Abstract

The right information can foster behavior change towards energy conservation – given that the receiving individuals pay attention to the feedback provided and integrate the information in their decision making. As human information processing capabilities are limited, intervention designers need to choose content carefully to avoid information overload. Based on energy consumption and survey data collected in field trial, this article investigates the attention paid to different elements of the user interface (N=426) and establishes a relationship to actual energy conservation. We find that self-reported attention paid to content explains only very little of the measured behavior change (explanatory power of approx. 3%). The article is a first step towards better understanding the black box of feedback interventions in the energy sector. The results highlight the importance of collecting real-world data on behavior – rather than relying on self-reported user perceptions – in the resource consumption context and beyond.

Keywords

Eco-feedback, feedback elements, selective attention, behavior change, field study, HCI

Introduction

Energy consumption has various negative consequences on the natural environment, including the depletion of limited natural resources and the generation of carbon emissions and other pollutants. Beyond technical measures to improve energy efficiency both on the supply and demand side, high hopes have been placed on feedback interventions (FI) as a politically feasible strategy for reigning in energy demand from the behavioral perspective. Defined as the “process of giving people information about their behavior that can be used to reinforce and/or modify future actions” (Karlin et al. 2015, p. 1205), policymakers hope that feedback will allow people to better manage their consumption and to identify effective strategies for a sustainable usage of energy. The recent massive roll-out of smart meters in many countries enables the collection and analysis of fine-granular energy consumption data and, visualized on a user interface (UI), these data make more timely and detailed feedback on energy use technically feasible (European Commission 2014).

While the infrastructure for information systems (IS)-enabled feedback is in place, the path from being exposed to feedback to its impact in terms of energy conservation is still not fully understood. Most FIs provide a variety of content simultaneously, including weekly, daily, or hourly kWh-usage, social comparisons, cost, energy conservation tips, etc. (Götz and Hahnel 2016). Given the limited information processing capacity of the human brain, only meaningful content should be provided to avoid information overload (Kluger and DeNisi 1996; Wickens et al. 2012). So far, surprisingly few studies have analyzed...
which elements of the feedback receive user attention and how attention translates into behavior change. In order to make future FIs more effective in driving behavior change and achieving the targeted outcomes, we investigate the following two research questions:

RQ1  *When exposed to multiple feedback elements related to their current energy consumption, which elements do users pay attention to?*

RQ2  *To what extent does self-reported attention explain behavioral outcomes regarding energy conservation?*

In this article, we shed light on the path from a feedback stimulus to energy conservation by investigating selective attention and its effect on behavior change. On a theoretical ground, the paper contributes to current knowledge about FI in a way that it considers the human brain's limited attention when examining feedback effects. We build on a previously conducted large-scale randomized controlled field trial (RCT) that found energy conservation effects of 22% when providing individuals with feedback on shower consumption (Tiefenbeck et al. 2016). While most consumers are not aware of the large amount of energy contained in hot water, water heating is, in fact, the second largest domestic energy end use (eia 2013) and offers large conservation potential. The FI on shower consumption studied contains four different feedback elements. While the overall impact of the intervention is analyzed in a first journal article, this present article combines the effects with additional survey data of 426 Swiss households a) to investigate the attention paid to the four different feedback elements and b) to assess the relationship between self-reported attention and actual energy conservation. Thus, we take a first step towards disentangling the effects of a feedback intervention by understanding the impact of single feedback elements. Doing so, we employ methodology techniques from and contribute to both, behavioral economics (RCT to derive valid conclusions about the effectiveness of a FI) and HCI (considering user needs for the eco-feedback UI).

**Energy FIs from Two Perspectives: Behavioral Economics and HCI**

High hopes have recently been placed on web portals, apps, car dashboards or in-home displays as means to foster energy conservation. FIs may enable individuals to quantify the power draw of different appliances, to gauge the impact of their activities on their utility bill and on the environment, and to make better informed decisions regarding their own energy use (Abrahamse et al. 2005; Loock et al. 2013; Steg and Vlek 2009). Although the majority of people state that they care about the environment and that they are willing to contribute to its protection (Diekmann et al. 2009), in the absence of accurate information, most people find it difficult to assess the impact of their action on their energy use and carbon footprint (Attari 2014; Burgess and Nye 2008). The mere provision of feedback, however, does not necessarily lead to behavior change, given the complexity of human behavior dynamics (Carver and Scheier 1982; Hargreaves et al. 2013). In particular, Karlin et al. (2015) describe four key characteristics of energy consumption that may affect the effectiveness of FIs in that domain: energy use is abstract (individuals do not deliberately want to use energy; they consume products and services, whose delivery requires energy); it is non-sensory (we cannot directly see it); it is typically based on multiple behaviors, which makes it hard to relate a single action to summary reports (e.g., aggregated electricity bills on a household level); and energy use is of low relevance to most individuals, as its consequences (e.g., carbon emissions, air pollution, climate change) do not directly affect the individual in a timely matter.

Over the past few years, behavioral economists and environmental psychologists have conducted a plethora of large-scale studies investigating the impact of FIs on aggregated household electricity use. Recent meta-studies report average electricity savings of 0 - 5%; as electricity represents a quarter of residential energy use, this translates into 0 - 1.3% of household energy consumption (Buchanan et al. 2015; McKerracher and Torriti 2013). The FI we study in this article took another approach: individuals received real-time feedback on one specific, energy-intensive activity at the point of decision-making, while the individual could still adjust her behavior in response to the feedback. The average treatment effect (energy savings) of 22% on the target behavior showering translates into 5% of the participants’ household energy use (Tiefenbeck et al. 2016). These kinds of large-scale studies evaluate the impact on energy use for different experimental groups or different population segments (e.g., by income, age, or education). Yet, most FIs consist of a bundle of different content elements (e.g., recent consumption, historic comparisons, social comparisons, etc.). By appealing to different psychological mechanisms (e.g., standard-feedback gap, social norms, goal
setting) with different elements, feedback designers hope to maximize the impact of those interventions. As a result, it remains unclear which elements participants actually pay attention to and to what extent the different feedback elements contribute to the observed behavioral outcome (e.g., energy conservation). Given individuals’ limited attention in information processing (Kluger and DeNisi 1996), it is conceivable that the savings are driven by a single element that individuals primarily pay attention to, whereas the other elements would be a mere distraction.

Research on eco-feedback systems in the HCI domain evaluates the UI from the user perspective and takes into account that individuals might have difficulties understanding certain content such as numerical values like kWh or tons of CO₂ emission (Bartram 2015; Hargreaves et al. 2010). To tackle this issue, a common practice is to represent energy use in metrics that are more tangible or visible (e.g., costs or relative comparisons with the energy use of familiar domestic appliances) (Froehlich et al. 2010). While a few studies have made first efforts to understand the impact of individual UI elements on user acceptance and behavior, those findings are typically based on very small sample sizes. In their meta-study on eco-feedback studies from the HCI discipline, Froehlich et al. (2010) identify additional shortcomings in the applied study methodologies that make it difficult to derive valid conclusions: only 4 of the 8 considered experiments have measured behavior change; none of the studies included a control group and only a single one collected baseline (i.e., pre-intervention) data. Likewise, Froehlich et al. (2012) present a series of hypothetical configurations of an in-home display to 571 online survey respondents and ask them to state their intention to use those systems, yet the participants did not interact with the technology in practice. Hargreaves et al. (2010, 2013) deployed different in-home displays monitoring electricity use in 275 households and studied how users engage with the different visualized content elements over a 12-month period. They conducted interviews with selected households (N=15), which allow in-depth insights about the users’ actual interaction with the different systems. In particular, user engagement diminished significantly over time; the study did, however, not quantify effects on behavior and electricity consumption. In the domain of hot water consumption, an ambient shower display with a green (resp. red) light for below- (resp. above-) average consumption) outperformed numeric feedback on water consumption regarding both, resource conservation and user experience (Kuznetsov and Paulos 2010). Yet, the findings of that study are based on a very small sample of three households who took 5-12 showers each. These examples show the HCI community’s interest in the topic and its endeavor to integrate user needs in the UI development process. Yet, in the energy context where sensor data is needed to calculate actual impact of the technology studied, most existing HCI studies are based on hypothetical preference questions (participants did not interact with the technology of interest for real), are decoupled from behavioral outcomes, or use study designs that do not allow to establish a causal relationship between the intervention (treatment) and the outcomes observed.

**Hypotheses Development**

For answering the research questions as stated in the introduction, we build on Kluger and DeNisi’s feedback intervention theory (FIT) (1996), a model that describes how and under what circumstances FIs successfully affect behavior (performance). The relevant blocks of FIT for our work are: (a) comparisons of feedback to goals or standards (“feedback-standard gaps”), (b) locus of attention towards the target behavior and (c) attention being limited. Being exposed to a FI, individuals compare their performance with (internal or external) goals or standards and – in most cases – attempt to attain the standard by adjusting their behavior. FIT further states that an intervention steers attention to the target behavior and that only feedback-standard gaps that receive attention actively participate in behavior regulation. Given limited attention, individuals will not integrate all the information available, but focus on selected elements of a FI and compare those with standards that are meaningful to them. The provision of elements that are not meaningful to the individual or of more feedback elements than the individual can process will not lead to better performance (e.g., larger feedback effects). Already Carver & Scheier (1982) stated that they “do not believe that simply accessing such information inevitably ensures that it will be reflected (as a superordinate reference value) in the person’s behavior” (p. 120). In that context, Kluger & DeNisi (1996) suggest not to consider the locus of attention an “all or nothing” phenomenon, but rather a “probabilistic process, where most attention is likely to be at one foci, but it can be present simultaneously […] across several standards” (p. 262).
Cognitive psychologists view the human brain as an information processing system, which creates responses as output to stimuli. A widely-used model that builds on limited attention is Wickens et al.’s information processing model (2012) in which a human senses an input, perceives it, and if selected for further processing, selects and executes a response followed by feedback from the system environment. In turn, the human senses the feedback and follows the iterative cycle. As attention is limited, we expect individuals to selectively direct their attention to a subset of the feedback content provided and thus, hypothesize that

**H1** When being exposed to different feedback elements simultaneously, individuals do not pay attention to all of them to the same degree and rather focus their attention on a single element or a subset of elements.

Further, and drawing on traditional FIT and its locus of attention (Kluger and DeNisi 1996), we expect that only feedback elements that receive attention affect behavior and conjecture that,

**H2** Individuals who state they pay more attention to a certain feedback element conserve more energy than individuals who do not.

Figure 1 illustrates our research model by visualizing the process chain from the provision of feedback over selective attention to a behavioral response that translates into a measureable impact on energy use.

![Research Model](image)

**Figure 1: Research Model (FE=feedback element; grey shades illustrate different levels of attention paid to the elements)**

**Methodology**

We test our hypotheses on a dataset collected in a field experiment that evaluated the effectiveness of real-time feedback on energy consumption in the shower. The experiment lasted two months. The 633 participating households were randomly assigned to a treatment group (with real-time information) or a control group (no real-time information, served as a reference group for the energy savings). While the behavioral outcomes in terms of the magnitude of energy conservation (22%) have already been published in a first journal article (Tiefenbeck et al. 2016), the present article investigates the attention paid to the different feedback elements and assesses the relationship of self-reported attention with actual energy conservation. In a post-intervention survey, participants were asked to indicate to what extent they had paid attention to the different display elements on 5-point Likert scales (1 = not at all, 5 = very much, N/A = “I have not perceived the element”). The questions are based on Froehlich et al. (2012), Froehlich (2011), and Froehlich et al. (2010). Shower data was collected in a real-world environment with the help of the smart shower meter amphiro a1 that tracks and visualizes resource consumption at the same time. Study participants installed the device (for handheld showers only) themselves without any tools between the shower hose and the showerhead; thus, the display is located at eye level. As soon as the tap is open, the device harvests energy from the water flow to power the sensors (water flow and temperature),

1 To be precise, we investigate sub-hypotheses on our four elements (to be introduced later on): H2.1: water consumption; H2.2: energy consumption; H2.3: energy efficiency class; H2.4: polar bear animation
microprocessor, and UI to display feedback on the ongoing shower. Data on every shower taken is stored in an internal memory, which was read out by the researchers at the end of the study after having mailed the devices to the research facilities.

The UI of the study devices features four different elements related to resource consumption since the beginning of the ongoing shower and which can be considered as feedback elements according to FIT (Kluger and DeNisi 1996): (a) energy consumption (in [k]Wh), (b) water consumption (in liters), (c) an energy efficiency class (from A to G) and (d) a playful and emotional element in the form of a polar bear. Figure 2 shows the smart shower meter with snapshots of representative display configurations.

![Figure 2: The UI of the smart shower meter with typical snapshots](image)

**Energy consumption** – The element consists of a number and the unit [k]Wh; it is the most accurate representation of energy use from a physical point of view. As we expected most individuals not to be very familiar with the metric (Bartram 2015; Hargreaves et al. 2010), we also included additional feedback elements that are more tangible and easier to relate to (Froehlich et al., 2010).

**Water consumption** – Though the study was framed as an energy conservation program targeting hot water use (cold water conservation is not an issue in water-rich Switzerland), we also included a counter for water as (1) water is visible and (2) individuals deal with the measurement unit liters on a daily basis. With the onset of a new shower, the device starts counting from zero in tenths of liters (up to a theoretical limit of 1999).

**Energy efficiency class** – To provide a simple rating of the efficiency of their ongoing shower, we included a dynamic energy efficiency class rating, which ranges from A (efficient) to G (inefficient). Most individuals in Europe are familiar with energy efficiency scales from the labels that indicate the energy efficiency of household appliances (e.g., refrigerators, washing machines). Every shower starts in rating A; depending on the amount of energy used for this particular shower, the metric progresses to B, then C, etc. at predefined intervals of .525 kWh (except for A that ranges from 0 to .7 kWh). The scale was defined based on the energy use distribution a shower dataset from a pilot study to ensure a “reasonable” distribution of expected outcomes and to avoid extreme anchor effects (Loock et al. 2013): On the one hand, only exceptionally long showers should end up in class G; on the other hand, the rating of an average shower (class B or C) should convey that there is still some room for improvement. With only seven different categories (A...G), the energy efficiency class is less granular than liters and kWh; on the other hand, a single letter may be simpler to process and recall.

**Polar bear animation** – The forth element conveying information about resource consumption on the ongoing shower is an animation depicting a polar bear on an ice floe. When the energy consumption exceeds certain predefined thresholds, the size of the ice floe shrinks until the entire scene finally disappears (at 2 The screen also displays a fifth element, water temperature (in °C), which does not contain any information regarding progress of the ongoing shower (consumption), though.)

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2.80 kWh. The animation is an emotional visualization of energy consumption (Kosara 2007; Pierce et al. 2008), which highlights the impact of individual consumption on the natural environment in line with the norm-activation model (Froehlich et al. 2012). Similar elements have been used in other studies to visualize energy use (Dillahunt and Mankoff 2014; Huber and Hilty 2015).

**Data Analysis and Results**

Which display elements did the participants in the treatment group (N=426) pay attention to that made them realize these large savings? Table 1 contains the descriptive statistics of the four display elements and Figure 3 presents bar charts with the detailed Likert scale distribution.

As Table 1 indicates, participants paid most attention to the feedback element on water consumption, followed by energy consumption and energy efficiency class, with the polar bear animation ranking last. Only two participants stated having paid no attention at all to any of the elements, another 14 households stated having paid the same degree of attention to all four elements. As Figure 3 indicates, almost all participants paid a lot of attention to the water consumption element. Regarding the three other elements, there is large heterogeneity in the level of attention paid to them. We conducted Wilcoxon signed-rank tests, which reveal that the differences in attention paid to the four elements are all significant: participants paid significantly more attention to water consumption than to energy consumption (Z = 12.52, p < .001, r = .65); the latter, in turn, received significantly more attention than the energy efficiency class (Z = 3.41, p < .001, r = .18); the polar bear animation received least attention (Z = 3.48, p < .001, r = .18). H1 is supported: participants do not pay attention to all elements presented, they selectively focus their attention on a subset of the feedback elements.

<table>
<thead>
<tr>
<th>Attention</th>
<th>N</th>
<th>Mean</th>
<th>sd</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water consumption</td>
<td>415</td>
<td>4.48</td>
<td>0.81</td>
</tr>
<tr>
<td>Energy consumption</td>
<td>375</td>
<td>3.41</td>
<td>1.30</td>
</tr>
<tr>
<td>Energy efficiency</td>
<td>395</td>
<td>3.14</td>
<td>1.29</td>
</tr>
<tr>
<td>Polar bear animation</td>
<td>374</td>
<td>2.81</td>
<td>1.43</td>
</tr>
</tbody>
</table>

Table 1: Descriptive statistics for element attention

Attention paid to different display elements is one issue, but from an energy efficiency point of view, the more relevant question is how successful the elements were in inducing the actual energy savings of 22% on average. Therefore, we ran regressions to estimate how the self-reported attention paid to the different display elements affects savings effects. To reduce potential bias from missing values in case someone is unsure whether she has seen the elements, we focus on the individuals who could give answers to the four questions (N=346). Figure 4 displays a structural model visualizing the results for the relationships between the different constructs and energy savings.

For individuals with a high ex-ante use (baseline consumption) it is easier to reduce their energy consumption compared to participants who have already started from a low consumption level (Tiefenbeck et al. 2016). The influence of ex-ante consumption on subsequent savings in our experiment is very strong: A 1-kWh higher ex-ante use translates into .360 kWh higher savings (p<.001). Thus, to obtain the influence of attention without the confounding effects of different starting conditions, we control for ex-ante consumption. The model results indicate that the level of attention paid to the two feedback elements water consumption and energy efficiency class has a positive and significant impact on energy conservation, supporting H2.1 and H2.3. Individuals with a 1-point higher score on the 5-point Likert scale for attention paid to water consumption exhibit energy savings that are .095 kWh (p<.05) larger – an increase of 16% on...
the average savings effect of 0.59 kWh per shower; those with a 1-point higher score on attention paid to the energy efficiency class saved .073 kWh (p<.05) more. Interestingly, individuals who paid a higher level of attention to the polar bear conserved significantly less resources than those who paid less attention to the animation - a one-point increase in attention to the animation reduces energy savings by .059 kWh (p<.05). Hence, we reject H2.4 and state that the element with the emotional character did not foster resource savings in our experiment. The correlation between attention paid to energy consumption in kWh and actual energy savings is not significant, thus we also reject H2.2.

While the attention paid to the elements water use and energy efficiency class is positive and significant, the results indicate that self-reported attention explains only 3.3% of the variance in energy savings. Attention paid to the four feedback elements and ex-ante use jointly explain 47.3% of the variance in savings – yet ex-ante consumption alone already explains 44.0% of the variance, thus the marginal explanatory power of self-reported attention is very small.

Figure 4: Research model and findings

Water consumption – Despite the explicit focus of the study on energy conservation and the fact that Switzerland has abundant water resources, participants paid by far most attention to the numeric element displaying water consumption in liters. Furthermore, participants who paid a high level of attention to that element saved more energy than those individuals who did not. Thus, in the case of energy use related to water heating (the second largest residential energy end use), water consumption should be used as a feedback representation which people can easily relate to.

Energy consumption – The display element for energy consumption in kWh received considerably less attention. This could be due to the fact that the unit kWh is not easy to relate to (Bartram 2015; Hargreaves et al. 2010). We did not find a significant correlation between the level of attention paid to that element and actual energy savings.

Energy efficiency class – The element that received the third-highest attention score was energy efficiency class. Individuals who stated paying a high level of attention to it saved more energy than individuals who did not.

Polar bear animation – The lowest ranked element, the polar bear animation, was also the element with the highest variance in user evaluation. That controversy is in line with the findings of Froehlich et al. (2012) who also report large heterogeneity in the attention rating of similar elements. In fact, the polar bear splits our sample in segments by demographics: women, younger, and less educated individuals pay more attention to it. The results regarding age and gender are in line with previous research on gamification (Koivisto and Hamari 2014). Regarding the actual impact of the element on energy consumption, we find that people reporting having paid a lot of attention to the polar bear exhibited significantly smaller
conservation effects. A possible explanation could be limited attention: the element may distract attention away from the other feedback elements, yet may be less effective than other feedback elements in inducing behavior change.

Contributions and Limitations

Like other large-scale studies on FIs for resource conservation, we measure the impact of an artifact that features several feedback elements. Yet this article assesses the attention paid to the individual feedback elements and evaluates whether self-reported attention levels correlate with actual energy savings. The article responds to numerous recent calls from prominent IS scholars for more empirical research that addresses societal issues (Gholami et al. 2016; Gupta 2017; Rai 2017). To the best of our knowledge, this is the first study investigating attention paid to different UI elements that does so a) with a large sample (N=426), b) with participants who actually used the feedback technology for several weeks in their daily lives, c) that evaluates to what extent self-reported attention translates into actual energy savings, and d) that calculates those savings based on randomized controlled trial (to disentangle savings induced by the treatment from external influences like seasonal effects). Thus, the study combines rigorous research methodologies from behavioral economics (large sample, difference-in-differences design, random group assignment, collection of real-world consumption data) and HCI (user evaluations of content displayed).

We find evidence for selective attention, more precisely, study participants focused on some feedback elements more than on others (H1). In our specific case of hot water consumption in the shower, participants paid by far most attention to the element water consumption (in liters), followed by energy consumption (in kWh) and energy efficiency class, and least attention to the playful polar bear animation. This may be explained by the fact that water and energy consumption were dynamic numerical attributes, whereas the information contained in the energy efficiency class and the polar bear animation was more condensed and hence, those representations were more static. We conjecture that in the case of real-time feedback, more dynamic content is better suited: More concrete consumption information allows to reflect current behavior in a more granular way. While from a physics point of view, kWh would be the most accurate metric to display energy consumption, participants paid more attention to the element water consumption. We attribute this finding to the fact that the water is both, visible and tangible, and to the fact that consumers can easily relate to liters (resp. gallons for U.S. citizens), as they are exposed to this metric in many other situations (e.g., when buying milk in the supermarket, consuming beverages at a restaurant, or refueling their cars at the gas station).

Regarding actual behavioral outcomes (H2.1-H2.4), we find that individuals paying attention to water and energy efficiency class saved significantly more energy, while those who paid more attention to the polar bear animation saved less energy. For attention paid to energy consumption in kWh we did not find a significant correlation with actual behavior. The fact that this self-reported attention only explains 3% of variance in behavior, on the one hand, highlights the importance of baseline data as it is the strongest predictor of energy savings. On the other hand, it calls for experiments that collect more real-world data instead of relying on self-reported user perceptions of needs. To better understand the role of attention, future research could take advantage of new technologies like eye-tracking devices to overcome self-report biases.

The results of this field study are subject to some limitations. First, the content evaluation is based on the experience with a particular feedback technology; its generalizability to other domains and technologies has to be assessed by future research. Second, in contrast to design science studies that focus on the development process of an artifact, we evaluate attention paid to different elements of an existing artifact and its real-world impact. The article thus responds to the call by Gholami et al. (2016) who have criticized the lack of IS studies that investigate the real-world impact of IS artifacts on environmental protection. Taking advantage of an existing product allows us to collect reliable measurement data from a large number of individuals who actually interacted with the IS for several weeks. On the downside, this approach implies that our freedom to vary the content displayed (e.g., variation of font size or colored elements) was limited to the four feedback elements of the existing UI. Some of the specific design choices of the artifact investigated (e.g., size and placement of display elements) may also have affected the outcomes. The polar bear animation may be particularly affected by these constraints. Furthermore, our findings are based on
an opt-in sample of residents of the same country (Switzerland). Resource conservation studies with opt-in samples generally harbor the risk that the results might be biased by self-selection effects, i.e., that particularly "green-minded" individuals select into these kinds of studies. To assess that risk, we measured environmental attitudes of our study participants with the same survey items developed by Diekmann et al. (2009) who had collected environmental attitudes from a representative Swiss sample (N=3,352). In fact, our sample is slightly less environmentally friendly than the average Swiss citizen. Moreover, like in most other FI studies, the energy savings measured are outcomes of several elements displayed. It would be interesting to assess the effect of the different display elements on energy saving behavior in isolation. Based on the current setup, we can report correlations ("Individuals who report paying a high level of attention to x save y kWh"); a thorough identification of the impact of each element by itself on energy savings would require displaying a single element to different experimental groups, which is a next step we are currently working on. Finally, the self-reported data on user attention might be subject to social desirability bias or experimenter demand effects, inducing participants to indicate higher scores on the survey scales to please the researchers. While our work is a first step towards understanding how attention to different feedback elements affects actual behavioral outcomes, many more steps are necessary to uncover all the underlying processes that will allow us to build more powerful FIs. With a more detailed understanding of these processes, the IS community will have all the ingredients necessary to make a meaningful difference to the societal problems related to environmental degradation.

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Eco-Feedback Interventions: Selective Attention and Actual Behavior Change


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