SHORT-TERM SPARK OR SUSTAINED IMPACT? INVESTIGATING THE LONG-TERM EFFECT OF REAL-TIME FEEDBACK

Research in Progress - Track 21- Sustainably Digital

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Abstract

In order to adopt sustainable practices and strategies, organizations and individuals need to understand the environmental impact of their behavior and the knowledge about successful resource conservation strategies. Information Systems research and real-time feedback systems in particular can help to bridge this "environmental literacy gap". In previous work, we presented an IS artifact that presents consumers with behavior-specific information on their energy and water consumption in real time. We found that this approach reduces energy and water consumption by 22%. In this work-in-progress paper, we address the open question of effect persistence in the long term. We analyze 17,612 data points collected in a 12-month field study from 50 households. First analyses indicate that the effect remains stable over time. In line with literature on "data push" systems, we argue that feedback systems should not require an additional step of user action to access the feedback which may be a barrier to longer effect persistence of information systems.

Keywords: Energy and water conservation, real-time feedback system, effect persistence, data push system

1 Introduction

The growing demand for energy and water fuels a variety of environmental and geopolitical problems, creating a growing policy interest in resource conservation. Aside from technical parameters, behavior has been identified as the most important factor governing energy consumption. Most individuals are generally motivated to engage in pro-environmental behavior as they inherently care about the environment (Naderi, 2011). However, at the same time, many tend to have a poor understanding of how much energy (Attari et al., 2010; Gardner and Stern, 2008) and water they use (Attari, 2014) in their daily lives: Individuals regularly underestimate their personal resource consumption, have fundamental misconceptions of the relative resource intensity of different aspects of their life, and often misjudge the effectiveness of resource conservation strategies.

While many firms have already implemented environmental management systems, households still lack the tools to monitor and improve their energy or water consumption. As of today, most households continue to receive yearly, quarterly, or at best monthly utility bills for their electricity, gas, and water consumption. On those bills, the quantity of resources consumed is aggregated over the entire billing period and on the household level. This makes it virtually impossible for people to understand the contribution of individual appliances, to make the link between specific actions and its environmental impact, and to focus on environmentally significant action that make an actual difference (Gardner and Stern, 2008). Just like larger organizations, in order to adopt sustainable practices and strategies, households necessitate *“new data regarding environmental impacts, new information about causes and effects, and knowledge sharing about what works, what doesn’t, and why.“* (Melville, 2010). This is a large missed opportunity: The residential sector accounts for approximately 25% (resp. 22%) of total primary energy consumption in the EU-27 (resp. the U.S.) (European Environment Agency, 2012; U.S. Department of Energy, 2012).

The ongoing progress of information and communication technology (ICT) and in particular the ongoing large-scale deployment of smart meters open up new avenues to effectively bring meaningful and actionable resource consumption information to the attention of individuals. By 2020, 195 million electricity smart meters will be deployed in the EU alone (European Commission, 2014). This corresponds to a roll-out that covers 72% of utility consumers in the EU.

While the deployment of ICT is an important and necessary step forward to empower consumers, these technologies are still struggling with issues of acceptance, conservation impact, and cost-effectiveness. The most widespread approach of displaying smart metering information to residential consumers today is the use of in-home displays (IHDs) and web portals. While the information is displayed in a much timelier manner than on traditional utility bills, electricity use is still aggregated on the household level. These approaches thus leave the burden of identifying high-impact domains or energy guzzlers with the consumer. In the field, the impact of this approach does not live up to the high hopes that had originally been placed on them (Darby, 2006): Recent large-scale smart metering trials document electricity savings between 3 and 5% (Degen et al., 2013; McKerracher and Torriti, 2013; Schleich et al., 2013).

For smart metering and related feedback technologies to fully unfold their full potential, it will take a “concerted effort by researchers, policymakers, and businesses to do the "engineering" work of translating behavioral science insights into scaled interventions, moving continuously from the laboratory to the field to practice.” (Allcott and Mullainathan, 2010). Information Systems (IS) research at the intersection of human behavior, organizations, and technology seems particularly amenable to lead these concerted multidisciplinary efforts. IS research “can make an important contribution to knowledge […] to the creation and evaluation of systems that break new ground in environmental responsibility” (Melville, 2010). In this context, a plethora of studies and meta-analyses have investigated which attributes of an IS artifact facilitate the adoption and the effectiveness of these technologies. Technology features that were identified as relevant for the effectiveness of feedback information by meta-studies (Darby, 2006; Ehrhardt Martinez et al., 2010; Fischer, 2008) include frequency, duration, timeliness, content, breakdown, medium and way of presentation, and comparisons.

In previous work, we have presented an IS artifact that was designed with these features in mind, aiming at substantially increasing the impact of feedback systems on energy conservation. In (Tiefenbeck et al., 2013), we presented an IS artifact that provides individuals with real-time feedback on energy and water consumption of a specific behavior and already *during* the resource consumption. We chose showering as a common and highly resource-intense activity: In less than 5 minutes, the average person uses 44 liters of hot water, which requires at least 1.6 kWh to heat it up (Tiefenbeck et al., forthcoming). In a two-month study with 697 Swiss households, we were able to demonstrate that this kind of feedback system can have a large impact on behavior and resource consumption: Participants reduced both their energy and their water consumption by 22% on average. This large treatment effect also lead to large absolute savings: Projected to one year, the average person reduces her energy consumption by 200 kWh and her water consumption by 3900 liters of drinking water – plus the considerable energy losses of the heating system. The feedback system alone achieves per-household energy savings that are similar in high as the transition from incandescent light bulb LED lighting systems.

Aside from the effect size, the pivotal question in the evaluation of feedback technologies is the persistence of the saving effects. It is still unclear whether behavior changes induced by information systems are stable or whether individuals fall back into their old habits after a short time. In order to be accepted as feasible policy and cost-effective solution for energy conservation, information systems researchers need to prove that the impact of such technologies is not just short-lived, but that these systems create a lasting impact on user behavior. In this work-in-progress paper, we present a follow-up study to (Tiefenbeck et al., forthcoming) which investigates the question of long-term persistence of saving effects for real-time feedback systems.

2 Related work

Feedback interventions have proven themselves as a cost-effective and scalable instrument to reduce residential energy consumption (Allcott and Mullainathan, 2010; Allcott and Rogers, 2014).

One of the key questions in the context of the savings achieved is their persistence. A meta-study carried out by (Ehrhardt Martinez et al., 2010) concludes that the vast majority of savings from feedback interventions can be attributed to behavior change, not to investments into more energy-efficient technologies or building materials. As a result, the persistence of the reduction depends on the persistence of the change in everyday practices. In a feedback study on water consumption, (Fielding et al., 2013) find that once the intervention ends, the effect eventually dissipates and households return to their pre-intervention levels of consumption. In a similar vein, in a study with 300 Dutch households on feedback provided on in-home displays, (van Dam et al., 2010) find that the savings persist neither in the households who return the monitor after the initial four-month study period, nor in those who continue using the feedback device.

By contrast, (Ayres et al., 2009) report persistent conservation effects throughout a seven- resp. twelve-month study duration. (Raw and Ross, 2011) also report persistent conservation gains for electricity smart meters to the end of the AECON trial (duration ranging between one and two years). (Foster and Mazur Stommen, 2012) reviewed various pilot studies in the U.S., the U.K. and Ireland and find that with the exception of one trial, all studies that tested for effect persistence report persistent savings over the course of the pilots (up to 21 months).

(Allcott and Rogers, 2014) present an analysis that analyses long-term efficiency campaigns comprising 234,000 households over four or five years. Their focus of analysis, however, are campaigns using periodic ‘home energy reports’, not feedback technologies that provided users with information in a timely manner. Nevertheless, also with respect to the sheer sample size and duration of the study, the results are of interest. The authors find that saving effects of such paper-based campaigns are much more persistent than previously assumed in cost-benefit analyses. Although the immediate conservation response to the first home energy report is followed by a relatively quick decay of the effect, the authors observe cyclical, yet diminishing patterns of action and backsliding as response to subsequent reports. As the intervention continues over time, the effects become more and more persistent. If the intervention is discontinued after two years, the effects only decay with a rate of 10-20%. The authors conclude that the cost-effectiveness of these programs has been dramatically underestimated in the past. In the light of the discrepancy in the findings of effect persistence, Boyd (2014) contrasts the approaches of “data push” versus “data pull". This debate had also been brought up by other authors (Foster and Mazur Stommen, 2012; Froehlich et al., 2010). All argue that most web portals and IHDs require an additional step of user action to access the feedback information (“data pull”). This may be a barrier to longer effect persistence. The authors thus conjecture that the future of real-time feedback lies in systems with data push.

The aforementioned studies are based on feedback technologies that present information to consumers that is aggregated on the household level. Yet it has also been shown that feedback works best when it is delivered frequently, timely, clearly, and on specific actions which individuals can easily influence (Ehrhardt Martinez et al., 2010). So far, most IT artefacts with a behavior-specific focus presented in academic literature still have not overcome prototype status. Taking the example of devices promoting water conservation, we find indeed number of innovative studies presenting different concepts for data visualization to promote sustainable behavior in this domain, in most cases, in the shower. Examples include (Arroyo et al., 2005; Kappel and Grechenig, 2009; Kuznetsov and Paulos, 2010; Laschke et al., 2011). However, all these systems concentrate on establishing a proof of concept/operation and interface design and share the shortcomings of a very limited number of study subjects, lack of verifiable research hypotheses, or, in the case of (Willis et al., 2010), lack a clean research design.

3 Methodology

3.1 Overview

The study presented here is a 12-month follow-up study of an earlier 2-month study with 697 Swiss households carried out by ETH Zurich, by the University of Lausanne and by the University of Bamberg with ewz, an electricity company in Zurich (December 2012 – February 2013). In the 2-month study, three different and specialized study versions of the Amphiro smart shower meters had been deployed randomly among the participants to investigate the impact of the IS artifact in a randomized controlled trial. All participating households were customers of the local utility company ewz and had opted into the study. In order to simplify an accompanying survey, only one- and two-person households were eligible to participate.

Aside from the shower data collected, participants had also filled out surveys before and after the study. Those surveys collected mainly demographic information, assessed personality and attitudes (before the intervention), and participants’ experience with the device (after the intervention). In that earlier study, we were able to show that the real-time feedback provided reduced energy and water consumption by 22% (Tiefenbeck et al., forthcoming). The study presented here is a follow-up study that investigates the effectiveness of the real-time feedback in the long run.

3.2 IS artifact used to measure, display, and store information

The IS artifact used for the purpose of this study is the amphiro a1 smart shower meter developed by Amphiro AG, a spinoff company of ETH Zurich. The device measures and stores time series data on shower behavior and provides users with real-time feedback at the point of consumption, directly in the shower. The smart shower meter integrates between the shower hose and the handheld shower-head. In the development of the artifact, particular attention was paid to facilitate the installation and use of the device in order to reduce barriers for adoption and the need for maintenance. As a result, the device can be installed by the users without any tools in less than a minute. Furthermore, the shower meter is energy-autarkic: A built-in micro-generator harvests energy from the water flow, supplying the device with the power required for its processing unit and display. This self-powering concept eliminates the need for batteries and allows tracking behavior over extended periods of time. During each shower, the device continuously measures the water temperature and generator speed. Based on these data, water use, energy use and energy efficiency class of the current shower are permanently calculated. The standard device displays real-time feedback on water use (in tenths of liters) and energy consumption (in Wh / kWh) from the beginning of the shower along with water temperature and an energy efficiency class; the latter is visualized by a letter ranging from A to G and accompanied by a polar bear animation. The device can store data of up to 507 showers in standard mode and 205 showers when configured to specialized study operation settings. Showers can be interrupted to three minutes (e.g., for lathering up); if the shower is continued after a short interruption, the device resumes its operation. If no water flows through the device for more than three minutes, the final values are stored as a shower and the device restarts from zero next time the water is turned on. Water extractions below five liters are not considered as showers and are not stored. The rationale is that most of these small water extractions serve other purposes (e.g., for flower watering or bathtub cleaning).

3.3 Participants

Upon completion of the 2-month study, all participants who had sent in their study devices for the data readout received standard devices with regular firmware (capable of storing up to 507 showers instead of 205). The devices were shipped to the households in March 2013. Participants were not informed that they might be asked again to ship back their shower meter one year later.

Beginning of April 2014, they were contacted via email inviting them to participate in the long-term study. They were informed that participation in the study involved that they ship back their smart shower meter once more (free of charge) for the data readout and to fill out another online survey.

Eighty households responded to the study call and filled out the survey. Based on the survey responses, fifty participating households were chosen according to the following criteria:

- Willingness to return the device for a read-out
- No long absences during the long-term study
- Must not have moved during the study
- Must not have replaced the amphiro a1 device
- Household composition must not have changed
- Agreement with the data privacy protection statement
- Completion of the questionnaire

The main goal of the survey was to filter out households that did not fulfil the criteria listed above. In addition, the survey also assessed technology affinity of the participants. This new part was aimed at detecting whether only tech savvy people participated in the study, which would bias results. Finally, the survey asked participants the most important question in the survey: whether they were willing to send the device back for a new data readout.

3.4 Data collection and processing

A total of 50 devices fulfilled all the requirements and the devices and shipped back their shower meters for data readout. After the readout, participants received their devices back. Altogether, data of 17,612 showers were collected during 12 months from 50 households. 19 out of those 50 households had been in the control group of the 2-month study, 31 of them were treatment households who had received real-time feedback also during the two-month study. In addition to the 12-month datasets collected for the purpose of this study, the 2-month datasets from those households are also available. The full duration of the study thus spans from December 2012 to April 2014. Between the 2-month study and the 12-month study, one month of data is missing (data readout for the 2-month study and two-way shipping).

The data readout was carried out using a dedicated optical readout terminal with a webcam and a self-written readout application. The readout process is described in detail in (Tiefenbeck et al., 2013). Once the readout process was completed, the data were inspected for sanity and outliers. Corrupted data can easily be identified based on the flow rate. Typical values range between 5 and 15 liters / minute. In a second step, each dataset was analyzed for outliers: For each household, the temperature and volume mean were calculated; data points that were more than two standard deviations above or below the mean were filtered out. However, our analysis shows no significant difference between the results from filtered and non-filtered data. The results are thus robust and not driven by outliers.

3.5 Data analysis

The study aims to investigate the stability of the real-time feedback effects over longer period of time (one year). Before we analyze the long-term shower behavior of the 50 households and compare it with the treatment period from the short-term study, we assess whether the participants of the long-term study are significantly different from the initial pool of participants who completed the short-term study. The goal is to determine whether the results of the long-terms study may be distorted by self-selection biases.

In the first step, the study therefore evaluates whether the subset of long-term participants is significantly different from the pool of short-term participants. This is performed by running t-tests on 51 parameters. These parameters comprise all characteristics that were identified as predictors of shower behavior or conservation impact in the two-month study. These include water consumption per shower during the baseline period of the 2-month study, shower water temperature, household demographics, personality, environmental attitude, initial intention to conserve energy, and perception of the device (after the two-month study).

We find that long-term study participants do not significantly differ from the short-term sample in 50 out of the 51 parameters characteristics investigated. In particular, the average baseline water consumption is statistically the same (MST = 44.4 liters, SDST = 27.5 liters, MLT = 47.2 liters, SDLT = 24.3 liters, p=0.5407). Of all 51 parameters analyzed, the two groups only differ in a single parameter: They perceived the device as significantly more interesting than the treatment group members of the short-term study – what is not surprising given that the control group’s device only display water temperature. This parameter was measured as one of 14 items in a semantic differential with 7-point scales between two semantic poles (MST = 1.07, SDST = 1.15, MLT = 1.61, SDLT = 0.80, p = 0.0012). This parameter, however, was not a significant predictor of the conservation effect in the short-term study. Overall, while caution is warranted with the self-selective nature of the recruitment process, we do not find any evidence that the subsample that opted into the long-term study significantly differs from the larger pool of short-term study participants in any important dimension.

3.6 Qualitative analysis – day-by-day means for water volume per shower

The main analysis takes day-by-day means of water volume per shower as a first step to determine whether the treatment effect from the short-term study is persistent after a year of continuous feedback. Figure 1 shows raw data with day-by-day means of shower volume. The data for this graph are calculated by averaging all showers for each individual day in both short- and long-term studies. Only 31 households that were in the treatment groups were considered. The gap in the figure, between the 60th and 90th day, is the period when short-term data was readout and when devices were sent back to the participants. The data points on the left (blue) are the data of the short-term study and the data on the right (red) are from the same participants but in the long-term study.

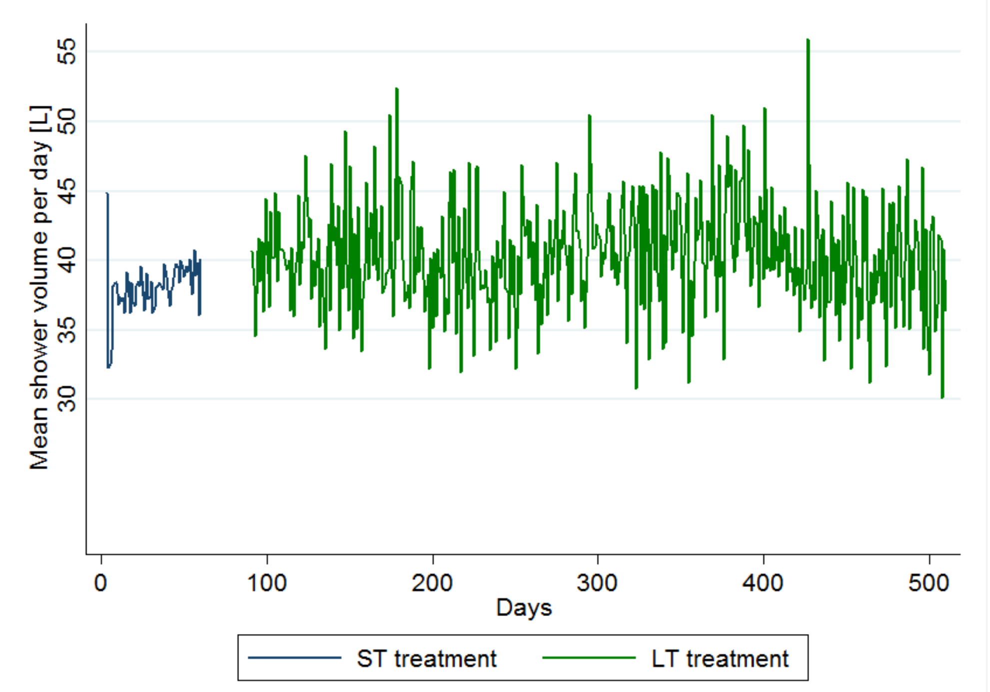

Figure 2. Day-by-day means of water volume of the per shower of the 31 treatment group households during the intervention period two month study (in blue) and during the subsequent 12-month study (in green)

Table 1 presents the results of a simple preliminary analysis for a first quantitative impression. It compares water and energy use and average water temperature per shower in with the 12-month study (April 2013 – April 2014) with the consumption of the treatment households during the intervention period of the 2-month study (after the baseline period of 10 showers). The average water consumption per shower in the 12-month period (40.1 liters) is similar to the treatment group's consumption in the 2-month study (40.8 liters). The difference between those two periods is not significant. The table also shows that the average water temperature and, consequently, average energy consumption per shower, decreased slightly but significantly. However, we attribute that effect to seasonal patterns, with participants taking less hot showers in summer which decrease the average of the 12-month data, compared to the two-month data captured in winter. This approach, however, only gives a first impression and is not ideal for the dataset. Data points are not clustered at the household level. This implies that households with a higher number of showers (2-person households in particular) are given an undue weight in the estimate. The approach does also not account for shower distribution over time. A regression model is therefore more suitable to analyze the time series data. A fixed-effects model that also accounts for time trends (seasonal patterns) will be the method of choice for further analyses.

Period	**Variable**	**Mean**	**SD error**	**95% confidence interval**	
	Volume [l]	40.75	0.22	40.31	41.19
	Temperature [°C]	36.31	0.02	36.28	36.35
Short-term study	Energy [kWh]	1.47	0.01	1.46	1.50
	Volume [l]	40.12	0.15	39.82	40.41
	Temperature [°C]	35.94	0.02	35.90	35.99
Long-term study	Energy [kWh]	1.43	0.01	1.42	1.44

Table 1. Day-to-day means of the short- and long-term studies for the 31 treatment group households

3.7 Outlook on further analysis

The simple analysis presented in the previous paragraph gave a first impression of the results. They indicate that the effects remain relatively stable also over longer periods of time (12 months after the original study). This approach chosen so far, however, only gives a first impression and is not ideal for the dataset. For instance, data points are not clustered at the household level. This implies that households with a higher number of showers (2-person households in particular) are given an undue weight in the estimate. The approach does also not account for shower distribution over time, nor does it take into account seasonal trends yet which influence all participating households alike.

In the future analysis of the dataset, we will use a regression model which is more suited to analyze the time series data. We will use a fixed-effects model to control for time-invariant household-specific factors (e.g., type of shower) and estimate the model with ordinary least squares. In that model, will also include time trends to account for seasonal patterns. While the sample of households participating in the long-term study described in this paper is relatively small, the results of these analysis will help to answer with greater confidence whether the large conservation impact of the artifact described in (Tiefenbeck et al., forthcoming) is also persistent over time. The question of effect persistence is key to the cost-benefit analysis and to the projections we make in our large-scale studies.

4 Conclusion

As technology ownership and use increasingly migrates from larger organizations to customers and other stakeholders, considerable information capacity is placed in the hands of users. That implies that the responsibility for the environment no longer rests with the government or some large organization (Pitt et al., 2011). IS researchers and professionals can make valuable contributions on how to best leverage the potential of IS in the hands of empowered users in households, companies and other types of organizations. The artefact presented in this paper differs from existing information systems in several ways: It provides feedback on a specific behavior, thus providing actionable information to consumers. Furthermore, it is automatically activated and does not require any additional user interaction to access the feedback. In line with existing literature on “data push” systems, this may remove a key barrier to longer effect persistence of such systems and may be a reason for the very large effect on energy consumption.

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