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Occupant's thermal preference diversity in residential air-conditioning use: A study in Osaka, Japan

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Abstract: *The diverse occupant's behaviour (OB) has been identified as a significant impact on household air-conditioner (AC) energy use. However, the stochastic feature of occupant's individual preference in AC use is seldom studied due to the limitation of appliance-level energy data. This study aims to analyze the inter-occupant OB diversity based on the monitoring bigdata of AC load in a residential community of 586 households in Osaka, Japan. First, household's thermal preference was quantitatively identified from AC load profiles. Clustering analysis is then employed for labeling and classification of the target households with different thermal preference types. Results show 4 typical behavioral patterns, namely sensitive & active users, sensitive but inactive users, insensitive but active users, insensitive & inactive users, with a share of dwellings in the community of 36%, 31%, 19%, and 14%, respectively. Such household-level benchmarking could provide an informative reference for the modeling and simulation of residential AC usage.*

Keywords: Residential air-conditioning use; thermal preference; clustering analysis

1. INTRODUCTION

1.1 Background

Occupant behaviour (OB) has been recognized as a crucial factor influencing building energy performance. Yousefi et al. [1] investigated the influence of occupant lifestyle patterns on the energy performance of residential buildings with different envelopes in various Iranian climate zones. The results showed an underestimated interaction between OB and various factors, including envelope material, fluctuation of thermal energy use patterns, and building sustainability. Blight and Coley [2] also investigated the effect of OB on the energy consumption of passive design dwellings in the UK. A sensitivity analysis was conducted based on the dataset of the bottom-up building energy simulation, with results indicating the relation between the energy demand of a household and particular behavioral variables of the residents. Adnan et al. [3] applied a self-administered questionnaire targeting 123 households in Rafah, indicating that residents are aware of energy conservation in residential buildings and have good attention to achieving reduction in energy demand. These studies clearly suggest a significant role of OB, which are embedded in a building energy system and determine the energy demand in an interactive manner.

The air-conditioning usage, among various end-uses in residential sector, is a major contributor to the total household electricity consumption [4,5]. Substantial research has also been done on OB from the perspective of adaptive thermal comfort since the pioneering work by Fritsch et al. [6]. AC consumption can vary greatly among apartments even with the same building envelope due to the residents' various usage behaviour of the AC system. Murtyas et al. [7] investigated the energy consumption in a hotel in Indonesia and found that occupants' using behaviour of HVAC system and other devices were dominantly affecting the total electricity demand. The relationship between cooling energy and influencing factors including climate, OB and dwelling types was estimated by Yun et al. [8] for residential buildings in the USA. It was concluded that OB is the most significant factor that determines AC operation. Occupant behavior concerning daily AC usage can be stochastic, diverse, and complex, especially in the residential sector [9]. Residents with split AC units can control the operation state in accordance with their own thermal preference. An et al. [10] concluded that diverse OB patterns such as different operation schedules lead to greatly varied consumption simulation results. Operation schedules closer to actual household usage would have significant use to obtain more accurate simulation results. Similarly, Clevenger and Haymaker [11] found that different settings of OB-related variables as inputs of energy consumption simulation would result in a maximum of 150% discrepancy in final results. Consequently, a precise and comprehensive understanding of OB-related information can be crucial when predicting and simulating the end-use of AC consumption. Low-quality inputs associated with OB of AC usage may lead to grand discrepancy that deviate from practical situations.

Existing studies conducted to analyze AC usage main consist of the following steps: exploring the relation between impacting factors and AC usage, statistical analysis of AC usage measurement data, and quantitative model construction for possible prediction of AC usage behavior. In terms of the influencing factors, various factors, including outdoor air temperature, indoor temperature, time of day, and individual factors such as age and gender were regarded as critical indicators to AC usage behaviour. For instance, the measurement data of three dwellings in China was used by Ren et al. [12] to develop a quantitative stochastic model for prediction of AC on/off state considering both environmental triggers and event triggers. Tanimoto and Hagishima [13] used field measurement data on five familial and three single dwellings to derive the functions of state-transitional probability of residential air-to-air heat pumps from the off to on state and from the on to off state. Yao [14] used a field study to measure the usage of AC in a typical apartment in China and developed a stochastic occupant model of AC usage that can be combined with building simulations. A probability model was also proposed to quantify the occurrence of turning on/off AC related to indoor temperature and the time of day. Diao et al. [15] also adopted a bottom-up approach incorporated with a clustering analysis of OB patterns. The accuracy of the prediction results was then compared to that based on the ASHRAE standard schedule.

1.2 Research gap

Our literature search indicated that the existing studies have demonstrated that there are significant individual differences in the thermal-related OB in residential AC usage. Such individual behavioral preference was also found by some research to show significant correlations with AC operation behaviour and energy consumption. Nevertheless, research on thermal preference to date has largely not included a comprehensive analysis of occupant's AC operation behaviour. Consequently, there are rare clear quantitative conclusions of the individual preferences with multiple behavioral features.

In addition, we found that most previous studies were derived from the measurement study of several or dozens of households and focused on the statistical AC usage behavior exploring with limited diversity patterns. Detailed and complicated models were also developed based on small sample size case studies due to data access limitations in residential buildings. However, the realistic diversity of OB can be hardly reproduced with insufficient sample size of households. Diverse OB in terms of thermal preference in residential community with large population is seldom investigated.

1.3 Objectives

To overcome the abovementioned limitations, a bigdata of appliance-level interval energy consumption in a real community were used to analyze the AC usage behavior. The objectives of this study are as follows:

- To identify multiple diverse behavioral features concerning occupants' thermal preference based on daily AC usage behaviour
- To quantitatively reproduce the distribution of individual difference in OB across the target community.
- To achieve household benchmarking in terms of thermal preference with OB-clustering that can provide a good reference for potential bottom-up simulation model of AC energy consumption and a better understanding of behavioral patterns in residential AC usage.

The remainder of the paper is structured as follows. Section 2 presents the outline of the dataset and the necessary data treatment process. Section 3 covers the statistical analysis results of several thermal preference features in AC usage behaviour. Section 4 discusses clustering analysis based on previous results and household labelling in terms of individual thermal preference pattern. Section 5 presents an overall conclusion and discussion of the present study.

2. DATASET OUTLINE

2.1 Surveyed community description

The electricity consumption database used in the present study was obtained from a 20-story residential building located in Osaka. Tables 1 and 2 present a summary of the database and target building. The building consists of 586 dwelling units and an energy consumption of 18 branches. The appliance level consumption of each branch was recorded for each dwelling at 1-min intervals from January 2013 to December 2014. Using this dataset, we identified the electricity consumption of the room air conditioners. It is to be noted that in the following part of this paper, we focus on cooling use in living and dining rooms because cooling in bedrooms primarily occurs during sleeping hours, the impact of ambient temperature on occupants' controlling behaviour is relatively low compared to the case in living and dining rooms where most occupants are active. In addition, the model types of the AC units in the bedrooms were unknown.

Table 1. Outline of energy demand data

Measurement items	Electricity of total and breakdown consists of 18 branches in each dwelling.
Minimum measurement unit	0.017 W
Measurement period	1 January 2013 ~ 31 December 2014
Measurement interval	1 min

Table 2. Outline of target residential community

Location	Settu City, Osaka, Japan
Number of stories	20
Completion date	January, 2011
Structure	Reinforced concrete structure
Building envelopes	External walls: internal insulation with air layer, U-value 0.441 W/m^2K^1 Windows: Low-E double-glazing
Number of dwellings	Total 586 dwellings 38 dwellings: 2 bedrooms + LDK* (55.1 m2) 391 dwellings: 3 bedrooms + LDK* (71.2 m2) 157 dwellings: 4 bedrooms + LDK* (83.6 m2)

* LDK refers to a unified space used for living rooms, dining rooms, and kitchens.

The dwellings comprised two to four bedrooms, one living and dining room connected to the kitchen. Fig.1 depicts a typical layout of the investigated dwellings. Regarding the building envelope, multiple insulation layers, including polyurethane foam and air-filled cavity, were applied within the apartment's external walls. Information on family composition, occupation, gender, and age for each dwelling was not disclosed because of privacy protection. Regarding the building envelope, multiple insulation layers, including polyurethane foam and an air-filled cavity, were applied on the building's external walls. The same type of AC manufactured by the same company was installed in the living room of all the surveyed dwellings during construction. The annual performance factor (APF) of these ACs ranged from 4.7 to 6.7, depending on the floor area. In contrast, the AC installed in the bedrooms was purchased and installed by each resident. Information on the family composition, occupation, gender, and age of each dwelling was not disclosed because of privacy protection.

A part of the dwelling units of the original dataset includes missing values, a long absence of occupants, and other measurement errors. Thus, a data cleaning process was conducted to exclude invalid data from households with the above problems and to reduce the original 586 households to 482.

2.2 Meteorological condition

For the investigated period from in 2013 and 2014, the dry bulb temperatures observed at the Toyonaka weather station of the Automated Meteorological Data Acquisition System (AMeDAS) were used for the analysis. AMeDAS is a high-resolution surface-observation network system developed by the Japan Meteorological Agency for collecting regional weather data. Considering that the distance between the weather station and target building was 10 km, the influence of it on the accuracy of meteorological parameters is negligible. Fig.2 shows the annual variation in the daily average, maximum, and minimum outdoor air temperatures in 2013 and 2014 in Osaka. A distinct monthly cycle can be observed in the temperature variation, in which the outdoor air temperature reached its peak in August and experienced a lower level in early summer in June and late summer in September. Information on the summertime temperature and sunlight hours is presented in Table 3.

Fig. 1. Typical layout of the dwelling unit of the surveyed residential building.

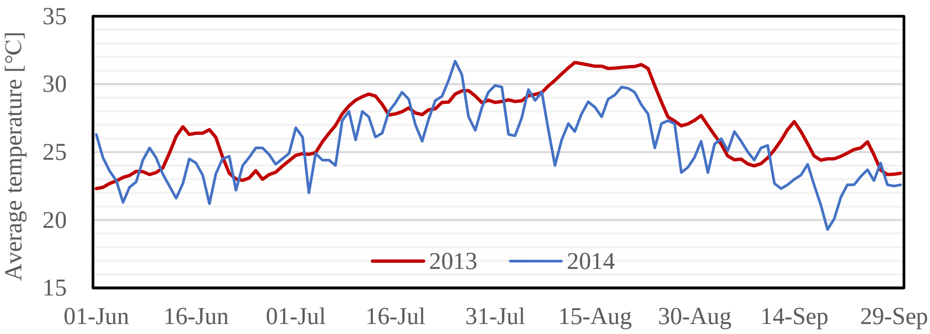


Fig. 2. Monthly variation in the daily average of outdoor air temperature in Osaka.

Table 3. Summertime temperature and sunlight hours of target region

Year	Month	Average temperature [°C]	Hours of sunlight [h]
	June	24.1	203.1
	Jul	27.9	222.5
2013	Aug	29.8	255.9
	Sept	25.0	220.7
	June	23.9	212.5
	Jul	27.4	208.8
2014	Aug	27.5	249.6
	Sept	23.5	198.0

3. THERMAL PREFERENCE IDENTIFICATION

3.1 AC usage feature selection

Thermal preference, as the main objective of this study, refers to the occupant's different requirements for a comfortable indoor thermal environment. Such diverse demands can be reflected in the control behaviour of AC units or monitoring parameters during daily cooling operations. In existing research, the variety of occupant's thermal environment requirements is mainly indicated by multiple features regarding AC usage, including AC set-point adjustment [16,17], trigger temperature [18] and duration of daily cooling operation [19], etc. Information of indoor air temperature was not included in the measurement data used in this work. Consequently, the following part of feature generation mainly focuses on cooling duration and the impact of outdoor air temperature on occupants' AC operation behaviour. The aggregation of hourly and daily load profiles was then performed for each AC unit as a row index.

3.2 Daily AC usage rate

daily AC usage rate is first defined as a variable to represent occupants' individual degree of reliance on AC cooling. As indicated by eq. (1), It is calculated as the ratio of daily cooling duration normalized by the daily hours of occupancy in the target rooms.

$$ACUR_h = \sum_{d=0}^{D} \frac{\sum_{i=0}^{23} AC\_state_{i,d,h}}{\sum_{i=0}^{23} Occ\_state_{i,d,h}} / D \qquad (1)$$

where,
$ACUR_h$ represents averaged daily AC usage rate of the h[th] household, $h \in [0,482]$.
$AC\_state_{i,d,h}$ denotes the on/off state of target AC in h[th] household at hour i in day d, with a value of 0 indicating off state and 1 for on state. $i \in [0,23]$, $d \in [0, D]$.
$OCC\_state_{i,d,h}$ denotes the state of occupancy target AC in h[th] household at hour i in day d, with a value of 0 indicating no occupancy and 1 for room occupied.
D for the total investigation period including four months in two consecutive years is 244.
It should be noted that occupancy hour is here utilized to normalize AC usage duration to exclude the influence of diverse daily routine of occupancy schedules on the results of thermal preference.

3.2.1 Occupancy schedule detection

Since direct observation of occupancy information could not be included in the measurement data, it is necessary to make assumptions about the occupancy state based on the energy load variation in target rooms.
With the obtained appliance-level load data, the occupancy schedule is first detected using load profiles of lighting and appliance usage in the target living and dining room for each house. Fig.3 gives the scheme for the generation of hour occupancy schedules. On/off state of the lighting system could be directly summarized as one reference for hourly occupancy detection. For the case of electrical devices, a daily baseline load was first calculated. Then additional appliance usage above the threshold level can be identified.
As a result, an example of detected daily occupancy patterns for a single household is illustrated in Fig.4. a binary condition of hourly occupancy is summarized for each day, in which the vertical axis is 1 when the room is occupied by at least one resident, and 0 when no resident stays in the room during the specific hour. The curve indicates the daily variation pattern of the average occupancy proportion in the target house.

3.2.2 AC operation schedule and usage rate

Based on the energy data with 1-min intervals, all sequences of the continuous AC load profile started by switching on and ended by switching off were identified throughout the summer season. Hourly on/off state of room AC units was similarly calculated across the investigated period for each dwelling. Fig.5 gives the scatter plot of total AC duration and electricity consumption for each household. During the investigation period from June to September for consecutive two years, the household's total cooling operation time shows a significant diversity from 100 to 3200 hours, with total electricity consumed by room AC units varying in the range of 1200 kwh.
The results of daily AC usage rate are shown in Fig.6. Great diversity could also be seen among the investigated 482 dwellings. Results revealed that 74.7% of the investigated dwellings had an average AC usage rate between 0.4 and 0.7. On the other hand, extremely intensive AC users, who tended to constantly rely on AC cooling during their stay in the living and dining room (with an AC usage rate above 0.8), also accounts for 14.9% of the whole community.

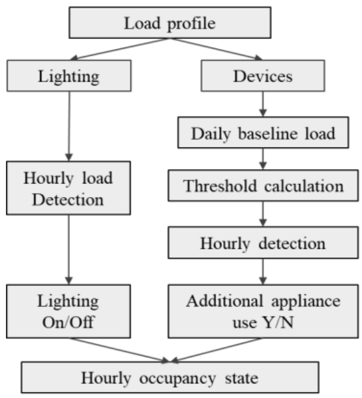


Fig. 3. Scheme of hourly occupancy schedule generation.

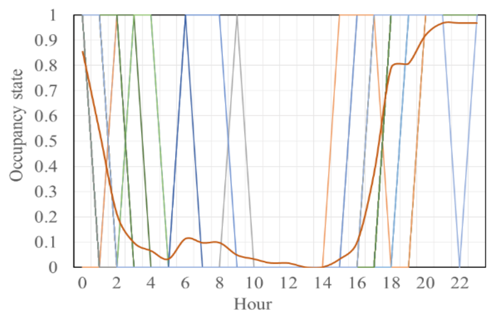


Fig. 4. Example of detected daily occupancy patterns for one household with average probability curve.

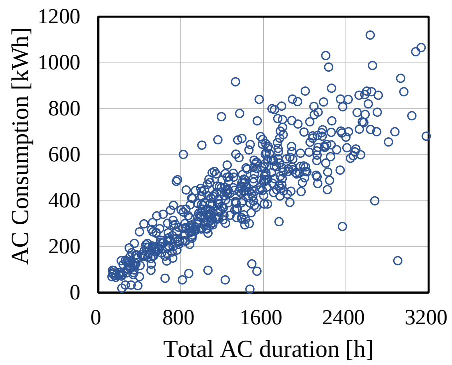


Fig. 5. Scatter plot of total AC duration and electricity consumption for each household in the investigation period.

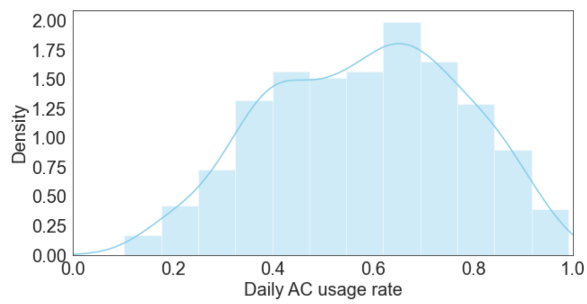
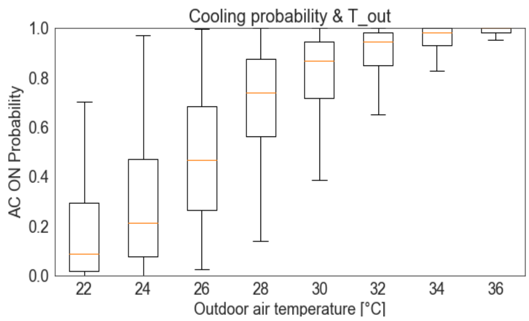


Fig. 6. Density distribution of daily AC usage rate across the investigated 482 dwellings.

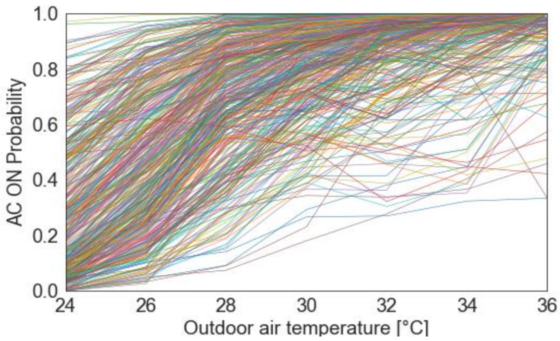
3.3 Thermal sensitivity

Ambient air temperature is considered the primary and essential cause of cooling usage and people's thermal adjustment behaviour in summer season. In terms of AC-related behavioral feature, the occupant's reaction to the variation in outdoor thermal environment should be regarded as an important index of individual thermal preference.

As shown in Fig. 7, with a 2-degree resolution of outdoor air temperature, the average AC operating probability curve for each dwelling tended to increase with the growing ambient temperature. In the boxplot, a huge difference in AC operating probability existed among the 482 dwellings when outdoor temperature ranged between 24 to 28°C. Such diversity in occupant's adaption promptly narrowed when the outdoor temperature rose above 30°C and the probability reaches near 1 for almost all dwellings at 34°C. The second figure has also revealed the positive correlation between the household's AC use potential and outdoor thermal conditions. that the vast majority of the investigated dwellings had a cooling use proportion over 0.6 when the outdoor temperature is greater than 28°C. In addition, clear diversity can also be observed in the beginning point and gradient of each curve, indicating that the degree of sensitivity to the ambient temperature change varied greatly from dwelling to dwelling.



(a) Boxplot of AC ON probability in different outdoor air temperature ranges



(b) Household's AC on probability variation with outdoor air temperature change

Fig. 7. AC operating probability at different outdoor air temperature with 2-degree resolution.

In this study, thermal sensitivity was proposed to be another indicator as quantification of a household's thermal preference. It was defined as the average gradient of households AC operating probability to the increasing outdoor air temperature, calculated by eq. (2).

$$(TS_h) = \frac{P_{max,h} - P_0}{T_{pmax,h} - T_0} \quad (2)$$

where,

TS_h denotes thermal sensitivity level of the h^{th} household.

$P_{max,h}$ indicates the maximum AC operating probability for the h^{th} household, and P_0 represents the AC operating probability in the lowest temperature range (22~24°C).

$T_{pmax,h}$ indicates the outdoor air temperature when AC operating probability reaches the maximum level and T_0 represents the lower limit of outdoor air temperature.

The density distribution of the household thermal sensitivity across the investigated 482 dwellings is illustrated in Fig.8.

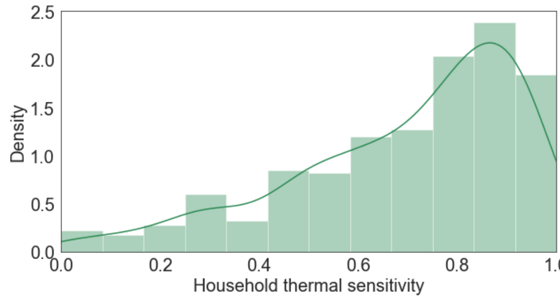


Fig. 8. Density distribution of the household thermal sensitivity across the investigated 482 dwellings.

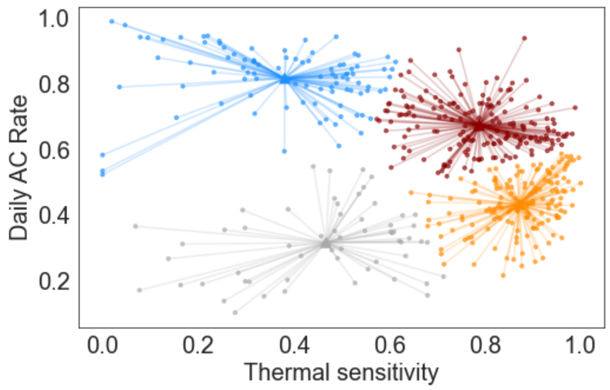
4. THERMAL PREFERENCE CLUSTERING

Previous studies have revealed that AC turning on/off behaviour is associated with multiple OB-related features of individual traits. In recent years, clustering analysis has been used to discover diverse energy use patterns of household appliances [20] as well as to identify typical occupant patterns in AC usage [21]. In this study, the k-means method, which was first used by James MacQueen [22] and universally used as the most popular algorithm for clustering analysis, was applied to identify typical occupant patterns in thermal preference. K-means divides all the points in the dataset into k non-overlapping clusters, and each data point belongs to only one group, which assigns data points to a cluster such that the sum of the measured distance between the data points and the cluster's centroid is at the minimum. The Python package scikit-learn [23] was used in this step.

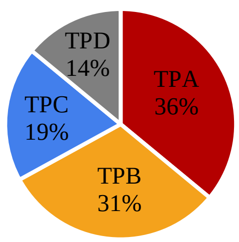
After feature engineering, household's AC usage behaviour in living and dining room in 482 households were clustered. Clustering results of thermal preference patterns across the 482 investigated dwellings were illustrated in Fig.9. Four typical types of households with different thermal preference patterns were concluded in the scatter plot.

- TPA: households sensitive to outdoor temperature change with also high reliance on AC cooling.
- TPB: households sensitive to outdoor temperature change while relatively low AC overall cooling operation.
- TPC: households with intensive AC cooling operation regardless of the variation of the ambient thermal environment.
- TPD: households are neither sensitive to outdoor temperature nor have frequent AC cooling use.

It can be found that sensitive & active AC users (TPA) and sensitive & non-active users (TPB), who both showed an adaptive behavioral tendency to temperature change, account for 67% of dwellings in the community. In addition, households with no clear behavioral change according to the outdoor temperature, could also be greatly intensive cooling users (TPC). Residents of each dwelling were labeled with a certain categorical pattern by this clustering analysis. Such categorical patterns of thermal preference could be an informative reference to the future construction of a prediction model.



(a) Scatter plot of four typical clusters of thermal preference pattern



(b) Share of each cluster

Fig. 9. Clustering results of thermal preference patterns across 482 dwellings.

5. CONCLUSION

Based on appliance-level energy data in a residential building, this study focuses on the diverse thermal preference patterns across the whole community. Statistical analysis of the AC load profiles has identified and quantified the behavioral features such as occupant's thermal sensitivity and daily AC usage rate among the investigated 482 dwellings. Clustering analysis was then applied to obtain household behavioral labeling with results of four typical thermal preference patterns. The main findings are summarized as follows:

- The thermal preference for AC usage in the specific household was extracted from simple AC loads data with two variables: daily AC usage rate and thermal sensitivity to the outdoor thermal environment.
- The distribution of individual thermal preference was quantitatively reproduced, showing 4 typical behavioral patterns: sensitive & active users, sensitive but inactive users, insensitive but active users, and insensitive & inactive users, with a share of dwellings in the community of 36%, 31%, 19%, 14%, respectively.
- Household-level labeling and benchmarking concerning OB-related features were achieved to provide an informative reference for the establishment of AC usage prediction model.

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