Association for Information Systems
AIS Electronic Library (AISeL)

Research Papers | ECIS 2016 Proceedings

Summer 6-15-2016

# LONG-LASTING EFFECTS OR SHORT-TERM SPARK? ON THE PERSISTENCE OF BEHAVIOUR CHANGE INDUCED BY REAL-TIME FEEDBACK ON RESOURCE CONSUMPTION

Verena Tiefenbeck
*ETH Zurich*, vtiefenbeck@ethz.ch

Vojkan Tasic
*ETH Zurich*, vtasic@ethz.ch

Samuel Schöb
*University of Bamberg*, samuel.schoeb@uni-bamberg.de

Thorsten Staake
*University of Bamberg*, thorsten.staake@uni-bamberg.de

# LONG-LASTING EFFECTS OR SHORT-TERM SPARK? ON THE PERSISTENCE OF BEHAVIOUR CHANGE INDUCED BY REAL-TIME FEEDBACK ON RESOURCE CONSUMPTION

*Research Paper*

Tiefenbeck, Verena, ETH Zurich, Zurich, Switzerland, vtiefenbeck@ethz.ch

Tasic, Vojkan, ETH Zurich, Zurich, Switzerland, vtasic@ethz.ch

Schöb, Samuel, University of Bamberg, Germany, samuel.schoeb@uni-bamberg.de

Staake, Thorsten, University of Bamberg, Germany, thorsten.staake@uni-bamberg.de

## Abstract

*In the promotion of sustainable consumer behaviour, it is important to establish a mental relation between one's behaviour and its environmental impact. High hopes rest on timely feedback on personal energy consumption in order to create this link. Great efforts are being put into the development of information systems to achieve this, and smart meters are being deployed as an enabling technology worldwide. Recent smart metering trials, which provide feedback on aggregate household electricity consumption, report moderate savings of 2-5%. There is, however, a vivid controversy about consumer interest and continuous use of these technologies in the long run. This uncertainty introduces substantial risk to the deployment of these technologies, as the persistence of savings is crucial for the cost-benefit analyses and scalability of these programs. This paper investigates the long-term stability of the behaviour change induced by a real-time feedback technology. Our initial study found average energy savings of 22% for the target behaviour. In this study, we analyse 17,612 data points collected in a one-year follow-up field study. The results suggest that the effects of behaviour-specific feedback on energy consumption do not exhibit a significant decay, indicating that this kind of technology successfully induces persistent behaviour change.*

*Keywords: Sustainability, demand-side, field experiment, IS artefact, user behaviour, green IS, effect persistence.*

## 1 Introduction

Energy and water are vital to the well-being of our societies. The growing demand for these limited resources is one of the biggest global challenges (UN News Centre, 2014) with fundamental environmental (e.g., carbon emissions and depletion of resources) and geopolitical (e.g., energy security and access to drinking water) implications. In addition to technical parameters, behaviour has been identified as the most important factor governing resource consumption. As a result, interest has substantially grown over the past few years in technologies and policy measures which can successfully promote sustainable behaviour and resource conservation.

Information systems (IS) can play a key role in this context: while the overwhelming majority of people inherently care about the environment (Naderi, 2011), most have a very limited understanding of the environmental footprint of their daily actions (Attari, 2014; Gardner and Stern, 2008) or even hold fundamental misconceptions about energy end uses (Attari et al., 2010). Therefore, individuals' conservation efforts often focus on low-impact domains such as lighting, yet fail to address high-impact domains. A prominent example of this is space and water heating, which jointly account for 80% of residential energy end use in the European Union (Lapillonne et al., 2014). The poor level of understanding of these high-impact domains is hardly surprising, as the information available to consumers today is still limited to yearly, quarterly, or at best monthly utility bills. Additionally, this information is typically aggregated to the household level and over the entire billing period. As a result, it is almost impossible for individuals to assess the impact of a specific behaviour (e.g., turning up the air conditioner) on energy consumption or carbon emissions, and to prioritize potential conservation efforts accordingly.

While many firms and larger organizations already have installed building management systems to monitor and control various energy and water end uses, households still lack the tools to understand how they could effectively reduce their environmental impact. 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). Just like larger organizations, in order to adopt sustainable practices and strategies, households would benefit from *"new data regarding environmental impacts, new information about causes and effects, and knowledge sharing about what works, what doesn't, and why"* (Melville, 2010, p. 2). IS can help individuals identify inefficient appliances, understand the environmental outcomes of their daily actions, and focus their conservation efforts on environmentally significant behaviours.

Transparency of consumption and "consumer empowerment" are key arguments for the ongoing rollout of 195 million electricity smart meters that are projected to be installed in the EU by 2020, by then covering 72% of utility consumers in the EU (European Commission, 2014). However, the high hopes that initially had been placed on feedback information have not been met: reported savings of larger smart metering trials range between 2-5% (McKerracher and Torriti, 2013; Schleich et al., 2013), falling short of the initially anticipated 5-15% (Darby, 2006).

In particular, there is an ongoing debate in the field whether or not feedback technologies successfully engage individuals in the long run (see Related Work section). At least in the case of larger deployments, the rollout of IS artefacts like in-home displays (IHDs) or web portals to monitor the electricity or gas consumption of one's home are pushed by utility companies, not by consumer demand for these technologies. While a considerable number of consumers may initially exhibit interest in these IS artefacts, many studies find that most individuals lose interest quickly: the number of user interactions with these kind of web sites or IHDs drops dramatically within the first month; in many cases, the interaction is limited to a single trial (Schleich et al., 2013; Degen et al., 2013). Maybe not surprisingly, the short-lived engagement of consumers with those technologies results only in rather modest savings effects.

For smart metering technologies and related IS to unfold their full potential, collaborations are needed that reach across the disciplinary boundaries (Tavoni and Levin, 2014). 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, p. 1). In particular, IS research has already developed a solid body of knowledge on technology adoption (Benbasat and Barki, 2007; Venkatesh et al., 2007), also in the consumer context (Venkatesh et al., 2012). However, relatively few studies and models investigate the continuous use of technologies in the long run and, in particular, whether the influence of IS artefacts on behaviour is persistent. Yet, understanding the impact of IS artefacts on target behaviours in the long run and assessing the persistence of IS-enabled behaviour change is crucial beyond the domain of resource conservation. A variety of IS artefacts have been developed to support individuals with behaviour change in manifold domains like job strain (Kowatsch et al., 2015), physical exercise (Lehto et al., 2013) or smoking cessation (Whittaker et al., 2012). Research in social psychology has shown that the factors influencing the initiation of a behaviour (e.g., starting and exercise program or a diet) are different from the factors influencing the maintenance of those behaviours (Ronis et al., 1989). Developing IS that successfully induce individuals to lose weight or to reduce their resource consumption is one important step; yet the success of an IS hinges on its capability to support the individuals in maintaining the new behaviours (Bhattacherjee, 2001).

This paper investigates the impact of a real-time feedback technology on resource consumption in the long run. Instead of collecting self-reported data on the intention to use the technology in the future, we analyse granular energy and water use data to determine the persistence of the behaviour change induced by the IS artefact. While most smart metering studies use IS that visualize aggregated feedback on resource consumption at the household level, we use an IS artefact that provides individuals with real-time feedback on energy and water consumption of a specific behaviour: showering. We chose showering as target behaviour for three main reasons: first, water heating is the second largest energy end use in the average European or U.S. home (Eia, 2013; BAFU, 2013). In fact, showering is a particularly energy-intensive behaviour: the energy required for one second of showering is sufficient to power a laptop for two hours. Second, given its short duration of a few minutes, the individual does needs to pay attention over extended periods of time to achieve large absolute savings. Third, most individuals are not aware of the nexus between hot water and energy use, leaving large saving potential untapped.

In (Tiefenbeck, 2014), we have evaluated the savings effect of that technology in a randomized controlled field trial with 697 households over two months. The results show that treated households reduced both their energy and their water use for the target behaviour by 22% on average, reducing the overall energy consumption of the participating households by 5%. In a recent research-in-progress (RIP) paper (Tasic et al., 2015), we have raised the question of the long-term stability of the effects in our two-month study and outlined a few first (mainly qualitative) results. Note that parts of the related work and parts of the methodology section have already been part of the RIP paper. For the sake of readability, we integrate the relevant paragraphs in their original or in a revised form. The current research paper provides more thorough analysis methods and results and discusses the implications of our findings for feedback technologies and for the IS research community.

# 2 Related Work

In this chapter, we give an overview of the current status of IS-enabled feedback in the resource conservation context and on previous research on continuous technology use and the persistence of behaviour change (both in the context of resource conservation and in the broader behaviour change literature).

## 2.1 IS-enabled feedback on resource consumption

Behavioural interventions are increasingly viewed as a politically feasible instrument to promote resource conservation and to increase energy efficiency quickly, at scale, and in addition to technological efficiency gains (Allcott and Mullainathan, 2010; Allcott, 2011). Today, the majority of households continue to receive only periodic paper bills on their electricity, gas and water consumption. Yet the ongoing deployment of millions of smart meters (European Commission, 2014) opens up new possibilities to provide consumers with feedback on their resource consumption and opportunities for energy conservation. The most widespread approach of displaying smart metering information to residential consumers today is the use of in-home displays (IHDs) and web portals (Ehrhardt Martinez et al., 2010). Recent meta-studies found moderate savings effects in the order of 2-5% (McKerracher and Torriti, 2013; Schleich et al., 2013). The aforementioned studies are based on technologies that present feedback to consumers that is aggregated on the household level. These systems leave the burden of identifying high-impact domains or energy guzzlers to the consumer (Faruqui et al., 2010). Previous research shows 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 IS artefacts providing real-time feedback on a specific behaviour presented in academic literature still have not overcome prototype status. Taking the example of our target behaviour showering, we find indeed number of innovative studies presenting different concepts for data visualization to promote sustainable behaviour in this domain. 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, do not investigate verifiable research hypotheses, or, in the case of (Willis et al., 2010), lack a clean research design.

## 2.2 Continuous technology use and persistence of behaviour change

IS research has developed a solid body of knowledge on technology adoption. For instance, Venkatesh et al. (2003) have combined different existing technology acceptance models into the Unified Theory of Acceptance and Use of Technology (UTAUT1). The continuous use of technologies and the long-term impact of technology use has received less attention so far. Venkatesh et al. (2012) have extended the UTAUT framework to the UTAUT2, which explain continuous usage intentions and behaviour in the consumer context. In a similar vein, Bhattacherjee (2001) has developed a model of IS Continuance that explains continuous use intention based on the Expectation-Confirmation-Theory by Oliver (1980). A later framework by Premkumar & Bhattacherjee (2008) integrated the model of IS Continuance and TAM. Most recently, Bhattacherjee and Lin (2015) developed the Unified Model of IT continuance. In contrast to the previous models, this framework also analyses (self-reported) continuance behaviour (and not only intention). The authors of that framework recommend assessing usage behaviour one month after the adoption of the IS; in other words, while the model addresses continuous technology use, it does not assess long-term behaviour. In fact, most of the existing IS research on continuous technology use is based on hypothetical questions explaining the usage intention of fictive IS that are not being used later on (e.g., Alaiad and Zhou 2014; Hsu et al. 2013; Lai and Lai 2014). Yet little is still known about the impact of IS on real-world behaviour and in particular, whether IS can successfully induce and support persistent behaviour change.

The persistence of behaviour change – whether induced by IS or not – has previously been discussed both in the context of energy conservation and in the broader social science literature. The "Social Cognitive Theory" (Bandura, 1986) posits the concept of self-efficacy as central to the persistence of behaviour change: (Schwarzer, 2008) refined the term to the concept of "maintenance self-efficacy" as *"optimistic beliefs about one's capability to deal with barriers that arise during the maintenance period,"* helping individuals prevent relapse to old patterns. (Prochaska and Diclemente, 1986) combined the concept of self-efficacy with other concepts on behaviour change and persistence into the "Transtheoretical Model". The model distinguishes five stages of change in a process that unfolds over time. In the final stage ("maintenance") individuals are less tempted to relapse to their old behaviours. Literature on habit formation suggests that it takes on average two months for modified daily actions to become an automated process that no longer requires self-control (Lally et al., 2010).

In the energy conservation domain, 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 behaviour 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. There is currently a vivid debate among scholars and practitioners alike whether or not feedback technologies can induce persistent energy savings. The evidence from prior research is mixed.

On the one hand, (Ayres et al., 2009) reported persistent conservation effects throughout a seven- resp. one-year study duration. (Raw et al., 2011) also reported 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 found 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) presented an analysis that analyses long-term efficiency campaigns comprising 234,000 households over four or five years. While they analysed paper-based periodic 'home energy reports', and not more advanced feedback technologies, the results are of interest given the sheer sample size and duration of the study. The authors find that the immediate conservation response to the first home energy report is followed by a relatively quick decay of the effect, yet observe cyclical, diminishing patterns of action and backsliding in response to the paper reports. If the intervention is being discontinued after two years, the effects decay only with a rate of 10-20%. The authors conclude that the savings effects of such paper-based campaigns are much more persistent than previously assumed in cost-benefit analyses.

On the other hand, a number of feedback studies report that savings effects eventually dissipate and that households return to pre-intervention consumption levels (e.g., Fielding et al. (2013); van Dam et al. (2010)). Faruqui et al., (2010) and Gilbert and Zivin (2013) find that current systems fail to engage individuals over longer periods of time. Hargreaves et al., (2013, p. 126) find that in-home displays to monitor domestic electricity consumption “gradually become ‘backgrounded’ within normal household routines” often end up in the drawer after a few weeks or as soon as the battery is empty (van Rensburg, 2008). In a feedback study on water consumption, Fielding et al. (2013) found that once the intervention ends, the effect eventually dissipates and households return to their pre-intervention levels of consumption. In a similar vein, a study with 300 Dutch households on feedback provided on in-home displays, (van Dam et al., 2010) found 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. (Buchanan et al., 2014) analysed online user reports on energy monitors and concluded that after an initial stage of enthusiasm even motivated consumers start to pay less attention to the monitors and they fade into the background. A more recent meta-review by Buchanan et al. (2015, p. 94) concluded that *“the effect of feedback on energy consumption is insubstantial with information strategies resulting on average, in short-term reductions of only 2% which may or may not persist in the long term.”* Overall, despite the resources devoted to behaviour change programs in energy efficiency and other domains, evidence on the long-term impact of those interventions so far is mixed.

### 2.3 Research gap, contribution, and hypotheses

Existing research in the IS investigates factors driving the adoption and use of IS. Self-reported, not measured data are being used to understand individuals’ intention to use technologies. Yet, self-reported usage intention does not necessarily imply actual behaviour. Moreover, in many cases, technology use is only a means to an end: it enables individuals to increase their productivity, to monitor their health, or to reduce their energy consumption. Yet, there is a lack of studies in the IS domain that measure actual outcomes of technology use, in particular in the long run.

In this paper, we investigate actual outcomes of technology use: in a field study with 50 households, we measure the impact of behaviour-specific real-time feedback on individuals’ resource consumption in the long run. For that purpose, we collect granular data on the energy (and water) consumption in the shower over a total period of 16 months. In contrast to prior studies, we investigate the long-term impact of a technology that provides individuals with real-time feedback on a specific behaviour. The overarching research question of this paper is:

**How does real-time feedback on resource use affect consumer behaviour in the long run? Does the initial large conservation effect, triggered by the technology, persist or weaken over time?**

In order to answer this overarching question, we carefully compare characteristics and results of the initial study (N=697) with the (self-selected) subset of households who participated in the one-year follow-up study. We investigate the following hypotheses:

H1: The subsample participating in the one-year study is not significantly different from the original sample on relevant observable characteristics.

H2: Energy (and water) consumption per shower in the one-year study is not substantially different from participants’ behaviour during the two-month study.

H3: There is no strong change in the consumption during the course of the one-year study.

## 3 Methodology

As outlined in the introduction, the study described here is a one-year follow-up of a two-month study that took place from December 2012 to February 2013. While the two-month study showed that real-time feedback can induce substantial behaviour change and energy savings with a relatively large sample, the goal of this follow-up study is to shed light on the question how continuous technology use affects consumer behaviour in the long run – in other words, if the large treatment effects induced by the technology are stable over time.

In order to understand the analysis approach chosen in this paper, it is necessary to be aware of the research design and key results of the two-month study described in (Tiefenbeck, 2014). All 697 participating households received an IS artefact that measured and recorded the energy and water use of every shower taken. The two-month study followed a difference-in-difference (DiD) design (Taber, 2012): two thirds of the participants had randomly been assigned to the treatment group. After a short baseline period (10 showers), during which the IS artefact displayed only water temperature, they received real-time feedback on their energy and water consumption in the shower. The remaining third of the participants had been assigned to the control group: the IS artefact displayed only water temperate throughout the two-month study. This enabled us to precisely determine the savings effects using robust regression analysis. Treated households reduced both their energy and their water consumption by 22% on average. The per-household energy savings are equivalent to the electricity consumption of two modern refrigerators (Michel et al., 2015). We were thus able to show that real-time feedback can induce substantial behaviour change and resource conservation, at least in the short- to medium-term.

For the long-term study presented here, we could have continued running the experiment using the DiD approach. In practice, however, it is not realistic that participants accept an IS artefact in their shower that does not display relevant feedback for an entire year. The study would probably suffer from attrition biases (more control group households dropping out). Therefore, we chose an alternative approach: we took the two-month study as a reference period against which we compare the subsequent one-year study. In the one-year study, all households received real-time feedback. We will compare day-by-day means and time trends, and control for seasonal trends. In addition to the measurements, we administered surveys before and after the study to collect socio-demographic data, personality traits, environmental attitudes, and participants' experience with the device. We use the survey data to compare the original sample with the participants of the one-year study. The following sections briefly describe the IS artefact used, the sample of participants, the data collection, and data analysis.

## 3.1 IS artefact used to measure, display, and store information

The IS artefact used in this study is the *amphiro a1* smart shower meter. The device measures and stores data on every shower taken and provides users with real-time feedback while they take their shower. Users can install the smart shower meter between the shower hose and the handheld showerhead without any tools a minute. The device measures and stores flow rates, water volume, and temperature for each shower. Treatment group devices displayed real-time feedback on water use (in tenths of litres) and energy consumption (in [k]Wh), along with temperature and energy efficiency class (A-G); the latter is accompanied by a polar bear animation. The artefact is described more in detail in (Tiefenbeck, 2014).


*Figure 1. Snapshot of the information displayed by the smart shower meter. The screen can toggle to display energy use and the energy efficiency class in the upper part.*

## 3.2 Participants

All participants of the two-month study (including the subset who participated in the follow-up study) lived in the Zurich metropolitan area and were recruited in collaboration with the local utility company. Participation was limited to one- and two-person households for technical reasons (Tiefenbeck, 2014). Table 4 in the Appendix contains detailed information on demographics and other potentially relevant variables (e.g., environmental attitudes, personality traits). Upon completion of the two-month study, all participants who had sent in their study devices for the data readout received them back with a cleared memory and in a configuration capable of storing 507 showers. In March 2013, the devices were returned to the households, who were not informed at that point that they might be asked later on to send in their shower meter one year later for another analysis. Beginning of April 2014, 294 households were invited to participate in the long-term study. They were informed that the researchers wanted to collect long-term shower data and 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. To reduce selection bias, the email further stated that their dataset was of interest to the researchers regardless of whether or not they had recently still paid attention to the smart shower meter. The remaining 403 participants of the two-month study were not contacted for various reasons: 107 of them had registered on the manufacturer's online portal, which allowed them to track their shower behaviour over time. As the interaction with the portal might bias their behaviour beyond the influence of the real-time feedback, we excluded them. Nineteen households did not wish to receive the device back after the two-month study, twelve had not shipped the device back, another seven had not filled out the final survey; 98 households did not wish to be contacted with further information on studies; 57 devices had been replaced during or after the two-month study, thus no coherent dataset was be available from these households; finally, 103 households had contacted the researchers for various reasons, including relocation, long absence, communication issues, removal of the device, or simply questions and comments regarding the device or study. In hindsight, the latter criterion imposed an unnecessarily strict restriction, which could have been relaxed to increase the number of participants. Eighty households responded to the call and filled out the survey. Based on the survey, 50 households were chosen according to the following criteria: completion of the questionnaire, willingness to ship back the device for another data read-out, agreement with the data privacy protection statement, no long absences during the long-term study, no relocation, no replacement of the smart shower meter, and no change in household composition.

For the one-year study, households were recruited both from the treatment ("2mT") and from the control ("2mC") group of the two-month study (Figure 2). In Section 4.1, we show that the composition of the sample does not introduce a considerable sampling bias.

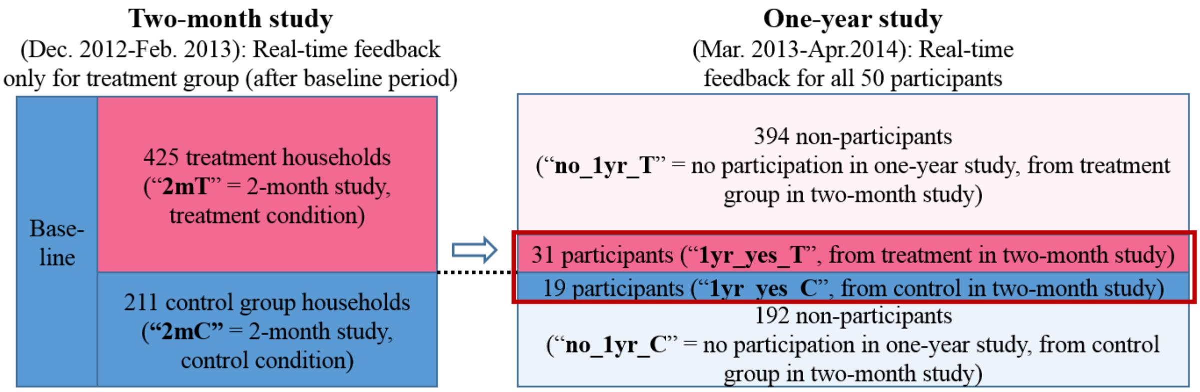


*Figure 2. All households in the one-year study had previously participated in the two-month study, yet in different experimental conditions: 31in the treatment and 19 in the control group. In the one-year study, all participants received real-time feedback.*

## 3.3 Data collection and pre-processing in the one-year study

A total of 50 households fulfilled all the requirements for the one-year study and sent in their shower meters for the data readout. After the readout, participants received their devices back. Altogether, data of 17,612 showers were recorded during twelve months in the 50 households. In addition to the one-year datasets collected for the purpose of this study, the two-month datasets from those households are also available. The full duration of the study thus spans from December 2012 to April 2014. Between the two-month study and the one-year study, one month of data is missing (data readout for the two-month study and two-way shipping).

As a pre-test, each dataset was analysed for outliers: for each household, the temperature and volume mean were calculated; data points more than two standard deviations above or below the mean were flagged as outliers. Most of these outliers were extractions of a small quantity of water at an unusually cold or hot water temperature, probably for bathroom cleaning purposes. We ran our analyses with and without excluding these outliers. The results obtained with the filtered and the non-filtered dataset were not significantly different. The results are thus robust and not driven by outliers.

# 4 Data Analysis and Results

The study aims to investigate the stability of the real-time feedback effects over a longer period of time (one year). We will proceed in four steps. In step 1, we evaluate whether the subset of households who participated in the one-year study ("1yr-yes") is significantly different from the non-participants ("no_1yr") on any relevant known characteristics. This step is important to assess whether the participants of the one-year study are representative for the original sample of the two-month study. In step 2, we compare day-by-day means of the water and energy consumption during the one-year study with the two-month study to get a first impression of the dynamics over time. In step 3, we refine the analytical approach: we calculate a fixed-effects regression model to control for time-invariant household-specific factors (e.g., type of shower). This approach also ensures that households with a high shower frequency do not unduly influence the results. In the fourth step, we conduct a trend analysis on the one-year dataset of all 50 households to capture time trends.

## 4.1 Step 1: comparison of known characteristics to assess sampling bias

In step 1, we evaluate whether the households participating in the one-year study ("1yr-yes") are representative of the original sample. We used both the shower data and the survey data to assess whether the 50 "1yr-yes"-households are different from those who did not participate ("no_1yr"). We ran t-tests on a set of 51 parameters (Table 4, in the appendix), including all characteristics that had been identified as predictors of the shower behaviour or treatment effect in the two-month study. Some of these parameters are affected by the experimental condition the household had been assigned to in the two-month study: obviously, the control group used more energy and water per shower in the two-month study (after all, this was the goal of the intervention). Not surprisingly, the control group's perception of the device was also affected: they had rated the device as less interesting and enjoyable after the two-month study than the treatment group. Therefore, we run the comparison on known characteristics twice: first, for treatment households only ("T_only", N=425), i.e., we compare the 31 households who participated in the one-year study ("1yr_yes_T") with the remaining 394 treatment households who did not ("no_1yr_T"); second, we ran the tests for treatment and control group households combined ("combi").

Either way, we find little difference between the participants of the one-year study and their corresponding group of non-participants. Most importantly, in both specifications, the mean baseline water consumption is statistically not different between the two study samples. For the "T_only" comparison, participants and non-participants of the one-year study differ only in a single parameter: participants of the one-year study had rated the device as significantly more enjoyable than households who did not participate in the one-year study. This parameter was measured on a 7-point scale between two semantic poles, ranging from -3 to +3 ($M_{noLT} = 1.07$, $M_{LT} = 1.61$, $SD_{noLT} = 1.15$, $SD_{LT} = 0.80$, $p = 0.0012$***).

This is barely surprising: participants who gave the device a low rating on that scale may not have continued using the device for another year. This parameter, however, was not a significant predictor of the conservation effect in the two-month study. When comparing participants and non-participants from the treatment and control group combined, the perception of the device is strongly biased by the fraction of control group participants. Participants in the long-term study are also significantly younger and have a higher tendency to compare themselves with their peers. The latter, however, was also not a predictor for the response to the real-time feedback. While age was an (indirect) predictor of savings, the difference in this parameter stems from the control group participants; participants and non-participants from the treatment group do not significantly differ in their age. Table 4 in the appendix contains the full list of test statistics for the comparisons.

Table 1 compares treatment households who participated in the one-year study with those who did not with respect to their shower behaviour during the intervention phase of the two-month study. There is no significant difference in the water temperature and in the energy consumption per shower. Remarkably, while water and energy use during the baseline phase had statistically been the same for participants and non-participants of the one-year study, those who participated in the one-year study used *more* water during the intervention period (small, but significant difference). Thus instead of a self-selection towards particularly motivated households, the households that opted into the one-year study had even been slightly less responsive to the initial treatment than those who ended up not participating in the one-year study. However, for our key variable of interest (energy), the consumption was not statistically different between participants and non-participants. Among the 51 observed characteristics, we hardly observe any difference between the participants of the two studies. Hypothesis H1 is supported: based on the relevant observed variables, we find no evidence that the subsample participating in the one-year study is different from the original sample.

| Intervention period of two-month study | N | | Mean | | SD | | p |
|---|---|---|---|---|---|---|---|
| | no_1yr_T | 1yr_yes_T | no_1yr_T | 1yr_yes_T | no_1yr_T | 1yr_yes_T | |
| Volume per shower [L] | 395 | 31 | 38.1 | 39.7 | 29.4 | 23.7 | 0.041** |
| Temperature [°C] | 395 | 31 | 36.2 | 36.3 | 3.4 | 3.0 | 0.150 |
| Energy per shower [kWh] | 395 | 31 | 2.64 | 2.73 | 2.17 | 1.71 | 0.104 |

*Table 1. Comparison between participants (“1yr_yes_T”) and non-participants (“no_1yr_T”) of the one-year study.*

## 4.2 Step 2: day-by-day means of water use per shower and comparison of means between one-year study and two-month study

In order to determine the persistence of the treatment effect after more than a year of feedback, we compare the shower behaviour in the one-year study with the behaviour in the two-month study. In this step, we need to restrict our analysis to the 31 households who had been in the treatment group in the two-month study (“1yr_yes_T”): the 19 “1yr_yes_C” households were exposed to real-time feedback in the one-year study, but had not been so in the two-month study. Therefore, for them a comparison between the two studies would be strongly confounded with the activation of the real-time feedback. Table 2 shows the results of a first crude quantitative analysis: a comparison of the mean water and energy use, and temperature between the two studies for the 31 households who had access to real-time feedback in both studies. One can see the treatment effect in the two-month study – a reduction of 7.5 litres in water use and 0.57 kWh in heat energy – over the baseline period.

| | Baseline period of two-month study | | Intervention period of two-month study | | One-year study | |
|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD |
| Volume per shower [L] | 47.2 | 31.5 | 39.7 | 23.7 | 40.4 | 24.6 |
| Temperature [ºC] | 36.6 | 2.9 | 36.3 | 3.0 | 36.2 | 2.9 |
| Energy per shower [kWh] | 3.30 | 2.35 | 2.73 | 1.72 | 2.75 | 1.72 |
| N° of observations | 286 | | 1,605 | | 11,065 | |

*Table 2: Mean values for key shower characteristics of the 31 treatment households in the two-month study (baseline vs. intervention period) and in the one-year study.*

## 4.3 Step 3: quantitative results from fixed-effects regression model

While the results in step 2 gave a first impression of the overall trend, the methodological approach suffers from several shortcomings. First of all, it cannot control for biases introduced by unobserved variables. For instance, the approach did not control for the amount of cold water it takes at the beginning of a shower until the water has reached a pleasant temperature. Second, households with a larger number of showers receive an undue weight in the estimate. The approach in step 2 also does also not yet take into account seasonal trends which influence all participating households alike. In the absence of a control group (in the one-year study), this may bias the results. We therefore estimate a fixed-effect model with ordinary least squares. This allows us to control for time-invariant, household-specific factors (e.g., showerhead efficiency) and to include time trends to account for seasonal patterns. The following fixed-effects model is used to analyse and compare short- and long-term data:

$$y_{it}=\alpha_i+\beta T_{it}+\gamma t+\varepsilon_{it}$$

In that model, $y_{it}$ is the dependent variable (water and energy consumption, respectively) at day t in household i. The individual fixed effect $\alpha_i$ eliminates all variance from time-invariant unobserved characteristics (e.g., type of shower head). $T_{it}$ is a binary dummy variable that equals zero during the two-month study and one during the one-year study. The term $\gamma t$ is a seasonal correction factor to correct for outdoor temperature; $\varepsilon_{it}$ is an error term. We report standard errors clustered at the household level. Table 3 presents the results.

| **Regressing shower water use** | **Coeff.** | **Std. Err.** | **t** | **p** | **95% Conf. interval** | |
|---|---|---|---|---|---|---|
| Outdoor temperature | -0.07 | 0.02 | -3.07 | 0.002*** | -0.12 | -0.03 |
| Dummy for one-year study | 1.64 | 0.54 | 3.07 | 0.002*** | 0.59 | 2.70 |
| Constant | 38.52 | 0.47 | 81.90 | 0.000*** | 37.60 | 39.45 |

| **Regressing shower energy use** | **Coeff.** | **Std. Err.** | **t** | **p** | **95% Conf. interval** | |
|---|---|---|---|---|---|---|
| Outdoor temperature | -0.004 | 0.002 | -2.54 | 0.011** | -0.008 | -0.001 |
| Dummy for one-year study | 0.071 | 0.038 | 1.88 | 0.061* | -0.003 | 0.145 |
| Constant | 2.649 | 0.033 | 79.93 | 0.000*** | 2.584 | 2.714 |

| **Regressing shower temperature** | **Coeff.** | **Std. Err.** | **t** | **p** | **95% Conf. interval** | |
|---|---|---|---|---|---|---|
| Outdoor temperature | 0.00 | 0.00 | -0.8 | 0.422 | -0.01 | 0.00 |
| Dummy for one-year study | -0.16 | 0.07 | -2.4 | 0.016** | -0.30 | -0.03 |
| Constant | 36.30 | 0.06 | 610.7 | 0.000*** | 36.18 | 36.41 |

*Table 3: Results of the fixed-effects model estimation for water volume, energy use and temperature.*

The results of the fixed-effects model (Table 3) show that outdoor temperature has a (highly) significant negative impact on water and energy consumption, but not on shower temperature: Individuals tend to use more water (and as a result of that, more energy) on colder days, but do not take warmer showers. Yet more importantly, the results shows the difference between the two-month study and the one-year study after controlling for outdoor temperature: the average shower in the one-year study uses 1.64 litres more water; the difference is significant. On the other hand, the average shower in the one-year study is slightly, yet significantly colder. For energy consumption, the difference between two-month and one-year study per shower is not significant at an alpha level of 0.05.

Hence, the results of the fixed-effect model regression are mixed: energy use per shower is not significantly higher in the one-year study than in the two-month study. Water temperature has dropped slightly (by 0.16°C), yet significantly after controlling for outside temperature. Water consumption, on the other hand, has slightly increased by 1.64 litres. The next step will analyse the trend for water (as the least stable variable) more in detail.

### 4.4 Step 4: time trend analysis

While the results of step 3 did not indicate a significant difference in the per-shower use of energy between the two studies, the essential question is whether the significant increase in water consumption between the two studies is an ongoing trend or whether it reaches saturation after a while. The goal of the fourth step is thus to understand whether the effects stabilize over time. Figure 5 gives a visual impression of the per-shower water consumption over time for the one-year study. For this purpose, we analysed water consumption in the one-year dataset by using a fixed-effects model with variable ‘days’ as a covariate. Again, we estimate a fixed-effect model using ordinary least squares. As we use only data from the one-year study this time, we can use also run the regression on all 50 households (15,237 data points). The resulting trend indicates an increase in the water consumption of 2.1 ml per day (p=0.054*). Thus, the increase is just above the 0.05 significance level. When taking the 31 households from the treatment group alone, the increase is clearly insignificant (p=0.492).

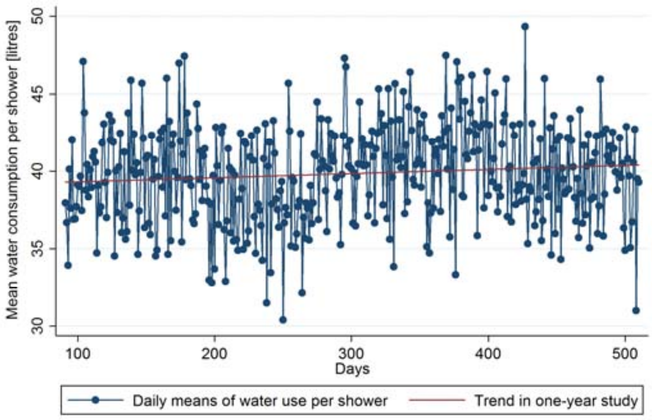


Figure 3. Trend analysis for water use per shower during the one-year study (N=50)

## 5 Discussion

In this section, we will first discuss the specific findings for the specific context of behaviour-specific real-time feedback, then discuss limitations, and finally present the contributions of this paper to IS theory.

## 5.1 Discussion of the results: effect stability of real-time feedback

In this paper, we evaluated the persistence of behaviour change, induced by an IS artefact that provides feedback on individual energy and water use in the shower. To the best of our knowledge, this is the first study to investigate how behaviour-specific real-time feedback affects behaviour in the long term.

In a first step, we verified whether the participants of the one-year study were representative for the larger pool of households of the two-month study. The results indicate that the subset of households hardly differs in any of the know characteristics. Hence we can rule out a self-selection of particularly responsive households and consider their behaviour as a good proxy for the behaviour of the original sample. The results of the fixed-effects regression in step 3 indicate no significant change in the energy consumption between the two-month study to the subsequent one-year study, a slight (yet significant) decrease in the water temperature, and a significant increase for water consumption of 1.64 litres per shower. These results imply that the initial treatment effect of 22% on energy consumption remains unchanged, while the treatment effect on water consumption declines from 22% to 18%. Finally, step 4 investigates time trends in the water consumption per shower in the one-year study. The results indicate a small daily increase of 2.1 ml, which would increase water use per shower by 0.75 litres over the course of one year; when taking all 50 households in the one-year study, the trends just misses the 5%-significance level (p=0.054); when analysing treatment households only, the time trend is clearly insignificant (p=0.492). In any case, the slope is very flat compared to the daily increase of 52 ml observed in the two-month study. In the two-month study, the upward trend in the treatment group had been mirrored by the control group, resulting in a stable difference between the two groups (i.e, a stable treatment effect). Different stability tests did not show any evidence for a weakening of the treatment effect the two-month study. Our conjecture is that fading Hawthorne effects (altered behaviour of participants resulting from their awareness of being a part of an experimental study, see (Levitt and List, 2011)) might explain the initial increase and subsequent convergence of water consumption towards a stable behaviour. Due to the lack of a control group in the one-year study, we cannot rule out with certainty the possibility of a slight increase in water consumption over time relative to the level of the two-month study. On the other hand, the increase is only jointly significant and by a factor of 25 smaller than in the two-month study. In any case, even if water consumption was subject to a steady daily increase of 2.1 ml, then the initial conservation impact would take 12 years to fully dissipate. The results indicate even more persistent treatment effects for energy consumption: the difference in energy use per shower between the two-month study and the one-year study is not significant.

The findings of our paper contribute to the ongoing discussion of the persistence of behavioural interventions. Several reasons might explain why the savings effects in our study appear to be more persistent than in other studies that found that the conservation effects eventually dissipated. First, the other studies investigated feedback on electricity or gas use that is aggregated to the household level; on that case, the individual needs to identify herself actions that have a meaningful conservation impact. By contrast, the IS artefact studied in this paper provides concrete and actionable feedback to the user. Second, the specific focus of the feedback on an energy-intensive behaviour requires only a short span of user attention of a few seconds or minutes per day. Third, while most web portals and IHDs require an active step of the consumer to access the feedback information ("data pull"), the IS artefact studied here automatically displays the feedback as soon as the water is turned on. That distinction between "data push" versus "data pull" technologies has previously been brought up by other researchers as a means to overcome barriers to the long-term use of feedback technologies and to achieve more persistent behaviour change and savings effects (Froehlich et al., 2010; Foster and Mazur Stommen, 2012, Boyd, 2014).

## 5.2 Limitations

Despite our efforts with the implementation and analysis of this study, some aspects could be improved in future studies. First, the sample is relatively small, at least in comparison to the large sample of the original study. A larger sample might help to increase the confidence in the findings and their external validity. Second, the two-month study had greatly benefited from the DiD design, i.e., the existence of a control group. In practice, it may be difficult to implement the study with a control group for a duration that spans over an entire year. While most households accept a device in the shower that only displays temperature for a limited period of time, dropout rates among the control group households might drastically increase in a one-year study, introducing new sources of bias. Third, while the study described here spans over a much longer period than the initial study and although we are aware of no other study that investigates the impact of a real-time IS artefact over such a long time, is still remains to be seen how individuals respond over even longer periods of time, e.g., after five years. Behavioural theory predicts that by then repeated behaviours will long have stabilized into new habits (Lally and Gardner, 2013). The results of our two studies support evidence for such a stabilization effect. Clearly, more research is needed to better understand the persistence of behavioural changes induced by IS artefacts. Future work should investigate the adoption of behaviour-specific/real-time feedback systems, the role of habit formation, and the validity of the findings, also in other domains like healthcare.

### 5.3 Contributions of this paper

While IS research has developed a solid understanding of the factors driving technology adoption, much less is known about the long-term use of technologies. Our study complements existing IS research on continuous technology use in several ways: first, we investigate continuous use of an actual IS artefact, not hypothetical questions on the usage intention of a fictive technology. Second, our study relies on actual measurement data, not self-reports. Third, our analysis expands the focus to technology use in the long term (over a period of 16 months altogether). Finally, we do not consider technology use as an end in itself, but as a means to an end: instead of analysing participants' level of interaction with the real-time IS artefact, we measure the outcome of the technology use: how the real-time feedback displayed by the IS artefact affects energy and water use in the long term. With respect to the existing literature on feedback interventions in the resource conservation domain, we add to the ongoing debate about persistence of the effects. Our results indicate that real-time feedback on a specific behaviour can successfully reduce energy and water consumption in the long run: over the 16 month timespan of the two studies, we find little to no evidence for a substantial decay of the initial large conservation effect.

## 6 Conclusion

IS can help to promote sustainable consumer behaviour. In the context of smart metering, various feedback technologies are being deployed to encourage conservation behaviour among consumers. Yet, there is a vivid debate about consumer interest and continuous use of these technologies in the long run. This paper investigates the long-term stability of the behaviour change induced by a real-time feedback technology. The study was designed as a follow-up experiment of a larger two-month study with 697 households that found a treatment effect of 22% for the target behaviour. The follow-up study collected granular energy and water consumption data from 50 households over the course of one year. The results suggest that the effects of behaviour-specific feedback on energy consumption do not exhibit a significant decay, indicating that this kind of technology successfully induces large and persistent savings effects. The question of effect persistence is pivotal for cost-benefit analyses to determine whether a new technology should be developed or deployed. Beyond the domain of energy consumption, this paper contributes to IS research on continuous technology use in several ways: our study investigates continuous use of an actual IS artefact, relies on actual measurement data (instead of self-reports), and extends the temporal focus to long-term use of technologies. Finally, by quantifying the impact on resource consumption, our paper investigates technology use as means to an end, rather than as an end in itself.

# 7 Appendix

| Variable name | N | | mean | | SD | | p |
|---|---|---|---|---|---|---|---|
| | no_1yr _T | 1yr_yes _T | no_1yr _T | 1yr_yes _T | no_1yr _T | 1yr_yes _T | |
| Baseline volume mean (per shower) | 395 | 31 | 44.4 | 47.2 | 27.5 | 24.3 | 0.5407 |
| Baseline temperature mean | 395 | 31 | 36.2 | 36.7 | 2.7 | 2.4 | 0.2662 |
| Age | 378 | 31 | 46.3 | 42.5 | 14.3 | 13.7 | 0.1542 |
| Environmental attitude (1=low, 5=high) | 378 | 30 | 3.31 | 3.70 | 0.90 | 0.65 | 0.1882 |
| Income | 357 | 29 | 6.11 | 6.45 | 2.89 | 3.27 | 0.5919 |
| Tendency to observe others | 377 | 30 | 3.57 | 3.27 | 1.05 | 1.08 | 0.1471 |
| Tendency to compare with others | 376 | 29 | 2.72 | 3.14 | 1.05 | 1.27 | 0.0916* |
| Measure performance against peers | 371 | 30 | 2.77 | 2.83 | 1.07 | 1.34 | 0.8052 |
| Measure performance against goals | 378 | 30 | 3.96 | 3.80 | 0.89 | 1.06 | 0.4427 |
| Housing situation | 375 | 30 | 1.92 | 1.83 | 0.28 | 0.38 | 0.2434 |
| Extraversion | 376 | 30 | 4.37 | 3.87 | 1.50 | 1.72 | 0.1308 |
| Agreeableness reverse | 372 | 30 | 3.23 | 3.23 | 1.45 | 1.36 | 0.9984 |
| Conscientiousness | 375 | 30 | 5.73 | 6.00 | 1.05 | 0.79 | 0.085* |
| Neuroticism | 377 | 30 | 2.37 | 2.70 | 1.31 | 1.47 | 0.2459 |
| Openness | 378 | 30 | 5.79 | 5.63 | 1.08 | 1.00 | 0.4065 |
| Extraversion reverse | 375 | 30 | 3.85 | 4.00 | 1.67 | 1.70 | 0.6404 |
| Agreeableness | 376 | 30 | 5.28 | 5.17 | 1.13 | 1.12 | 0.5989 |
| Conscientiousness reverse | 374 | 30 | 2.02 | 2.47 | 1.26 | 1.63 | 0.157 |
| Neuroticism reverse | 375 | 30 | 5.07 | 5.17 | 1.29 | 1.32 | 0.6908 |
| Openness reverse | 376 | 30 | 2.67 | 2.93 | 1.35 | 1.39 | 0.319 |
| Ability to reduce consumption (post) | 389 | 31 | 3.12 | 3.223 | 1.28 | 1.33 | 0.675 |
| Moral obligation to reduce use (post) | 389 | 31 | 2.87 | 3.03 | 1.21 | 1.33 | 0.5053 |
| Overall satisfaction with the device | 390 | 31 | 4.27 | 4.45 | 0.94 | 0.68 | 0.1693 |
| Considered flow restrictor | 390 | 31 | 2.03 | 2.26 | 1.31 | 1.41 | 0.3924 |
| Device perception: comprehensible | 390 | 31 | -2.15 | -2.13 | 1.10 | 1.15 | 0.9176 |
| Device perception: vague | 390 | 31 | 1.86 | 1.45 | 1.43 | 1.69 | 0.1952 |
| Device perception: precise | 390 | 31 | -1.73 | -1.58 | 1.15 | 1.29 | 0.5395 |
| Device perception: effective | 390 | 31 | -1.32 | -1.58 | 1.43 | 1.20 | 0.2526 |
| Device perception: useless | 390 | 31 | 1.67 | 1.81 | 1.36 | 1.28 | 0.5699 |
| Device perception: pleasant | 390 | 31 | -0.74 | -1.06 | 1.58 | 1.24 | 0.1818 |
| Device perception: stressful | 390 | 31 | 0.14 | 0.16 | 1.20 | 1.07 | 0.9304 |
| Device perception: ordinary | 390 | 31 | 1.49 | 1.84 | 1.20 | 0.97 | 0.0662* |
| Device perception: boring | 390 | 31 | 1.87 | 2.06 | 1.16 | 1.06 | 0.3473 |
| Device perception: annoying | 390 | 31 | 0.81 | 1.00 | 1.26 | 1.37 | 0.4475 |
| Device perception: novel | 390 | 31 | -1.24 | -1.03 | 1.55 | 1.30 | 0.4089 |
| Device perception: emotional | 390 | 31 | 0.77 | 0.39 | 1.51 | 1.75 | 0.2445 |
| Device perception: inanimate | 390 | 31 | 1.07 | 1.61 | 1.15 | 0.80 | 0.0012*** |
| Paid little attention to device recently | 389 | 31 | 2.70 | 2.45 | 1.52 | 1.46 | 0.3652 |
| Device helped me save water | 386 | 31 | 3.50 | 3.61 | 1.20 | 1.05 | 0.5828 |
| Device helped me save energy | 386 | 31 | 3.37 | 3.39 | 1.21 | 1.12 | 0.908 |
| Device annoyed me | 386 | 30 | 2.00 | 1.67 | 1.24 | 1.03 | 0.1037 |
| Energy conservation motivated by bear | 370 | 29 | 2.85 | 3.10 | 1.40 | 1.37 | 0.3482 |
| Compared water use w/ hh. members | 188 | 15 | 2.35 | 2.73 | 1.31 | 1.33 | 0.3006 |
| Compared energy use w/hh. members | 188 | 15 | 1.65 | 1.80 | 1.06 | 1.15 | 0.6281 |
| Compared efficiency w/ hh. members | 187 | 15 | 2.04 | 2.27 | 1.21 | 1.22 | 0.5044 |
| Discussed feedback values in hh. | 191 | 15 | 2.20 | 2.33 | 1.03 | 0.90 | 0.6034 |
| Discussed consumption in household | 191 | 15 | 2.06 | 1.93 | 0.88 | 0.80 | 0.5566 |
| Would recommend the device | 388 | 31 | 3.74 | 3.77 | 0.98 | 0.76 | 0.8139 |
| Energy conservation is important | 395 | 31 | 5.70 | 5.68 | 1.01 | 0.87 | 0.8976 |
| Ability to reduce consumption (pre) | 395 | 31 | 4.15 | 4.03 | 1.47 | 1.54 | 0.6719 |
| Intend to reduce consumption | 395 | 31 | 5.18 | 5.42 | 1.37 | 1.39 | 0.3647 |

*Table 4. Comparison (t-tests) of 51 shower and participant characteristics between the treatment group members who participated in the one-year study and those who did not. *, ** and *** indicate significance at the 10, 5, and 1 percent level, respectively.*

## References


Alaiad, A and L. Zhou (2014). “The determinants of home healthcare robots adoption: An empirical investigation.” *International Journal of Medical Informatics* 83 (11), 825-840.

Allcott, H. (2011). “Social Norms and Energy Conservation.” *Journal of Public Economics* 95 (9), 1082-1095.

Allcott, H. and S. Mullainathan (2010). “Behavior and Energy Policy.” *Science* 327 (5970), 1204-1205.

Allcott, H. and T. Rogers (2014). “The Short-Run and Long-Run Effects of Behavioral Interventions: Experimental Evidence from Energy Conservation.” *American Economic Review* 104(10), 3003-3037.

Arroyo, E., L. Bonanni and T. Selker (2005). “Waterbot: Exploring Feedback and Persuasive Techniques at the Sink.” In: *Proceedings of the SIGCHI conference on Human factors in computing systems.* Ed. by W. Kellogg. New York: USA, p. 631.

Asensio, O. I. and M. A. Delmas (2015). “Nonprice Incentives and Energy Conservation.” *Proceedings of the National Academy of Sciences* 112 (6), E510-E515.

Attari, S. Z. (2014). “Perceptions of Water Use.” *Proceedings of the National Academy of Sciences* 111 (14), 5129-5134.

Attari, S. Z., M. L. DeKay, C. I. Davidson and W. Bruine de Bruin (2010). “Public Perceptions of Energy Consumption and Savings.” *Proceedings of the National Academy of Sciences.* 107 (37), 16054-16059.

Ayres, I., S. Raseman and A. Shih (2009). “Evidence from Two Large Field Experiments That Peer Comparison Feedback Can Reduce Residential Energy Usage.” *Journal of Law, Economics and Organization* 15386(9), 1-35.

BAFU (2013). *Charts and Evaluations: Households and Consumption.* URL: http://www.bafu.admin.ch/umwelt/ 10822/12896/index.html?lang=en (visited on 29/07/2014).

Bandura, A. (1986). *Social Foundations of Thought and Action: A Social Cognitive Theory. Vol. xiii. Prentice-Hall Series in Social Learning Theory*. New Jersey: Englewood Cliffs.

Benbasat, I. and H. Barki (2007). “Quo Vadis TAM?” *Journal of the Association for Information Systems* 8 (4), 211-218.

Bhattacherjee, A. (2001). “Understanding Information Systems Continuance: An Expectation-Confirmation Model.” *MIS Quarterly* 25 (3), 351-370.

Bhattacherjee, A. and C. Lin (2015). “A unified model of IT continuance: three complementary perspectives and crossover effects”. *European Journal of Information Systems* 24 (4), 364-373.

Boyd, R. (2014). *C3 – Energy. Ideas. Change. 2.2.8 Visible Metering - A Literature Review.* Technical Report to the City of Edmonton, January. URL: http://www.edmonton.ca/city_government/documents/PDF/Report_6_-_Visible_Metering.pdf (visited on 04/10/2014)

Buchanan, K., R. Russo and B. Anderson (2015). “The Question of Energy Reduction: The Problem(s) with Feedback.” *Energy Policy* 77, 89-96.

Degen, K., C. Efferson, F. Frei, L. Götte and R. Lalive (2013). *Smart Metering, Beratung Oder Sozialer Vergleich: Was Beeinflusst Den Elektrizitätsverbrauch?* Bern: Ittigen.

Ehrhardt Martinez, K., K. A. Donnelly and S. Laitner (2010). *Advanced Metering Initiatives and Residential Feedback Programs: A Meta-Review for Household Electricity-Saving Opportunities.* Research Report JM-2010-26-06. Renewable and Sustainable Institute, University of Colorado.

Eia (2013). *Today in Energy - Heating and Cooling no Longer Majority of U.S. Home Energy Use.* URL: https://www.eia.gov/todayinenergy/detail.cfm?id=10271 (visited on 01/02/2016).

European Commission (2014). *Benchmarking Smart Metering Deployment in the EU-27 with a Focus on Electricity.* Technical Report JM-2014-06. European Commission.

European Environment Agency (2012). *Households and Industry Responsible for Half of EU Greenhouse Gas Emissions from Fossil Fuels*. URL: http://www.eea.europa.eu/highlights/households-and-industry-responsible-for/ (visited on 04/24/2013)

Faruqui, A., S. Sergici and A. Sharif (2010). "The Impact of Informational Feedback on Energy Consumption - A Survey of the Experimental Evidence." *Energy* 35 (4), 1598-1608.

Fielding, K. S., A. Spinks, S. Russell, R. McCrea, R. Stewart and J. Gardner (2013). "An Experimental Test of Voluntary Strategies to Promote Urban Water Demand Management." *Journal of Environmental Management* 114, 343-351.

Foster, B. and S. Mazur Stommen (2012). *Results from Recent Real-Time Feedback.* Research Report JM-2012-23-02. American Council for an Energy-Efficient Economy.

Froehlich, J., L. Findlater and J. Landay (2010). "The Design of Eco-Feedback Technology." In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. Ed. by E. Mynatt. IEEE Pervasive Computing 8. New York: USA, p1999.

Gardner, G. T. and P. C. Stern (2008). "The Short List: The Most Effective Actions U.S. Households Can Take to Curb Climate Change." *Environment* 50, 12-23.

Gilbert, B. and J. S. G. Zivin (2013). "Dynamic Salience with Intermittent Billing: Evidence from Smart Electricity Meters." *Journal of Economic Behavior and Organization* 107, 176-190

Hargreaves, T., M. Nye and J. Burgess (2013). "Keeping Energy Visible? Exploring How Householders Interact with Feedback from Smart Energy Monitors in the Longer Term." *Energy Policy* 52, 126-134.

Hsu, C., M. Lee and C. Su (2013). "The Role of Privacy Protection in Healthcare Information Systems Adoption." *Journal of Medical Systems* 37 (5), 1-12.

Kappel, K. and T. Grechenig (2009). "'Show-Me': Water Consumption at a Glance to Promote Water Conservation in the Shower." In: *Proceedings of the 4th International Conference on Persuasive Technology.* Ed. by. S. Chatterjee. Persuasive '09. New York: USA, p. 1.

Kowatsch, T., F. Wahle, A. Filler, F. Kehr, D. Volland, S. Haug, G. Jenny, G. Bauer and E. Fleisch (2015). "Towards Short-Term Detection of Job Strain in Knowledge Workers with a Minimal-Invasive Information System Service: Theoretical Foundation and Experimental Design." In: *Proceeding of the European Conference on Information Systems 2015*. Research-in-Progress Paper. Münster: Germany.

Kuznetsov, S. and E. Paulos (2010). "UpStream: Motivating Water Conservation with Low-Cost Water Flow Sensing and Persuasive Displays." In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems.* Applied Energy, 83. New York: USA, p. 1851.

Lai, I. and D. Lai (2014). "User acceptance of mobile commerce: an empirical study in Macau." *International Journal of Systems Science* 45 (6), 1321-1331.

Lally, P. and B. Gardner (2013). "Promoting Habit Formation." *Health Psychology Review* 7 (sup1), S137-S158.

Lapillonne, B., K. Pollier and N. Samci (2014). *Energy Efficiency Trends for Households in the EU.* Technical Report. JM-2015-05. Enerdata Research & Consulting Company.

Laschke, M., M. Hassenzahl, S. Diefenbach and M. Tippkaemper (2011). "With a Little Help from a Friend: A Shower Calendar to Save Water." In: *Proceeding of the CHI 2011 Conference on Human Factors in Computing*. Extended Abstracts on Human Factors in Computing Systems. Vancouver: Canada, p. 633.

Lehto, T., H. Oinas-Kukkonen, T. Pätiälä and O. Saarelma (2013). "Virtual Health Coaching for Consumers: A Persuasive Systems Design Perspective." *International Journal of Networking and Virtual Organisations* 13 (1), 24-41.

Levitt, S. D. and J. A., List (2011). "Was There Really a Hawthorne Effect at the Hawthorne Plant? An Analysis of the Original Illumination Experiments." *American Economic Journal: Applied Economics* 3 (1), 224-238.

McKerracher, C. and J. Torriti (2013). "Energy Consumption Feedback in Perspective: Integrating Australian Data to Meta-Analyses on in-Home Displays." *Energy Efficiency* 6 (2), 387-405.

Melville, N. (2010). "Information Systems Innovation for Environmental Sustainability." *Management Information Systems Quarterly* 34 (1), 1-21.

Michel, A., S. Attali and E. Bush (2015). *Energy efficiency of White Goods in Europe: monitoring the* *market with sales data*. URL: http://www.topten.eu/uploads/File/WhiteGoods_in_Europe_June15.pdf (visiton on 04/05/2016).

Naderi, I. (2011). "Green Behavior: Concern for the Self or Others." In: *Proceedings of AMA Summer Educators' Conference*. Chicago: USA, p.163.

Pajares, F., and T.C. Urdan (2006). *Self-efficacy Beliefs of Adolescents*. Greenwich: IAP.

Premkumar G. and A. Bhattacherjee (2008). "Explaining information technology usage: A test of competing models." *Omega* 36 (1), 64-75.

Prochaska, J. and C. Diclemente (1986). *Toward a Comprehensive Model of Change.* 1st Edition. New York: Philadelphia.

Raw, G., D. Ross and AECOM (2011). *Energy Demand Research Project: Final Analysis - AECOM.* 2.2nd Edition. Hertfordshire: Brazilian Computer Society.

Ronis, D. L., J. F. Yates and J. P. Kirscht (1989). "Attitudes, Decision, and Habits as Determinants of Repeated Behaviour." *Attitude Structure and Function* 3, 213-240.

Schleich, J., M. Klobasa, S. Goelz and M. Brunner (2013). "Effects of Feedback on Residential Electricity Demand - Findings from a Field Trial in Austria." *Energy Policy* 61, 1097-1106.

Taber, C. (2012). *Difference in Differences*. Lecture at the University of Wisconsin-Madison, February 01. URL: http://www.ssc.wisc.edu/~ctaber/742/diffdiff.pdf (visited on 04/04/2016).

Tasic, V., V. Tiefenbeck, S. Schöb and T. Staake (2015). „Short-term Spark or Sustained Impact? Investigating the Long-term Effect of Real-time Feedback." In: *Proceeding of the European Conference on Information Systems 2015*. Research-in-Progress Paper. Münster: Germany.

Tavoni, A. and S. Levin (2014). "Managing the Climate Commons at the Nexus of Ecology, Behaviour and Economics." *Nature Climate Change* 4 (12), 1057-1063.

Tiefenbeck, V. (2014). "Behavioral Interventions to Reduce Residential Energy and Water Consumption: Impact, Mechanism, and Side Effects." PhD thesis. ETH Zurich.

U.S. Department of Energy (2012). *Buildings Energy Data Book.* Maryland: Silver Spring.

UN News Centre (2014). *Tackling Water, Sanitation, Energy Nexus Key to Sustainable Future – UN Officials.* URL:http://www.un.org/apps/news/story.asp?NewsID=47165#.VvP1s5MrK89/ (visited on 05/01/2015)

van Dam, S. S., C. A. Bakker and J. D. M. van Hal (2010). "Home Energy Monitors: Impact over the Medium-Term." *Building Research & Information, Special Section: Transition Pathways to a Low Carbon Economy* 38 (5), 458-469.

van Rensburg, L. (2008). *Energy Demand Research Project: Review of Progress for Period 04/2008 – 08/2008.* Technical Report JM-2009-27-03. The Office of Gas and Electricity Markets.

Venkatesh, V., F. Davis and M. G. Morris (2007). "Dead Or Alive? The Development, Trajectory And Future Of Technology Adoption Research." *Journal of the Association for Information Systems* 8(4), 267-286.

Venkatesh, V., J. Y. L. Thong and X. Xu (2012). "Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology." *Journal of Social Issues* 36(1), 157-178.

Whittaker, R., H. McRobbie, C. Bullen, R. Borland, A. Rodgers and Y. Gu (2012). *"*Mobile Phone-Based Interventions for Smoking Cessation.*"* *Sao Paulo Medical Journal* 128(2), 106-107.

Willis, R. M., R. A. Stewart, K. Panuwatwanich, S. Jones and A. Kyriakides (2010). "Alarming Visual Display Monitors Affecting Shower End Use Water and Energy Conservation in Australian Residential Households." *Resources, Conservation and Recycling* 54 (12), 1117-1127.