One Size Does Not Fit All: Establishing the Need for Targeted Eco-Feedback

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Abstract

Despite all improvements in buildings shell, equipment, and design, CO₂ emissions from buildings are increasing. Since occupants spend more than 87% of their time indoors, they are inseparable and significant elements of building system dynamics. Hence, there is a great potential for energy efficiency in buildings using a wide range of programs such as intervention and eco-feedback. Despite the high level of individual differences and intra-class variability of occupants' behaviors, the current state-of-the-art eco-feedback programs treat all the occupants uniformly and do not target and tailor the feedback. Therefore, it leaves an opportunity to increase the efficacy of eco-feedback systems through the designing of tailored and targeted programs. In this paper, we conducted a comprehensive analysis and tested hypotheses on occupants' behavioral responses to a normative comparison feedback program, in addition to the impact of notifications on the level of engagement of each group of occupants. We categorized occupants who participated in the normative comparison feedback program into three groups (i.e. low, medium, and high energy consumers) based on their baseline energy consumption, and tested 9 hypotheses. A mixed-effect regression model (MRM) and a paired t-test was implemented to evaluate the proposed hypotheses. The hypotheses examine the variability of occupants' responses under the same eco-feedback program, and the effectiveness of notifications on reinforcing occupants' engagement in these programs. The contribution of this paper is two-fold: (1) reporting that the effectiveness of the notifications in eco-feedback programs are initially highly dependent on the type and the nature of the program, and then the interval and the content of the notification, and (2) demonstrating the variability of occupants' behavioral responses under the same normative comparison eco-

feedback program. These findings indicate the need for a shift in focus toward targeted and tailored feedback programs which treat occupants based on their characteristics. Moreover, they highlight the need for eco-feedback design, development, testing and implementation research that acknowledges and addresses differences in occupant responses to feedback.

Keywords

Eco-feedback; Energy Efficiency; Historical Comparison; Normative Comparison; Occupant Behavior

1. Introduction

The building sector is accountable for almost 40% of energy-use in the US [1]. Despite all improvements in building shell, equipment, and design, there is still room for further improvement of building energy consumption. As major energy-use sources, such as HVAC and lighting systems, become more efficient, the share of miscellaneous energy consumption (e.g. plug loads) which are commonly controlled by building occupants increase. Thus, it calls for investigating potential occupant-based energy saving opportunities in buildings. Since occupants spend more than 87% of their time indoors [2], buildings can benefit from a wide range of programs such as intervention and eco-feedback.

Although occupants can be a potential contributing component of building energy efficiency, due to high intra-class variability, complexity, and uncertainty of their behaviors, finding an appropriate motivation, estimating their potential energy savings, and sustaining changes in behavior are challenging. The behavior targeted in such energy efficiency programs is environmentally significant behavior [3]. More precisely, a subcategory of environmentally significant behaviors referred to as private-sphere environmentalism behavior. This subcategory is defined as a type of behavior in the private sphere that is focused on purchase, use, and disposal of personal and household products and equipment which have environmental impact [3]. In the past decade, a fair body of literature has been shaped around this topic with the primary focus on residential occupants' energy efficiency, and only a secondary focus on the commercial sector. Despite the significant progress being made in the field of occupant energy efficiency across building types, existing developed programs treat occupants uniformly. Yet, we know that motivations, demographics, habits, working conditions, and many other characteristics of the occupants are considerably different. This discrepancy between the variability of occupants' characteristics and the fact that they are treated

uniformly is the point of departure for this paper. We examine the variability of occupants' responses to a uniform eco-feedback study.

In this paper, we build on a previous study [4] conducted in a 6 story commercial building located in Denver, CO, to examine the effect of occupants' energy saving responses to a real-time eco-feedback program launched at their work place. The occupants' energy consumption were monitored at a workstation-level using wireless smart meters and they were provided with normative and historical comparison feedback based on their randomly assigned study group. We ranked and divided the occupants that participated in a normative comparison group into three categories (i.e. high, medium, and low energy consumers) and implemented a mixed-effect regression model (MRM) approach to test multiple hypotheses regarding the variability of behavioral responses received from occupants who participated in a normative comparison feedback program. Furthermore, the level of engagement (i.e. logins to the system after receiving a notification) of occupants in each group was tested using a paired t-test in order to investigate the effectiveness of notifications sent throughout the study.

2. Related Work

There is a vast body of knowledge focused on occupants' energy efficiency in buildings. The majority of these efforts have been focused on residential buildings. Among a wide range of occupant-based energy efficiency programs, eco-feedback systems have been demonstrated to be among the more effective approaches. Thus, in this section, we provide a comprehensive literature review on the variety of eco-feedback programs implemented in commercial and residential buildings. First, we address the studies conducted in the residential sector with all psychological, computational, and design elements taken into account. Then, we review commercial building eco-feedback studies and discuss the existing gaps of knowledge in each area.

Eco-feedback studies in residential buildings can be categorized based on various characteristics. In this study, we have chosen to distinguish the studies based on their feedback resolution, psychological motivators, feedback methods, and the length of the experiments. Eco-feedback programs incorporate a wide range of feedback methods starting with the most conventional paper-based approaches [5, 6], to advanced computer-based feedback [7-11], and in-home display units [12-16]. The frequency and resolution of feedback is usually correlated with the level of technology incorporated in each program; however, one literature review conducted on eco-feedback systems [17] found frequent feedback along with digital presentation to be among the most important elements of such systems.

Allcott [5] conducted a comprehensive analysis on a massive dataset captured through Opower Inc. and reported that among monthly, bi-monthly, and quarterly feedback provided to occupants, quarterly feedback was the most effective frequency considering the cost-benefit analysis of the program. While the body of research is in favor of more frequent feedback provided to occupants, the cost-effectiveness analysis favors less frequent feedback.

Feedback studies in residential buildings have been conducted in a wide range of lengths and sample sizes. Naturally, the longer the length of the study and the larger the sample size, the more reliable the results. Thus, the studies can be divided broadly into two categories: short-term and long-term. Based on the literature, the short-term effect of eco-feedback studies are relatively stronger than the long-term effect, meaning that the energy savings are higher and occupants are more engaged in the beginning of the program [18]. In terms of occupants' engagement in the program measured by the number of logins to the online platforms, visiting in-home displays, and also responding to the notifications sent out during the study, the general trend supports the decay of engagement over time [19]. However, studies have shown that the engagement and savings diminish to an extent and reach a plateau at some point [18]. Moreover, it has been established that the number of visits to eco-feedback platforms are statistically correlated to the level of energy savings over time [7].

There are various psychological motivators implemented in the aforementioned studies to motivate occupants to sustainably save energy. Social norms [5, 10, 20-23], historical comparison [11, 13, 24-26], goal setting [12, 27, 28], and many other approaches have been implemented in studies to evaluate the effectiveness of each on inducing energy savings. The social norm (e.g. normative comparison) has been shown to be among the most effective approaches [6]. Despite the limited efforts on targeting utilities' customers [29, 30] and understanding the underlying correlations between occupants' behavior and their energy consumption [31, 32], these programs (e.g. normative comparison, historical comparison, etc.) treat all occupants uniformly regardless of their characteristics, demographic information, and habits, which may lead to weak response from a substantial group of occupants who are not motivated by a non-differentiated eco-feedback program. Unfortunately, the effect of non-differentiated feedback has not been employed to improve the engagement and motivation of all occupants in eco-feedback studies. A tailored and targeted energy efficiency program may enhance the efficacy of such programs. The literature measures the efficacy of the energy feedback studies with the primary scale of percentage of energy savings compared to the baseline, and a secondary scale of the level of engagement of occupants in the program [33, 34]. The level of engagement is measured based on the number of logins and the amount of time occupants spend in

energy feedback platforms understanding their energy consumption patterns and learning how to reduce their energy consumption.

Commercial sector eco-feedback programs differ from residential sector programs for several reasons. In the commercial sector (especially office buildings), the majority of occupants do not have direct financial incentives to save energy in the building [35]. Moreover, in office buildings, productivity is a major concern of all employees [36], thus introducing the challenging issue of a productivity, comfort, and energy efficiency trade-off in the workplace. Similar to residential buildings, there are studies incorporating various psychological motivators in commercial eco-feedback systems. Social norms, historical comparison, and goal setting are the most dominant. Nevertheless, we lack long-term eco-feedback studies in the commercial sector to determine the long-term energy efficiency potential of occupant conservation programs. In terms of feedback methods, the approaches vary from energy efficiency campaigns [35] to real-time feedback [37-40]. Despite one limited effort in providing personalized feedback in commercial buildings [41], none of the aforementioned studies differentiate occupants with respect to their responses.

Considering the high intra-class variability in occupants' characteristics such as perception of energy consumption and information [42, 43], understanding of feedback content [44, 45], knowledge of energy efficiency [42, 46], attitude [31], awareness of energy consumption [47, 48], literacy [48, 49], motivation [50], demographics [32, 42], social and economic information [50-52], habits, and work schedules, it is surprising that eco-feedback studies conducted in the residential and commercial sectors have not examined these differences and incorporated them to provide occupants with various psychological motivators, tailored feedback information, and personalized feedback frequency to enhance the efficacy of current energy efficiency programs.

In this paper, we take initial steps to examine whether non-differentiated feedback is effective. We examined three study groups: an organizational feedback group (i.e. received normative comparison feedback), an individual feedback group (i.e. received only individual feedback), and a control group (i.e. received no feedback) and monitored them for a period of three months. We then examined the occupant responses and reaction to normative comparison feedback provided in the course of the study. Moreover, we conducted a complementary analysis on statistical significance of the response rates (i.e. number of logins) to the notifications sent throughout the study, regardless of the energy savings obtained after each notification. In other words, we segregate the effect of

notifications on energy savings from the logins to the platform. A mixed-effect regression model (MRM) was implemented along with a paired *t*-test for the sake of evaluation.

3. Methodology

Workstation energy consumption was collected using wireless smart meters. The workstation appliances were not identical, however, desktop computers or laptops, desk lamps, and, in some cases, printers were the most common appliances. All appliances were connected to a power strip and the power strip energy data was captured through commercially available wireless plug load monitoring sensors. Each group of plug load monitors, depending on the location, communicate via 900 MHz RF signal with a central router that uploads the data to our database through an Ethernet connection. Please refer to [40] for further information regarding the infrastructure of our experiment. Occupants' interactions with an online platform, "BizWatts" [40], was monitored by capturing the date and duration of the logins, along with the clickstreams on the website. In order to create the group variables, we categorized occupants assigned to the normative comparison groups based on their energy consumption in the baseline period into three quantiles. Therefore, we have five groups in total: historical comparison (i.e. the group receiving historical comparison feedback where their energy consumption was compared to their historical energy use), normative comparison (i.e. the group receiving normative comparison feedback where their energy consumption was compared to their peers), and three subgroups (i.e. low, medium, and high energy consumers) extracted from the normative comparison group based on their baseline performance. The low energy consumers baseline energy consumption ranged from 98 KWh to 203 KWh with a mean of 151 KWh. The medium energy consumption varied between 203 KWh to 464 KWh, with a mean of 263 KWh. The high energy consumers used between 264KWh to 1038 KWh with a mean of 644 KWh. These two pieces of information enabled us to conduct a comprehensive analysis on occupants' response to a normative comparison study, in addition to a thorough analysis on notification impact on occupants' engagement in the study. The methodology section is divided into two parts. The first addresses the mixed-effect regression model used to analyze the variability of responses received from occupants based on their performance in the normative comparison feedback group. The second section explains the methodology used to test the response rates to each notification sent out during the study as a reminder to reinforce occupants' participation in the program.

3.1. Normative Comparison Response Analysis

Traditional longitudinal data analysis methods (e.g. ANOVA and MANOVA) are of limited use in our case due to the underlying assumptions regarding missing data across time, and the variance-covariance structure of the repeated measures [53]. To study the change of behavior in the normative comparison feedback group, we implemented a mixed-effect regression model to model the difference of log-transformed energy consumption before and after the baseline. There are several characteristics that make MRMs a more compelling approach in this study. First, since time is treated as a continuous variable, subjects are not required to be measured on the same number of data points [53]. Second, in order to capture any potential deviations of the subjects from the general trend, MRM can estimate the change for each subject [53]. And finally, MRM is capable of capturing the potential existing within-subject correlations.

Energy-use data was transformed into log scale because it did not have symmetry in the original scale. To control for the individual differences that might affect the trend over the length of the study, we calculated the average of baseline usage for each participant. To model the nonlinear energy behavior trajectory across time, we considered linear and/or quadratic time effects as fixed effects. Higher orders of time effect are not considered because of the small sample size. A group variable was included in the model to examine the effect on energy changes. The interactions between the group variable and time effects were also considered in the model. We included linear and/or quadratic random time effects to capture the possible variation in the rates of change across individuals. That is, we assumed that each individual can have a different pattern of energy-use over the study period. Equation (1) represents the final model chosen among all various combinations of variables, effects, and orders described above. The Akaike Information Criterion (AIC) [54, 55], which is a relative measure of statistical model quality, was used to select an appropriate model. The selected model includes linear, quadratic time effects and group variable as fixed effects, along with linear, quadratic random time effects. The interactions between the group variable and time effects are not statistically significant. All the analyses were performed in SAS 9.3.

$$y_{ij} = \beta_0 + \beta_1 \text{Week}_{ij} + \beta_2 \text{Week}_{ij}^2 + \beta_3 \text{Group}_i + v_{0i} + v_{1i} \text{Week}_{ij} + v_{2i} \text{Week}_{ij}^2 + \varepsilon_{ij} , \quad (1)$$

where y_{ij} is the log of average energy usage at week j for subject i minus the baseline usage, $Week_{ij}$ takes values in $\{1, \dots, 10\}$, and $\varepsilon_{ij} \sim N(0, \sigma^2)$. Here $i = 1, \dots, 75$ (number of subjects), $j = 1, \dots, n_i$ (number of weeks).

Because we used the control group as a reference group in the model, the interpretation of the model parameters is as follows:

- β_0 : average week 0 response (difference in log transformation of energy-use) for control group
- β_1 : average weekly linear change for control group
- β_2 : average weekly quadratic change for control group
- β_3 : average week 0 response change difference between groups
- v_{0i} : individual deviation from average intercept
- v_{1i} : individual deviation from average linear change
- v_{2i} : individual deviation from average quadratic change.

We calculate the variation of energy consumption for each group with respect to the baseline to further evaluate the effect of the eco-feedback program on the study groups. To do so, the following four hypotheses are formulated:

- Hypothesis 1: Low energy consumers in the normative comparison group changed their behavior statistically after the study was launched.
- Hypothesis 2: Medium energy consumers in the normative comparison group changed their behavior statistically after the study was launched.
- Hypothesis 3: High energy consumers in the normative comparison group changed their behavior statistically after the study was launched.
- Hypothesis 4: The historical comparison group occupants changed their behavior statistically after the study was launched.

The corresponding p-values for each hypothesis are provided in section 4.1 which determine the rejection of null hypotheses.

3.2. Notification Impact Analysis

In order to evaluate the statistical significance of notifications' impact on occupants' engagement in our eco-feedback platform, we categorized occupants based on the eco-feedback program they participated in. There are a total number of 5 notifications sent in the period of 69 days with an uneven interval between notifications. In order to assess the impact of notifications on occupants' engagement in the programs, we chose a three day window based on [19] recommendation to have a time window longer than weekends, and also to consider the possibility of delays in checking the emails (i.e. notifications). Thus, we summed up the number of logins three days prior and after each notification was sent (excluding the day notification was provided) and implemented a Kolmogorov-Smirnov hypothesis test [56] to check the normality of the data. Since our data is normally distributed, a paired t-test method was used to test the hypotheses proposed below to assess the effectiveness of notifications in engaging occupants in our study. Moreover, the average logins prior to and after each notification was calculated to investigate the variation of engagement levels among various groups.

- Hypothesis 5: The normative comparison group's engagement level changed statistically after receiving each notification.
- Hypothesis 6: The historical comparison group's engagement level changed statistically after receiving each notification.
- Hypothesis 7: The normative comparison group's low energy consumers' engagement level changed statistically after receiving a notification.
- Hypothesis 8: The normative comparison group's medium energy consumers' engagement level changed statistically after receiving a notification.
- Hypothesis 9: The normative comparison group's high energy consumers' engagement level changed statistically after receiving a notification.

Fig 1 illustrates all occupants' logins during the study. The number of logins are distinguished by colors as labeled in the color bar. There were 82 total logins to the system with an average 0.75 logins per person for the historical comparison group, and an average 2.34 logins per person for the normative comparison group. The notification dates

are represented with arrows at the bottom of the figure, and occupants are categorized based on their groups on the left side (the numbers on the Y-axis represent the range of subject/occupants IDs).

Figure 1. Surface plot of daily logins

In the following section, we report the results obtained from our MRM analysis, evaluate the p-values calculated for each hypotheses proposed in this section, and discuss the implications of our findings.

4. Results and Discussion

The results obtained from the aforementioned analyses are reported in two separate sections, following the methodology structure. Section 4.1 addresses the hypotheses designed to test the occupants' responses to the normative comparison feedback based on their baseline energy consumption in the group. While, section 4.2 reports the results obtained for the five hypotheses designed to test the effectiveness of notifications in engaging individuals in the program in each group.

4.1. Normative Comparison Response Analysis

As described in section 3.1, we implemented SAS 9.3 to fit various MRMs with fixed and random linear/polynomial time effects in this study. After performing a log transformation on the weekly energy consumption data, the best model was chosen using the lowest AIC [54, 55]. The selected model includes linear, quadratic time effects and group variable as fixed effects, along with linear, quadratic random time effects. The p-values are reported for evaluating the hypotheses proposed in section 3.1. Table 1 includes the results for each study group's energy-use behavior compared to the control group with respect to the baseline.

Table 1. Occupants' behavior change results compared to control group during the eco-feedback study

Groups	Energy Consumption Level	p-value	Energy Variation
Normative Comparison	High	0.1066	-10.5%
	Medium	0.0930*	1.2%
	Low	0.0191**	-2.5%
Historical Comparison		0.1720	-3.8%

*0.05 < p-value ≤ 0.1, marginally significant

**p-value ≤ 0.05, significant

The p-values obtained for each hypothesis assess the level of energy-use change with respect to the control group. In the normative comparison group, the medium energy consumers results marginally (i.e. $0.05 < \text{p-value} \leq 0.1$) reject the null hypothesis 2. It has to be noted that unexpectedly, the level of energy consumption was increased with respect to the baseline for medium energy consumers. The low energy consumers results statistically (i.e. $\text{p-value} \leq 0.05$) reject the null hypothesis 1, while decreasing the level of energy consumption compared to the baseline period, implicating the effectiveness of normative comparison eco-feedback programs on low energy consumers. This finding contradicts the previous works published in the field of residential sector normative comparison feedback systems reporting the potential existence of a boomerang effect [5]. On the other hand, there is not enough evidence to reject the null hypothesis for high energy consumers in the same group. The historical comparison group, did not show a statistically significant change of behavior compared to both their baseline and the control group. Thus, we

could not find enough evidence to reject the other null hypotheses 3 and 4. In summary, the statistical status of the proposed hypotheses are as follows:

- Hypothesis 1: Low energy consumers in the normative comparison group statistically changed their behavior after the study was launched.
 - Null hypothesis statistically *rejected*, energy consumption *decreased*.
- Hypothesis 2: Medium energy consumers in the normative comparison group statistically changed their behavior after the study was launched.
 - Null hypothesis marginally *rejected*, energy consumption *increased*.
- Hypothesis 3: High energy consumers in the normative comparison group statistically changed their behavior after the study was launched.
 - Null hypothesis is *not rejected*, energy consumption decreased.
- Hypothesis 4: The historical comparison group occupants statistically changed their behavior after the study was launched.
 - Null hypothesis is *not rejected*, energy consumption decreased.

The obtained results support our conjecture that responses to a uniform eco-feedback program by various groups categorized based on their energy consumption vary. If different energy consumption level groups respond differently to the same feedback, then it suggests we may need targeted and tailored approaches to induce energy savings in all categories of occupants regardless of their behavioral and characteristic differences.

4.2. Notification Impact Analysis

In this study, we recorded the duration and dates of logins made into the eco-feedback system for each user. 5 notifications were sent with 7 to 21 day intervals in-between as reminders to reinforce users' engagement in the program. Since all of our groups passed the Kolmogorov-Smirnov normality test, we implemented a paired t-test to evaluate the aforementioned hypotheses in section 3.2. Table 2(a) demonstrates all p-values obtained for each group, for each notification, while Table 2(b) demonstrates the engagement variations averaged over three days prior to and after each notification.

Table 2. Occupants' engagement results during the eco-feedback program after each notification

(a)

Study Groups		Notification Dates				
		May 7 th	May 14 th	May 27 th	June 17 th	June 30 th
Normative Comparison Group	p-values	0.0533*	0.0090**	0.0304**	0.3282	0.0829*
Historical Comparison Group		0.3388	0.1661	0.3388	0.3388	NAN

*0.05 < p-value ≤ 0.1, marginally significant

**p-value ≤ 0.05, significant

(b)

Study Groups		Notification Dates				
		May 7 th	May 14 th	May 27 th	June 17 th	June 30 th
Normative Comparison Group	Engagement Variations	+0.48*	+0.43**	+0.26**	-0.09	+0.13*
Historical Comparison Group		+0.08	+0.17	+0.25	+0.08	0

*0.05 < p-value ≤ 0.1, marginally significant

**p-value ≤ 0.05, significant

The p-values obtained for the normative comparison group provides relatively strong evidence to reject null hypothesis 5. More specifically, when looking at the entire normative comparison study group, in 4 out of 5 notifications, the results marginally or significantly support the effect of notifications sent out during the study in increasing the level of engagement of the occupants in the program. Moreover, the average number of logins per person in these 4 instances increased after each notification compared to the previous 3 days. However, due to an uneven distribution of the intervals between notifications, the fourth notification did not statistically change the level of engagement and a decreasing trend in the level of engagement was observed for two potential reasons. First, the

delay between the 3rd and the 4th notification is close to 3 weeks which is the longest lag in this study. Furthermore, referring to Fig 1, it could be observed that some occupants returned to the eco-feedback platform 1-2 weeks before they received any notifications from us, suggesting a potential periodic performance observation behavior shaping among occupants. Some values are reported as NaNs in Table 2; that is a result of 0/0 p-value generated due to a zero variance obtained from having identical datasets in the *t*-test calculation, and implies the insignificance of the hypotheses test results. There is not enough evidence to reject the 6th null hypothesis. Thus, it suggests the lack of effectiveness of notifications sent out to the historical comparison group. In another attempt, we concatenated the responses to all five notifications sent out during the study for each group and subgroup, and conducted a paired *t*-test to evaluate the overall response to all five hypotheses proposed in section 3.2 regardless of their dates. Because of this, we restricted the constraint for significance to a p-value of less than 0.05. The results of statistical tests along with the average variation of engagement level in each group are provided in Table 3.

Table 3. Occupants' engagement results during the eco-feedback program for all notifications

Groups	Energy Consumption Level	All Notifications			
Normative Comparison Group	Low	p-values	0.0318**	Engagement Variation	+0.17
	Medium		0.0132**		+0.42
	High		0.0577		+0.13
	All		0.0003**		+0.24
Historical Comparison Group			0.0514		+0.12

***p-value ≤ 0.05, significant*

Table 3 demonstrates a strong support for rejecting null hypotheses designed for low and medium energy consumers in the normative comparison group and also all normative comparison participants as a single group (i.e. Hypotheses 5, 7, and 8), while the historical comparison group, and high energy consumers in the normative comparison group lack statistical support for rejecting the null hypotheses (i.e. Hypotheses 6 and 9). In other words, the overall effect on notifications sent in this study were stronger on the low and medium energy consumers in the normative

comparison group, while not being statistically effective on the high energy consumers. Furthermore, the normative comparison group (as a single unit) was encouraged by notifications to login to their accounts and check their energy consumption. On the other hand, the historical comparison group did not show a statistical change of behavior as a result of received notifications. In the following section, we discuss the limitations of our study and suggest the future venues of research.

5. Limitations & Future Research

There are a few limitations in this study which prevented us from further investigating the underlying causes of behavioral changes observed among occupants in the normative and historical comparison eco-feedback programs. First, there was no demographic information collected in order to find any potential correlations between energy saving patterns and occupants' characteristics. Second, the length of the study was only 69 days, which does not provide sufficient information to determine the potential decay of occupants' engagement and energy efficiency in the long-term. The number of occupants involved in this study was only 35. 12 employees participated in historical comparison feedback study, and 23 in the normative comparison. The limited number of sample data potentially increases the variance, while decreasing the reliability of the reported results. However, this sample was adequate to demonstrate the important variances in responses to and engagement with feedback across occupants.

As reported in this paper, occupants did not exhibit uniform behaviors, and even demonstrated different performance levels while being in the same study group (i.e. normative comparison feedback group). Therefore, it highlights a great opportunity to investigate the methods and effect of tailored and targeted eco-feedback systems which maximize the potential energy saving of each individual in buildings. The results suggest that targeted eco-feedback programs have a great potential to further improve the efficacy of energy efficiency programs through tailoring both the notifications and the psychological motivators applied to each individual. Furthermore, the feedback provided in previous studies/programs did not have any subject-oriented context or information, and did not consider individual schedules, duties, workstation appliances, and many other impacting elements. Therefore, it provides an opportunity to examine context-aware and timely feedback tailored based on each individual's characteristics in these programs in future research. Current literature suffers from a lack of understanding of feedback components that can effectively enhance energy efficiency in each targeted category of occupants. Therefore, future research should focus on identifying the root causes of occupant differences, and tailoring the

feedback using proper psychological motivators, effective representation, personalized information, and practical tips to further induce energy efficiency.

6. Conclusion

In this paper, we conducted a comprehensive analysis and hypothesis test on occupants' behavioral responses to normative comparison feedback programs, in addition to the impact of the notifications sent throughout the study on the level of engagement of each group of occupants. We categorized the occupants who participated in the normative comparison feedback program into three groups (i.e. low, medium, and high energy consumers) based on their baseline energy consumption, and tested 4 hypotheses to assess the existence of potential behavioral differences among occupants in response to a normative comparison eco-feedback study. The results reported a significant change of behavior for low energy consumers, while indicating a decrease in the level of energy consumption. The medium energy consumers did marginally change their behavior compared to the baseline, with an unexpected increase in the level of energy consumption. The implication of these results suggest the need for targeted and tailored eco-feedback, which treats individuals based on their behaviors, habits, characteristics, etc. Multiple hypotheses tests were conducted to investigate the effectiveness of the notifications sent during the study on occupants' engagement in the program (measured by the number of logins before and after each notification). The results support the positive and significant change of low and medium energy consumers' engagement in normative comparison feedback based on their responses to the notifications. However, the high energy consumers' engagement in normative comparison feedback did not significantly change under the influence of notifications. Moreover, when comparing the entire normative comparison group to the historical comparison group, the normative comparison group was statistically and positively affected by notifications while the historical comparison was not. To illustrate, the normative comparison group statistically responded to all notifications except the fourth one, whereas, the historical comparison group did not show any significant response to any of the notifications. The root cause of the lack of response to the fourth notification in the normative comparison group could be found in the longer interval between the third and fourth notifications. Furthermore, when concatenating the responses to all notifications, the statistical results further confirm the significance level of the normative comparison group's response to notifications, while the historical comparison group did not achieve a significant result.

The major implications of the aforementioned findings are two-fold. First, the results supporting the variability of behavioral responses under the same normative comparison program demonstrate the need for new venues of research in developing tailored and targeted energy efficiency programs in buildings. Second, the impact of notifications observed in this study initially emphasizes the importance of the nature of the program rather than the count and interval of the notifications. Though, the timing and the duration between the notifications can be an important factor as the 4th notification in this study did not receive significant response due to the potential longer interval. In conclusion, the contribution of this paper is in providing a comprehensive analysis on the effect of notifications on occupants' engagement with an eco-feedback system, and claiming that the effectiveness of the notifications are highly dependent on external factors. Furthermore, we provide insight on variability of occupants' response to similar normative comparison eco-feedback, which suggests that future research on eco-feedback design, development, implementation, and analysis acknowledge and address user differences and incorporate tailored feedback to enhance the efficacy of eco-feedback programs.

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