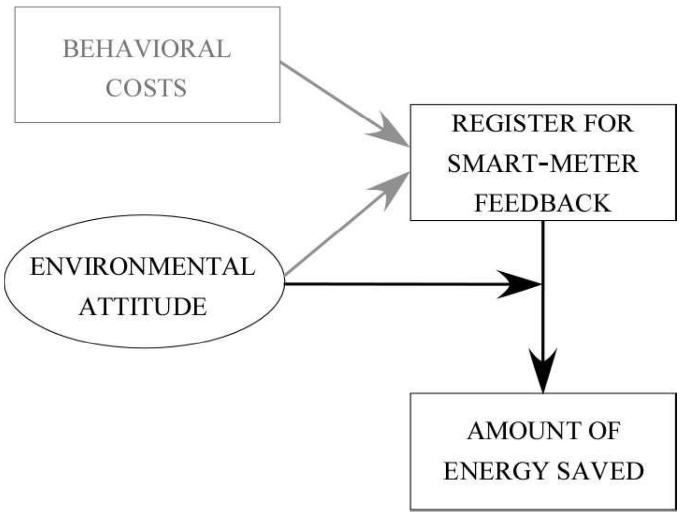

Figure 1. Environmental attitude's role in explaining the effect of registering for smart-meter feedback on energy savings.

However, saving energy with smart-meter-based feedback depends on not only *whether* someone registers for a feedback portal but also *how rigorously* the person makes use of the provided feedback and engages in various energy-saving behaviors. Expectedly, registering to receive smart-meter-based feedback leads to energy savings only when a person aspires to save energy with a certain degree of rigor.

1.4 Research Goals

To better understand why smart-meter-based feedback interventions typically lag behind the presumed energy-saving potential of the technology, we need a more complete understanding of the interplay between attitude, behavior, and the consequences of this behavior in terms of energy savings (i.e., the impact of this behavior; see Figure 1). We expect a person's environmental attitude to control *how rigorously* he or she implements energy-saving opportunities. Therefore, in this research, we tested the moderating role of environmental attitude on the influence of a specific manifest behavior—necessary to receive feedback: registering for a smart-meter feedback portal—on the energy savings amounts (see black arrows in Figure 1), the ultimate consequences of the manifest behavior.

2. Method

2.1 Participants and Procedure

The quasi-experiment was conducted in a region in Germany where a local energy supplier had equipped all of its customers' households with smart meters between 2009 and 2011. The energy supplier offered a web-based feedback portal that provided customers with individual information about their household's electricity use. Upon voluntary registration, customers received an individual password with which they could sign in to the feedback portal on the Internet. In the feedback portal, customers could view their energy consumption per day, per quarter year, or as trend information (whether electricity use was increasing or decreasing compared with previous levels of consumption).

In April 2013, all 448 private customers who were registered for the feedback portal at that time and 448 randomly chosen nonregistered customers were contacted and asked to fill out either a paper-pencil version of a questionnaire with a free return envelope or an online version of the same questionnaire (the web link was sent with the same letter). As an incentive, 20 vouchers of €20 each for an online retailer were offered to participants in a raffle. The questionnaire contained a measure of environmental attitude, questions about their individual consultation of the feedback portal, and sociodemographic questions. By participating in the study, customers also granted us access to their energy consumption data.

Of the registered customers, 154 returned the questionnaire (participation rate 34.4%). Of the nonregistered customers, 93 returned the questionnaire (participation rate 20.8%). Registered customers participated in the study at a significantly higher rate than nonregistered customers, $\chi^2(1) = 20.80$, $p < .001$.

The energy supplier gave the researchers access to annual energy consumption data for each household that participated in the study for the years 2008 to 2012. Consumption in 2008 was used as the prior consumption level, which served as a covariate in our study. Energy savings per household were estimated as the difference in annual electricity consumption between 2008 (i.e., before the installation of smart meters) and 2012 (i.e., after the installation) for each participating household. Our dependent variable was the annual amounts of savings, computed as one fourth of the savings over the 4-year period.

Energy consumption data that could be used to calculate energy savings between 2008 and 2012 were available for 188 participants overall (missing energy consumption data for at least one of the two measurements led to the exclusion of 25 [16.2%] registered and 34 [36.6%] nonregistered participants). One participant was excluded due to an implausible energy saving amount (17,167 kWh) that exceeded the mean energy savings by more than nine standard deviations. Another participant was excluded due to an extremely low environmental attitude level that deviated by more than 3.8 standard deviations from the mean, leaving a sample of $N = 186$ participants in total ($n = 127$ registered, $n = 59$ nonregistered).

In this sample, 23.7% were women (5.4% did not indicate their gender), and the mean age was 56.5 years (*SD* = 11.0), with no age difference between registered and nonregistered participants, $F(1, 180) < 0.01$, $p = .97$. The proportion of female participants was lower among the registered participants (19.5%) than among the nonregistered participants (36.2%), $\chi^2(1) = 5.80$, $p = .02$. Household size was slightly higher in the registered group ($M = 2.79$ people; $SD = 1.06$) than in the nonregistered group ($M = 2.34$, $SD = 1.21$), $F(1, 179) = 6.44$, $p = .01$. Type of residency was assessed as *rented apartment*, *owned apartment*, *rented single-family home*, and *owned single-family home*. Groups differed significantly regarding type of residency, $\chi^2(3) = 22.97$, $p < .001$. Participants who were registered owned a single-family house considerably more often (86.9%) than the nonregistered participants (57.1%). Registered participants also fell into a higher income category such that 51.5% of registered participants had an income of €3,000 or higher per month in comparison with 25.0% of nonregistered participants ($U = 1592.00$, $p = .002$). Registered participants did not differ in their levels of environmental attitude ($M = 0.23$, $SD = 0.80$) from nonregistered participants ($M = 0.21$, $SD = 0.81$), $F(1, 184) = 0.04$, $p = .84$. The level of prior energy consumption was significantly higher among registered participants ($M = 5057.4$ kWh, $SD = 2391.9$) than among nonregistered participants ($M = 3443.9$ kWh, $SD = 2269.6$), $F(1, 184) = 18.93$, $p < .001$.

2.2 Measures

In our research, we expected that feedback would become effective in terms of energy savings through registering for the feedback portal. As a moderator of this effect, environmental attitude was investigated.

Environmental attitude. Environmental attitude was measured with 40 self-reported behavior items as proposed by Kaiser et al. (2010; Kaiser, Merten, & Wetzel, 2018). Thirty-eight of the items were adopted from a well-established measure by Kaiser and Wilson (2004). This measure of environmental attitude is known to be behavior- (e.g., Kaiser

& Byrka, 2015; Taube, Kibbe, Vetter, Adler, & Kaiser, 2018) and impact-relevant (Arnold, Kibbe, Hartig, & Kaiser, 2018). To avoid any kind of overlap with the dependent variable, we excluded behavior items that addressed frugal use or saving of energy at home from Kaiser and Wilson's instrument.

Responses were recorded on a 5-point scale regarding the frequency of the behavior for 27 items (1 = *never*, 2 = *seldom*, 3 = *occasionally*, 4 = *often*, 5 = *always*) and in a dichotomous *yes/no* format for 13 items. For all items, the option NA = *not applicable* was available for behaviors that did not apply to a person's situation (e.g., the item "I drive at a maximum speed of 100 km/h on highways" does not apply to a person who does not have a driver's license).

In line with common practice (Kaiser et al., 2010), the dichotomous Rasch model was used to estimate each person's attitude level (for more information about the Rasch model, see, e.g., Bond & Fox, 2012). To use this model, all polytomous items had to be converted into a dichotomous format, with the responses *never, seldom,* and *occasionally* coded as 0 to represent nonreliable pro-environmental engagement and the response options *often* and *always* coded as 1 to represent reliable pro-environmental engagement. Environmental attitude was assessed in logits, which represent the natural logarithm of the ratio of engaging versus not engaging in pro-environmental behavior across all self-report items. Larger positive logits reflect a more pronounced environmental attitude.

Person separation reliability indicated that the scale was reasonably accurate (rel = .73). Fit values showed an acceptable model fit with mean square (MS) values: $0.88 \leq MS \leq 1.13$ (for reference values, see Wright, Linacre, Gustafson, & Martin-Löf, 1994).

3. Results

We report our results in two sections. First, we explored whether registering for the smart-meter feedback led to energy savings and tested the anticipated moderating influence of environmental attitude. Second, we applied propensity score matching to control for potential biases in our quasi-experimental design and repeated our first analysis with a propensity-score-matched sample.

3.1 Registration Effect

We tested the *registration effect* by comparing registered and nonregistered households. For this test, we applied a three-step hierarchical regression model. In the first step, we tested whether registration (vs. nonregistration) had an effect on energy savings. In the second step, we controlled for the effect of prior energy consumption level. In the third step, we tested the moderating effect of environmental attitude (see Table 1).

We found no overall difference in energy savings between participants who were registered (M = 121.8 kWh, SD = 330.7) and those who were not registered (M = 82.0 kWh, SD = 228.6) for the feedback portal, $F(1, 184) = 0.70$, $p = .41$. Including the covariate prior consumption level in Step 2 led to a significant model, $F(2, 183) = 18.31$, $p < .001$, that explained 16.7% of the variance in energy savings. Adding the moderation effect in Step 3 (i.e., the interaction between environmental attitude and registration) increased the explained variance to 21.9%, $F(4, 181) = 12.65$, $p < .001$. The significant interaction pointed to an attitude-dependent effect of registration, $F(1, 181) = 6.88$, $p = .01$, explaining a unique portion of 3.0% of the variance in energy savings. In other words, registering for the feedback portal had increased energy savings with increasing environmental attitude levels.

Prior energy consumption level had the strongest effect on energy savings. Notably, there was no significant interaction between prior energy consumption level and registration, $F(1, 182) = 0.26$, $p = .61$. Therefore, prior energy consumption did not moderate the energy-saving effect of registration.

Table 1

Effect of Feedback Portal Registration on Energy Savings Moderated by Environmental Attitude

Step	Predictor	*B(SE)*	β	*p*	R^2
1	Constant	82.0 (39.4)		.04	
	Registration	39.8 (47.6)	.06	.41	.004
2	Constant	-96.9 (46.9)		.04	
	Registration	-44.0 (45.9)	-.07	.34	
	Prior consumption level	0.5 (0.01)	.42	<.001	.17
3	Constant	-98.4 (47.1)		.04	
	Registration	-79.6 (46.2)	-.12	.09	
	Prior consumption level	0.1 (0.01)	.45	<.001	
	Environmental attitude[1]	-37.7 (43.8)	-.10	.39	
	Interaction (Registration*EA)	139.1 (53.0)	.31	.01	.22

Notes. EA = Environmental attitude.

With the Johnson-Neyman technique, we were able to identify two points on the environmental attitude continuum where the difference in energy savings between the registered and nonregistered participants became statistically significant (Spiller, Fitzsimons, Lynch, & McClelland, 2013). To determine the Johnson-Neyman regions of significance of the moderation effect, we applied a 90% confidence interval to account for the rather small sample size. One Johnson-Neyman point was at an environmental attitude level of 0.03 logits, below which participants in the intervention group saved less energy than participants in the control group, at least 75.8 kWh less. The second Johnson-Neyman point was at 1.59 logits, above which registered participants saved significantly more energy than nonregistered participants, at least 141.2 kWh more (see Figure 2, Panel a).

[1] Environmental attitude did also not have an effect on energy savings, $F(1, 184) = 1.66$, $p = .20$, when tested as a single determinant.

The conditional effect of registering for feedback depending on environmental attitude is important from a practical perspective because only 5.9% of the participants in our sample even reached an attitude level as high as 1.59 logits. However, not all individuals with a sufficiently high attitude level were also registered for the feedback portal. Only nine participants jointly satisfied both requirements: They registered for the portal and simultaneously had a sufficiently high attitude level for saving energy. In other words, our empirical data did not support a general effect of smart-meter-based feedback on energy savings. Only with a sufficiently high level of environmental attitude did registration for feedback as a pro-environmental behavior effectively lead to a measurable environmental impact (i.e., energy savings), and this applied to only an elected group of people. With a low level of environmental attitude (i.e., below 0.03 logits, 41.9% of the sample), registered participants even saved significantly less.

3.2 Controlling for potential group bias

The quasi-experimental design of our study and the self-selection of participants into the intervention group posed a risk of systematic bias between groups. These confounding influences could alternatively account for our reported moderated registration effect. To validate the results of our first analysis, we applied propensity score matching (see Rosenbaum & Rubin, 1983; Shadish, Cook, & Campbell, 2002) to level out the observed group differences. In propensity score matching, covariates are used to predict the probability that a person will be in the intervention group, and pairs with similar probabilities are matched between the intervention and control groups. We used the potential confounders sex, education level, household size, and type of residency to predict the probability of belonging to the intervention group (i.e., the propensity score), $\chi^2(4) = 16.0$, $p = .003$, Nagelkerke's $R^2 = .19$, and then matched nearest-neighbor pairs across the intervention and control groups (deviation tolerance = .03). Due to the unequal group sizes, we allowed 1:2 matching and matched up to two intervention group participants to one control group participant to maximize the sample size of the matched sample. In this way, we were able to match 27 controls with 65 intervention group participants and succeeded in having two groups that were similar on the matching variables: sex, $\chi^2(1) = 0.01$, $p = .94$; education, $F(1, 90) = 0.52$, $p = .48$; household size, $F(1, 90) = 0.44$, $p = .51$; and type of residency, $F(1, 90) = 3.19$, $p = .08$. Income was not included in the propensity score matching due to missing values and the potential additional loss of even more participants. We assume that income is to some extent reflected in type of residency and education. The matching procedure in fact leveled out the group difference on income, $F(1, 70) = 0.19$, $p = .74$.

We repeated the three-step regression analysis with the propensity-score-matched sample ($N = 92$; see Table 2). Once again, registration for the feedback portal did not have an effect on energy savings, $F(1, 90) = 0.002$, $p = .97$. Including the level of prior consumption as a covariate in Step 2 led to a significant model, $F(2, 89) = 6.46$, $p = .002$, that explained 12.7% of the variance in energy savings. In Step 3, the explained variance increased to 21.7%, $F(4, 87) = 6.04$, $p < .001$, and the interaction was again significant, $F(1, 87) = 5.39$, $p = .02$, uniquely explaining 4.9% of the variance in energy savings.

Table 2

Effect of Feedback Portal Registration on Energy Savings Moderated by Environmental Attitude in a Propensity-Score-Matched Subsample

Step	Predictor	*B(SE)*	β	*p*	R^2
1	Constant	120.6 (55.7)		.03	
	Registration	2.8 (66.3)	.004	.97	< .001
2	Constant	-67.7 (74.1)		.36	
	Registration	-28.0 (62.9)	-.04	.66	
	Prior consumption level	0.04 (0.01)	.36	.001	.13
3	Constant	-50.7 (77.7)		.52	
	Registration	-89.4 (67.0)	-.14	.19	

Prior consumption level	0.05 (0.01)	.38	< .001	
Environmental attitude	-69.8 (70.0)	-.20	.32	
Interaction (Registration*EA)	184.6 (79.5)	.47	.02	.22

Notes. EA = Environmental attitude.

To determine the Johnson-Neyman regions of significance in the moderation effect, we again applied a 90% confidence interval. We identified one Johnson-Neyman point at an environmental attitude level of -0.19 logits, which implies that participants with a lower environmental attitude level in the registration group saved less energy compared with the control group, at least 124.4 kWh less. The second Johnson-Neyman point was at 1.40 logits on the environmental attitude scale, indicating that the participants in the registration group with attitude levels above this point saved more energy than the control group, at least 169.7 kWh more.

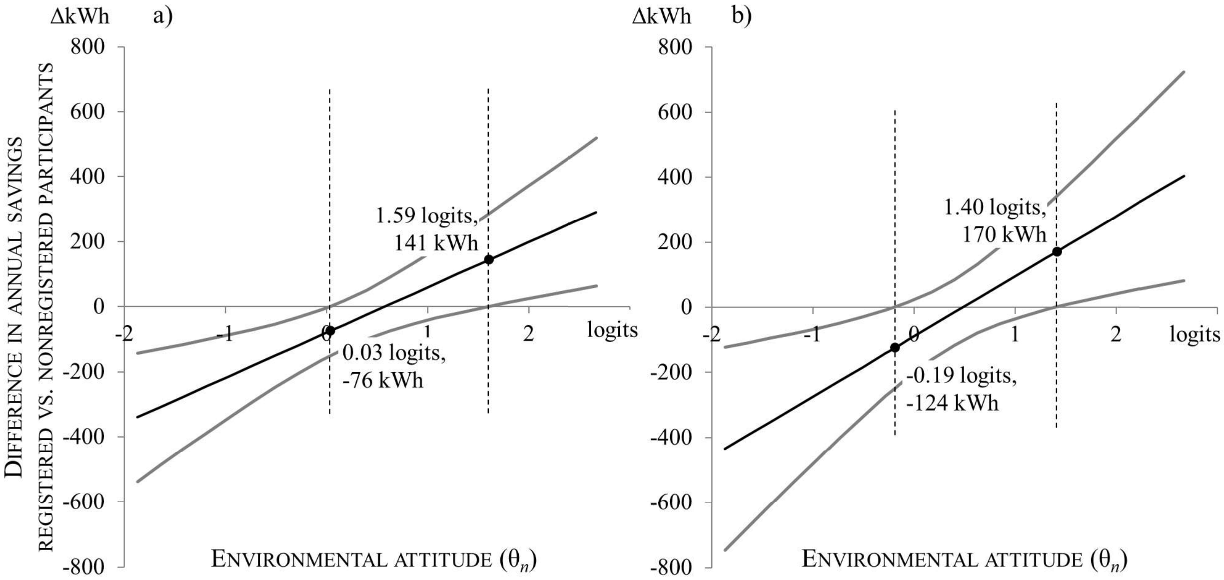

Figure 2. Conditional effect of registration on energy savings depending on the extent of environmental attitude in the full sample (Panel a) and in the propensity-score-matched subsample (Panel b), confirming that the effect is not accountable to any of the confounding influences. Johnson-Neyman points (i.e., where the 90% confidence intervals do not include zero) are indicated by vertical dashed lines and are specified by black dots and corresponding coordinate information.

4. Discussion

In our research, we found the expected attitude-dependent effect of engaging in smart-meter-based feedback use on the amount of energy saved in kWh (see Figure 1). Only people who held a certain level of environmental attitude saved more energy after they registered for the feedback portal than people who did not register. In other words, effectively saving energy depends not only on a person's engagement in such an opportunity per se—i.e., registering for a web portal—but also on how rigorously the person makes use of this energy-saving opportunity. With our research, we were able to empirically confirm the presumed attitude-dependence of behavior effects in terms of amount of energy saved. With regard to Figure 1, we aimed to shift the focus from explaining specific pro-environmental behavior (e.g., registering for smart-meter feedback) to explaining the impact on the promotion of sustainability that such a behavior (change) has (e.g., in terms of achieved energy savings). We provided evidence that a personal inclination to protect the environment (i.e., his or her environmental attitude) is crucial for such behaviors to be translated into a measurable impact (e.g., amount of energy saved). Theoretically, this perspective highlights the importance of considering environmental attitude, a personal factor, with regard to the selective efficacy of interventions, which at the same time is of high practical relevance (e.g., when implementing energy-saving measures in the field).

In contrast to most contemporary measurement models of environmental attitude, we followed a measurement approach that makes use of the cost order of an array of behavioral manifestations to measure attitudes (see, e.g., Campbell, 1963; Kaiser et al., 2010). Consistent with this idea, Rasch-type models were proposed as the optimum models for measuring attitude (see Kaiser et al., 2010; Kaiser & Wilson, in press; Kaiser et al., 2013). Previous findings have supported the notion that personal attitudes can be inferred from verbal acts such as self-reports of past engagement in environmentally protective behaviors (Kaiser et al., 2018; Urban, 2016). The theoretically anticipated connection between environmental attitude and manifest environmentally protective behavior has been corroborated with numerous activities (see, e.g., Arnold & Kaiser, 2018; Kaiser & Byrka, 2015; Taube et al., 2018), and even with environmental impact (e.g., energy savings, carbon emissions). We therefore regard this measure of environmental attitude as a reliable and valid instrument useful both for psychological science and for practical application when informing policy makers.[2]

Our finding that the effectiveness of smart-meter-based feedback depends on attitude indicates that the disparity between the forecasted and the actual amounts of energy savings recorded in smart-meter-feedback interventions (see, e.g., Gölz, 2017) is in part due to the comparatively small levels of commitment to protect the environment. This general lack of personal commitment is even more dramatic because we have to regard our sample as nonrepresentative of the general population of Germany but biased toward a comparatively higher level of environmental attitude (see next section) so that we probably even overestimated the share of potential energy savers (see also Abrahamse et al., 2005; Kaiser & Byrka, 2011; Kaiser & Henn, 2017; Kaiser, Woelki, & Vllasaliu, 2011).

With our quasi-experimental design, we ran the risk that systematic differences between our intervention group (i.e., people who voluntarily registered for a feedback portal) and the control group (i.e., people who had the same opportunity but did not register) would confound our effects. We thus applied propensity score matching to exclude possible alternative explanations. The attitude dependency of smart-meter efficacy was even more pronounced in the propensity-score-matched sample (as indicated by the higher regression weight of the interaction term and the steeper slope of the effect in Figure 2b). Thus, our effect seems not biased by the recognized confounding variables. Nevertheless, we cannot exclude the possibility that other confounding variables could be accountable for the results.

[2] Deriving people's attitude levels from behavior and subsequently explaining behavior with said attitudes may appear to be like getting caught a logical fallacy (see, e.g., De Houwer, Gawronski, & Barnes-Holmes, 2013). Within the Campbell Paradigm, this logical fallacy can be avoided when measuring attitudes and explaining behavior are treated as two separate tasks involving distinct behaviors (for the detailed argument, see Kaiser & Wilson, in press).

Future research on attitude-dependence of energy-saving interventions could implement more experimental designs (see, e.g., Houde, Todd, Sudarshan, Flora, & Armel, 2013; Tiefenbeck et al., 2016).

Self-selection effects are, by contrast, a crucial issue when it comes to estimating the potential of smart-meter-based feedback. The effectiveness of feedback depends on the voluntary processing of the feedback information by the electricity consumers. This will most likely not be executed randomly but by those who are interested in knowing about or already committed to change their energy consumption (see Figure 1 for the influence of environmental attitude on registering for feedback). A quasi-experimental design mimics the fact that in real life feedback would also attract people rather committed to energy-saving.

The amount of energy savings depended to a large degree on prior energy consumption levels: Especially households with high levels of consumption tended to reduce their energy consumption throughout the duration of study. This trend is in line with other research (see, e.g., Brandon & Lewis, 1999; Houde et al., 2013; Tiefenbeck et al., 2016). Importantly, high prior consumption levels did not interact with feedback registration: high prior consumption led to more energy savings, irrespective of whether people were registered for feedback or not.

Moreover, both registered and nonregistered participants saved energy on average (M_{2008} = 4,546 kWh, SD_{2008} = 2,465; M_{2012} = 4,109 kWh, SD_{2008} = 2,266), $t(185) = 4.93$, $p < .001$, but our design did not allow us to draw conclusions about why this happened. The general energy savings could be due to external factors (e.g., Zeitgeist or more investment in energy-efficient appliances) or due to a self-selection-caused bias in the sample (e.g., participants with interest in topics related to energy saving). What we can exclude though is a Hawthorne effect because people were not aware of the study at the time of consumption: They were invited in 2013 to participate, and energy consumption data were provided retrospectively by the energy supplier for the years since 2008.

4.1 Limitations

Notwithstanding the advantage of its ecological validity, our quasi-experimental field research comes with limitations. An important one is extremely noisy estimates of people's energy consumption and—due to uncertainty about the exact dates of smart-meter installations—the systematic overestimation of the opportunity to save energy in households. The price we paid in our research was comparatively low proportions of explained variance in energy savings.

Household energy consumption typically depends on a plethora of factors: household composition and size, available technology and living space, the economic situation, and specific weather conditions to name a few. These and many other factors feed into the level of energy consumption and represent bias for person-level analyses in which the energy consumption of households is—as in our case—taken as the consumption level of individuals. Moreover, even though the person who was asked to participate in the study was always the same person who held the contract with the energy supplier, there was a chance that the household member who registered for the feedback portal was not the person who filled out the study questionnaire. We do not regard this to be a major problem because people living in close proximity to each other are known to hold rather similar attitudes (see Festinger, Schachter, & Back, 1950). Accordingly, the energy saving activities of couples living in the same household are correlated (Seebauer, Fleiß, & Schweighart, 2017). We further view the measurement of the intervention effects on the household level as functional because households and not persons receive feedback opportunities in real life.

We cannot rule out the possibility, as set forth by feedback intervention theory, that the smart-meter-based feedback intervention used in our study actually created or fueled people's motivation to reduce their energy consumption (see, e.g., Karlin et al., 2015) because we did not measure people's motivation (i.e., their environmental attitude) prior to the intervention.

We also did not measure participants' inclination to save money (or any other goal that could be pursued by saving energy). In principle, however, our argument applies to motives other than environmental protection (e.g., money saving) as well: Not everyone would be expected to save energy through feedback but those who are sufficiently motivated to save money would be. Both goals (i.e., saving money and protecting the environment) can elicit energy-saving intentions (see Steinhorst, Klöckner, & Matthies, 2015) and can thus be addressed by feedback programs.

Because smart-meter deployment occurred consecutively between 2009 and 2011, participants' access to the smart-meter-based energy consumption feedback—and their chance to save energy with it—varied a great deal. Without exact deployment dates, we used 2008 (certainly before deployment) and 2012 (certainly after deployment) as our reference years. With this crude approximation, we reduced our chances of finding energy savings because we systematically overestimated the availability of smart-meter-based feedback in households and, thus, each household's chance to save energy with it.

Given the noisiness of the data on energy savings, it is not surprising that the absolute amount of explained variance was moderate. It is thus even more remarkable that we found that a *single* psychological factor (i.e., environmental attitude) was relevant for the amount of energy that people saved with smart-meter-based feedback, even if the incremental variance (i.e., 3-5%) that could be attributed to the moderation effect was quite small.

Whereas we regard self-selection into the (quasi-experimental) feedback condition as a smaller problem (see above), self-selection into the study (i.e., participation) probably led to a biased sample compared with the general population, and thus, the generalizability of the results is limited (see Kaiser & Henn, 2017; Kaiser, Otto, & Schuler, 2015). Response rates were significantly different between the registered and the nonregistered group and resulted in a control group that was considerably smaller than the intervention group; however, their environmental attitude levels were similar. This suggests that in both groups, predominantly environmentally engaged people participated, but among the registered customers, environmentally engaged people were overrepresented, and thus, the participation rate was higher than among the nonregistered. Environmentally engaged people were thereby overrepresented in our study. This point is supported by a comparison with a representative sample (see Otto, Kröhne, & Richter, 2018), which had a lower environmental attitude level (M = -0.13, SD = 0.91) than the study sample (M = 0.20; SD = 0.76), $F(1, 654) = 19.2$, $p < .001$.[3]

Due to the quasi-experimental design, we cannot definitively assert that environmental attitude moderates a feedback opportunity in its influence on energy savings. Nevertheless, we at heart excluded several alternative explanations with our propensity-score-matched comparison for conditional energy saving. More rigorously controlling for confounding variables (e.g., by more extensive propensity score matching, regression discontinuity, or instrumental variable designs; see, e.g., Kim & Steiner, 2016; Shadish et al., 2002) and using larger sample sizes in future research could help consolidate our proposed moderator (see Figure 1).

4.2 Practical Implications

One lesson to be learned from our research is—if energy saving was the prime target—a complete roll-out of smart meters for an entire population might not be reasonable from a cost-benefit point of view. We say this because only a minority of recipients would be sufficiently motivated to use smart-meter-based feedback rigorously enough. In our sample, 6% of the participants had environmental attitude levels that were high enough. However, due to our overly pro-environmental sample, we probably overestimated the share of the population that would save energy under the conditions of our study. Note, however, that the specific threshold of the environmental attitude level that we reported is not generalizable but

[3] Note that for this direct comparison of the mean values of environmental attitude, the two samples were jointly calibrated (see Bond & Fox, 2012) using this study's measurement instrument, which differed slightly from Otto et al.'s (2018) in that it did not contain energy-saving-related items.

is rather intervention-specific. It serves to demonstrate the conditional effect that as such can also be expected in other behavior-change measures.

Another lesson that readers might believe they have learned from our research is that, to have more ecological relevance, behavior-change interventions should target end-state behaviors (e.g., switching off lights) rather than non-end-state behaviors (e.g., registering for feedback; see, e.g., Schultz, 2014). This would, however, be a misrepresentation of our main results. Rather, what matters is the number of activities people engage in and the rigor with which they engage in each one of them. In other words, reducing people's harmful impact on the environment depends on people's propensity to protect the environment (i.e., their environmental attitude). As such, to be able to significantly reduce people's impact would require people's environmental attitude to grow a great deal, which is nothing less than an overall lifestyle change (see, e.g., Otto et al., 2014).

4.3 Conclusions

People's registration for smart-meter-based feedback leads to energy savings and significant ecological alleviations only when a person holds a sufficiently high level of environmental attitude. This is because effective environmental protection and climate mitigation depend not only on a person's engagement in such opportunities but on the rigor with which the person makes use of them. A person's environmental attitude level is crucial in two ways: It controls not only whether people engage in mitigation activities but also how rigorously people implement these activities (see Figure 1). With our research, we offer a more complete understanding of the interplay between attitude, behavior, and the ecological impact of behavior.

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