Center for Sustainable Energy Systems CSE

UNDERSTANDING THE IMPACT OF USER EFFORT ON ELECTRICITY FEEDBACK AND ENERGY SAVINGS
HARVARD BOTANICAL GARDENS STUDY

Final Report by:

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This document reports the results of an experimental study designed, developed, and executed by Janelle LaMarche, Olga Sachs, and Chris Giebe.

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1. Introduction

Residential energy consumption accounts for 22% of the United States' total energy demand (Ehrhardt-Martinez, et al., 2010). Despite trends of increasing electricity consumption, residential buildings are potential targets for substantial electricity savings (Dietz, et al., 2009). Given current policy trends and savings potential, models predict that residential, commercial, and industrial buildings could curb electricity consumption to an annual growth rate of 0.83% for 2008 to 2030, down from the current projected growth rate of 1.07% (Siddiqui, 2009). By giving immediate visibility to otherwise invisible consequences of consumption, feedback has been shown to be an effective method of promoting whole-home energy savings of between 4% and 12% (Ehrhardt-Martinez, et al., 2010). Despite the significant potential for savings in this area, numerous studies on energy feedback have shown that a key outstanding problem is how to maintain energy savings and user engagement over the long-term. Users need to stay personally motivated to keep interacting with the information (Fogg, 2009), and the novelty of a new technology often diminishes quickly after an initial period of effectiveness (LaMarche, et al., 2012). Therefore, even though initial energy savings may be found, they often decrease or disappear after a few months.

Fogg (2009) proposes a framework for behavior change that relies on three components: 1) *motivation*, the propensity to engage in a specific action, 2) *ability*, the technical and cognitive capacity to perform a specific action, and 3) *triggers* that facilitate and spark engagement. Behavioral change using triggers has been highly successful in the field of persuasive technology.

One type of trigger involves actively reminding participants with visual prompts. The current study evaluates how this type of alert impacts the effectiveness of electricity feedback, namely the level of user engagement and energy savings.[1] In this study, we empirically investigated this issue by allowing users to get their own feedback through a web portal, and providing some of these users with alerts about their consumption and reminders to access the web portal. This manipulated the amount of required effort to be informed about one's electricity usage.

The treatment group that received biweekly email alerts needed to exert less effort to obtain feedback about their energy consumption than the treatment group that received no alerts. In addition to providing the email group with electricity usage data, we expected the email alerts to act as triggers for energy saving behavior. The email condition required low user effort to obtain feedback, which should make it easier for participants to understand and reduce their energy consumption. Those in the non-email group, however, needed to be self-motivated to change their behavior. Without an external trigger, this group had to remember to access the web portal on their own, a more difficult task that required a higher level of user effort. Additionally, because the participants in this study did not pay for their own electricity, they were not economically motivated to conserve electricity. A third group had no access to their energy usage data, and, like the non-email group, they were not sent reminders about their consumption and feedback.

[1]Please note that although we refer to "energy" consumption in this report, we are only speaking about electricity usage. Other sources of energy, such as natural gas, were not tracked or analyzed in this study.

We hypothesized that participants who received energy feedback through regular alerts would be more successful in saving energy than the control participants and participants who only had access to the web portal. However, we were also interested in the initial period of interaction with web portal features and how interaction changed over time.

2. Experimental Design

Our independent variable was feedback type. The three levels of this variable were a pseudo-control group and two treatment groups. Both of the treatment groups had access to an online energy tracker, but only one group, the email group, was sent biweekly email alerts about their energy usage. The non-email group did not receive these alerts. The pseudo-control group had no access to energy feedback. A breakdown of the groups is shown in Table 1.

The pseudo-control group was not a true “control” because there was a selection bias: the treatment groups opted in to the study, while the control subjects had to opt out if they did not want to participate. Thus, the treatment population was self-selecting, and represents a group of people with different characteristics, whose energy usage behavior might be different from our pseudo-control group even without our manipulation of feedback type. For this reason, our analysis of the pseudo-control group is limited and should be considered a behavioral reference rather than a real “control” for the treatment groups.

The participants that made up the email and non-email groups were able to access a free energy monitoring web portal called myEragy. Both the email and non-email groups could use the website to see data on their energy use in real time, with 1-minute resolution. The pseudo-control group had no access to feedback on their electricity usage.

Those in the email group were also sent biweekly email alerts on their energy consumption (low user effort), while the participants in the non-email group did not receive feedback emails (high user effort). These emails reminded participants that their energy consumption was being tracked, provided feedback on their historical usage levels, and prompted users to check the myEragy portal for further information about their consumption.

Table 1. Details of the pseudo-control, email, and non-email groups.

	Email Group	Non-Email Group	Pseudo-Control Group
Characteristics of participants	These groups are composed of self-selected individuals who volunteered to participate in the study.		This group is composed of residents who did not opt out of the study.
Access to feedback	myEragy web portal Biweekly email alerts	myEragy web portal	None
User effort to obtain feedback	Low	High	N/A
Number of participants	22	22	58

The dependent variable in this study was weekly electricity usage (kWh), which was tracked for all three groups by eGauge home energy devices. The data acquisition technology and process are described in greater detail below. Interaction with the web portal was also tracked for the email and non-email groups.

3. Participants

Participants were temporary renters of 102 apartments in the Harvard Botanic Gardens apartment buildings. All residents are affiliated with Harvard University, as the Botanic Gardens residence is part of graduate and family housing at Harvard University. The Botanic Gardens residence[2] was built in 1949, with major renovations in 1993. The site comprises seven buildings in Cambridge, MA, with a total of 117 units ranging from one to three bedrooms.

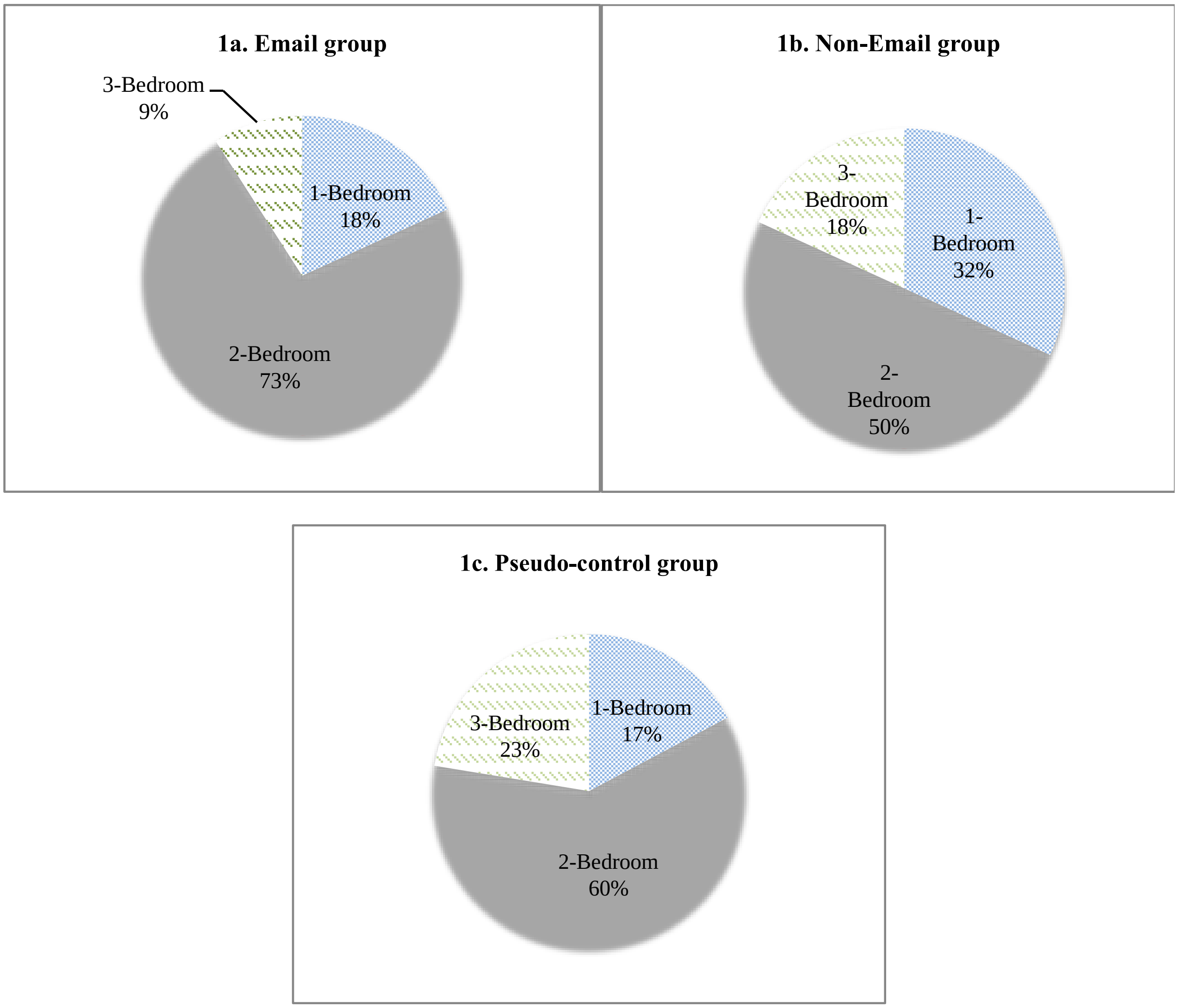
As part of the Building America effort, participants were recruited through Harvard University email services and fliers. Subjects for the treatment groups responded to recruitment on an opt-in basis, and pseudo-control subjects were acquired on an opt-out basis. After 2 units were excluded due to errors with the data and 1 participant left the study, 102 out of 117 units were included in the final data set.

Because participants opted in to the treatment groups, there is a selection bias in this sample. As explained above, those subjects who opted in to the study came from one self-selecting population, whereas the pseudo-control participants were from a population with different characteristics. The opt-in subjects were then randomly assigned to either the email or non-email group. Accordingly, the analysis on the differences between the two treatment groups is more robust than the differences between the treatment and pseudo-control groups.

In the final analysis, the email treatment group included a total of 22 subjects, with 4 one-bedroom, 16 two-bedroom, and 2 three-bedroom apartments. The non-email treatment group was composed of 22 units, with 7 one-bedroom, 11 two-bedroom, and 4 three-bedroom apartments. The pseudo-control group

[2] http://www.huhousing.harvard.edu/BotanicGardensMA/index.aspx

had 58 units, with 10 one-bedroom, 35 two-bedroom, and 13 three-bedroom apartments. The percentage breakdown of these groups is shown below, in Figures 1a-c.



Figures 1a-c. Types of units included in each group.

Tenants of the Botanic Gardens apartments do not pay electricity bills, and Harvard University requested that we omit cost-related energy feedback. This was an important challenge for our study because the participants did not have the usual economic motivation to conserve electricity. This study deepens our understanding of the motivations of user populations that are *not* driven primarily by energy cost savings, such as students in dormitories and hotel guests. While this factor is not representative of the average residential consumer, it allows us to better isolate the effectiveness of the feedback method itself, specifically the presentation medium and the amount of effort needed to access feedback.

4. Materials & Procedure

4.1. Data Acquisition Setup

We installed the *eGauge* energy monitoring system at the electrical mains in the seven buildings at the Botanic Gardens site. This system is compatible with a third party data-hosting site, *myEragy*. Harvard University RESNET provided network support. This setup is illustrated in Figure 2.

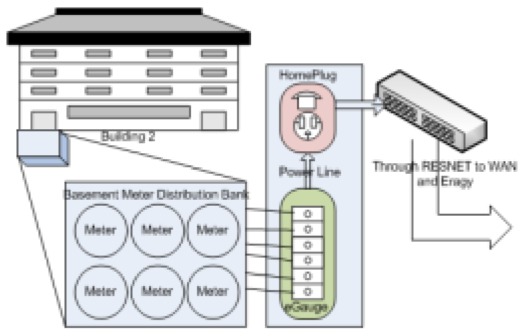


Figure 2. Data acquisition setup for Harvard Botanic Gardens.

EGauge is a web-based electric energy and power meter that measures both electricity consumption and generation on multiple circuits. The data can be viewed through the built-in web-server, or pushed to another server. The display is updated every second, allowing immediate feedback. The device, shown in Figure 3, records the most recent 30 years of data in its built-in solid-state memory.

Figure 3. eGauge data system. Image from www.egauge.net.

For this study, participants in the treatment groups accessed their electricity consumption data through the myEragy website[3]. The Eragy Web Portal is a software service that provides a display of energy use. As a web application, Eragy has remote spatial proximity to energy use behavior, and requires a medium effort to access information. The user is afforded a low degree of interactivity, and the interface is not customizable. Eragy offers a mid-level degree of actionability, providing the user with necessary information and some general tips for energy savings on a relatively low number of actions. This includes suggestions for reducing electricity use, but does not advise users on environmentally friendly actions in the realms of transportation or other resource consumption. Figure 4 is a screenshot of the myEragy dashboard. Please see the Appendix for additional ratings of the interface's characteristics.

The electricity consumption data is taken from the users' electricity meter, and can be viewed in 1-minute, 10-minute, hour, day, month, and year time spans on the Energy Usage tab, shown in Figure 5. Data is presented to the user graphically in a relatively complex fashion, and graphs provide specific measurements with mouse rollover. Energy consumption is measured in kilowatt-hours (kWh). Users are able to compare their energy use to their own past consumption.

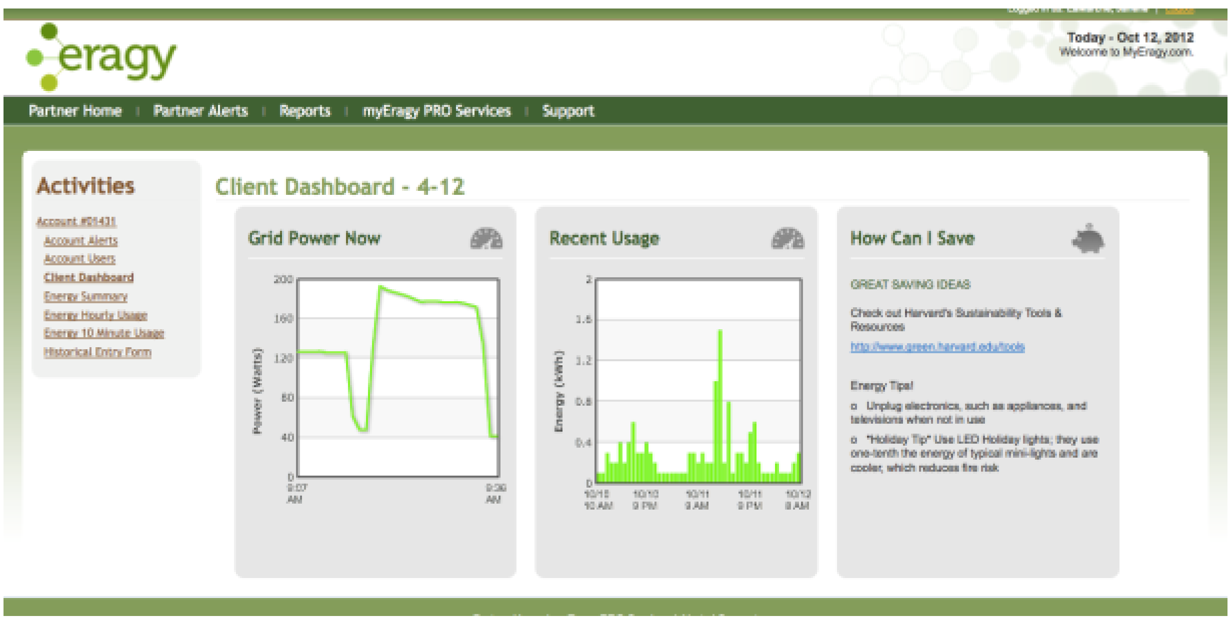


Figure 4. myEragy client dashboard, at www.myeragy.com. The client's dashboard page is a simple overview that shows total power, energy usage, and a client message. This message can be changed over time to incorporate monthly or seasonal tips.

[3] http://www.myeragy.com

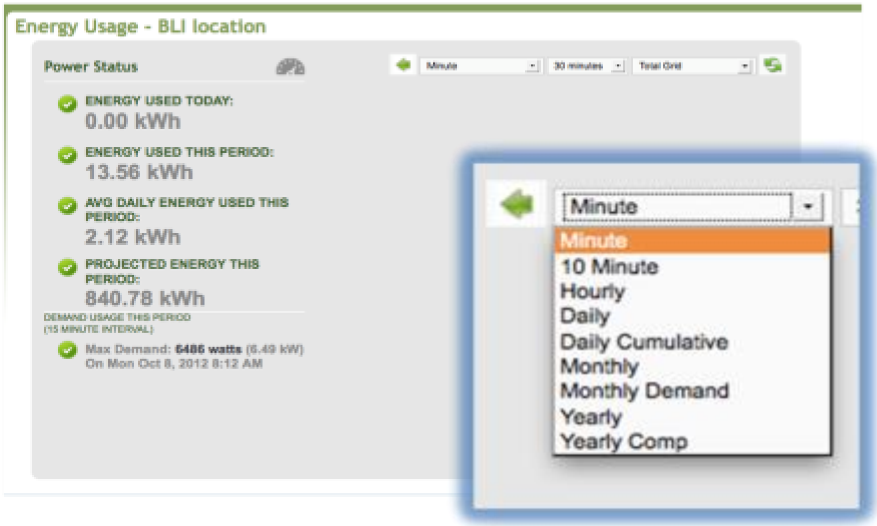


Figure 5. myEragy Energy Usage tab and detail of data resolution options, at www.myeragy.com. This energy tab allows clients to investigate their usage for different time periods. Depending on the resolution selected, the portal will display a bar graph or real-time data.

4.2. Procedure

Data were logged through posts to the Eragy website, with 1-minute resolution. The data acquisition team automated data transfer between Eragy and Fraunhofer, and sent data files to the energy management team at weekly intervals. These data were stored in a database and used as the basis for all data aggregations, visualizations, and analyses. Energy usage was tracked beginning October 1, 2012 and ending May 13, 2013. The experiment was set up over the first two weeks of October, between October 1 and October 15, so the data collected during this period were not analyzed; our analyses focus on the 30-week period beginning October 15.

At the beginning of the study period, all participants in the treatment groups received an initial email instructing them on how to log on to the myEragy website. The email group subsequently received biweekly email alerts that noted their average energy consumption for the past 2 weeks compared to the preceding 2-week period. It also reminded participants that they had access to the web portal, with a link to the website. Below is an example of the message sent to participants in the email group, through mid-January 2013:

> Dear Botanic Gardens Resident,
> From October 29 to November 12, your average weekly electricity consumption increased 3.3% when compared to the previous two weeks.
> Don't forget to log in to your myEragy energy tracker to get more information and tips on your own energy use!
> Thank you,

Beginning with the emails sent on January 22, the average weekly electricity usage was noted in kilowatt hours, along with the change in consumption:

> Dear Botanic Gardens Resident,
> From April 1 to April 15, you consumed an average of 32.82 kilowatt hours per week, as compared to 40.02 kilowatt hours per week for the previous two weeks. Your average weekly electricity consumption decreased 17.98%.
> Don't forget to log in to your myEragy energy tracker to get more information and tips on your own energy use!
> Thank you,

Non-email group participants received no information regarding their energy consumption unless they consulted the myEragy website. There was no option for non-email participants to set up email alerts from the myEragy portal.

In addition to energy usage data, we monitored participant interaction with the Eragy system, tracking the dates and frequency of login. In January, the middle of the academic year, an online survey was emailed to those participants who had visited the myEragy website at least once. It asked about participants' experience with the Eragy energy tracker, and further asked participants in the email group for their opinions on the email reminders. Feedback from the survey prompted the additional electricity consumption information (kWh) being added to the emails.

4.3. Analyses

We collected data on the average power for each apartment in a given week, which was then converted to Kilowatt-Hours (multiplying by 168 hours - 1 week and dividing by 1000) to give the total energy consumed during that week.

These data were then standardized for the number of bedrooms in each apartment, and averaged for each group. This was done to account for the unequal distribution of apartment sizes in each group, shown in Figures 1a-c. Standardization gave us 30 data points for each group, given in Table 2, which were used in the initial analyses. The average electricity usage, before standardization, can be seen in Figure 6.

Because electricity consumption may not increase proportionally with the number of bedrooms in an apartment, we studied the relationship using a multi-linear regression model, introducing the number of rooms as a categorical variable. This was done to ensure we were not introducing a confound into the analysis by standardizing the data according to the number of bedrooms. With R_{adj}^2 of 0.644, the multi-linear regression model shows that although the weekly consumption is not entirely explained by the number of rooms in each apartment, an increase in the number of rooms significantly affects overall electricity consumption. See the Appendix for more information on this regression model. Because of the selection bias distinguishing the treatment group from the pseudo-control group, we first used a Mann-Whitney test to compare the distribution of electricity usage between the email and non-email groups. Afterwards, we compared the consumption of the email, non-email, and pseudo-control groups using a one-way analysis of variance (ANOVA). Using the standardized data, we analyzed all three groups (the email, non-email, and pseudo-control), to determine whether their electricity consumption differed. We further analyzed the consumption of the two treatment groups to examine the effects of the email alert. The pseudo-control was not included in this second set of analyses.

Few participants interacted with the myEragy website and fewer responded to the survey. Our analysis of this data is qualitative in nature because there were not enough survey responses or interaction data to perform a statistically meaningful analysis. However, this information is interesting to consider in conjunction with the electricity consumption data.

Table 2. Average weekly electricity consumption per bedroom (kWh/week).

	Email Group	**Non-Email Group**	**Pseudo-Control Group**
Week 1	26.90	25.80	30.29
Week 2	27.41	26.17	30.55
Week 3	30.09	25.00	31.49
Week 4	34.33	24.72	34.93
Week 5	30.77	25.74	33.94
Week 6	30.69	25.10	32.77
Week 7	34.99	29.54	36.96
Week 8	33.24	29.57	35.23
Week 9	31.16	28.80	36.57
Week 10	34.35	28.28	33.84
Week 11	29.90	27.09	28.84
Week 12	32.92	27.99	33.15
Week 13	31.70	26.24	33.30
Week 14	31.49	27.08	34.90
Week 15	36.82	34.37	42.01
Week 16	34.64	33.40	38.25
Week 17	41.48	36.04	41.54
Week 18	34.84	33.24	36.37
Week 19	37.49	33.92	39.01
Week 20	34.11	28.65	34.90
Week 21	34.63	30.37	33.45
Week 22	30.66	27.28	29.99
Week 23	38.25	26.11	28.21
Week 24	30.30	28.07	29.68
Week 25	31.09	27.96	27.02
Week 26	29.10	27.50	26.87
Week 27	28.80	27.35	26.60
Week 28	27.44	27.92	26.14
Week 29	25.66	25.39	24.26
Week 30	23.77	28.03	24.49

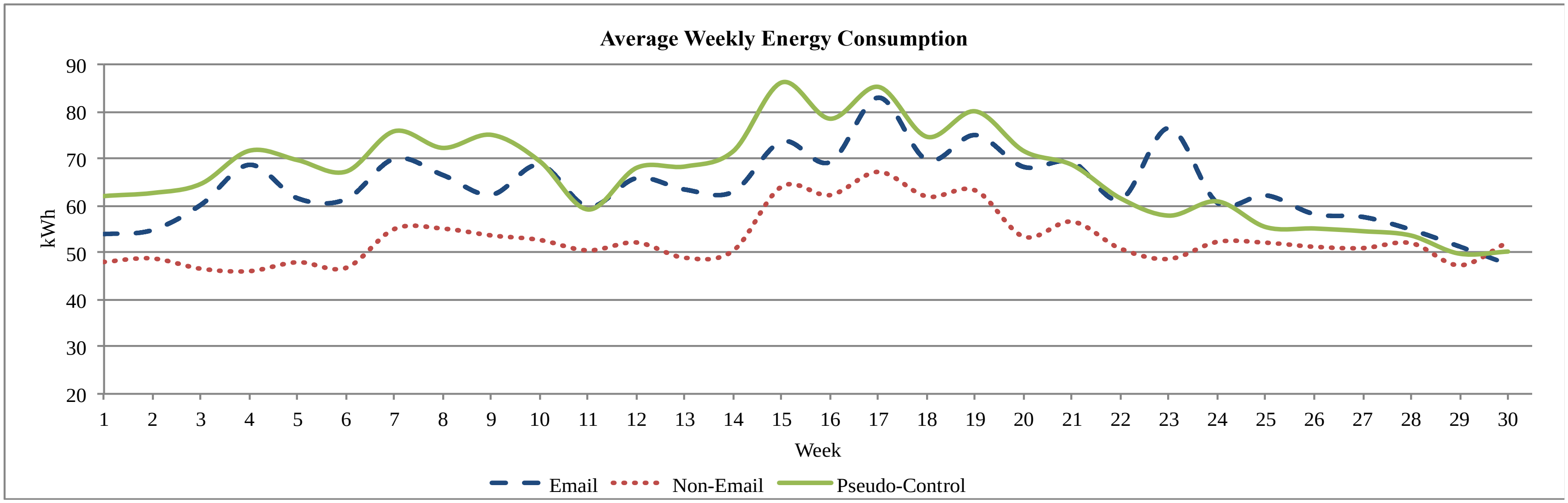


Figure 6. Average weekly electricity usage by group. This graph shows the amount of energy (kWh) used by an average unit in each group. The data shown are not standardized to account for differences in apartment sizes. For the final analysis, we used the standardized data in Table 2.

5. Results

5.1. Understanding the significance of the treatment on the experimental groups

This section to understand the significance if we can statistically prove The null hypothesis, that the average difference between the groups is the same after treatment, indicating that the treatment has no significant impact.

1) The alternative hypothesis, that the application of a treatment actually does produce a difference between the averages of the two groups.

Inferential statistics show that there is a significant difference between the groups, and therefore we reject the null hypothesis. The next step is to test whether this difference happened by chance, or in other words we will evaluate the likelihood of a Type II Error[4]. The statistical measures that evaluate the likelihood of these errors are effect size and power. The effect size measures the strength of the phenomenon. In post hoc analysis, the effect size is calculated from the observed data, and it estimates the magnitude of the difference between sample means. For ANOVA designs, Cohen (1988) proposed the following scale to evaluate the magnitude of an effect, f (Eq. 1).

[4] Concluding that there is an effect when an effect is not truly present is known as a Type II error.

Table 3. Cohen's scale

Effect size (f)	Description
0.10	Small
0.25	Medium
0.40	Large

$$\text{Eq. 1: } f = \sqrt{\frac{\left(\frac{|\bar{x}_1 - \bar{x}_2|}{\sqrt{\frac{\sigma_1^2 + \sigma_2^2}{2}}}\right)^2}{2k}}$$

where f = effect size; $\bar{x}_n$ = average of level n; σ_n^2 = variance of level n; and k = number of groups or levels.

Power is the likelihood that we have correctly concluded there is a significant result, when there is a real difference present. A power analysis requires an estimate of non-concentrality (λ), which is the effect size multiplied by a sample size factor.

Here we present the results of post hoc calculations of the effect size and the power achieved by our study. As shown in Table 4 below, our study has a large effect size (f = 0.45) and high power of 93%, so we are unlikely to be making a Type II error.

Table 4. Results of power and effect size calculations for the interaction between the email and non-email groups.

	Value	Description
f (effect size)	0.45	Large
Alpha error probability (α)	0.05	
Non-concentrality parameter (λ)	12.43	
Critical F	4	
Numerator df	1	
Denominator df	58	
Power (1 - β)	0.93	High power

5.2. Electricity Usage—Treatment Groups

First, we analyzed the email and non-email groups, both from the same self-selecting population. The means and standard deviations for all three groups can be seen in Table 5.

Table 5. Descriptive statistics for the email, non-email, and control groups (kWh/bedroom/week).

		Email	Non-Email	Pseudo-control
N		30	30	30
Mean		31.97	28.42	32.52
Median		31.32	27.94	27.94
Std. Deviation		3.91	3.00	4.75
Std. Error		0.71	0.55	0.87
95% Confidence Interval for Mean	*Lower Bound*	30.51	27.30	30.75
	Upper Bound	33.43	29.54	34.29
Minimum		23.77	24.72	24.26
Maximum		41.48	36.04	42.01
Range		17.70	11.32	17.75

Levene's test for equality of variances for the email and non-email groups was not significant, $F(1, 58) = 2.42$, $p = .125$. The significance level is greater than .05, so the variances are not different enough to have been drawn from two separate populations; the email and non-email groups likely come from similar populations.

To determine whether the difference in usage was significant, we performed a Mann-Whitney Test. The null hypothesis states that the distribution of energy consumption is the same across the email and non-email groups, and the alternative hypothesis is that the distribution of energy consumption differs across the two groups. This test showed a significant difference between the email and non-email groups, $U = 199$, $p < .001$, $r = -.48$. The distribution of electricity usage levels for the email group (*Mdn.* = 31.32) was significantly higher than that of the non-email group (*Mdn.* = 27.94). The distributions of the two groups are different enough that this result most likely did not occur by chance, and the difference between the email and non-email groups is due to our manipulation of feedback type. The results in Tables 6 below are for the Mann-Whitney Test.

Table 6. Table of ranks for Mann-Whitney test on the email and non-email groups. The Mann-Whitney test ranks all data points in ascending order, regardless of group (lowest value = 1, next lowest value = 2, etc.). Separated back into their respective groups, the ranks are then added and averaged, giving the Sum of Ranks and Mean Rank above. Higher ranks indicate greater electricity consumption. The email group had significantly higher electricity usage than the non-email group, $p < .001$.

	Treatment Type	N	Mean Rank	Sum of Ranks
kWh / Bedroom	Email	30	38.87	1166
	Non-Email	30	22.13	664

5.3. Electricity Usage—All Groups

In a further analysis, we tested for differences between the two treatment groups and the pseudo-control group. For descriptive statistics of the pseudo-control group, see Table 5. It is important to remember that there was a selection bias for establishing the treatment and pseudo-control groups, with the treatment groups being self-selected. Therefore, any similarities or differences found by the ANOVA below reflect behavioral outcomes only, and do not imply that the treatment subjects and pseudo-control subjects come from the same or different populations.

To perform a one-way ANOVA between the three groups, we first tested for homogeneity of variances. The results of Levene's test on the three groups were significant, $F(2, 87) = 3.79$, $p = .026$, indicating that the population variances might not be equal. Consequently, the assumption of homogeneity of variances has been violated and we report Welch's *F*, which adjusts for this violation. The one-way ANOVA showed that there was a significant difference between at least two of the groups, *Welch's* $F(2, 55.99) = 11.73$, $p < .001$.

For our post hoc analysis, we used the Games-Howell procedure to determine which of the groups were different from the others. This procedure accounts for differences in variance and sample size between groups.

Table 7. Games-Howell post hoc comparisons. The non-email group is significantly different from both the email and control groups, but the email and control groups are not significantly different from each other.

Group	Mean	Mean Difference ($\overline{X}_i - \overline{X}_j$)		
		Email	Non-Email	Pseudo-Control
Email	31.97	--		
Non-Email	28.42	3.54 ($p < .001$)	--	
Pseudo-control	32.52	-.55 ($p = .9$, n.s.)	-4.10 ($p < .001$)	--

The post hoc comparisons in Table 7 indicated that the energy consumption of the non-email group ($M = 28.42$, $SD = 3.00$) was significantly lower than the consumption of both the email group ($M = 31.97$, $SD = 3.91$) and pseudo-control group ($M = 32.52$, $SD = 4.75$). Interestingly, although the email group's consumption was slightly lower than that of the pseudo-control group, the email and pseudo-control groups were not significantly different from one another.

5.4. Web Portal Interaction

Of the participants with access to the myEragy web portal, 9 from the non-email group and 9 from the email group ever logged into the website, while 13 from each group never logged in. Since the number of participants interacting with the Eragy tracker was the same for both groups, it seems that the email alerts did not encourage more subjects to track their energy consumption on the website.

Most users accessed the website 5 or fewer times, with 2 participants logging on more frequently. Both of these frequent users were in the non-email group, logging in 9 and 14 times respectively.

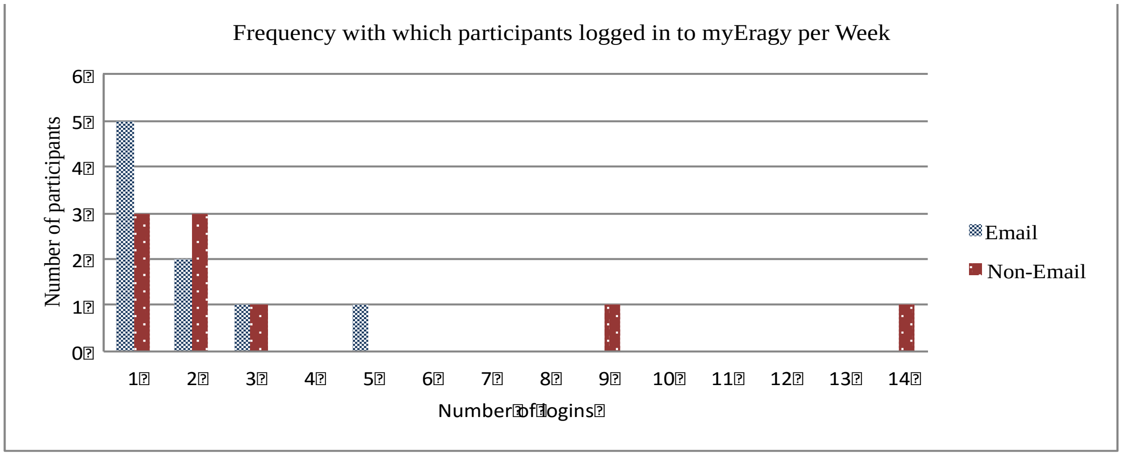


Figure 7. Frequency with which participants logged in to myEragy portal.

Although participants had access to the Eragy energy tracker for the duration of the study, which ran until mid-May, the last visit to the website occurred on January 27, 2013. In Figure 8 below, the vertical gray lines correspond to the dates when email alerts were sent to the email group.

A large proportion of the logins occurred within the first 5 days of website access, with 35% of all email group logins and 46% of all non-email group logins occurring during this period. Excluding these initial visits, email group participants logged in more often on days when email alerts were sent out, or the day after the alerts were sent. Between October 20, 2012, and the end of the study, 7 of 11 total logins for the email group were on the day of or day after an alert, while only 4 of 19 logins occurred on these same dates for the non-email group. However, never more than 2 email group subjects logged in on any given day. From this, it seems that although the email alerts acted as triggers for the email group to log into the myEragy portal, this was not more effective than just giving participants access to the website. Additionally, it did not keep the email group engaged longer, as both groups stopped visiting the website by the end of January.

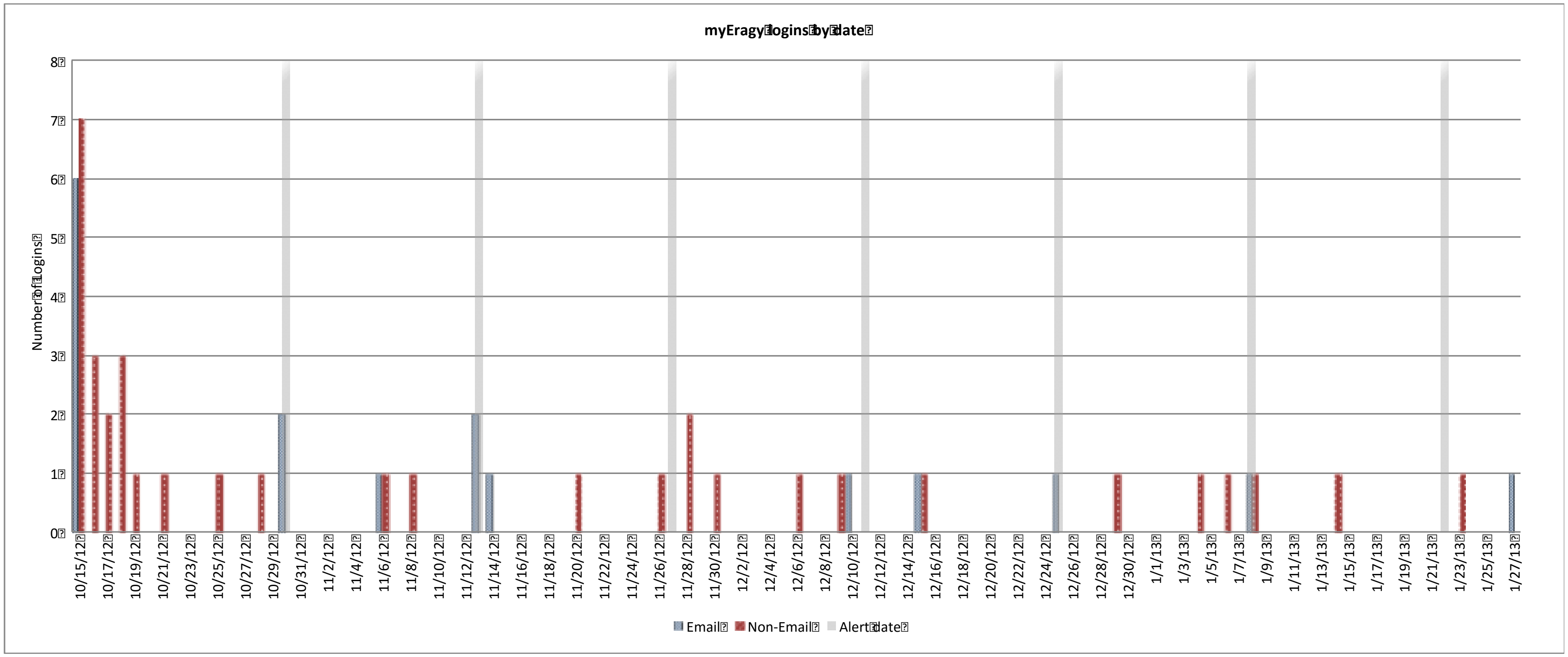


Figure 8. Unique logins to the myEragy web portal during the study period, by date. The vertical gray bars indicate dates when feedback was sent to the email group.

5.5. Survey

Seven participants from the email group and 4 participants from the non-email group completed the online survey administered in January. The survey was only sent to those 18 participants who had logged in to the Eragy website at least once.

Although there were not enough respondents for this to be statistically significant, 6 of the 7 email respondents thought the myEragy energy tracker was useful, while 3 of 4 non-email participants thought it was *not* useful. Similarly, 5 of 7 people from the email group thought that the Eragy tracker was helping them to save money, but none of the non-email participants thought it was doing so. This is an interesting response from the email group, since none of the participants paid for electricity themselves, regardless of how much they used; electricity and other utilities were covered by Harvard University Housing.

In answer to a free response question, one participant from the email group stated, “I don't really log on to the tracker site, so the emails are the only consistent way I pay attention.” This would suggest that instead of acting as a trigger for action, the emails provided awareness without necessitating any action on the part of the participant.

6. Conclusions & Discussion

The group of participants who received biweekly emails about their electricity consumption used more electricity than the group who did not receive these emails. Both groups had access to the myEragy online energy tracker, but the same number of participants from each group accessed it, usually 5 or fewer times in the 7-month period of the study. Additionally, the email group did not differ significantly from the pseudo-control group, while the non-email group used significantly less electricity per week than either the email group or the pseudo-control group.

These results are somewhat contrary to our initial expectations. We hypothesized that the email alerts would facilitate energy savings by decreasing the effort it took to track consumption, and keep participants engaged with the Eragy tracker for a longer period of time. However, the email group consistently used more electricity, and did not use the energy tracker more frequently than the non-email group. The email alerts did make it easier to keep track of energy consumption, but did not lead to energy savings. In fact, the email group’s level of electricity usage was much closer to that of the pseudo-control group, which had no access to feedback, than it was to the non-email group.

One potential explanation for this outcome is that it might be necessary to require a certain level of user effort in order to successfully motivate the more difficult behavior of decreasing energy usage. People want to act consistently with previous decisions, so that smaller initial requests often increase compliance with larger subsequent requests (Freedman & Fraser, 1966). All participants in the treatment groups agreed to have their energy usage tracked, and to get feedback on their consumption. To remain consistent with this decision, the non-email group needed to exercise a certain amount of effort to acquire feedback—that is, they had to be self-motivated enough to log onto the website. Once they were already doing this small action of interacting with the energy tracker, they may have been more willing to elevate their commitment to saving energy and actually reduce their energy use. For the email group, however, the biweekly emails provided feedback without any action on the part of the subjects. The email group's extra consciousness of their electricity consumption could have been enough for them to feel consistent with their decision to participate in the study and save energy, without actually changing their behavior. This is corroborated by the survey respondent who said that they relied on the email alerts to monitor their consumption, and did not interact with the Eragy tracker.

The email alerts did not act as effective triggers, as we had intended. Although email participants who used the website generally did so after receiving an email alert, this only seems to have affected *when* the email group logged on, rather than how often. However, this conclusion is speculative because of the overall low level of interaction with the myEragy website. The email alerts also did not trigger the intended difference in electricity consumption, possibly because given the level of information provided by the emails, instead of acting as alerts, they could have acted as a replacement for consulting the website.

Additionally, the email participants who completed the survey had the impression that the Eragy website was helping them to save money, even though they were not responsible for paying the electric bills. However, from our analysis of the usage levels of the three groups, it appears that the email group was closer to the pseudo-control group than the non-email group in their electricity consumption. The email group, from the self-selecting participants, came from a different base population than the pseudo-control group, and differed in terms of exposure to our intervention. Despite these differences, the two groups ended up using similar amounts of electricity. Logically, the non-email group should be the one that is more similar to the pseudo-control group, since neither of them received automatic feedback alerts. As argued above, we speculate that this may be due to the extremely low user effort required of the email participants, cancelling out the differences in participant selection and energy feedback.

A limitation of this study is the lack of a baseline for electricity consumption for each group, before the beginning of our intervention, and a true control group. Without a baseline measurement or a true control group, it is difficult to determine how much the email and non-email groups increased or decreased their electricity consumption as a result of the intervention.

Considering the limited interaction with the website, the Eragy web portal itself does not seem to have been particularly successful with our participants. The 2 non-email participants who visited the Eragy tracker most frequently would have been entirely self-motivated to do so. The email group, which was already getting alerts about their usage, did not have any incentive to log into the website more than the non-email group, if they logged in at all.

The visits stopped entirely by the end of January. It is probable that users lost interest in the website or forgot they had access to it, since most users only logged in a handful of times at the beginning of the study. It is also possible that non-email participants assumed the mid-year survey about the myEragy portal marked the end of the study, since they would not have received any further communication from the researchers to remind them of their continued access to myEragy[5]. For the email group, the last visit came only a few days after actual consumption data was added to the email alerts. This extra information may have rendered the myEragy website unnecessary for the email group.

Around the same time, the Botanic Gardens residence, as part of Harvard University Housing, may have seen a significant amount of turnover between the Fall and Spring semesters. It is possible that tenants left partway through the study, and may or may not have been replaced by a new tenant. We did not have access to this information, and could not incorporate it into the analysis.

Additionally, as stated earlier, the treatment groups are a self-selected population. They chose to participate in a study on energy consumption, and may have been more inclined to save energy in general. This inclination would be their only incentive to reduce electricity use, since they do not pay their own electricity bills. It is possible that with a different, bill-paying population, there would have been different results; wanting to "save energy" for its own sake may not be enough motivation.

6.1. Future Directions

To ensure that the email message acts as a trigger instead of a replacement for actively tracking electricity consumption, the alerts could offer more concrete suggestions, targeting simple behaviors instead of the complex, abstract concept of "energy savings". An example of a more concrete message would be sending a text message to the subject's phone before they would normally leave for work in the morning, telling them how much electricity they used last month and reminding them to turn the lights off while no one is home. This is more in line with Fogg's (2009) behavioral change model.

Another option would be to give participants a challenging energy-saving goal. Previous research has shown that feedback was effective in promoting energy savings when participants had a difficult goal of reducing energy use by 20%, while the group that had the easy goal of 2%, as well as the groups that received no feedback, did not differ significantly from a control group (Becker, 1978). Those participants were also given information about how much energy common household appliances use, providing them with concrete hints for reducing electricity consumption.

The web portal interaction might increase if the Eragy portal provided more content. People in this study seemed willing to try the website once, but did not continue to use it after their initial visits. In this case, there was no "novelty" effect where initially frequent usage declined after a period of time, because there was no interest in using the website from the majority of the participants. Thus, there was no energy monitoring behavior for the emails to help maintain.

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[5] A 2 x 2 ANOVA, excluding the data for Christmas week and spring break, showed that the non-email group's electricity usage for the Fall semester (M = 27.46, SD = 2.59), through the end of January, was slightly lower than the group's usage for the Spring semester (M = 29.65, SD = 3.19), although the difference was not significant, $F(1, 56) = 1.17$, $p = .285$. Some participants may have thought the study was over, and began using more electricity.The usage for the email group showed almost no difference, averaging 31.92 kWh per week in the Fall and 31.72 kWh per week in the Spring.

Although the email group in this study used more electricity, they were at least provided with information about their energy consumption, and a handful of participants actually felt like they were saving money. Among those who are not yet motivated to change their behavior, awareness of energy consumption could lead to action in the future.

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Appendix

Eragy Web Portal

Analysis of the Eragy feedback system informed by Froehlich (2009) feedback design parameters as well as an ontology of products that we created.

Sensing or Display	Display
Update Frequency	Real-time
Spatial Proximity To Behavior	Remote
Attentional Demand	Attentive
Effort To Access Information	Medium
Degree Of Interactivity	Low
Interface Customizability	Low
Webpage Manifestation	Yes
In-Home Display Manifestation	No
Ambience	Non-ambient
Display Size	Large
Degree Of Actionability	Med
Anomaly Alerts	Yes
Personalization	Low
Number of actions informed	Few
Sensing System-Data Source	Fully Automated
Data Granularity	House
Sampling Frequency	Real-time
Sensing Source	Full-Home
Pragmatic Data Representation	Yes
Data Storage Time Window	year
Temporal Grouping By Minute	Yes
Temporal Grouping By Hour	Yes
Temporal Grouping By Day	Yes
Temporal Grouping By Week	Yes
Temporal Grouping By Month	Yes
Temporal Grouping≥Year	Yes
Data Granularity House	Yes
Visual Complexity	Complex
Primary Visual Encoding	Graphical
Resource Measurement	Yes
Cost Measurement	Yes
Primary View-Time-Series	Yes
Data Grouping By Time	Yes

Private Data	Yes
Social Data Sharing	Household
Comparison Target-Self	Available
Comparison Target-Past	Available
Comparison Value-Absolute	Available
Existing Values	1
Framing	1
Feed Forward	2

Multilinear regression model

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.808[a]	.653	.644	8.40064	.653	78.910	2	84	.000	.511

a. Predictors: (Constant), Dumm2, Dumm1

b. Dependent Variable: AvekWh

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	Constant	70.960	1.560		45.488	.000	67.858	74.062		
	Dumm1	-26.221	2.206	-.883	-11.886	.000	-30.608	-21.834	.750	1.333
	Dumm2	-5.339	2.206	-.180	-2.420	.018	-9.726	-.952	.750	1.333

a. Dependent Variable: AvekWh