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Overcoming Salience Bias: How Real-Time Feedback Fosters Resource Conservation

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Abstract. Inattention and imperfect information bias behavior toward the salient and immediately visible. This distortion creates costs for individuals, the organizations in which they work, and society at large. We show that an effective way to overcome this bias is by making the implications of one's behavior salient in real time, while individuals can directly adapt. In a large-scale field experiment, we gave participants real-time feedback on the resource consumption of a daily, energy-intensive activity (showering). We find that real-time feedback reduced resource consumption for the target behavior by 22%. At the household level, this led to much larger conservation gains in absolute terms than conventional policy interventions that provide aggregate feedback on resource use. High baseline users displayed a larger conservation effect, in line with the notion that real-time feedback helps eliminate "slack" in resource use. The approach is cost effective, is technically applicable to the vast majority of households, and generated savings of 1.2 kWh per day and household, which exceeds the average energy use for lighting. The intervention also shows how digitalization in our everyday lives makes information available that can help individuals overcome salience bias and act more in line with their preferences.

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1. Introduction

Living up to our ideals can be challenging. Most people want to protect the environment, lead healthy lives, and manage their businesses effectively—and yet often fail to do so in their everyday lives. Part of the discrepancy between individuals' aspirations and their daily behavior can be attributed to salience bias at the moment of decision making: some features of a decision are often vivid and perceptible, while others are diffuse and difficult to quantify. This creates a bias in favor of the salient (Kahneman et al. 1982, Bordalo et al. 2012, Allcott and Wozny 2013), leading individuals to make suboptimal decisions in both their professional and their private lives. For instance, the delicious smell and taste of a cake is often more salient than the calories and nutritional aspects of that craving, prompting many individuals to let their dietary resolutions slide. In the corporate world, managers often tend to neglect the cost and duration of ancillary business processes such as compliance, or administrative tasks, as these processes are much less visible to them than the organization's core business. This often results in costly planning errors (Hirshleifer 2008). Salience bias can also cause present-biased behavior if immediate rewards are more visible than the long-term costs of a behavior (Milkman et al. 2008, Loewenstein 1996). Likewise, despite heightened concern about privacy issues among the general public (European Commission 2011), many individuals hardly hesitate to disclose sensitive personal data to smartphone applications and online services that provide immediate benefits in terms of fun or convenience (Kehr et al. 2015). As Kehr (2016) shows, a more salient presentation of privacy aspects at the moment of decision making can mitigate the bias toward perceived benefits and remind consumers of the risks involved in sharing sensitive data. In general, salience bias compounds a variety of problems including insufficient risk management, overspending, and unhealthy lifestyles—with costly consequences for individuals, organizations, and society at large.

One domain that is particularly prone to salience bias is resource consumption: the benefits of energy or water use are usually immediate and perceptible, whereas the negative implications in terms of costs and emissions from energy generation are typically elusive and difficult to gauge for the individual. For example, while the pleasant sensation of a warm shower is immediately felt, few individuals are aware of how much energy and water this action involves (Attari et al. 2010, Attari 2014). Although many people indicate that they are willing to make sacrifices to protect the environment (Diekmann et al. 2009, Naderi 2011), the asymmetric visibility of immediate benefits versus elusive resource use makes conservation a particularly challenging endeavor. As a result, even those individuals who want to use natural resources efficiently and avoid waste, or try to purchase ecologically friendly products, often do not follow through with their intentions (Gutsell and Inzlicht 2013). Even worse, individuals engage in ineffective conservation efforts while believing that they are doing their part (Attari et al. 2010, Attari 2014, Delmas and Lessem 2014)—at the expense of less obvious measures that could create a meaningful impact (Gardner and Stern 2008). The lack of salience of resource use may be one of the reasons why environmental attitudes are poor predictors of resource consumption (Gatersleben et al. 2002, Kollmuss and Agyeman 2002), contributing to the attitude–behavior gap widely discussed in psychology and related fields (Fishbein and Ajzen 1975, Ajzen and Fishbein 1980). Correcting salience bias in environmentally significant decisions would benefit not only individuals but also organizations and society. Energy use is an important cost factor in industry and a major geopolitical asset, and emissions from energy production cause health problems and contribute to global warming, which compound a wide variety of economic, social, and political challenges.

In this paper, we attempt to directly address salience bias in the context of resource conservation. Our target activity is showering: in the course of less than five minutes, a typical individual in our sample uses 45 liters of hot water, which requires on average 2.6 kWh to heat it up (for comparison, the average household in Switzerland and in the European Union uses 1.0 kWh for lighting per day (Lapillonne et al. 2015, Prognos 2015), and a modern refrigerator uses 0.63 kWh per day (Michel et al. 2015)). Thus, showering is a highly resource-intensive activity. In a randomized, controlled trial with 697 households, we provided participants with smart shower meters. The devices have the ability to provide real-time feedback on energy and water consumption in a simple and intuitive way, while and where individuals engage in the behavior. The devices are attached below the handle of the showerhead, making the display with the feedback easily visible for users while they take their shower.

Our intervention differs from existing feedback interventions. A widely used policy is to provide feedback about one's past consumption, such as periodic "home energy reports." These reports contain historical electricity consumption data, convey social norms through comparisons with homes in the neighborhood, and provide energy conservation tips (Allcott and Mullainathan 2010). Home energy reports reduce *electricity* consumption by roughly 2% (Allcott and Mullainathan 2010, Costa and Kahn 2013, Allcott and Rogers 2014) or 0.5% of a household's *energy* use.[1] Similar reports on household water use yield reductions in water consumption between 0% and 5% (Ferraro and Price 2013, Mitchell and Chesnutt 2013, Bernedo et al. 2014, Schultz et al. 2016, Brent et al. 2015). Thus, the treatment effects are not larger for feedback on household water use than on aggregated electricity consumption. A potential explanation for the moderate effect size of those reports might be that by providing feedback on past resource consumption, they only enable consumers to change *future* behavior; yet in many cases, good resolutions fall prey to procrastination and relapse (Norcross and Vangarelli 1988).

Other behavioral interventions use smart meter data to provide timely feedback about aggregate electricity consumption through in-home displays or web portals. Recent electricity smart metering trials report treatment effects between 2% and 5% (Degen et al. 2013, McKerracher and Torriti 2013, Buchanan et al. 2015). A metareview on smart metering studies, however, qualifies the savings induced by in-home displays as "insubstantial" (Buchanan et al. 2015, p. 94). In all cases, the feedback information is aggregate and not delivered at the point where the decision is being made, blurring the link between the current action and its impact on resource consumption. Feedback systems that break electricity consumption down into end-use categories (e.g., lighting, heating and cooling systems, refrigerator, dishwasher, plug loads) can help consumers identify the key areas of electricity use in their home. Based on that information, they can focus their conservation efforts on those categories. Asensio and Delmas (2015) show that this approach, when combined with information about the environmental and health impact of energy consumption, already increases conservation effects to 8% of electricity use (or 2% of household energy use).

By contrast, our intervention provided individuals with real-time feedback on a specific behavior while and where they engaged in it. This approach allowed them to directly take action if the status of the ongoing behavior was not in line with their preferences (Kluger and DeNisi 1996). We find a statistically significant and quantitatively very large effect of the intervention: real-time feedback on a specific activity (showering) reduced the resource consumption of that target behavior by roughly 22%. Remarkably, the intervention yielded its full treatment effect from the first instance the feedback was being provided. Hence, the intervention did not require a frequent or repeated exposure of the individuals to unfold its potential. In addition, we do also not observe an attenuation of the treatment effect: the impact of the intervention was stable over the two-month study period.

While it is interesting to note that our intervention caused a much larger relative shift in the target behavior than studies providing aggregate feedback, the relevant comparison for policy purposes is the aggregate savings in energy and carbon emissions at the household level. For the average Swiss household (2.1 persons), the energy savings of our intervention amount to 1.2 kWh per day, simultaneously curbing daily water consumption by 20 liters. Putting the effects into perspective, the savings exceed the daily electricity use for lighting (1.0 kWh) of the average Swiss household (Prognos 2015) and are equivalent to the daily consumption of two typical European refrigerators (Michel et al. 2015). Our setting allows for a comparison with conservation effects of existing feedback interventions, since all the participants had previously completed an electricity smart metering study (Degen et al. 2013). The average conservation effect in the electricity smart metering trial was 0.2 kWh per household per day—a result that is in line with the findings of most comparable smart metering trials in Europe (McKerracher and Torriti 2013, Schleich et al. 2013). These savings translate into a 1.0% reduction in the participants' household *energy* use. By contrast, the 1.2 kWh reduction on the target behavior in our study reduced their household energy use by 5.0%. Thus, providing real-time feedback on a specific behavior created an energy conservation effect that was five to six times larger than providing aggregate feedback about a broader measure of energy or electricity use to the same population. This is remarkable given that the narrow focus on a single activity left the individuals only with one margin of adjustment (how they shower), rather than the whole set of behaviors targeted in previous studies providing aggregate feedback.

We also examine whether real-time feedback enhances awareness of the resource use, as this is a necessary condition to reduce salience bias. Interestingly, studies providing aggregate consumption feedback could not find evidence of an improved awareness of one's energy use (Degen et al. 2013, Mitchell and Chesnutt 2013). By contrast, we find strong improvements of estimated water use among the individuals who received real-time feedback, whereas the control group's awareness did not change over the study period.

The large behavioral response also allows us to examine whether the reaction to real-time feedback differs in subsamples in interesting ways. Previous studies have found that conservation effects are larger for high baseline users than for users who start out with a more efficient resource use (Allcott 2011, Ferraro and Price 2013, Degen et al. 2013, Allcott and Rogers 2014, Schultz et al. 2016, Brent et al. 2015). In addition, previous research suggests that stronger environmental attitudes (Abrahamse et al. 2005, Delmas and Lessem 2014) and an affinity to quantify behavior (Swan 2013) should lead to a stronger conservation effect in response to real-time feedback.

We find a very large and robust interaction of baseline use with real-time feedback. For every 1 kWh increase in baseline consumption, the conservation effect of real-time feedback increased by 0.32 kWh, leading to a much larger behavioral response for high baseline users: while the average user displayed a conservation effect of about 0.56 kWh, the top quintile of baseline users saved almost three times as much (1.47 kWh).

A stronger environmental attitude and a stronger affinity to quantify behavior also tended to create a larger conservation effect. Both interaction effects are quantitatively meaningful. For instance, individuals who scored in the bottom quintile of environmental attitude displayed a conservation effect of 0.5 kWh—still a large effect. Individuals in the top quintile saved 0.75 kWh, almost 40% more.

Overall, the results from the subgroups shed some light on possible mechanisms behind the effect of real-time feedback on resource conservation. The result that high baseline users respond more to the treatment is routinely interpreted as eliminating previous slack that is hypothesized to be larger in the consumption of high baseline users.[2] Yet this raises the question of where this slack originates, and salience bias provides a simple and straightforward interpretation: inattention and imperfect information may contribute to high resource use that is not rooted in a strong preference for it. Real-time feedback directs attention to it and helps individuals eliminate this slack—more so when slack is higher. Thus, real-time feedback can help individuals make choices more closely aligned with their innate preferences. The fact that both a stronger environmental attitude and a stronger affinity to quantify behavior predict a larger conservation effect is consonant with this interpretation. Furthermore, we also find that differences in these preferences produce larger differences in conservation effects when baseline use is high, i.e., when "slack" in baseline use is particularly large. While, ultimately, our data do not allow us to rule out that other mechanisms may simultaneously play a role, we interpret the results as consistent with the explanation that making resource use visible in real time decreases salience bias.

The properties of the behavioral response we uncover also set our intervention apart from other policies. Regulatory approaches (e.g., banning high-flow showerheads) limit individuals' freedom of choice and are subject to the standard criticism of economics that the imposed change in behavior does not take into account individual differences in the costs of changing behavior (see, e.g., Frank and Glass 1991).[3] Providing real-time feedback demonstrably does not fall into this category, as we show that individuals with a stronger preference for environmental protection exhibit a stronger conservation effect—as efficiency dictates. Interestingly, our study also shows that individuals prefer to cut the shower short rather than adjusting the flow rate of water, thus highlighting another inefficiency of current policy proposals in this domain. Another often-discussed policy measure is price increases through environmental levies (Wolak 2011, Jessoe and Rapson 2014). Yet households typically exhibit low sensitivity to price increases in resource consumption (Levitt and List 2009, Azevedo et al. 2011, Bolderdijk et al. 2013, Jessoe and Rapson 2014)—which may also be partly due to salience bias. Similarly, information campaigns (e.g., energy conservation tips) have proven largely ineffective in fostering resource conservation (Abrahamse et al. 2005). Our results also raise the scope for complementarities between better control over consumption through real-time feedback and pricing, as consumers may be able to make better-informed choices when provided with real-time feedback. On a more general level, our study suggests that real-time feedback may be a potent remedy against salience bias in other domains of behavior and inspire useful policies for individuals, firms, and governments alike.

The remainder of this paper is structured as follows: Section 2 presents the experimental design, measurements, and survey constructs we use in this study, and it explains the recruitment strategy. Section 3 lays out the behavioral results and probes into the psychological mechanisms behind the observed treatment differences. Section 4 concludes the paper with a discussion of the results and presents implications and potential applications in several domains.

2. Experimental Setup

2.1. Implementation of the Behavior-Specific Real-Time Feedback

In our framed field experiment (Harrison and List 2004, List 2011), we provided individuals with real-time feedback on the resource consumption of a specific behavior while they engaged in it. Thus, we made resource consumption salient while individuals could directly adapt their behavior in response to the real-time feedback. We chose showering as a highly energy-intensive activity: water heating is the second-largest residential energy end use in Europe and in the United States, accounting for 14%–18% of the average home's energy use (Swiss Federal Office for the Environment 2013, U.S. Energy Information Administration 2013). The average shower consumes 2.6 kWh of energy in only four minutes (see Section 1.4 of the supplementary information)—with the same amount of energy, one could power nearly 2,300 compact fluorescent light bulbs (17 W each) over the same period of time.

We measured and recorded data on individual showers with the amphiro a1 smart shower meter depicted in Figure 1. The device is mounted by the users between the shower hose and the hand-held showerhead (which more than 95% of showers in Europe have). It features a liquid crystal display, and the feedback is easily visible to individuals while they shower. The device calculates the lower bound of energy use based on the standard engineering formula for heat energy ($Q = m \times c_p \times \Delta T$, with heat energy Q, mass of water m, heat capacity c_p, and ΔT the difference between the measured water temperature and cold

Figure 1. (Color online) The Feedback and Measurement Device Used in This Study

Notes. On the left, a snapshot of the feedback displayed by the smart shower meter. On the right, the device installed between the showerhead and shower hose.

water temperature). Average energy losses are taken into account in the evaluation process based on a detailed breakdown of residential water heating systems in Switzerland (see Section 1.4 and Table S5 in the supplementary information for details).

The display harvests the energy required for its operation from the water flow: it activates as soon as the water is turned on and switches off three minutes after the end of a shower (Tiefenbeck et al. 2013). This eliminates the need for batteries and allows tracking behavior over extended periods of time. This, however, comes at a cost: while the device can measure the duration of showers (and of interruptions of the water flow during showers), the absence of a battery implies that the device is unaware of the global time; showers are thus recorded in temporal order, but without a time stamp. Therefore, our unit of analysis is a shower, not a day, as commonly used in other studies. We will return to this point in Section 3. The shower meters were deployed for two months and recorded energy and water consumption, average water temperature, interruptions, and duration of each shower (see Section 1.1 in the supplementary information for a more detailed description).

2.2. Experimental Conditions

We implemented three experimental conditions. In the *real-time condition*, the device displayed water use in tenths of liters. Thus, it provided individuals with objective and easily understood feedback on their resource consumption during a shower.[4] The device also displayed water temperature in degrees Celsius, energy consumption in kilowatt-hours, an energy efficiency rating (ranging from A to G), and a polar bear animation (i.e., an ice floe that progressively shrinks as the amount of energy used increases) (see Section 1.1 in the supplementary information for a more detailed description of the elements displayed).

In a second condition, the *real-time plus past feedback* group, the display showed all these elements and, in addition to that, the total amount of water used in the previous shower. In a two-person household, this may add an element of pressure, as the impact of one's behavior can be seen by the other person. In fact, several earlier behavioral interventions in the energy context (using aggregate feedback on past behavior) have found an explicit role of psychological pressure (Schultz et al. 2007, Gromet et al. 2013, Delmas and Lessem 2014), induced by peer pressure or guilt (Schultz et al. 2007, Gromet et al. 2013, Delmas and Lessem 2014). Psychological pressure has been found to be an important driver of prosocial behavior in other domains, such as charitable donations or voting (DellaVigna et al. 2012; Gneezy et al. 2010, 2012; Gerber et al. 2008, 2010). The visibility of one's resource consumption to another household member might be particularly relevant, as several studies on consumer decisions have shown that close peers and family members exert a particularly large influence on individuals' decisions (Bearden and Etzel 1982, Loock et al. 2012, Poldin et al. 2016).

Note that the perception of the feedback displayed in the two treatment conditions is subjective: in general, individuals' personal goals and standards define whether the resource consumption displayed is perceived as a positive result (within the individual's standard) or as a negative outcome (exceeding that standard). The discrepancy between feedback and individuals' standards has been identified as a fundamental source for motivational processes (Kluger and DeNisi 1996): while knowledge of positive results can reinforce and encourage behavior, knowledge of negative results can be seen as a punishment and discourage behavior (Karlin et al. 2015). In our study, neither the smart shower meter nor the accompanying materials (e.g., user manual) conveyed social comparisons with other individuals (e.g., average energy or water consumption per shower) that could serve as a clear alternative reference point (except for the information on the previous shower in the real-time plus past feedback group).

In the control condition, we supplied no feedback on energy and water consumption: the device displayed only water temperature. Once the water reaches the temperature desired by the user, water temperature is rather static in nature in the course of a typical shower. In theory, one could also envision a "pure" control group without any feedback displayed. By displaying water temperature from the onset of every shower, control group participants are also aware that the device is correctly installed and measuring data, just like in the treatment conditions. Furthermore, from a practical point of view, it would be difficult to ask participants to install a pure measurement device that does not deliver any benefits to the user: without any information shown, participants might think the device is broken, and they might be more likely to drop out of the study, which could introduce attrition bias in the control group.

To measure all participants' water use under identical conditions, the intervention phase with feedback in the two experimental conditions was proceeded by a baseline phase during which only the water temperature was displayed to those two groups as well, just like in the control condition.

Control group manuals explained that water temperature is an important factor to influence energy consumption. Treatment group manuals stated that the device would display only water temperature during an initial familiarization phase. After that, the device would automatically start to display energy and water consumption as well. Neither the purpose of the initial period as a baseline phase nor its duration (10 showers) was disclosed to the participants. All materials sent to the participants (invitation letter, survey invitations, and user manual) framed the study as an *energy efficiency* study (water conservation is less of a policy priority in water-rich Switzerland). The materials highlighted the large amount of residential energy consumed by water heating (e.g., "water heating is the second largest energy end use in a typical household") and that the smart shower meter would help users keep an eye on their energy consumption. The accompanying user manuals explained that the device measures water consumption and temperature and calculates energy consumption.

2.3. Sample

Participating households were recruited among a larger sample of 5,919 residential customers of the Swiss utility company ewz. All of them had access to the Internet and had previously participated in an electricity smart metering study (Degen et al. 2013). At the end of that study, they were told that they would (unconditionally) receive the smart shower meter amphiro a1 as a thank-you gift. The size of the study had been limited up front to 700 households for cost and implementation reasons. Because of memory constraints of the smart shower meter, only one- and two-person households could be admitted. As a result of that technical restriction on household size, none of the households included children or teenagers. To participate, individuals interested in the study needed to fill out an online survey (see Section 2.4) and agree to share their shower data with the researchers. From those registered who fulfilled the qualification criteria (the number of household members in particular; see Section 1.2 in the supplementary information for details), we chose participants on a first-come-first-served basis. Our sample of participants has thus actively opted into our study. As in any other study with an opt-in design, this raises the question whether the results might be subject to potential biases of self-selection. Therefore, in a first step, we compared the demographics of our study participants with all 3,989 one- and two-person households who had participated in the electricity smart metering study (the restriction of our study to one- and two-person households was for technical reasons; therefore we need to compare our sample with that corresponding reference group and not with all households). Table S1 of the supplementary information displays the descriptive statistics. As the results of the t-tests show, none of the t-test statistics indicates a significant difference between participants and nonparticipants at the 0.05 level. Thus, the subset of participants who participated in our study does not differ in its demographics from the corresponding group of households that had participated in the electricity smart metering study. In a second step, we compared our study sample with national statistics and a Swiss environmental survey that had been conducted with a representative sample of households (Diekmann et al. 2009). Compared with the general population of Switzerland, our sample is younger and more educated, but also significantly *less* environmentally friendly ($p < 0.01$; see Section 1.2 in the supplementary information and (Diekmann et al. 2009)). Given the metropolitan service territory of ewz, the more urban lifestyle of our sample compared with the average Swiss citizen is in line with the utility company's general customer base. Of the initial 697 households, shower data are available from 636 devices and a complete set of all surveys from 620 households. Among the 61 households whose shower data are not available, 37 did not send back their shower meter or had dropped out of the study for various reasons (including unrelated events such as hospitalization or breakup of partnerships), and 24 data sets from devices that were defective or had the wrong software installed could not be used.

2.4. Survey Data

The measurement data were supplemented by surveys administered before and after the field experiment. The preexperimental survey collected sociodemographic data (e.g., age, gender, income, education, housing situation), information on the fuel type used for water heating, whether utility costs were included in the rent, personality factors (HEXACO Personality Inventory), and environmental attitudes (using the same wording and five-point Likert scale as the nationally representative sample by Diekmann et al. (2009)). Participants were also asked to estimate their water consumption per shower and to indicate to what extent they intended to conserve energy and water with the smart shower meter and in general. The postexperimental survey mainly consisted of five-point Likert scales assessing participants' perception of the smart shower meter: to what extent they (a) understood and (b) took interest in the different elements of feedback displayed by the smart shower meter, and whether they had encountered any usability issues. Again, participants were asked to estimate their water consumption per shower. Furthermore, the postexperimental survey collected self-reported behavioral responses to the intervention: self-reported changes in shower behavior, level of attention paid to the device in the previous two weeks, and self-set goals. For further details on the survey data collected, see Section 1.3 of the supplementary information.

2.5. Descriptive Statistics and Randomization Checks

Table 1 shows the group means for key sociodemographic variables, environmental attitude (rated on a

Table 1. Randomization Checks

Variable	Full sample	Control group	Real-time FB	Real-time + Past FB	F-statistics (p-value)
Household size (persons)	1.53	1.54	1.52	1.54	0.08
	(0.50)	(0.50)	(0.50)	(0.50)	(0.93)
Age (years)	46.3	46.6	46.4	45.8	0.17
	(14.4)	(14.4)	(14.3)	(14.3)	(0.85)
Fraction of women	0.50	0.50	0.48	0.52	0.66
	(0.38)	(0.39)	(0.39)	(0.37)	(0.52)
Monthly income (CHF)	8,175	8,059	8,637	7,816	2.17
	(3,972)	(3,824)	(4,218)	(3,825)	(0.12)
Environmental attitude	3.49	3.38	3.50	3.57	2.27
	(0.90)	(0.92)	(0.88)	(0.88)	(0.10)
N	601	196	202	203	
Mean baseline water use per shower (l)	44.8	43.6	44.4	46.1	0.48
	(26.5)	(25.4)	(24.3)	(29.2)	(0.62)
Mean baseline energy use per shower (kWh)	2.66	2.59	2.61	2.75	0.46
	(1.71)	(1.64)	(1.57)	(1.89)	(0.63)
Mean baseline water temperature (°C)	36.1	36.1	36.2	36.1	0.06
	(2.8)	(2.8)	(2.7)	(2.7)	(0.95)
Mean baseline shower time (s)	246.5	237.5	251.1	250.8	0.77
	(137.6)	(126.9)	(144.3)	(139.9)	(0.46)
Mean baseline water flow (l/min)	11.0	11.1	11.0	11.0	0.15
	(2.3)	(2.4)	(2.3)	(2.3)	(0.86)
N	636	209	215	212	

Notes. Descriptive statistics for the full sample and for each group individually. As the F-tests show, the randomization produced balance between the groups on the key observable characteristics. Shower data are available from 636 households, survey data from 620 households. The shower statistics are almost identical when restricting the sample to the survey takers. FB, feedback.

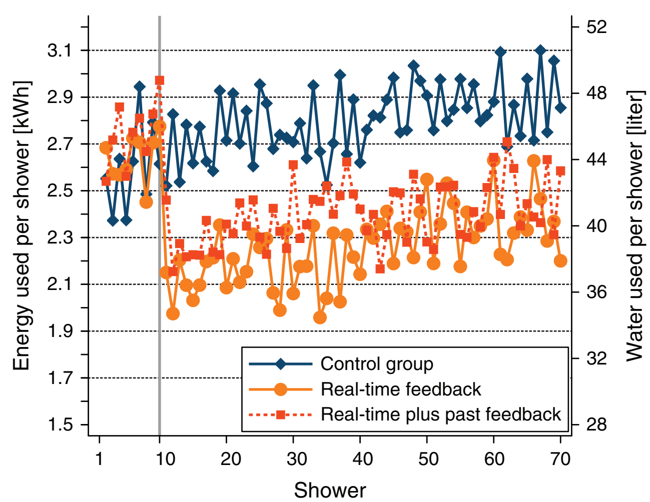
five-point Likert scale; see Section 1.3 in the supplementary information), and means of the key shower characteristics during the baseline period, both for the study sample combined and for each experimental condition separately. The standard deviation is reported below, in parentheses. In addition to the descriptive statistics, the fifth column contains the test statistics of the randomization checks performed on these key variables: we conducted a two-sided analysis of variance to verify whether the randomization has successfully produced balance on observable key characteristics between the three conditions before the onset of the treatment.[5] The fifth column of Table 1 contains the p-values of the F-tests on the (two-sided) hypothesis that the correlation with the condition T_1 and T_2 is zero. As the test statistics show, the randomization produced balanced groups on all these variables.

3. Results

3.1. The Impact of Real-Time Feedback on Energy and Water Consumption

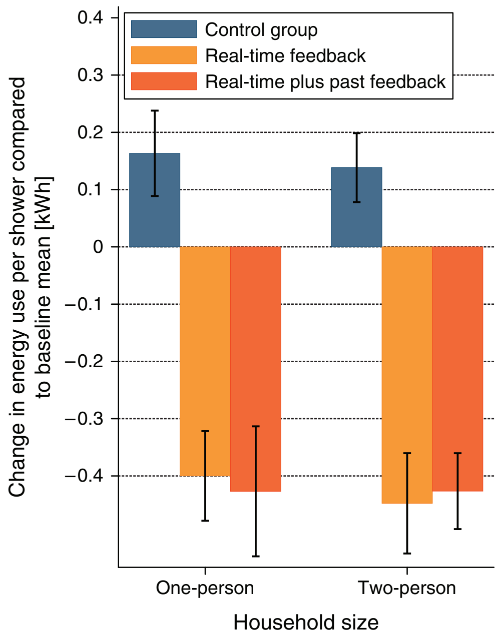
Figure 2 provides descriptive evidence of the effects of the behavior-specific real-time feedback. During the baseline period, all three study conditions use roughly the same amount of energy and water. With the onset of the real-time feedback in shower 11, resource consumption drops sharply in the two experimental groups: energy used per shower is approximately 0.59 kWh lower than in the control group and water use is 9.5 liters lower, amounting to a reduction of 22%

Figure 2. (Color online) The Impact of Real-Time Feedback on Energy (and Water) Consumption



Notes. The left axis reflects the average amount of energy used per shower in each experimental condition. The right axis reflects the corresponding *approximate* water use in liters (correlation coefficient of 0.989). Resource use drops by 22% upon activation of the display, and this treatment effect remains stable throughout the study ($p < 0.01$; see Table 2).

Figure 3. (Color online) Difference Estimates for One-Person and Two-Person Households



Notes. Each bar indicates the mean difference in energy use per shower during the intervention phase compared with energy use per shower during the baseline phase. The treatment effects are the same for one-person and two-person households. Adding feedback about the previous shower does not increase the treatment effect. Error bars represent mean ± SEM. See the supplementary information for details.

both in energy and water consumption for showering. Importantly, the treatment effects appear to be persistent throughout the two-month period of the study. There is no visual tendency for the gap between the experimental conditions and the control group to narrow.

Figure 3 displays the difference estimates for each of the treatment effects in one-person and two-person households. For each household, we calculate the difference between the average use during the intervention phase (showers 11 to the study's end) and subtract the mean during the baseline period. Comparing the averages between conditions allows us to gauge the treatment effects more precisely. The panel shows a mild increase in energy consumption per shower in the control group and a sharp reduction in each of the experimental conditions, with the standard error bars around the means indicating a highly significant difference between the treatment conditions and the control group for each of the household types but not across treatments or household types.

To test this formally, we estimate the model

$$y_{it} = \alpha_i + \beta_1 T_{1it} + \beta_2 T_{2it} + d_t + \epsilon_{it}, \tag{1}$$

where our dependent variable y_{it} is the energy used by household i in shower t. We include an individual fixed effect, α_i, for each household to eliminate all variances stemming from fixed differences in shower outcomes between households. The indicators T_{1it} and T_{2it} are all 0 for the first 10 showers and then take on the value of 1 if household i is assigned to the *real-time feedback* or *real-time plus past feedback* treatment, respectively. We also include a shower fixed effect, d_t, to capture time trends in the best possible way. The error term ϵ captures any unmodeled effects that are orthogonal to our treatment conditions by virtue of randomization. Thus, β_1 and β_2 indicate the difference between the respective experimental condition and the control group's energy use per shower.

To examine the stability of the treatment effects, we estimate

$$y_{it} = \alpha_i + \beta_1 T_{1it} + \beta_2 T_{2it} + \gamma_1 T_{1it} \cdot x_{it} + \gamma_2 T_{2it} \cdot x_{it} + d_t + \epsilon_{it}, \tag{2}$$

where x_{it} measures the fraction of the intervention period completed, i.e., $x_{it} = (t-11)/(K_i - 11)$, where K_i is the total number of showers taken by household i (and $x_{it} = 0$ for $t < 11$). In this specification, $x_{it} = 0$ at shower 11, the first shower in which the treatments are activated. Thus the interaction term vanishes at shower 11, and β_1 and β_2 have the interpretation of being the treatment effect of the respective condition at the intervention onset (shower 11). By contrast, $x_{it} = 1$ at the last shower recorded for household i. Thus, γ_1 and γ_2 measure any potential change in the treatment effect at the last shower recorded by fitting a linear trend to the treatment effects. Note that the progress indicator x_{it} refers to the fraction of showers out of the total number of showers recorded, not absolute time. As explained in Section 2.1, the smart shower meters record showers in sequential order and the duration of each shower, but they cannot measure the time between showers. For that reason, we use energy consumption *per shower* as the primary unit of analysis instead of energy use per day.[6]

Table 2 presents the results. The first column contains the overall treatment effects. The estimates confirm the visible impression from Figure 2: the large treatment effect on energy use is statistically highly significant. Columns (3) and (4) estimate the treatment effects separately for one-person and two-person households. The results show that the treatment effects are of similar magnitude for each of the treatments and for both household types. In fact, for each household type, we cannot reject the hypothesis that the two experimental conditions (real-time feedback and real-time plus past feedback) have the same impact on energy consumption per shower. We also test whether the treatments have the same impact on both household types, and we cannot reject the null hypothesis of identical effects at conventional significance levels (see the bottom rows of Table 2). Against the backdrop of other feedback studies (using aggregate feedback on past behavior) having found evidence that peer

Table 2. The Main Experimental Outcomes

	All households		One-person households	Two-person households
	(1)	(2)	(3)	(4)
Real-time feedback (=1)	−0.586***	−0.622***	−0.597***	−0.577***
	(0.073)	(0.079)	(0.104)	(0.103)
Real-time plus past feedback (=1)	−0.599***	−0.592***	−0.639***	−0.565***
	(0.080)	(0.088)	(0.141)	(0.090)
Real-time feedback $\times x_{it}$		−0.012		
		(0.077)		
Real-time plus past feedback $\times x_{it}$		0.073		
		(0.074)		
Constant	2.625***	2.627***	2.649***	2.617***
	(0.067)	(0.067)	(0.101)	(0.090)
t-test: Both treatments have the same effect on the dependent variable	$p = 0.88$		$p = 0.77$	$p = 0.92$
F-test: Equality of treatment effects across household types			$p = 0.91$	
R^2	0.441	0.441	0.530	0.381
Observations	45,036	45,036	16,068	28,968

Notes. The table displays the main treatment effects on energy use (in kilowatt-hours), controlling for household and time fixed effects. Standard errors are in parentheses, adjusted for clustering at the household level. See Equations (1) and (2) for a complete description of the statistical model.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

pressure is a relevant driver of conservation efforts, we find it interesting that no larger effects in two-person households—in particular, in those in the real-time plus past feedback condition, in which the resource consumption of the previous shower was visible to the next person taking a shower—were found. Our data do not suggest that the provision of that additional piece of information would increase the treatment effect.

Overall, the treatment effects are much larger than what conventional interventions using home energy reports (Allcott 2011, Allcott and Rogers 2014) or real-time feedback on aggregate electricity consumption (Degen et al. 2013) achieve.

Column (2) of Table 2 presents the results from the tests of temporal stability of the treatment effects. As can be seen, the estimated treatment effects at the beginning of the study (the estimates of β_1 and β_2) are virtually identical to the overall estimates in column (1). The estimates of γ_1 and γ_2 (the change in the treatment effects over the study period) are small and insignificant. Thus, there is no evidence that the treatment effect becomes any weaker over the duration of the treatment: it is just as large in the first shower as it is in the last. By contrast, existing feedback studies with access to smart meter data do not report similarly immediate or pronounced drops in consumption, even in the identical sample population (Degen et al. 2013). This shows that real-time feedback on a specific behavior generates a response that is qualitatively different: the full treatment effect is realized from the first time the treatment is active, and the intervention is stable over time.

3.2. Margins of Adjustment

While we have so far only considered overall energy use, it is also interesting to ask along what margins individuals adjusted their behavior: Did they cut their showers short? Or reduce the flow rate of the water? Did they reduce the water temperature? Table 3 provides an overview of the different margins of adjustment. In these regressions, the constant terms can be directly interpreted as the mean of the control group. In a first step (panel A), we calculated the treatment effects separately for the two treatments to verify whether the two treatments respond along the same margins of adjustment. As the p-values of F-test in Table 3 show, we find no evidence that the two treatments used different margins of adjustment. As a result, for parsimony, we collapsed the two treatment conditions T_{1it} and T_{2it} into one treatment indicator in the subsequent analyses, since the two treatments do not only have the same effect on energy use but also employ the same means to achieve that reduction (panel B).

The results show that, by far, the largest adjustment comes from cutting the shower short. The point estimate indicates that showers are cut 51 seconds short (over a baseline duration of about 4 minutes). We observe only very small reductions in the water flow rate of about 0.1 liters per minute, with the control group mean being approximately 11 liters per minute. We also observe a slight reduction in the water temperature in the treatment groups of about 0.3°C and a slight increase in the duration and number of

Table 3. Margins of Adjustment

	Shower time (seconds)	Flow rate (l/min)	Average temperature (°C)	Number of stops in water flow	Total break time (seconds)
			Panel A		
Real-time group ($T1$)	−51.60***	−0.140*	−0.371***	0.057***	5.90***
	(6.39)	(0.071)	(0.156)	(0.028)	(1.82)
Real-time plus past feedback ($T2$)	−50.18***	−0.165**	−0.260*	0.081***	2.67
	(6.54)	(0.069)	(0.139)	(0.029)	(2.10)
Constant	244.38***	10.998***	36.204***	0.530***	34.23***
	(5.92)	(0.047)	(0.138)	(0.028)	(1.95)
p-value F-test ($T1$=$T2$)	0.84	0.72	0.43	0.45	0.13
			Panel B		
Treatment (=1, groups collapsed)	−50.90***	−0.152**	−0.316**	0.069***	4.30**
	(5.41)	(0.061)	(0.130)	(0.024)	(1.65)
Constant	244.38	10.998***	36.205***	0.530***	34.22**
	(5.93)***	(0.047)	(0.138)	(0.028)	(1.94)
Implied change in energy use in % of control group mean	−20.8	−1.4	−1.3	n.d	−1.8
R^2	0.412	0.783	0.332	0.369	0.323
Observations	45,036	45,036	45,036	45,036	45,036

Notes. Difference-in-difference estimates of the treatment effects of real-time feedback on intermediate behavioral outcomes. Both experimental conditions are collapsed into one treatment indicator. The row "Implied change in energy use in % of control group mean" designates the change relative to the control group, holding all other margins constant. Heteroskedasticity-robust standard errors, adjusted for clustering at the household level, are in parentheses.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

times the individuals stop the water flow during the shower. The row "Implied change in energy use in % of control group mean" contains the effect of a *one-dimensional* change along that margin relative to the control group; note that these margins are not independent and that their effects are not strictly cumulative (e.g., if both shower duration and flow rate are decreased, the combined effect is smaller than the sum of the two individual effects, as each already reduces the denominator on which the effect can act). Thus, overall, the largest part of the observed energy conservation effect comes from individuals simply cutting their showers short, with only minor changes in other margins of adjustment, such as the flow rate or temperature of the water. The former result is also interesting in light of increased efforts to equip households with showerheads that restrict the water flow rate (Ball 2009, Power 2011): our results indicate that individuals are willing to reduce water consumption in the shower, but they only minimally reduce the flow rate.

In a final analysis, we also investigate whether the number of showers taken over the study period was not impacted by the treatments. We estimate the following equation:

$$y_i = \beta_0 + \beta_1 T_{1i} + \beta_2 T_{2i} + \epsilon_i, \tag{3}$$

where the dependent variable y_i in this case is the total number of showers of household i during the study period, and T_1 and T_2 are binary variables indicating assignment to the real-time feedback and real-time plus past feedback treatments, respectively. Table 4 displays the results. As can be seen, neither treatment has an effect on the total number of showers. Therefore, the intervention only affects behavior while showering but not the number of showers an individual takes. This is important for two reasons: on the one hand, this means that the consumers do not compensate the reduced consumption per shower by taking more showers. On the other hand, we find no evidence for a reduced shower frequency, which could create other negative externalities (from a hygiene point of view).

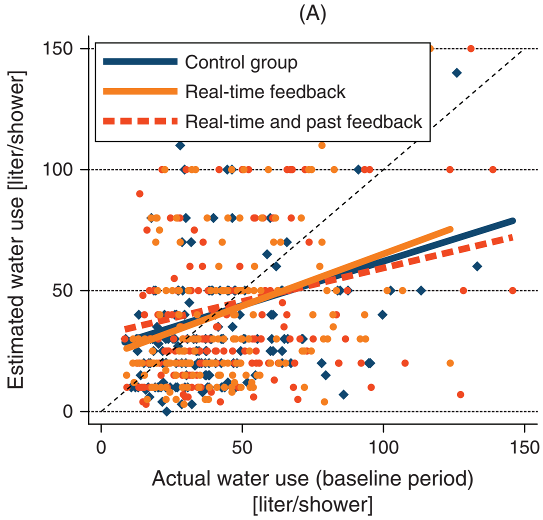
Table 4. The Treatment Effects on the Total Number of Showers

Household type	One-person	Two-person
Real-time feedback (=1)	2.131	2.198
	(3.754)	(5.725)
Real-time plus past information (=1)	5.030	3.911
	(3.737)	(5.505)
Constant	52.908***	86.216***
	(2.552)	(3.989)
R^2	0.006	0.001
Observations	296	332
F-test: No impact of the treatments on the number of showers	$p = 0.40$	$p = 0.78$

Notes. Linear regressions of the total number of showers on the treatment conditions. See the discussion of Equation (3) for more details. Heteroskedasticity-robust standard errors are in parentheses.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Figure 4. (Color online) Association Between Estimated and Actual Water Use per Shower Before (Panel A) and After (Panel B) the Intervention



Notes. The dashed black line at 45° represents a perfect association between estimated and actual water consumption per shower; the light gray lines and dashed lines (orange in the online version) (treatment groups) and dark gray lines (blue in the online version) (control group) display the group-specific fitted regression lines between estimated and actual water use.

3.3. The Impact on Awareness About Resource Use

We now examine whether we can replicate the result from earlier studies that feedback does *not* improve consumers' awareness of their resource consumption. Before and after the intervention period, we asked individuals to estimate how much water they use per shower. The results are visualized in Figure 4. Panel A shows the relationship between actual water consumption in the preintervention phase (measured during the baseline period). As can be seen, the relationship is positive, but the slope of the fitted regression line is far from 1, as it would be if individuals had an unbiased estimate of their water use. Thus, before the intervention, most individuals have a rather vague idea of how much water they are using. These findings are in line with (Attari 2014), who found that low users overestimate their use, while high users underestimate it. Panel B displays the relationship between actual and estimated water use after completion of the intervention. As can be seen in the panel, the relationship has become tighter for the two treatment conditions, but it remains rather flat for the control conditions.

To test for this more formally, we estimate one regression model corresponding to each of the two panels of Figure 4 of the following form:

$$\tilde{y}_i = \beta_0 + \beta_1 y_i + \beta_2 T_{1i} + \beta_3 T_{2i} + \beta_4 T_{1i} \cdot y_i + \beta_5 T_{2i} \cdot y_i + \epsilon_i, \quad (4)$$

where $\tilde{y}_i$ is household i's estimate of its average water use per shower (in liters). The variable y_i is the actual average water use of household i per shower (in liters). As before, the variables T_{1i} and T_{2i} are binary variables indicating whether a household was exposed to the real-time feedback or real-time and past feedback treatment, respectively. We also include interactions between the water use y_i and the treatment groups. Thus, the coefficients β_3 and β_4 indicate how the slope with respect to actual water use differs in the two treatment conditions relative to the control group. Comparing across the preintervention and postintervention equations allows us to examine whether estimated water use becomes more closely aligned with actual water use in the two treatment conditions in the postintervention phase. As usual, ϵ_i represents the error term. We estimated Equation (4) for the preintervention and postintervention separately but allowed their residuals to be correlated across equations, using a seemingly unrelated regressions (SUR) model.[7]

Table 5 displays the results. The first column in Table 5 shows that water use in the baseline period is positively associated with estimated water use, with a coefficient of 0.41, as seen in Figure 4. The association is statistically highly significant. The first column also shows that the relationships are the same across the three experimental conditions in the preintervention phase: both interaction terms are small in absolute magnitude and not statistically significant. Turning to the second column of Table 5, we see that this changes for the postintervention estimates. The association is still approximately the same for the control group. However, the two treatment conditions now exhibit a much stronger association between actual and estimated water use. In the real-time feedback condition, the slope increases by 0.62 (to roughly 0.94), and in the real-time plus past feedback condition, the slope increases by 0.48 (to roughly 0.8) compared with the

Table 5. Estimated and Actual Water Use

Measurement period	Baseline	Intervention
Actual water use	0.406***	0.320***
	(0.123)	(0.080)
Water use × Real-time feedback	0.024	0.625***
	(0.185)	(0.110)
Water use × Real-time and past feedback	−0.129	0.482***
	(0.170)	(0.164)
Real-time feedback (=1)	−0.066	−15.739***
	(7.988)	(4.709)
Real-time and past feedback (=1)	9.375	−12.496**
	(8.225)	(6.046)
Constant	22.261***	20.694***
	(5.163)	(4.044)
R^2	0.051	0.340
Observations	522	516

Notes. Seemingly unrelated regressions (SUR) between the estimated and actual water use in the three experimental conditions. Baseline estimated values were measured before the smart shower meter was deployed to households. Postintervention estimated values were measured after the devices had been collected from the households. See the discussion of Equation (4) for more details. Heteroskedasticity-robust standard errors are in parentheses.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

control group. Both increases are significant compared with the control group ($p < 0.01$, as can be seen in the table) and also if we test for significant increases in the interaction terms compared with the preintervention estimates ($p < 0.01$ in cross-equation tests for each of the treatments). The substantially tighter fit between actual and estimated water use can also be seen in the R^2 values of the two equations. While the R^2 is only 0.05 in the preintervention period, it rises to 0.34 in the postintervention period.

Thus, in contrast to other studies providing more aggregate, lagged feedback, real-time feedback increases awareness of resource use. This shows that the feedback gets to the users and provides a necessary first step for the intervention to reduce salience bias.

3.4. Analyses in Subgroups

In this subsection, we examine whether the response to real-time feedback differs in subgroups. This may help us to understand the underlying behavioral mechanisms behind the large observed treatment effects. We select the variables of interest based on hypotheses generated in the previous literature.

Previous studies show that households with high baseline use display a larger conservation effect when provided with feedback about their resource consumption (Allcott 2011, Degen et al. 2013, Ferraro and Price 2013, Allcott and Rogers 2014, Brent et al. 2015). We therefore include an interaction term of the average resource use, measured during the baseline phase of the study, with real-time feedback.

Several studies also show that individual attitudes influence the effectiveness of feedback interventions on resource conservation. In particular, a subject's innate desire to protect the environment is often associated with stronger efforts in response to feedback interventions (Abrahamse et al. 2005, Delmas and Lessem 2014). We use the survey response to an environmental attitude question, measured prior to the intervention, as our empirical proxy for this interaction effect. We also include a proxy for the tendency to quantify behavior as an interaction term, as the affinity for self-tracking progress toward goals has been shown to lead to larger behavior change in response to such interventions (Swan 2013).

Furthermore, as personality factors have been found to affect environmental engagement (Hirsh 2010, Milfont and Sibley 2012), and in particular, as informative of behavior change (Milfont and Sibley 2012), we also interact the treatment effect with the complete set of personality factors measured by the HEXACO Personality Inventory (Lee and Ashton 2004). Moreover, we include interactions with several demographic factors: income, age, and gender composition of the household. While the interpretation of their potential effect is less obvious, we include them in our analyses, as previous literature has found significant heterogeneity in response to similar interventions (Karlin et al. 2015).

We estimate the following model:

$$y_{it} = \alpha_i + \beta_1 T_{it} + \gamma_1' \mathbf{z}_i \cdot T_{it} + \gamma_2 \bar{y}_{i0} \cdot T_{it} + \delta_1' \mathbf{z}_i \cdot t + d_t + \epsilon_{it}, \tag{5}$$

where T_{it} is an indicator equal to 1 after shower 10 if household i is in either the real-time or real-time plus past feedback condition. As the two treatments had the same effect on overall energy use, on awareness, and on each of the margins of adjustment, we collapse both treatments into one. For the same reason, we also do not distinguish between different types of households. We interact the treatment effect with a vector of personality factors, $\mathbf{z}_i$, to test the different hypotheses. The variable $\bar{y}_{i0}$ is the mean per-shower energy consumption of household i during the baseline period (where none of the devices displayed any feedback about resource use). We also include interactions between the personality factors $\mathbf{z}_i$ and a time (shower) trend. We include these interaction terms to account for possible differences in Hawthorne effects that may be related to personality differences and to create characteristic-specific trends. As before, we include household fixed effects α_i and shower fixed effects d_t and adjust the standard errors for clustering at the household level.

Table 6 shows the results for the coefficient estimates of those interaction effects. In Table 7, we convert the treatment effects into conservation effects by reversing their sign, as we find that this eases the interpretation

Table 6. Interaction Effects of the Treatment with Household Characteristics

	(1)
Treatment effect (T_{it})	−0.625***
	(0.062)
$T_{it} \times \bar{y}_0$	−0.308***
	(0.071)
$T_{it} \times$ *Environmental attitude*	−0.160**
	(0.081)
$T_{it} \times$ *Quantifying goal progress*	−0.119**
	(0.060)
$T_{it} \times$ *Fraction female in household*	0.148
	(0.134)
$T_{it} \times$ *Age*	0.030
	(0.052)
$T_{it} \times$ *Household income*	0.011
	(0.014)
$T_{it} \times$ *Conscientiousness*	0.207*
	(0.107)
$T_{it} \times$ *Emotionality*	0.025
	(0.089)
$T_{it} \times$ *Honesty*	−0.031
	(0.074)
$T_{it} \times$ *Extroversion*	0.057
	(0.079)
$T_{it} \times$ *Agreeableness*	−0.034
	(0.073)
$T_{it} \times$ *Openness*	−0.003
	(0.078)
Constant	2.497***
	(0.078)
F-test: Significance of interactions with environmental attitude and tendency to quantify	$p = 0.02$
R^2	0.445
Observations	29,718

Notes. Treatment effects on energy use (in kilowatt-hours) depending on a range of household characteristics. The regressions control for household and time fixed effects, as well as time (shower) trends interacted with characteristics, as specified in Equation (5). Standard errors are in parentheses, adjusted for clustering at the household level.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

of the interaction effects. The table shows the coefficient estimates of the most interesting conservation effects and the predicted effects for the top and bottom quintiles in the distribution of each trait.

We find a significant interaction effect of the treatment with baseline use. As earlier studies have found, high baseline users display a larger conservation effect (Allcott 2011, Ferraro and Price 2013). The magnitude of the interaction effect is important: a 1 kWh increase in baseline use increases the treatment effect by approximately 0.32 kWh, i.e., by almost a third of the baseline difference. Table 7 shows that while the treatment effect for the average household is 0.62 kWh, the treatment effect on the highest quintile of baseline users is 1.47 kWh.

The results also show that attitudes toward the environment significantly moderate the treatment effect. The 20% with the weakest intent of preserving the environment display a conservation effect of 0.49 kWh per shower. Bearing in mind that our sample is less environmentally friendly than the average population in Switzerland, that figure is still remarkably high. A potential explanation could be that once the device is installed, the feedback is automatically visible, without requiring the user to take any action. As Schultz et al. (2016) argue, individuals who do not have strong preexisting attitudes about a topic may be persuaded by messages that are easily accessible. The top quintile conserve 0.74 kWh per shower—an almost 40% stronger treatment effect. Similarly, our measures of an individual's tendency to quantify progress toward goals strongly moderate the treatment effect. Moving from the bottom to the top quintile in that trait increases the treatment effect by 0.24 kWh.

As Table 6 shows, none of the interactions with the sociodemographic variables (income, age, and gender composition of the household) attains conventional levels of significance, and the point estimates of the coefficients are relatively small in magnitude. Regarding personality factors, higher conscientiousness slightly

Table 7. Analyses in Subgroups

	Baseline use	*Environmental attitude*	*Quantifying goal progress*	*Conscientiousness*	*Age*	*Gender* (1 = female, 0 = male)	*Income*
Hypothesized impact on conservation effect	+	+	+				
Estimated interaction effect	0.308***	0.160**	0.119**	−0.207*	−0.030	−0.148	−0.011
	(0.062)	(0.081)	(0.060)	(0.107)	(0.052)	(0.134)	(0.014)
Conservation effect on bottom quintile of characteristic	0.094	0.484	0.491	0.783	0.663	0.753	0.669
Top quintile of characteristic	1.423	0.737	0.739	0.493	0.581	0.526	0.581

Notes. Moderation of the conservation effect (= treatment effect with inverted sign) by the most interesting characteristics. The table displays the coefficient estimates of the conservation effects and their standard errors, clustered at the household level (in parentheses). See Section 2.2 in the supplementary information for details.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

reduces the conservation effect. While the interaction is only marginally significant, a potential interpretation could be that the intervention is more helpful for individuals who are less self-disciplined in following through with their good intentions (Packer et al. 2013). In contrast to Milfont and Sibley (2012), who state that personality differences might be informative, in particular for changes in environmental behavior, none of the other personality factors moderates the treatment effect in our study.

Overall, the interactions with the individual preference measures are easily reconciled with previous theoretical reasoning and evidence: stronger motivation to protect the environment and stronger affinity to quantification lead to larger behavioral changes in response to real-time feedback. In line with that reasoning, a common interpretation of the strong interaction of the treatment effect with baseline use is that high baseline users have more slack in consumption and therefore find it easier to cut down their energy use. This interpretation also hews closely to our hypothesized role of salience bias in resource consumption: salience bias may be the source of (at least part of) the slack that increases baseline consumption, and real-time feedback may help these individuals to regain control over their choices, leading to a larger conservation effect.

4. Discussion and Conclusion

Overall, our study shows that real-time feedback on a specific behavior can induce large behavioral changes. We observe a 22% reduction in the energy consumption for the target behavior, which translates into 5% of the participants' household energy use. Strikingly, the full effect unfolds immediately from the onset of the intervention and shows no sign of decay during the study. The quantitative savings effects, extrapolated to a year for one person, are substantial: an individual (showering once a day) saves 215 kWh of energy, 3,500 liters of water, and avoids 47 kg of carbon emissions[8] (see Section 3 in the supplementary information). This is 5 times as much energy and 11 times as much carbon dioxide as with interventions providing broad feedback about electricity use to the same population of participants (see Section 5 in the supplementary information and (Degen et al. 2013)).

Thus, our research suggests a novel strategy for behavioral interventions in resource conservation: the focus on a specific behavior and real-time feedback can yield a far greater effect than the provision of broader feedback (e.g., past household electricity or water usage). In part, this is due to a more persistent change in behavior in response to real-time feedback. The technology-based intervention makes it possible to provide feedback on a daily basis, as the target behavior takes place. We clearly find no evidence for a decay of the effect within the first two months. By contrast, with periodic home energy reports, the conservation effect tapers off within days of the arrival of the feedback letter (Allcott and Rogers 2014), as can be observed with many other aspirational behaviors (Dai et al. 2014). Information systems make it possible to provide feedback on a more regular and even daily basis. Yet the key to the large savings in our study does not appear to be a question of repetition or frequency—after all, the full effect unfolds from the onset of the intervention. Rather, we provide concrete information relevant to decision-making processes in real time, while individuals engage in a particular behavior. Our interpretation is that real-time feedback on a specific behavior addresses salience bias as the root cause, by allowing individuals to align their behavior more closely with their deeply ingrained preferences.

For the scalability of this kind of technology-enabled behavioral approach, it is important to exemplarily examine the cost effectiveness of our intervention.[9] From a household's perspective, in addition to being better able to choose resource use according to the household's preferences, the intervention also offers substantial cost savings over a three-year period, which we assume is the device's deterministic lifetime. For the average Swiss 2.1-person household, the reduction in energy and water use amounts to savings of USD 87 per year. Thus, the devices reach the break-even point after 9.3 months. Over the assumed lifetime of three years, this creates a net benefit of USD 193.[10] By contrast, in-home displays providing feedback on electricity consumption and home energy reports led to a reduction of 0.2 kWh per day among the same pool of households, or 86 kWh per year (Degen et al. 2013). Those savings would reduce the household's electricity bill by USD 51 over a three-year period, falling far short of covering the costs of the smart meter and of the in-home display (which are substantially higher and clearly do not result in a net benefit). Thus, technology investments that effectively improve behavioral control over resource use can have large monetary payoffs to households, and to a much larger extent than other forms of resource-conservation interventions in comparable households.

A second perspective for cost effectiveness is that of a policy maker, comparing the costs of different policies to reduce, e.g., carbon emissions, as is done in (Allcott and Mullainathan 2010). As Allcott and Mullainathan (2010) show, serving a household with a typical home energy report in the United States costs roughly USD 7.5 per year, generates, on average, electricity savings of 303 kWh per household, and contributes to a reduction in CO_2 of 122 kg. Allcott and Mullainathan (2010) assume a production price of 0.08 USD per kilowatt-hour. Thus, from the policy maker's perspective, the intervention reduces CO_2 *and* saves costs at the same time, yielding cost savings of

162 dollars per ton of CO_2 abated. By contrast, many investments in technology upgrades to abate CO_2 yield high costs per ton abated, not cost savings (McKinsey & Company 2009). In comparing these results to our intervention, we assume that the price of the device would be lower in the case of a large-scale rollout, and we set it at USD 40. This results in a substantially higher cost than the home energy reports in Allcott and Mullainathan (2010). However, because of the large conservation gains in the target behavior, the intervention saves 452 kWh per household and 97 kg of CO_2 per year—even though our households have much lower baseline energy use and lower CO_2 intensity than the average household in the United States, in Allcott and Mullainathan's calculations. We assume the same production price of 8 cents per kilowatt-hour of energy and obtain even larger savings per ton of CO_2 abated, of approximately USD 234.[11]

Two further features of our results suggest that behavior-specific real-time feedback is a desirable policy intervention. First, the approach shows some of the efficiency properties similar to price incentives: individuals with a large benefit from resource conservation (as measured by their environmental preference) respond more strongly to the treatment, as do individuals with low costs of processing real-time feedback (as measured by the tendency to quantify). Thus, the intervention causes stronger treatment effects for individuals with higher benefits/lower costs of adjustment. This can also be seen in the large interaction effect with baseline use: our intervention causes the largest conservation effects in individuals with a high baseline use without any additional prompting of such behavior. High baseline users reduce their consumption by close to 30%, thus even responding more strongly in relative terms than the average participant. By analogy, price incentives also tend to trigger stronger responses among individuals with lower costs of changing their behavior, a key efficiency property highlighted in almost every economics textbook (see, e.g., Frank and Glass 1991). By contrast, many regulatory interventions would not allow for such individual differences in costs and benefits to affect behavior: for example, imposing showerheads that reduce the water flow forces individuals to shower with lower water pressure (far below what the individuals in our study choose). Flow restrictors force individuals into a different pattern of consumption that causes additional costs to them, such as spending more time in the shower, thus making such interventions less desirable. Second, real-time feedback causes a large conservation effect even for individuals who show little inclination to engage in environmental conservation on their own. While a stronger desire to protect the environment leads to a larger conservation effect, the conservation effect is still substantial (0.51 kWh; see Table 6) even for the 20% of individuals of our sample who care the least about the environment.[12]

Similar interventions could also be designed to address salience bias in other areas of resource consumption: for instance, the cost and environmental impact of driving could be displayed in real time from the start of each trip, or the impact of current driving style on vehicle range, gasoline costs, or material strain. In practice, several car models such as the Toyota Prius already provide feedback to drivers on basic sustainability metrics on the car dashboard. There is, however, a lack of studies that evaluate the effectiveness of these measures in the field (Young et al. 2011).

An important question in this context is, of course, to what extent similarly large savings could be expected from similar feedback interventions in other domains. One could argue that showering is particularly prone to salience bias, or a more salient daily activity than other energy-consuming behaviors, or that individuals have a higher degree of control on their energy consumption in the shower than they do, for example, on the afterpurchase energy use of their refrigerator. But note that more than 70% of energy used by individuals and households is dedicated to only four categories: private vehicles, space heating, water heating, and air conditioning (Gardner and Stern 2008)—all of them involve highly visible behaviors with a high degree of user control. For instance, both driving behavior (Evans 1979) and the adjustment of thermostat settings (Kleiminger et al. 2014) have a large influence on fuel consumption. Devising similarly concrete feedback measures could also facilitate behavior change in these high impact domains. Moreover, these measures could help individuals to identify high impact domains and to overcome mental barriers to invest in equipment upgrades (e.g., buying a more fuel-efficient vehicle).

Beyond resource conservation, real-time feedback may also hold promise for many other domains where salience bias potentially distorts choices. Gabaix and Laibson (2006) show that when individuals do not pay attention to all attributes of a product, firms are incentivized to use pricing schemes that lead to inefficient consumption. In the terminology of Gabaix and Laibson (2006), our approach "unshrouds" an obscure product dimension and helps individuals make more informed choices. Examples from four different domains illustrate the broad range of potential applications. Jessoe and Rapson (2014) show that real-time feedback on electricity consumption helps consumers take advantage of time-of-use pricing: consumers who receive an in-home display with real-time feedback of their electricity consumption shift significantly more demand from peak to low price hours than consumers who only receive a notification of the price increase.

Another domain of application might be caloric intake: even though nutritional information is visible on the packaging of many goods, it can be difficult to keep track of the the caloric intake over the course of a day. Bollinger et al. (2011) show that displaying caloric information in restaurants reduces caloric intake by individuals. Thus, there is strong reason to believe that real-time feedback about caloric intake throughout the day would be helpful to individuals suffering from salience bias. One could devise clever mobile apps that allow the individual to assess the caloric intake of food rations in real time and over the course of the day. Again, real-time feedback could make demand for food substantially more elastic with respect to caloric intake.

In the domain of privacy protection, more salient feedback about the implications of one's choices may also be helpful. Affect-eliciting web content has been shown to bias risk and benefit perceptions toward increased information disclosure, inducing individuals to overleap deliberate decision-making processes (Kehr 2016, Kehr et al. 2015). Salience of privacy implications can mitigate this bias and thus reduce the adoption of services that contradict individuals' general privacy concerns.

Already today, the ubiquity of smartphones and sensors enables the collection of fine-grained data over vast periods of time and the measurement of behaviors that so far have escaped us. In today's newly registered cars, the information on the current consumption is already constantly being measured. New heating systems have the capability to store fuel consumption data. The ongoing digitalization of the energy sector with the advent of smart grid technologies and smart meter infrastructures, in combination with ambient displays, smart watches, and the like, will give rise to many real-time applications and enable new services, business models, and additional channels to reach consumers. In general, industry experts expect one trillion sensors to be connected to the Internet by 2022, enabling services ranging from connected homes and cars to wearable Internet, implantable technologies, and smart cities (World Economic Forum 2015). The "integration of the physical and digital worlds through networked sensors, actuators, embedded hardware..." (World Economic Forum 2015, p. 4) will open up even more possibilities to devise behavioral interventions that address salience in the future. For instance, workers could be warned of safety risks in their immediate environment (e.g., using wristband vibrations or Google Glass visualizations). The findings presented in this paper will hopefully motivate researchers and car manufacturers alike to use the information in an effective way.

Given the large number of potential applications, an important question in this context is how the effectiveness of real-time feedback would be affected if it were used more widely. It is possible that our effects are so strong precisely because real-time feedback is not ubiquitous, and therefore introducing it for one behavior may have particularly strong effects. Evidence from financial markets suggests that on days when news arrives fast, investors tend to react less to each piece of news (Hirshleifer et al. 2009, 2011). Similarly, if real-time feedback on many behaviors became available, it is possible that its effectiveness would decrease, as each channel of feedback may receive less attention than was the case in our intervention. One can also conceive that individuals end up being overwhelmed or annoyed if real-time feedback becomes ubiquitous. Therefore, it might be necessary both to prioritize application domains by their relevance to the individual and to focus on the high-impact behaviors in those domains. While our application shows that real-time feedback enables individuals to implement large behavioral changes, and that the resulting behavior seems more in line with their innate preferences, further research is needed to understand the optimal use of real-time feedback in multiple domains.

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Endnotes

[1] Note that electricity use represents only 24% of the residential final energy use in Europe (European Environment Agency 2015), which also comprises residential oil and gas consumption.

[2] We are grateful to the associate editor and a reviewer to suggest to us this interpretation.

[3] In the environmental context, these measures have been criticized as rigid and costly (Kolstad 2010), and oftentimes, they face strong public resistance (Ball 2009, Power 2011).

[4] Note that a liter (not a gallon) is the standard volume measurement unit in Europe.

[5] For that purpose, we estimate the following equation: $y_i = \beta_0 + \beta_1 T_{1i} + \beta_2 T_{2i} + \epsilon_i$. In that equation, y_i represents the different dependent variables of interest; T_1 and T_2 are indicators for the *real-time information* and *real-time plus past information* conditions, respectively.

[6] In later steps, when calculating the daily or yearly energy savings per household, we take into account the shower frequency by distributing the K_i showers recorded in a household equally over the two-month duration of the study. In fact, small errors in that allocation scheme (i.e., whether a shower was in fact taken one day sooner or later) are inconsequential to those aggregated outcomes. Furthermore, to minimize larger time allocation errors, both the prestudy

and the poststudy survey asked participants about extended periods of absence during the study (see Section 2.3).

[7] The SUR model estimates each equation by ordinary least squares but allows an individual's residual in the pre- and postintervention period to be correlated. It takes this into account when testing for differences in coefficients between the pre- and postintervention phases.

[8] The CO_2 reduction is calculated based on the Swiss energy mix for water heating. With the energy production mix of the United States, 82 kg of CO_2 would be avoided per person per year as a result of a higher carbon intensity of electricity generation and a higher share of electric water heaters in the United States

[9] We do not attempt to perform a full cost-benefit analysis that quantifies the impact of the intervention on overall welfare. This would require us to identify and estimate parameters in the household utility functions, which is beyond the scope of this paper.

[10] These calculations are based on the energy mix of households in Switzerland, at current resource prices. See Section 4 in the supplementary information for more details on the calculations.

[11] This number may at first sound perplexing, given the higher annual cost of the intervention (2.9 cents per kilowatt-hour) compared with Allcott and Mullainathan (2010) (2.5 cents per kilowatt-hour). However, at a marginal production price of 8 cents per kilowatt-hour, every device deployed delivers net savings (5.1 cents per kilowatt-hour) to the policy maker. Because of the lower CO_2 intensity of the Swiss energy mix (both for water heating and for electricity), more households need to be outfitted with the device to abate one ton of CO_2, each delivering additional savings to the policy maker. For details and calculations for the U.S. mix for electricity and water heating, please see Section 3 in the supplementary information.

[12] Recall that, on average, our sample is *less* environmentally friendly than the average population in Switzerland.

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