# Digitalization of Consumer Behavior – A Descriptive Analysis of Energy Use in the Shower

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**Abstract:** In order to develop effective technology- or behavior-based energy conservation measures, it is necessary to quantify the impact of consumer behavior and to understand what drives the variance in individuals' energy consumption. While sensors and communication technologies are becoming more and more ubiquitous, surprisingly little data is still available on many aspects of consumer behavior in the energy sector. Water heating is the second largest energy use in households – yet, data on hot water consumption and on factors influencing the variance in that domain is particularly scarce. We analyze a smart meter data set comprising 5,610 individual showers. We find that the average shower consumes 43.9 liters of water and 2.60 kWh heat energy. The high observed variance in consumption values within and between households suggests a large potential for energy savings. Furthermore, we investigate correlations between energy use and consumer characteristics (sociodemographic factors and environmental attitudes).

**Keywords:** Shower data, descriptive analysis, energy consumption, hot water, smart meter

## 1 Motivation and Context

In modern societies, a life without energy in unimaginable. Today's energy demand is mainly covered by fossil fuels. This drives environmental (e.g., carbon emissions) and geopolitical problems (e.g., energy security). Domestic emissions in the US and the UK accounts for about third of national emissions [BN08, GS08]; in Switzerland households consume 26,5% of total energy use [Sc14]. The international community of governments, companies and other organizations therefore pursue energy efficiency targets. Despite enormous investments in smart grid and smart metering infrastructure, most consumers still have a poor understanding of effective strategies for energy conservation [At14].

A particularly large domestic energy use is hot water consumption: With 18% of energy demand of private US households and 13% for European households, respectively

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[Re13, De13], it is the second largest domestic energy use after space heating. Yet, the majority of consumers are unaware of the large amount of energy contained in hot water. In fact, most people do not associate showering with energy consumption. Consequently, we expect a high saving potential for hot water consumption. Yet, before we evaluate energy efficiency means from technical and behavioral viewpoints, we first need to quantify the energy consumption associated with that behavior, gauge the variance in that behavior, and understand how humans consume hot water.

With decreasing prices for sensors measuring the full set of circumstances (e.g., GPS location, altimeter, aerial carbon dioxide) tracking one's life gets easier. Recently, a Swiss startup developed a smart meter for the shower that tracks hot water consumption with the help of a temperature and a flowrate sensor. In that way, hot water consumption data is gathered on a disaggregated level and allows a better understanding of the yet unexplored energy end use showering.

This paper analyzes such a shower data set comprising of 5,610 data points collected in 636 Swiss households in 2012. We study resource consumption in the shower by examining the consumption variables water volume, water temperature, flowrate, shower time and consumed energy. We observe variance patterns within and between households and analyze consumption for differences in age, gender, and attitude towards the environment.

Giving insights into human shower behavior based on the worldwide first large-scaled shower data set accesses one more domestic resource use which could not have been explained so far. Yet, we have to stress that all findings are based on our particular data and that this paper is in every respect descriptive. Please note that other articles based on the same data have been published so far; parts of the methodology section therefore correspond to our previous work [Ti16]. In the following we describe our methodology and present our results before we discuss their implications.

## 2 Study Design, Data Collection and Sample

We conducted a large-scale field study in cooperation with a local utility that gave the study device (smart shower meter) as a gift (unconditional of participating in our study) to 5,000 customers. Among these, 1- and 2-person households who agreed to answer two surveys and to make their shower data available to the researchers were eligible for the energy efficiency study with a limitation of 700 participating households (due to budget and logistic reasons). The purpose of the surveys was to get demographical data as well as the participant's attitude towards the environment. For the estimation of the latter, we used a scale provided in previous literature [Di07] 10 items (measured on 5-point Likert scales) assess individuals' level of environmental concern. In the following two months of winter 2012/ 2013, study participants installed the smart meters in their showers. The technology tracks all water extractions with the help of a flowrate and a temperature sensor and stores the data on the internal memory. At the end of the study, participants sent in their devices in order to have them manually read out before they were returned to the participants for good. The course of study was split into two periods: the baseline period which tracks shower behavior without of any contrived researcher interference (first ten tracked showers on the device) and the intervention period in which participants are provided with real-time information on their resource use (from shower eleven on). During the baseline period the smart meter displayed only temperature; we therefore limited the baseline period to ten showers per household in order to not bore the study participants. Later on in the intervention phase water and energy consumption, temperature and an energy efficiency class were shown. This paper first provides a descriptive analysis of the baseline data in order to give insights into human shower behavior[4] and then tried to explain variance in shower behavior with the help of demographics.

Overall, we collected survey and shower data from 636 Swiss households located in the region of Zurich. In total, we analyze shower behavior of 975 individuals, 50% of which are female. The mean age of study participants is 46.3 years with a standard derivation of 15.6 years. Regarding attitude toward the environment, our sample reflects well the Swiss society with a mean of 3.61 (SD=.46) compared to the mean score provided by Diekmann et al. (2009) of 3.64. The smart meter data comprises flowrate, temperature, shower time and volume of a total of more than 46’000 showers. Energy consumption is calculated using the standard engineering formula for heat energy ($E = m * cp * \Delta T / \eta$ , with heat energy E, mass of water m, heat capacity cp, $\Delta T$ the difference between the measured water temperature and cold water temperature, and $\eta$ the coefficient of energy efficiency. The latter depends on the type and age of the heating system. A study for the Swiss Office of Energy [De13] gives a detailed breakdown of residential water heating systems for Switzerland. The vast majority use fossil fuels (40% oil, 25% electric resistance heaters, 21% gas), with an average conversion efficiency of 65%. As mentioned in the previous section, baseline showers only (up to ten showers) are considered in this paper. Water extractions of below 4.5 liters are not considered a shower. With this we ensure that water extractions for cleaning or watering the plants will not distort average consumption values. Data points with more than 200 liters per shower or an average temperature of above 47°C were excluded as extreme outliers or measurement errors (85 showers). Furthermore, we discarded the first data point of every dataset, as its temperature and volume distribution strongly deviated from all other showers recorded. We assume that in many cases, the first water extraction was not an actual shower; instead, participants who had just completed the installation turned on the water for several seconds to see if the device worked and what information it displays. In all, this leaves us with up to nine data point per household for our data analysis (N = 5,610).

[4] We will not further discuss capabilities of the technology and the study period intervention. The energy savings – the main purpose of the study – are not subject of this paper but are discussed in other articles [Ti16].

## 3 Results

In a first step, we examine frequency distributions of the five dependent variables average temperature of a shower (in C°), water consumption (in liters), energy use (in kWh), flowrate (in liters per minute) and shower time (in minutes). Fig. 1 presents a visualization.

As can be seen in Fig. 1 the frequency distributions of temperature and flowrate are close to the normal distribution whereas resource consumption (water and energy) and shower time are skewed to the right. This pattern indicates that more people take quick showers than long excessive showers. Tab. 1 provides the descriptive statistics mean, standard derivation, minimum and maximum. In addition, we provide descriptive data of the best (lower 20%) and least performing participant groups (upper 20%) such as variances of variables within and between households.

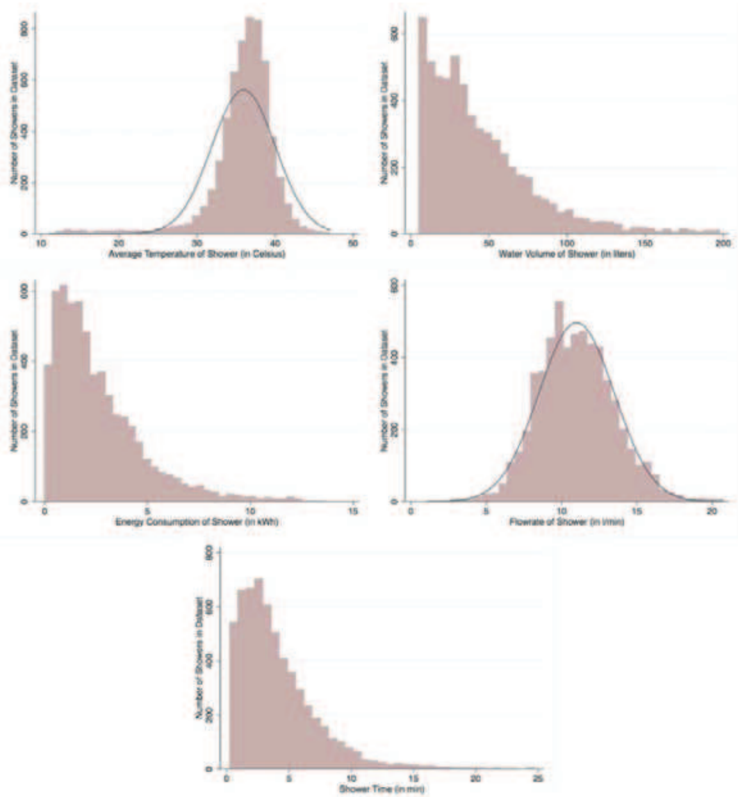


Fig. 1: Frequencies of Showers regarding Flowrate, Average Temperature, Water Consumption, Energy Consumption, and Shower Time

Tab. 1 shows that the average individual consumes 43.9 liters of hot water at a temperature of 36 C° when showering. This corresponds to 4 minutes showering at a flowrate of 11 liters per minute and to 2.60 kWh of energy to heat the water. We find a high variance in shower behavior: the bottom quintile of our sample use approximately 10 liters per shower, whereas the top quintile (upper 20%) use 100 liters, respectively. Tab. 1 further provides information on variances in shower behavior between and within households. N refers to the total number of considered showers and n to the number of households; T-bar is the average number of showers per household. For non-parametric variables we observe negative values as the within number refers to the deviation from each household's average. While between and within values for behavior related variables (water, energy, temperature and shower time) do not vary much; we find for the technical variable flowrate that variance within household is remarkably lower than between households. This shows that individuals are exposed to a rather predefined flowrate by their shower and are free to adapt the shower behavior (water consumption and temperature) to their individual comfort needs.

| | | *Mean* | *SD* | *Min* | *Max* | *Observations* |
|---|---|---|---|---|---|---|
| *Average Temperature (in C°)* | Overall | 36.0 | 4.09 | 11.0 | 47.0 | N = 5610 |
| | Lower 20% | 30.0 | 4.94 | 11.0 | 33.5 | N = 1075 |
| | Upper 20% | 39.9 | 1.47 | 38.5 | 47.0 | N = 1442 |
| | Between | | 2.68 | 18.6 | 43.1 | n = 636 |
| | Within | | 3.11 | 10.4 | 50.3 | T-bar = 8.82 |
| *Water Consumption (in liters)* | Overall | 43.9 | 33.7 | 5.00 | 198 | N = 5610 |
| | Lower 20% | 9.92 | 3.29 | 5.00 | 15.0 | N = 1060 |
| | Upper 20% | 97.6 | 30.1 | 66.0 | 198 | N = 1140 |
| | Between | | 24.9 | 8.33 | 152 | n = 636 |
| | Within | | 23.3 | -82.1 | 178 | T-bar = 8.82 |
| *Energy Consumption (in kWh)* | Overall | 2.60 | 2.15 | 0.00 | 13.6 | N = 5610 |
| | Lower 20% | 0.50 | 0.23 | 0.00 | 0.87 | N = 1122 |
| | Upper 20% | 6.05 | 1.98 | 3.98 | 13.6 | N = 1123 |
| | Between | | 1.60 | 0.16 | 9.23 | n = 636 |
| | Within | | 1.48 | -5.16 | 12.1 | T-bar = 8.82 |
| *Flowrate* | Overall | 11.0 | 2.52 | 1.07 | 20.7 | N = 5583 |
| *(in l/min)* | Lower 20% | 7.67 | 1.14 | 1.07 | 8.88 | N = 1108 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Upper 20% | 14.7 | 1.41 | 13.1 | 20.7 | N = 1118 |
| | Between | | 2.34 | 3.19 | 20.0 | n = 633 |
| | Within | | 0.98 | 4.56 | 16.9 | T-bar = 8.82 |
| *Shower Time (in minutes)* | Overall | 4.04 | 3.04 | 0.27 | 24.7 | N = 5583 |
| | Lower 20% | 0.98 | 0.36 | 0.27 | 1.58 | N = 1111 |
| | Upper 20% | 8.84 | 2.82 | 6.03 | 24.7 | N = 1124 |
| | Between | | 2.16 | 0.87 | 14.0 | n = 633 |
| | Within | | 2.16 | -6.75 | 18.5 | T-bar = 8.82 |

Tab. 1: Descriptive Shower Data and Analysis of Variance Within and Between Households

In a next step, we investigate the correlation of the five shower variables (temperature, water consumption, energy consumption, flowrate and shower time) with the explanatory variables age, gender, and attitude toward environment of study participants. Tab. 2 presents pairwise correlation coefficients along with their significance level. As energy use is a product of water consumption, shower time and temperature, these values are obviously highly correlated. Apart from this, we find all correlations to be under the threshold of .7, which makes multicollinearity issues in the later introduced regression model very unlikely [Do13]. We conjecture that discriminant validity is assured meaning that all variables measure different contents.

In a next analysis step we investigate whether demographics and attitude towards the environment are able to predict shower behavior. Tab. 3 presents regression estimation for all five dependent variables. For each, we list regression coefficients, their significances, the explanatory potential $R^2$, and the total number of showers considered N. The independent variables are coded as follows: age in years, fraction of females in household with 0 for men only and 1 for women only, and attitude towards the environment from 1= low to 5=high. Independent variables were mean-centered for interpreting regression output correctly.

| | *Temp.* | *Water* | *Energy* | *Flowr.* | *Time* | *Age* | *Fem.* | *Env.* |
|---|---|---|---|---|---|---|---|---|
| *Temperature* | 1 | | | | | | | |
| *Water* | .37*** | 1 | | | | | | |
| *Energy* | .44*** | .99*** | 1 | | | | | |
| *Flowrate* | -.02 | .22*** | .20*** | 1 | | | | |
| *Shower Time* | .40*** | .93*** | .93*** | -.08*** | 1 | | | |
| *Age* | -.22*** | -.24*** | -.26*** | .05* | -.26*** | 1 | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| *Females* | .03* | -.04** | -.03** | .00 | -.04** | .08*** | 1 | |
| *Environment* | -.03** | -.13*** | -.13*** | -.11*** | -.09*** | .14*** | .04** | 1 |

*** p<.01 ** p<.05 * p<.1

Tab. 2: Pairwise Correlations of Dependent and Independent Variables

| | | *DV* | | | | |
|---|---|---|---|---|---|---|
| | | *Temperature* | *Water* | *Energy* | *Flowrate* | *Shower Time* |
| *IV* | *Age* | -0.702*** | -5.868*** | -0.406*** | 0.124*** | -0.598*** |
| | *Females* | 0.452*** | -1.204 | -0.043 | -0.027 | -0.158 |
| | *Environment* | -0.025 | -7.795*** | -0.479*** | -0.668*** | -0.411*** |
| | *Constant* | 35.983*** | 43.784*** | 2.588*** | 10.998*** | 4.037*** |
| | $R^2$ | .049 | .068 | .076 | .017 | .074 |
| | *N* | 5117 | 5117 | 5117 | 5099 | 5099 |

*** p<0.01

Tab. 3: Regression Coefficients of Shower Data Explained by Age, Fraction of Females in Households, and Attitude Toward Environment

Age significantly determines shower behavior: Except for flowrate, age impacts all outcome variables negatively. Even though young peoples' flowrates are significantly lower, they shower longer and warmer and hence need more resources. On average, a 25-year old individual uses 3.54 kWh per shower while a 57-year old individual only needs 2.10 kWh per shower. In general, women shower significantly warmer than men. Yet, this does not influence shower consumption concerning used water and energy significantly. Attitude toward the environment does not impact the temperature of the water used, but, in fact, has an effect on shower time and consumed resources. The higher it is, the shorter are showers and less water and energy is consumed. Despite of the fact that these independent variables significantly explain variance of the outcome variables, the $R^2$ values indicate that their explanatory potential is relatively low: only up to 7.6% of variance (here: energy consumption) can be explained with the help of age, gender, and attitude towards the environment. We conjecture that yet-to-be-determined other factors explain shower behavior to a better degree.

## 4 Discussion

This paper presents the first analysis of shower data collected in a large-scaled field study. On average, a shower in our study needs 43.9 liters per shower accounting for 2.60 kWh. Increasing age and attitude toward the environment positively influence resource use in the shower: An increase by age of 10 years reduces the energy use by 0.41 kWh and an increase in attitude toward environment by 1 point (measured on a 5-point Likert scale) cuts energy use by 0.48 kWh. Analyzing the data regarding gender differences does not impact energy consumption. From the variance in measured variables, we conjecture that shower behavior is quite diverse and certainly leaves a huge potential for energy saving. Having confirmed this, research can now identify effective means to decrease energy consumption in the shower. This can be either realized by efficiency means (e.g., energy-saving shower heads) or curtailment (e.g., intervening in human behavior with real-time feedback).

The findings presented in this work are subject to two limitations. First, we have to take a Hawthorne effect into account, which might come with the smart meters being installed in the participants' showers. People might feel observed and might have therefore adapted their shower behavior accordingly because they knew that someone will analyze the collected data afterwards [MT13, Sc13]. When analyzing energy savings, the study design should always include a control group for the reason of Hawthorne effects. One can assume that consumption might be even higher than presented in our data. Second, most parts of this paper are descriptive in every respect and all findings are based on an opt-in sample of Swiss residents. The generalizability and scalability of the results have yet to be determined.

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