Effect of energy information provision on occupant’s behavior and energy consumption in public spaces

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Abstract. ‘Nudge’, which is a framework of altering people’s behaviour in a predictable way without large penalty or economic incentives, is applied to energy saving measures of buildings in several papers. However, most of them focus on energy saving in a private space such as home, and little research has been done for energy saving in a public space. In this research, field experiments were conducted with the aim of energy saving in a public space by offering information. Focusing on individual behavior in a public space, we provided information directly to an individual, not to a public. By using power taps and thermal sensors, the individual equipment electricity consumption during absence, which is considered as the amount of energy wasted, is calculated. The subjects were divided into three groups. Through the information provision, some people changed their behavior and reduced energy consumption by approximately 70%. Furthermore, it was found that those who originally consumed much energy even when absent might tend not to change behavior by receiving information. The results from this experiment will provide fresh insight into information provision such as data visualization for energy saving of a public space and be useful for life management of occupants.

1. Introduction
A method called ‘Nudge’, which is a framework to change people's behavior in a predictable way without large penalties or economic incentives, is used in the field of behavioral science [1]. There are several studies which have also applied this method to the energy conservation policy of the building and showed its effect.

Opower, which is a company that provide customer engagement platform for utilities in the United States, conducted a demonstration experiment to reduce electricity consumption by utilizing social normative messages comparing household electricity consumption with that of neighboring residents. It was estimated that this program reduced the electricity consumption of Opower customers by approximately 2% [2]. This reduction sustained over time for about a year [3]. Furthermore, it is reported that environmental nudges are most effective in relatively liberal communities and that targeted messaging may be more cost-effective than random assignment of information [4]. In addition, there is a systematic review of previous studies which showed empirical evidence on non-price interventions targeting energy conservation behavior of private households [5]. This concluded that interventions have the potential to significantly reduce energy consumption of private households, but that the size of effect vary enormously.
For an example in Japan, experiments using randomized controlled trials were conducted in order to investigate the effects of normative messages on motivational change for electricity conservation [6]. This revealed which types of respondents’ attributes, including personality traits, were most affected by normative messages provided.

In this way, the Nudge method is useful because it encourages behavior change of occupants in the building and brings about energy saving effect. However, most of the researches applied the Nudge method focused on the energy conservation in private spaces such as households. Few were conducted for the energy conservation in public spaces. One of the reasons is that in a public space there is no economic benefit even if people make efforts to save energy because they are not obliged to pay public utility charges. Therefore, energy conservation effect is not expected. However, electricity consumption in public spaces should not be neglected as is the case with private spaces. There ought to be a lot of potential for energy conservation in public spaces by intangible factors, which means things such as consciousness of people or policy.

In this research, we conducted field experiments through information provision and observed relationships between individual behaviors and electricity consumption in public spaces. We focused on providing personalized information to individual rather than general information for the public. Furthermore, we investigated the effect by providing the information which ranked subjects in terms of electricity consumption. Unlike the Opower’s case, energy conservation advice was not included in the information we provided. We investigated whether behavior change could be indirectly promoted by implicitly presenting social normality by ranking. We expect that such information provision will not make occupants feel disgusted.

The reason why energy is wasted can be that people forget to turn off the power supply of a PC or a display. In this research, the individual presence status and equipment electricity consumption are monitored. Then, wasted energy is quantified. Based on these data the personalized information is provided to each individual occupant. In this paper, we report an interim progress of the field experiment and the results of analysis of the data obtained at this stage.

The paper proceeds as follows. Section 2 gives how experiment was designed. Section 3 explains the specifications of equipment used in this experiment. In section 4, the algorithm of occupancy judgement and verification is discussed. In section 5, subjects’ individual analyses and energy saving effect are presented. Finally, section 6 concludes.

2. Experimental design

2.1. Conditions of information provision
The experiment was conducted in a laboratory room of the university, and subjects were 33 students who usually use and own their desks. Subjects were composed of students from three laboratories.

The experiment period is from October 29, 2018 to January 20, 2019. Measurement started on October 29, but information provision was not made until November 21. Information was provided for the first time on November 22. We provided information every other week. Information was printed on A4 paper, wrapped in an envelope and placed on each desk, or handed directly (Figure 1).

![Figure 1. Information is provided in an envelope.](image-url)
Subjects were divided into three groups like figure 2. There were 12 subjects in group 1, 12 in group 2 and 9 in group 3. Groups 1 and 2 were provided information as experimental groups, while group 3 was not provided as a control group. Group 1 was provided the data on individual’s electricity consumption per week and information obtained by ranking all subjects by a certain index. Group 2 provided only individual’s electricity consumption as information.

2.2. Contents of information
The layout of information for groups 1 and 2 is shown below. For group 1, the data on individual electricity consumption was printed on the surface of the paper provided as information (Figure 3). On the back side of the paper, the table with the ranking of subjects was printed (Figure 4). For group 2, nothing was printed on the back side, and only the data about electricity consumption was printed on the surface.

**Figure 3.** Electricity consumption data (Surface).

**Figure 4.** Ranking of index of wasting (Back side).
We used some values in the information we provided. The total electricity consumption \( E_{total} \) is the electricity consumption amount obtained every hour by the power tap. This value was provided as weekly accumulated value in the information. The electricity consumption during absence \( E_{absence} \) is the electricity consumption amount when leaving the seat. That value was calculated by the following equation (1) - (2) using the absent rate \( R \) and the total electricity consumption. Absent rate is the percentage of absence time in one hour. We also provided this value as weekly accumulated value in the information.

\[
R = \frac{T_{absence}}{T_{occupancy} + T_{absence}} \tag{1}
\]

\[
E_{absence} = E_{total} \times R \tag{2}
\]

Time in school \( T_{school} \) is the time from attendance to leave. Even if you leave your seat for a while, it is included in your time in school unless you leave your seat for more than 3 hours. Otherwise, it is not included as time in school. The trial is shown in figure 5. Wasted energy \( I_{wasting} \) is quantified by using the equation (3).

\[
I_{wasting} = \frac{E_{absence}}{T_{school}} \tag{3}
\]

Figure 5. Actual seating status and time while present in school.

The electricity consumption during absence was divided by the time in school in order to standardize. By doing this standardization, we reduced the unfairness by comparing the total amount. We ranked this value and provided the information to the students in group 1. The ranking allows us to see where we are positioned compared to others as you can see in figure 4. This refers to social normality [7, 8].

3. Equipment

3.1. Power tap

In order to measure the electricity consumption of individual’s equipment, a power tap with power measuring device shown in figure 6 was used. The power tap was installed at each subject’s desk. This measures the electricity consumption of 1 hour. Subjects connected their equipment such as PC, display, smartphone charger and task lighting to that power strip. Data is output as csv file.
3.2. Thermal sensor

Thermal sensors of figure 7 were used to analyze the status of individual subject’s occupancy. A single sensor can detect a range of 3.6 meters square as shown in figure 8. In order to cover the entire laboratory, nine sensors were installed to locations shown in figure 9. The radiant temperature can be sensed with a resolution of 256 (16 × 16) points. This sensor can detect the number of people with 16 (4 × 4) points resolution. However, we processed 256 divided temperature data and calculated with algorithm we propose for judging the status of the presence since it was difficult to judge whether people were in individual's seat. Data is measured at intervals of 10 seconds and can be output as csv files every day.

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Figure 6. Appearance of a power tap.

Figure 7. Appearance of a thermal sensor.

Figure 8. Sensing area of a thermal sensor.

Figure 9. Installation location of thermal sensors.
4. Verification experiments

4.1. Identification of seating position
Prior to the information provision experiment, it was necessary to first specify which grid thermal sensors detected as the individual desk. So, we seated in each subject’s chair and then chose 2 grids with the highest temperature among 256 divided grids of a thermal sensor. We determined those 2 grids as the seat of each person. The heat map when human was detected is shown in figure 10.

![Heat map when detecting human](image)

**Figure 10.** (a) Detecting image and (b) Heat map when detecting human.

4.2. Algorithm of occupancy judgement
The algorithm for detection whether an individual is present or absent in his / her seat is as follows.

i) Calculate the average temperature $t(n)$ of identified two grids of individuals at time $n$ ($0 \leq n \leq 8639$: 8640 data were obtained every 10 seconds in 24 hours).

ii) Calculate $T(n)$, which is moving average of the immediately before and after the current temperature $t(n)$, by using equation (4). The number of moving average temperature is defined as $X$.

$$T(n) = \frac{\sum t\left(n - \frac{X - 1}{2}\right) + t\left(n - \frac{X - 3}{2}\right) + \cdots + t\left(n + \frac{X - 3}{2}\right) + t\left(n + \frac{X - 1}{2}\right)}{X}$$  \hspace{1cm} (4)

iii) Calculate the temperature difference $dT(n)$ between the previous average temperature and the current average temperature by using equation (5).

$$dT(n) = T(n) - T(n - 1)$$  \hspace{1cm} (5)

iv) Set the temperature threshold to be $\Delta T$ for judging occupancy. Compare $dT(n)$ and $\Delta T$. According to the shown flow chart of figure 11, occupancy at time $n$ is determined.

v) The initial state is assumed to be present when $t(n)$ is $1.5$ °C or higher than the lowest value among the 256 grids of the thermal sensor. If not, assumed to be absent.

vi) When even one missing value is included in a term constituting $T(n)$, the presence state is also treated as a missing value. When the missing value is no longer included in the subsequent time, the state at that time is calculated in the same way as in v).
4.3. Threshold setting

In order to make the calculation result of the presence determination algorithm to be close to the actual presence status, multiple combinations of the moving average number (\(X\)) and the judgment temperature threshold (\(\Delta T\)) were examined. Thus, an optimum solution was determined.

First, we installed a camera on the ceiling to check the presence status in order to collect data about actual presence status. We calculated the matching rate between the actual presence status and the calculation result by the determination algorithm. We collected the data of seven people in total and selected a combination of \(X\) and \(\Delta T\) so that the consistency rate would improve. As a result, it was decided to adopt \(X\) as 9 pieces and \(\Delta T\) as 0.1 °C.

5. Results

5.1. Individual analysis

Analysis of individual subject was conducted from the viewpoints of whether the reduction effect of electricity consumption during absence was obtained through information provision. Figure 12 shows each period average and change rate of electricity consumption during absence before and after information provision.

Subjects with low electricity consumption during absence before information provision are considered to have a small margin for reduction. Therefore, it was assumed that information provision was effective if a subject who had high electricity consumption during absence before information provision had reduced that consumption after information provision. Contrarily, it was assumed that information provision was not effective if a subject who had high electricity consumption during absence before information provision had not reduced that consumption after information provision. Thus, we selected a subject who had effect and a subject who had no effect from groups 1 and 2, respectively.

Figure 11. Algorithm of occupancy judgement by using thermal sensor data.

Figure 12. each period average and change rate of electricity consumption during absence before and after information provision.
As an example of subjects who had effect, subject 29 from group 1 and subject 32 from group 2 was selected. On the other hand, subjects 27 from group 1 and subjects 28 from group 2 was selected as an example of subjects who had no effect. Figures of electricity consumption and time in school for subjects who obtained distinctive results in groups 1 and 2 throughout the experiment period as follows. The yellow vertical line indicates the timing of information provision. The shaded part is the period in which the data was missing. That data was removed in calculation.

Subject 29 of group 1 showed a significant decline of electricity consumption during absence (Figure 13). We can see a behavior change from this figure. Regarding subject 32 of group 2, no effect was seen at the first provision of information (Figure 14). However, the effect was seen at the second provision of information and the electricity consumption during absence was reduced. On the other hand, subject 27, who had high electricity consumption during absence among all subjects, did not reduce the value after information provision (Figure 15). The amount of electricity consumption during absence was always high. Behavior change by information provision is not seen at all throughout the experiment period. As for subject 28 of group 2, behavior change could not be seen be observed (Figure 16).

### Table 2: Summary of Energy Saving Effect

| Date   | Date   | Date   | Date   | Date   | Date   | Date   | Date   | Date   | Date   | Date   | Date   |
|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| 10/29  | 11/05  | 11/12  | 11/19  | 11/26  | 12/03  | 12/10  | 12/17  | 12/24  | 12/31  | 1/07   | 1/14   |
| 16     | 16     | 16     | 16     | 16     | 16     | 16     | 16     | 16     | 16     | 8      | 8      |
| 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      |
| 0.0    | 0.0    | 0.0    | 0.0    | 0.0    | 0.0    | 0.0    | 0.0    | 0.0    | 0.0    | 0.0    | 0.0    |
| 4.0    | 4.0    | 4.0    | 4.0    | 4.0    | 4.0    | 4.0    | 4.0    | 4.0    | 4.0    | 4.0    | 4.0    |

**Figure 13.** Electricity consumption and Time in school of Subject 29 (Group 1).

**Figure 14.** Electricity consumption and Time in school of Subject 32 (Group 2).

**Figure 15.** Electricity consumption and Time in school of Subject 27 (Group 1).

**Figure 16.** Electricity consumption and Time in school of Subject 28 (Group 2).

#### 5.2. Energy saving effect

Table 2 summarizes how much energy saving effect was achieved for these subjects and the entire group. The values in table 2 shows the period average of total electricity consumption before and after information provision and the change rate. Subjects 29 and 32 were able to obtain about 70 to 80% reduction effect by information provision. On the other hand, as in subjects 27 and 28, it was founded that those who had high electricity consumption during absence even after sending information had still consumed absolutely much energy even though they slightly reduced energy consumption.

For groups, the total electricity consumption of subjects in the entire group was first summed up, and the reduction rate was calculated before and after information provision. Group 1 was reduced by 20.2%, group 2 by 24.2% and group 3 by 3.6%. When focusing on the reduction rate of electricity consumption, the effect of information provision was seen. However, the effect due to the difference in the content of information was not seen.
Table 2. Change rate of total electricity consumption before and after information provision.

| Group | Subject | Before [Wh] | After [Wh] | Ratio [-] |
|-------|---------|-------------|------------|-----------|
| Group 1 | Sub. 29 | 1897.02 | 388.78 | -0.795 |
|        | Sub. 27 | 2778.99 | 2991.07 | +0.076 |
| Group 2 | Sub. 32 | 422.71 | 116.67 | -0.724 |
|        | Sub. 28 | 1193.44 | 1179.69 | -0.012 |
| Group 1 Total | 8575.11 | 6844.79 | -0.202 |
| Group 2 Total | 5563.80 | 4217.89 | -0.242 |
| Group 3 Total | 5318.50 | 5127.93 | -0.036 |

5.3. Hypothesis verification results on electricity consumption by providing information

Based on these results, the following two hypotheses were considered. First, those who originally use a lot of electricity do not have much effect even if they receive information. Next, if there is no information provision, the electricity consumption fluctuates randomly and the variance per day is large.

Regarding the first hypothesis, the relationship between the sum of electricity consumption during absence for three weeks before information provision for individuals and period average of the proportion of electricity consumption during absence to total electricity consumption after information provision is shown in figure 17. As a result of calculation of correlation coefficient, a moderate positive correlation was found ($r = 0.615$). When $t$ test was conducted, null hypothesis was not rejected at a significance level of 5% ($p = 0.00017$). So, it was found that those who originally had high electricity consumption during absence and tended to keep power supply did not possibly change their behavior and not obtain much effect through information provision.

With respect to the second hypothesis, figure 18 shows the variance of the proportion of electricity consumption during absence to total electricity consumption before and after information provision. Although group 3 was not provided information, group 3 is shown in parenthesis as reference for comparison in the same period. In group 1, the group average of variance of each subject decreased after information provision. On the other hand, that was increased in group 2. Next, group average of variance after information provision was statistically evaluated using one-way analysis of variance (ANOVA). As a preliminary test, we conducted Bartlett test at a significance level of 5% in order to verify whether the three specimens of groups 1, 2 and 3 were equidistant or not. As a result, the null hypothesis was not rejected and the population variance of the three specimens was equal ($p = 0.80$). Then, as a result of ANOVA, the null hypothesis was not rejected at a significance level of 5%, so it could not be said that there was a significant difference. Therefore, significant results were not obtained about relationship between variance and information provision ($p = 0.30$).

Figure 17. The relationship between the sum of electricity consumption during absence before information provision and period average of the proportion of electricity consumption during absence to total electricity consumption after information provision.

Figure 18. The variance of the proportion of electricity consumption during absence to total electricity consumption before and after information provision.
6. Discussion and Conclusion

In this experiment, the effect of information provision was seen to some subjects. For group which received information, the energy saving effect was larger than group which did not receive one. However, it was also found that the effect of information provision eventually depended on subjects. Subject 27 and 28 had originally much electricity consumption during absence and did not change their behavior by information provision. It is inferred that some subjects like these may be always processing calculation in their PCs. In that case, the way of providing information or the content of information needs to be revised. For example, the method of categorizing subjects by projects which they are engaged in may be efficient. Furthermore, the effect by the ranking information could not be seen clearly at this stage of the experiment. It may be necessary to change the contents of information and provide information considering personal characteristics. For future, we are planning to conduct a questionnaire survey and analyze the relationship between energy data and subjective opinion of subjects.

From the verification of hypothesis, it was founded that those who originally consume much energy may have less consciousness about energy saving than others. Even if those who originally consume relatively less energy change their behavior, the amount of energy reduced by them will be cancelled out as long as higher energy consumer did not reduce their energy. So, the way of making those peoples’ behavior change should be considered.

Although we could change only a few person’s behavior at this stage of this experiment through providing information, the data obtained by this research will bring new insight into the information provision such as data visualization for energy conservation in public spaces. In the future we will continue to collect data, increase the number of samples, and we are planning to conduct more detailed analyses. Finally, we expect that this research will be useful for life management of occupants and contribute to develop a new management system on the demand side.

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