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Typical energy-related behaviors and gender difference for cooling energy consumption

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A B S T R A C T

The aim of the study is to identify male and female typical energy-related behaviors that have a great influence on energy consumption, which provides reference for building designers and policy makers. Previous studies focused on investigating the influence of one or two specific kinds of energy-related behaviors on building energy consumption. Besides, significant differences between females and males regarding energy-related behaviors have been highlighted in many studies. However, an integrated and in-depth analysis of typical energy-related behavior and gender difference for cooling energy consumption is yet to be conducted. To fill this research gap, this paper investigated correlation between cooling energy consumption and energy-related behaviors with empirical data for different genders, and identified male and females' typical energy-related behaviors respectively by applying data mining approach. Data concerning energy use and energy-related behaviors were collected from Energy Management System and questionnaire respectively. Results show that there are significant differences in cooling energy consumption between genders. For both males and females, the daily average hours of air conditioning utilization, electric fans usage instead of air conditioner, and the ratio of occupancy in rooms are typical behaviors influencing cooling energy consumption. The comparative study between genders indicates that the frequency of air conditioner use is a typical behavior influencing cooling energy consumption, especially for females. However, thermal preferences have more noticeable influence on cooling energy consumption for males than females. The study not only helps improve modeling accuracy of occupant behavior in design simulation, but also helps prioritize efforts to guide occupant behavior in order to reduce building energy consumption in operation stage.

1. Introduction

The building sector is responsible for nearly 32% of global energy use, which contributes to 19% of total energy-related Green House Gas (GHG) emissions (Edenhofer et al., 2014; Tam et al., 2019). In consideration of energy conservation, the estimation of energy use in buildings is therefore a critical process during the design stage (Najjar et al., 2019). However, there is a significant gap of 2–3 times difference between the designed and actual building energy consumption (Wilde, 2014; Zou et al., 2018b). Occupant behavior was recognized as a primary source of this gap, since it was not well-represented in building energy design (Hong et al., 2017). In some simulation studies, occupant behavior was simplified as presence duration or occupancy schedule with a limitation of covering only one type of behavior (Jia et al., 2017). Occupants' active energy behaviors (e.g., opening/closing windows, lowering blinds, adjusting thermostats, turning lighting on/off, and adjusting clothing, etc.) are still not fully considered in current energy analysis tools (Elham et al., 2017; Tam, W.Y.V. et al., 2018). Due to the diversity of occupant behaviors, instead of developing complicated models of all behaviors, it is necessary to derive several kinds of typical occupant behaviors that represent the assemblage of occupants in a simplified way and thus, they could be regarded as reference for building designers and energy policy makers (Feng et al., 2016). The

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forecast of building energy consumption would be improved if the typical occupant behaviors were integrated into energy simulation programs. Therefore, it is critical to extract typical occupant behaviors and also necessary to identify effects of different types of energy-related behaviors on building energy consumption.

Many studies have investigated the impact of occupant behavior on building energy consumption so as to reduce the performance gap between the predicted and actual energy consumption in buildings (Tam, V. et al., 2018). Simulation-based studies have shown that office workers who carried out energy saving behaviors (e.g., dimming lights, turning off HVAC systems when not needed, and turning on plug loads & appliances only when needed) consumed up to 50% of energy less than those who do not (D'Oca et al., 2018). Al-Mumin et al. (2003) surveyed occupancy patterns and operation schedules of electrical appliances in 30 residences for thermal simulation. The surveyed occupants left all lights on when rooms were unoccupied, with the AC thermostat set at 22 °C. This pattern of occupant behavior increased the annual electricity consumption by 21% compared with the default data. The annual electricity consumption would be reduced by 39% if occupants turned off lights in empty rooms with air conditioning thermostat set at 24 °C instead. Occupant behaviors, such as temperature set-points and total hours of heating system utilization, have a notable impact on building energy performance (Rinaldi et al., 2018). Wang et al. (2015) developed a residential heating energy consumption model and indicated that temperature set-points significantly influenced heating energy use. Ahn and Park (2016) found that occupants' active control of a heating/cooling system (i.e., turn on/off) was strongly related with building energy consumption. To date, the studies examined the occupant behavior in buildings but with particular focus on only one or two specific types of behaviors (Elham et al., 2017; Zhang, Y. et al., 2018).

In addition, occupants interact with buildings to satisfy their environmental comfort, particularly their indoor thermal comfort needs or preferences. The differences in thermal preferences between male and female have been demonstrated by some researchers (Awan and Abbasi., 2013; Indraganti et al., 2015; Lan et al., 2007). For instance, Lan et al. (2007) found that women are more sensitive than men to the low operative temperature of air-conditioner. In other words, men prefer a lower thermal comfort temperature than women. Similar results are presented by Katafygiotou and Serghides (2014). Parsons (2002) concluded that, for the same metabolic activity and clothing insulation, males and females may behave differently to meet their thermal comfort. It seems environmental comfort between different genders strongly affects the way they consume energy in buildings. Nevertheless, few studies are conducted to research gender differences regarding energy-related behaviors currently, and further analysis is much more needed.

From the above literature review, it is concluded that researchers have confirmed the effects of occupant behavior on building energy consumption by focusing on specific kinds of energy-related behaviors. Significant differences between females and males regarding energy-related behaviors have been underlined in many studies. However, an integrated and in-depth analysis of typical energy-related behavior and gender difference in building energy consumption has been not conducted yet. Hence, the aim of this research is to extract male and female typical energy-related behaviors influencing building energy consumption. Specifically, two sub-objectives are covered as follows:

(1) To identify the effects of occupant behavior;
(2) To rank the effects of different types of energy-related behaviors for males and females.

As cooling energy accounts for more than 50% of the total building energy consumption in hot summer and warm winter zone (HE et al., 2013; Zhang, G. et al., 2018), this study investigated correlation between energy-related behaviors and cooling energy consumption in rooms. Then male and females' typical energy-related behaviors influencing cooling energy consumption were identified by applying data mining approach. The study not only helps improve modeling accuracy of occupant behavior in design simulation, but also prioritizes efforts at improvement of occupant energy-related behavior in order to reduce building energy consumption.

2. Methodology

2.1. Research method and process

The purpose of this study is to extract typical energy-related behaviors for men and women and compare their effects on cooling energy consumption. Note that typical energy-related behavior in this paper refers to the activities having great influence on building energy consumption. There are 130 sampled identical rooms (76 male and 54 female rooms). Fig. 1 presents the whole research process. Each step in this study is briefly explained as follows:

(1) A database was developed based on empirical data in terms of energy consumption and relevant influencing factors, such as climate, building information, and occupant behavior. Specially, the daily energy consumption of each room was provided by Energy Management System (EMS). A questionnaire survey was conducted to collect sample data regarding occupants' cooling energy-related behaviors for both male and female.
(2) Data transformation and normalization were conducted. Firstly, the cooling energy consumption of each room was extracted from the total energy consumption. Then, data normalization was conducted to deal with the inconsistencies in measured dataset.
(3) The individual effects of occupant behavior were identified among various influencing factors of cooling energy consumption. Through clustering analysis, variations in cooling energy consumption were analyzed, and the effects of occupant behavior on cooling energy consumption were then identified by controlling other influencing factors.
(4) After identifying the effects of occupant behavior, features of group energy behavior based on individual behavior were extracted by grey relational analysis. Then, the effects of different types of group energy-related behaviors on cooling energy consumption were further researched and ranked by grey relational analysis.
(5) Finally, the typical energy-related behaviors for males and females were extracted based on their ranks respectively.

2.2. Data collection

2.2.1. Energy consumption data

In order to identify typical energy-related behaviors influencing cooling energy consumption, field surveys were carried out from Sep.1, 2017 to Sep. 1, 2018 in two identical students' dormitory

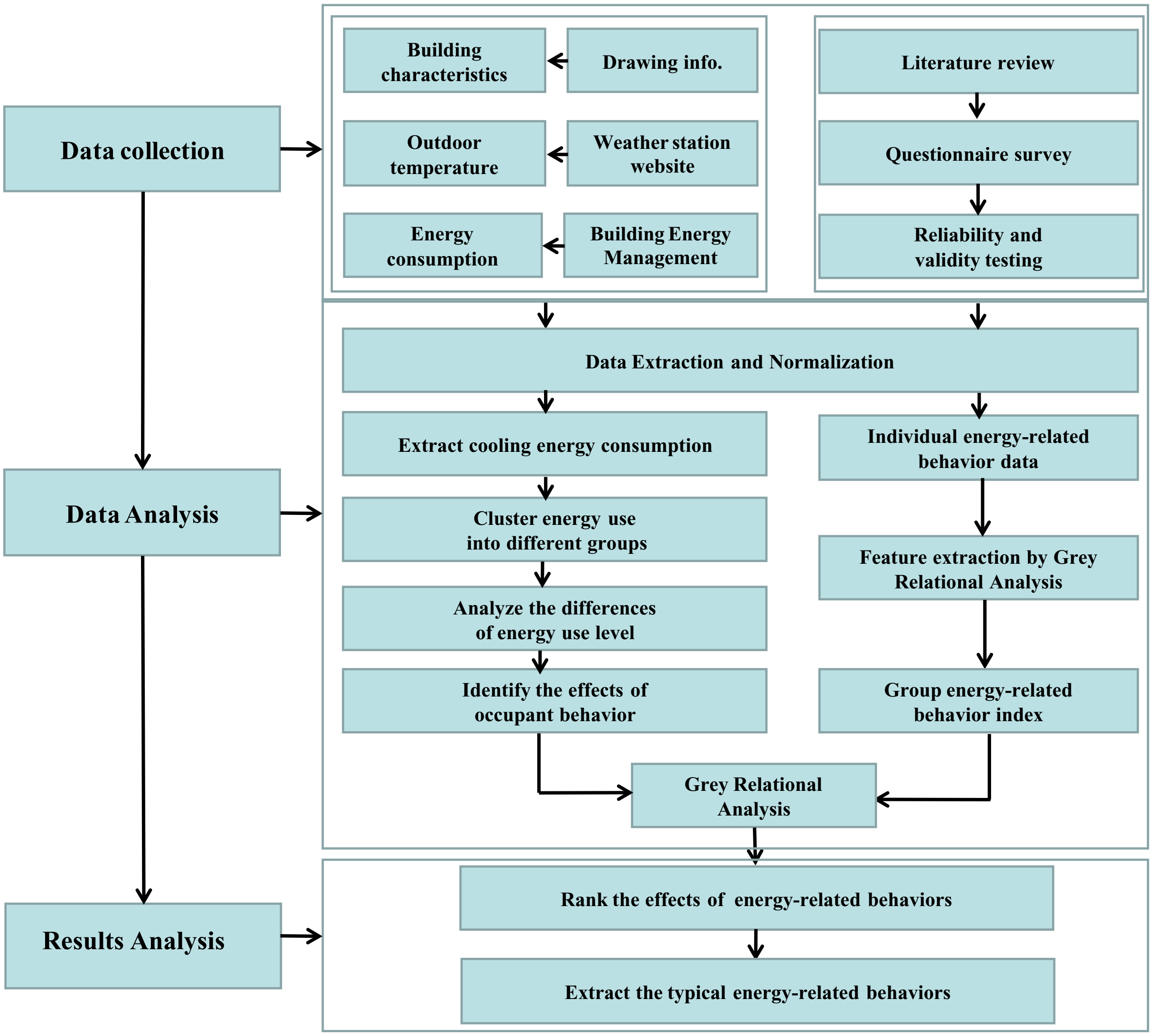

Fig. 1. Overview of the research methods and process.

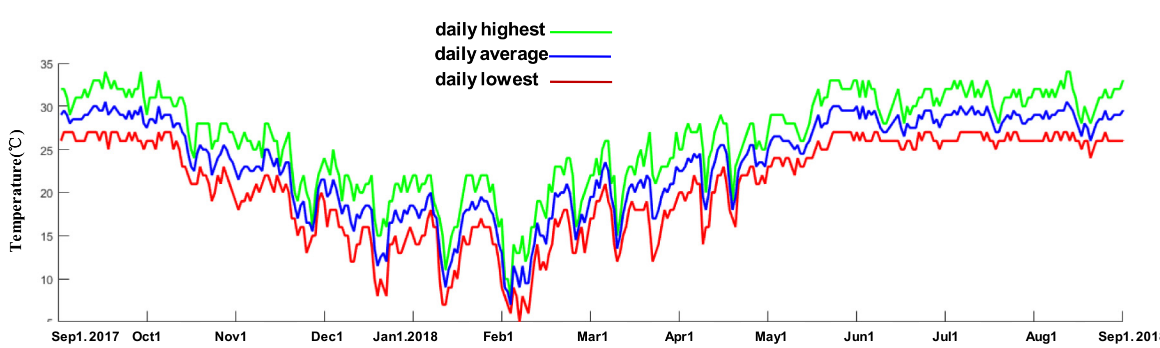

Fig. 2. Daily outdoor temperature of the investigation period (Sep1. 2017–Sep1. 2018) in Zhuhai.

buildings (i.e., hereinafter Building A and Building B), located in Zhuhai, China. Zhuhai is a typical cooling-oriented city in a hot summer and warm winter climate region, where cooling energy consumption accounts for the largest proportion. The daily outdoor temperature in Zhuhai is shown in Fig. 2.

Building A is for male students, while Building B is for female students. Fig. 3 shows the layout of building floor and room. A total of 130 identical rooms were surveyed in these two buildings, including 76 male rooms and 54 female rooms, and each room accommodates six students. All rooms are equipped with the same

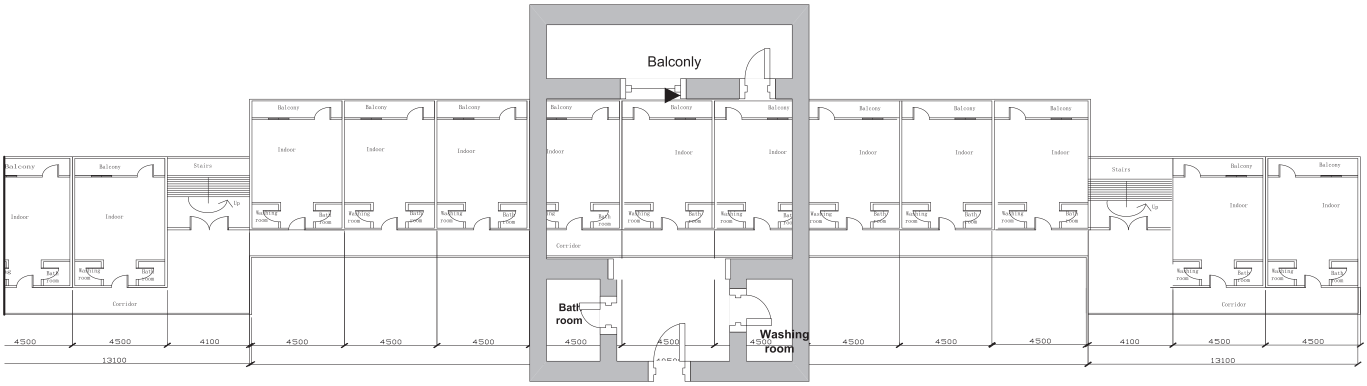

Fig. 3. Layout of the standard floor and dorm rooms.

cooling-related appliances, including an air conditioner and an electrical fan. The daily electricity usage data of each room in the investigation period was provided by Energy Management System. Notably, the daily electricity usage during the holidays, including winter holiday (February) and summer holiday (July and August), is zero, so the energy use during these days is excluded in this study.

2.2.2. Energy-related behavior theories and measurement

The data reflecting occupants' energy-related behaviors were collected mainly from questionnaires. According to the report of International Energy Agency (IEA), energy-related occupant behavior is defined as "observable actions or reactions of a person to adapt to ambient environmental conditions such as temperature, indoor air quality or sunlight" (Zou et al., 2018a). As explained by Nicol and Humphery's (2002) principle-"if change occurs such as to produce discomfort, people react in ways which tend to restore their comfort." Behavior is induced by the effect of certain stimuli, also called drivers of behavior (Tam, V. et al., 2018). A predictive curve of operating behaviors can be obtained presumably through understanding the correlation between drivers and behavior. Behavioral theories and models stem from the principle of social-psychology, for example, Theory of Complex Adaptive System (CAS), Theory of Planned Behavior (TPB), and Behavioral Cognitive Theory, considering the changeable human cognition process by connecting human and environment. From the perspective of CAS, Ding et al. (2019) integrated the observed behaviors and their influencing triggers (i.e. environment, event and habit), and proposed an ABM-based model to explore the relationship between occupant behavior and building energy consumption. Results show that occupancy is the most important factor for dormitory energy consumption, and reducing the time of air conditioner use have great potential for energy saving. Based on the TPB, Tetlow et al. (2015) developed an extending model of occupant behavior and found that occupants were interacting with small power "automatically", with habit accounting for 11% of the variation in workstation energy consumption. Besides, Hong et al. (2015) used behavioral cognitive theory to develop the DNA's framework, which suggests four components governing occupants' energy behavior: drivers, needs, actions and systems. In order to model air-conditioning behavior, Wang (2014) divided factors influencing occupants' operation of air-conditioning into environment triggered and event triggered. For example, whether occupants' switching on/off air conditioner is correlated with the indoor temperature or the daily event. The behavior "closing the curtains when feeling hot" is considered to be environment triggered, while the behavior "turning on air conditioner as long as entering rooms" belongs to event triggered (Feng et al., 2016; Wang, 2014). Based on behavioral theories, the questionnaire in this research was designed by referencing the occupant behavior modeling framework proposed by Wang (2014), who had proposed a new approach for quantitative description from an action-based view, and factors influencing occupants' cooling energy behavior are summarized into environment triggered, event triggered and habit triggered, shown in Table 1.

Based on the above behavioral theories, which are used to find the influencing factors for occupants to operate cooling-related systems and appliance, a questionnarie was initially designed, with focus on understanding energy-related behaviors rather than their change. Before the formal survey, pilot interviews were carried out to further check whether the energy-related behaviors listed in it are those mostly occur in actual daily life to influence cooling energy consumption. Then, a final questionnaire was formed, as shown in Appendix A. The questionnaire survey was conducted to obtain sample data regarding occupants' cooling energy behaviors.

The questionnaire comprised three parts, viz., (1) Part1: Respondents' information. This section included background or socio-demographics, serving to categorize the respondents by their gender, room NO., and floors. (2) Part2: Cooling behavior performance. This section investigated participants' cooling-related activities, with 13 factors affecting cooling energy consumption coded as Bi ($i = 1, 2, \ldots, 13$) in Table 1. A five-point summated scale was used in the first eight energy-related behaviors to investigate their behavioral performance levels ("always", "often", "occasionally", "rarely", "never"). (3) Part 3: Space was reserved for respondents to supplement any comments if necessary.

The reliability and validity of the survey data were tested (Cronbach $\alpha = 0.721 > 0.7$, $KMO = 0.728 > 0.7$), with all 13 items finally retained. A total of 450 questionnaires were distributed face to face. There are 410 valid questionnaires collected with at least two valid returns from each room. Among them, 230 questionnaires were from males, while 180 from females.

2.3. Data extraction and normalization

2.3.1. Extract cooling energy consumption

Since the end-use loads provided by EMS are the total energy consumption of each room, the cooling energy consumption needs to be extracted from the existing dataset. According to the average outdoor temperature, shown in Fig. 4, it can be categorized into hot

Table 1
Cooling-related behaviors.

Code	Items	Main influencing triggers
B1	Closing the curtains when feeling hot	Environment
B2	Turning on air conditioner as long as entering rooms	Event, habit
B3	Closing doors and windows before turning on air conditioner	Habit
B4	Opening doors and windows for ventilation instead of turning on air-conditioner	Habit
B5	Using fans instead of turning on air conditioner	Environment, habit
B6	Adjusting clothing to adapt to room temperature	Environment
B7	Switching off the air conditioner regularly when sleeping	Event, habit
B8	Turning off air conditioner when leaving room	Event, habit
B9	The daily average frequency of utilization of air conditioner in summer	Environment
B10	Ratio of occupancy in room	Event, habit
B11	Temperature set points of air conditioning	Environment
B12	Thermal preferences	Habit
B13	The daily average hours of air conditioner utilization in summer	Environment

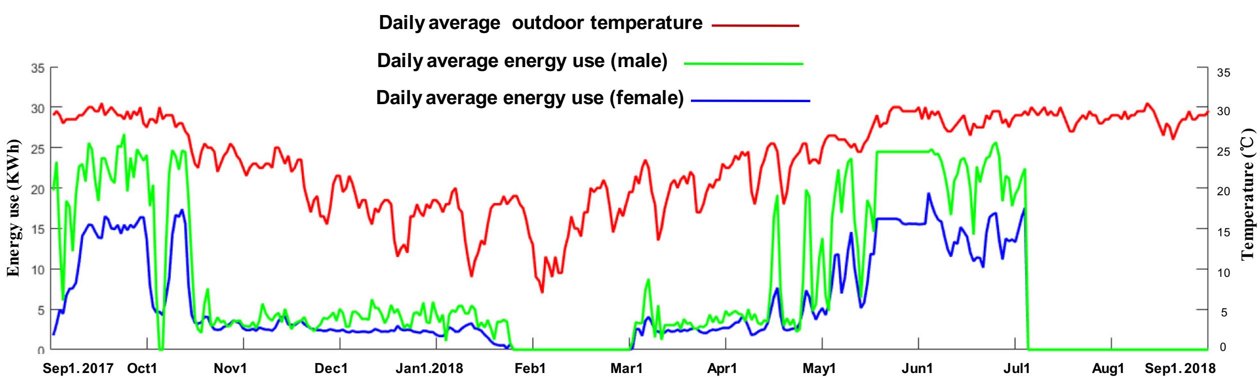

Fig. 4. Daily average outdoor temperature and daily average energy use.

season (May to September), transition season (April and October) and warm season (November to March). Statistic results suggest that energy consumption shows a marked seasonal variation. From Fig. 4, more energy was consumed during the hot season than the warm season. For the building A (male), the daily average energy usage ranged from 20 to 25 KWh during hot season, but 3 to 5 KWh in the warm season. However, females' daily average energy loads during the hot season centered around 10 to 17 KWh, with

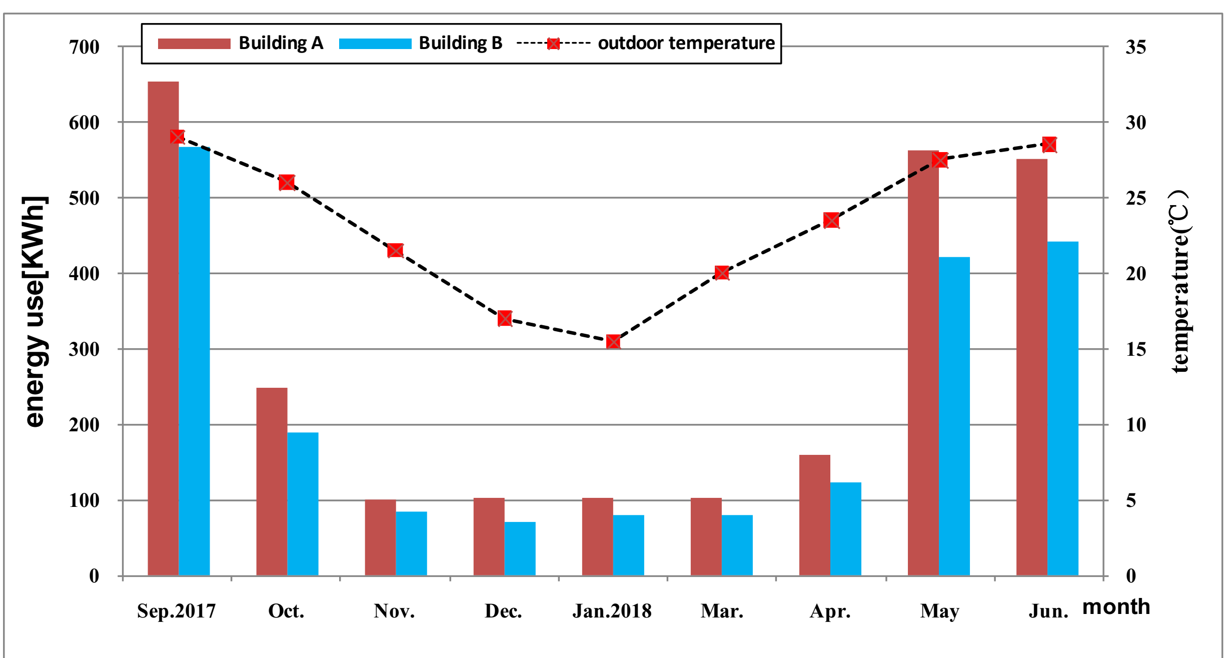

Fig. 5. Monthly average energy consumption of each building and monthly average outdoor temperature.

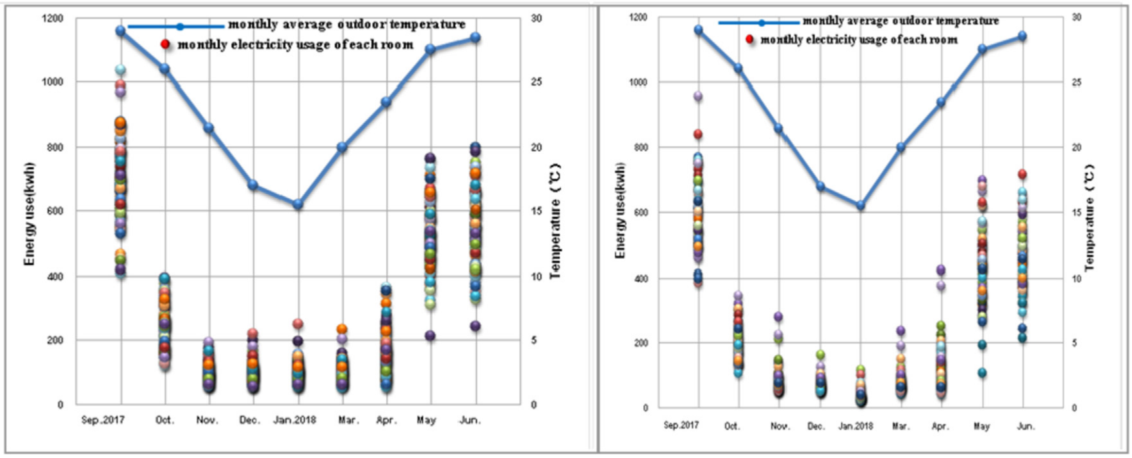

Fig. 6. Monthly electricity usage of each room and monthly average outdoor temperature (left: males; right: females).

3.17 KWh at minimum and 19.40 KWh at maximum, while varied between 2 and 4 KWh in the warm season. It could be deduced that the male consumed almost 1.2–1.5 times more energy than the female. Generally, the higher outdoor temperature was, the more energy was consumed. No matter males or females, the daily average energy during hot season was up to five times more than that in warmer season.

The similar situation can be seen from Fig. 5. The monthly average energy consumption of each building in hot season is about five times more than that in warm season. Specially, the monthly average energy consumption of buildings is similar with each other during the warm season, and a similar pattern in each room is found, shown in Fig. 6. It is found that the change of end-use loads indoors did not fluctuate wildly from month to month during the warm season. This might be due to the fact that in this season, the energy-related activities are mainly determined by the use of non-cooling electrical appliances like lighting, washing machine, and plugs, and occupants tend to keep their daily energy-use habits. Therefore, it is assumed that occupants keep their habits on non-cooling electrical appliances all year round in this study.

Unlike the warm season, with the increase of outdoor temperature, the energy consumption increases dramatically in other seasons. Particularly, the peak of energy consumption occurred in the hot season. Hence, compared with the warm season, this increment of energy use in the hot and transition season is defined as cooling energy consumption. The total energy consumption in one year could be divided into cooling and non-cooling energy consumption according to weather conditions (i.e., outdoor air temperature).

For room j, the non-cooling energy consumption per month (A_{NCj}) in formula (1) is considered to be constant, represented by the average of monthly total energy consumption T_{ij} during the warm season:

$$A_{NCj} = \frac{1}{N1}\sum_{i1=1}^{n} T_{ij} \quad (i_1 = 1,\ 3,\ 11,\ 12;\ j = 1,\ 2,\ 3, \ldots,\ m) \tag{1}$$

where T_{ij} is the total energy consumption of the room j in each month during the warm season, and N1 indicates the total of months during the warm season. Specifically, N1 equals to 4 in this study.

Then, the annual total cooling energy consumption of room j (T_{cj}) is extracted from the annual total energy consumption, seen in formula (2):

$$T_{cj} = T_{tj}\text{-}N^{*}A_{NCj} \tag{2}$$

Where T_{tj} is the annual total energy consumption of room j. N indicates the number of months when non-cooling energy is consumed in a year, viz., N = 9.

2.3.2. Data normalization

Before data analysis, it should be noted that dataset with different measured scales may lead to inconsistency. For example, the electricity energy loads have a larger range than that of the energy-related behavior values. Min-max normalization was performed to deal with the inconsistencies in measured dataset and to scale the values so that they fall within a predetermined range (Han, 2005). The main advantage of the min-max normalization lies in its ability to reserve the relationships of the original data, since it carries out a linear normalization. Assume that x_{max} and x_{min} are the original maximum and minimum values of a numerical attribute. By min-max normalization, a value of this attribute (x) can be transformed to x' in the new specified range [x'_{min}, x'_{max}], calculated by formula (3):

$$x' = \frac{x - x_{min}}{x_{max-x_{min}}}\left(x'_{max} - x'_{min}\right) \tag{3}$$

In this study, the new range is defined as [1, 5]. The annual cooling energy uses need to be transformed to [1, 5]. For energy-related behavior attributes such as B1–B8, their measurement i.e. [always, often, occasionally, rarely, never], can be transformed to [1, 2, 3, 4, 5] directly.

2.4. Cluster analysis

Cluster analysis is an important method for merging data objects into different clusters. Objects in the same cluster have a high similarity, while objects in different clusters have a low similarity (Han, 2005). Fig. 7 shows a clustering schema based on hypothetical room attributes. It contains various end-use loads, such as lighting, cooling, and heating.

This figure consists of m attributes and n instances. Each attribute represents a variable and each instance denotes a room. All the

	Instance	Attribute1 (Cooling energy use)	......	Attribute m (lighting energy use)
Cluster 1	Instance1	x	......	x
	......	......	......	
	Instance i	x	......	x
	......	......	......	
Cluster w	Instance j	x	......	x
	......	......	......	
	Instance n	x	......	x

Fig. 7. Clustering schema.

instances are grouped into w clusters. Accordingly, these w clusters are homogenous internally and heterogeneous among different clusters (Han, 2005). Such internal cohesion and external separation are based upon the various end-use loads, which can be mapped onto corresponding consumption patterns. If the influence of other objective factors on energy use is excluded, the variations in energy use among consumption patterns can be assumed to be caused by occupant behavior.

The dissimilarity between data objects is calculated using the distance between them in the cluster analysis. In this study, the most popular distance measurement, Euclidean distance, was used (Chen et al., 1996):

$$d(k, l) = \sqrt{(x_{k1} - x_{l1})^2 + (x_{k2} - x_{l2})^2 + \ldots + (x_{kn} - x_{ln})^2} \quad (4)$$

where $k = (x_{k1}, x_{k2}, \ldots, x_{kn})$ and $l = (x_{l1}, x_{l2}, \ldots, x_{ln})$ are rooms, in which, $x_{k1}, x_{k2}, \ldots, x_{kn}$ are n parameters of k and $x_{l1}, x_{l2}, \ldots, x_{ln}$ are n parameters of l.

Common clustering algorithms include K-means, K-medoid, and CLARANS. In this study, K-means is used due to its efficiency and wide applicability. Open-source data mining software Matlab7.0 was used to perform cluster analysis based on energy consumption data. According to the end-use loads, the energy consumption can be divided into three groups based on different energy use levels.

The K-means algorithm is one of the partition methods to solve a clustering problem. This algorithm consists of five steps (Chen et al., 1996; Yu et al., 2011):

(1) Randomly select k instances from the dataset as the initial cluster centers;
(2) Calculate the distance between each remaining instance and each initial chosen center;
(3) Assign each remaining instance to the cluster with the closest center;
(4) Recalculate the mean values, i.e., the cluster centers, of new clusters;
(5) Repeat steps 2 to 4 until the algorithm converges in order for stable cluster centers.

2.5. Grey relational analysis

On the basis of geometrical mathematics, grey relational analysis (GRA) has been proposed to search for grey relational grades and a grey relational order (i.e., the rank of grey relational grades). They can be utilized to describe primary trend relationships among relevant factors, and to identify the main factors that significantly influence predefined target factors (Deng, 1989). For example, if the cooling energy use is defined as the target factor, GRA can find grey relational grades for its various energy-related behaviors, such as temperature set points, the total hours of air-conditioning utilization, opening doors or windows, etc. These grey relational grades represent quantified effects of different energy-related behavior on cooling energy consumption. The larger the grey relational grade is, the more significant effects the factor exerts. Compared with other traditional statistical methods, the main advantages of GRA lie in its simplicity and ability to deal with small data sets, without strict compliance to certain statistical principles.

In this research, y_0 is defined as the objective sequence (measured data of target factor, i.e., cooling energy consumption), and y_i as the compared sequences (measured data of relevant factors, i.e., various types of energy-related behaviors):

$$y_0 = (y_0(1), y_0(2), \ldots, y_0(n)) \quad (5)$$

$$y_i = (y_i(1), y_i(2), \ldots, y_i(n)), \ i = 1, 2, \ldots, m \quad (6)$$

The procedure of GRA is described as follows:

Step 1. Normalize raw data (Min-max normalization is used in this study). y_0 and y_i are used to denote obtained normalized sequences;

Step 2. Calculate grey relational coefficients $\varepsilon_i(k)$, which is defined based on y_0 and y_i as:

$$\varepsilon_i(k) = \frac{\min\limits_{i}\min\limits_{k} |y_0(k) - y_i(k)| + \alpha \max\limits_{i}\max\limits_{k} |y_0(k) - y_i(k)|}{|y_0(k) - y_i(k)| + \alpha \max\limits_{i}\max\limits_{k} |y_0(k) - y_i(k)|}$$
$$(i = 1, 2, \ldots, m; \ k = 1, 2, \ldots, n) \quad (7)$$

where $0 < a < 1$, normally $a = 0.5$.

Step 3. Calculate grey relational grade (r_{ij}) in the following formula (8):

$$r_{ij} = \frac{1}{N}\sum_{k=1}^{n} \varepsilon_i(k) \quad (8)$$

Step 4. Rank the obtained grey relational grades, and thus, the grey relational order can be identified.

As is mentioned previously, grey relational grades were employed to extract group behavior features based on individual behaviors. Then it was applied to evaluate the effects of energy-related behaviors on cooling energy consumption at a group level to find out the typical ones. Notably, grey relational grades are numerical measures of factor influences on objective values, and the numeric values are between 0 and 1. Generally, $r > 0.9$ indicates a marked influence, $r > 0.8$ indicates a relatively marked influence, and $r > 0.7$ indicates a noticeable influence (Fu et al., 2001).

3. Results and discussion

3.1. Effects of occupant behavior

Since energy consumption is influenced by various factors, including climate, building envelope, building systems and equipment, as well as occupants and their behaviors (Huebner et al., 2016), it is necessary to identify the separate effects of occupant behavior. Unlike Yu et al. (2011) who clustered the grey relational coefficients between energy use and objective factors to obtain the similar objective factors, this paper selected typical cases that could adequately remove the objective influencing factors, and precisely identify the effects of occupant behavior on energy consumption. For samples of identical dorm rooms, apart from occupants' behavior and the building floor, other influencing factors of cooling energy consumption were controlled.

The rest steps are to identify the effects of occupant behavior on cooling energy consumption among factors of gender, floor, and behavior. Firstly, the effects of occupants' gender on the cooling energy consumption are identified by analysis of variance. Secondly, through cluster analysis, the cooling energy consumption is clustered into three consumption patterns based on different levels of energy usage. The variances in energy use among different consumption patterns are then analyzed with different floors by analysis of variance. Finally, if the floor has a negligible influence on cooling energy consumption, energy consumption gaps among different consumption patterns could be attributed to occupant behaviors.

3.1.1. Effects of genders

Analysis of variance was used to compare the difference of cooling energy consumption between genders. Provided that the significance threshold was defined as 0.05, the result indicated that there were significant differences in cooling energy consumption between different genders ($P < 0.05$), which was consistent with the findings of Zelezny et al. (2000). The energy-related behaviors of males and females were then researched respectively.

3.1.2. Effects of floors on different energy consumption patterns

Cluster analysis was applied to analyze cooling energy consumption for each gender group. Cooling energy consumption was grouped into three energy use patterns based on K-MEANS algorithm, viz., the austerity pattern, the normal pattern, and the over-use pattern as shown in Fig. 8 and Fig. 9, respectively. It showed that there are significant differences within the same gender group. Those in the over-use pattern seem to use almost 2–3 times cooling energy than those in the austerity pattern. For males, the annual total cooling energy consumption of the austerity ranged from 670.71 KWh to 1280.57 KWh, but 1690.31 KWh to 2098.01 KWh for the over-use. Alternatively, in the female group, the average of annual total cooling energy consumption is 784.41 KWh for the austerity, while 1675.78 KWh for the over-use.

For these rooms, apart from different floors and behaviors, other objective influencing factors of cooling energy consumption are controlled including climates, building envelope, installations, gender, etc., but it still shows great variations of cooling energy consumption in different dorm rooms. To research whether the floor variable influences or not, the effect of different floors on cooling energy consumption was further clustered as demonstrated in Fig. 10 and Fig. 11. From the results, cooling energy consumption on different floors is relatively even-distributed on the same level in both male and female rooms. Similarly, analysis of variance was then used to analyze the effect of different floors on cooling energy consumption under the same gender group, which indicate that the floor variable has no significant influence on cooling energy consumption ($P_{male} = 0.235 > 0.05$, $P_{female} = 0.098 > 0.05$). Hence, the cooling energy performance gap caused by different floors is ignored in the process of identifying the effects of occupant behavior. It is therefore concluded that the discrepancies (almost 2–3 times) in cooling energy consumption are the result of occupant behavior. This finding is in line with the result of Zhou et al.(2018) that occupant behavior led to the greatest differences (up to 3 times) in air conditioning cooling consumption by

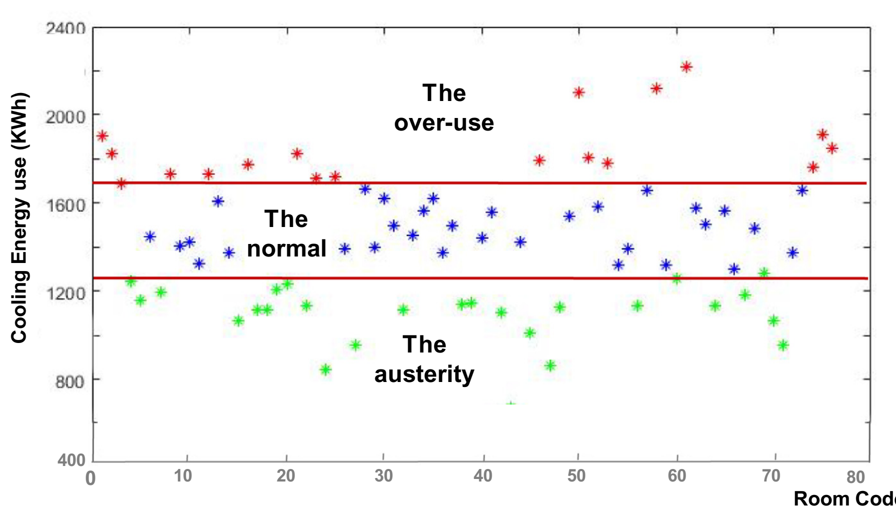

Fig. 8. The cooling energy consumption patterns (male rooms).

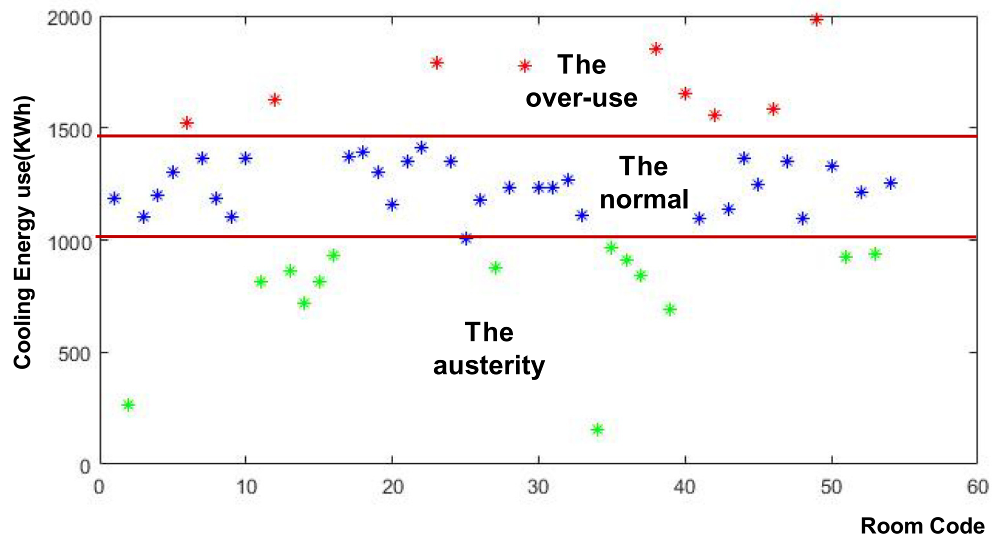

Fig. 9. The cooling energy consumption patterns (female rooms).

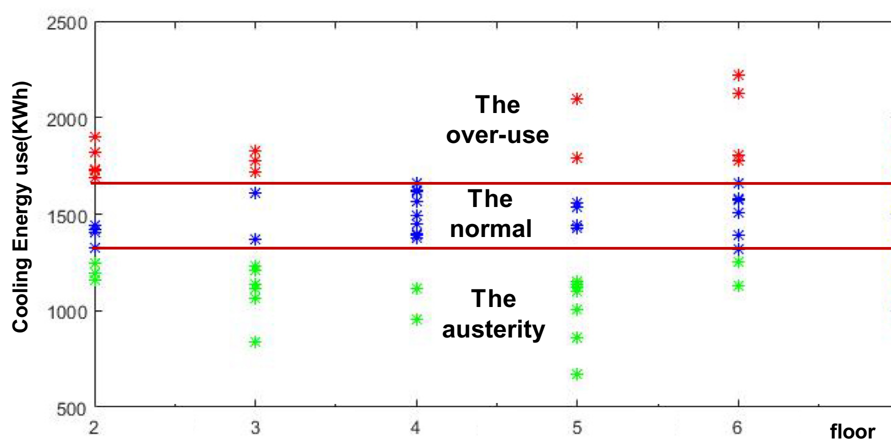

Fig. 10. The distribution of different consumption patterns on different floors (male rooms).

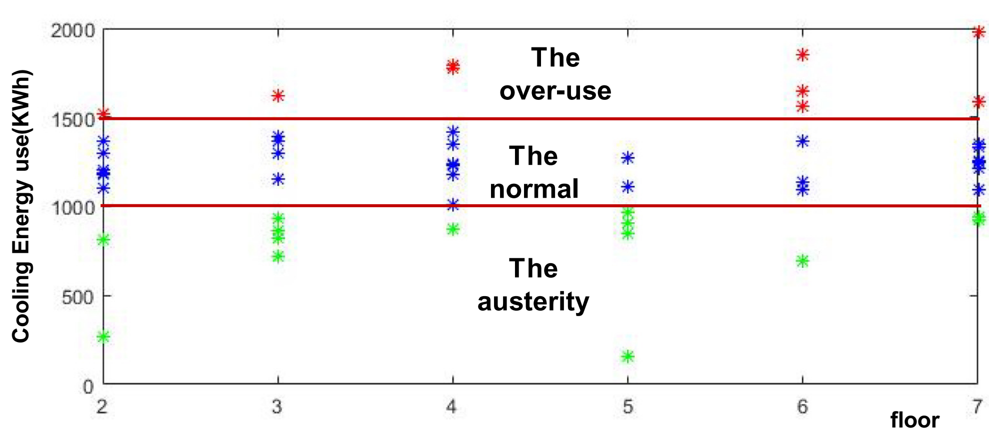

Fig. 11. The distribution of different consumption patterns on different floors (female rooms).

Table 2
Occupant behavior performance in one dorm room.

Room NO.	Room Code	Respondents NO.	B1	B2	B3	…	B13	Cooling energy usage
7604	**1**	1	3	3	1	…	2.67	**1316.76**
		2	4	1	4	…	2.67	
		3	4	3	4	…	2.33	
		4	2	3	3	…	2.67	
		5	3	2	2	…	3.00	

simulation.

3.2. Feature extraction of group energy behavior

Due to behavioral diversity, different occupants in the same room may behave differently. The behavior data collected through the questionnaire are based on individuals. However, the cooling energy consumption reflects the group's (viz., a room considered as a group) energy use. The difficulty lies in how to use individual behavior data to establish the relationship between group behavior and cooling energy consumption in a room. In other words, the relationships between individual behavior and group behavior need to be examined, and the characteristics of group behavior based on individuals shoud be analyzed.

In addtion, concerning different behavioral indicators, the effect of individual behavior on group behavior is different. This paper proposed a method for extracting features of group energy behavior based on individual behaviors. The group energy-related behavior feature index was defined by extracting five statistic indicators including the max, min, mean, mode, and median of each group. Then, the correlation coefficient between group behavior feature index and cooling energy consumption was calculated by grey relational analysis. The largest correlation coefficient was finally chosen to be the group behavior feature index. The higher the correlation coefficent is, the better it represents the group behavior.

Take NO. 7604 room as a group example. This group holds five individuals with each individual behaving quite differently from each other as shown in Table 2. As a result, the cooling energy consumption in this room is emerged from all individuals' behaviors on a group level. The following three steps are demonstrated to extract the group behavior feature.

Firstly, the feature index of each behavior indicator was calculated based on their individual behavior performance. For example, the group feature indexes of B13 are listed as max = 3.00, min = 2.33, mean = 2.67, mode = 2.67, median = 2.33, respectively.

Table 3
The grey relational grades for the relationship between group behavior features based on individual behaviors and cooling energy (males).

Variables	Grey relational grades				
	Max	Min	Mean	Mode	Median
B1	0.66	0.64	**0.68***	0.65	0.67
B2	0.62	0.63	**0.65***	0.63	0.63
B3	0.60	0.63	**0.67***	0.61	0.65
B4	0.65	0.66	**0.73***	0.69	0.72
B5	0.63	0.55	**0.64***	0.58	0.62
B6	0.67	0.64	**0.71***	0.67	0.69
B7	0.68	0.61	**0.70***	0.65	0.69
B8	0.66	0.61	**0.68***	0.62	0.65
B9	0.62	0.61	**0.67***	0.61	0.65
B10	**0.64***	0.57	0.63	0.60	0.62
B11	0.66	0.64	**0.68***	0.65	0.67
B12	0.67	0.64	**0.69***	0.66	0.69
B13	0.63	0.67	0.67	0.66	**0.68***

Table 4
The grey relational grades for the relationship between group behavior features based on individual behaviors and cooling energy (females).

Variables	Grey relational grades				
	Max	Min	Mean	Mode	Median
B1	**0.70***	0.57	0.65	0.59	0.64
B2	0.71	0.63	**0.71***	0.66	0.71
B3	**0.71***	0.57	0.68	0.62	0.68
B4	0.73	0.68	**0.77***	0.73	0.76
B5	**0.69***	0.51	0.61	0.56	0.58
B6	**0.73***	0.55	0.68	0.63	0.68
B7	0.63	0.57	**0.67***	0.59	0.65
B8	**0.70***	0.56	0.68	0.63	0.67
B9	**0.69***	0.61	0.69	0.65	0.69
B10	**0.66***	0.53	0.62	0.57	0.60
B11	**0.70***	0.57	0.65	0.59	0.64
B12	**0.68***	0.53	0.62	0.55	0.61
B13	0.66	0.70	**0.75***	0.69	0.72

Secondly, the correlation coefficient (i.e., grey retional grades) between the group feature index and cooling energy consumption is calculated by grey relational analysis. Table 3 and Table 4 showed the correlation coefficients calculated.

Finaly, the final group feature was chosen from the five types of feature indexes based on the largest correlation coefficient, as seen in Tables 3 and 4. For Variable B1, its mean value (0.68) shows the largest correlation (***coded)** between the group behavior and cooling energy consumption, so the mean is chosen as the final group behavior feature.

After extracting features of group energy-related behaviors from individual behaviors, grey relational analysis was further applied to examine and rank the effects of group energy-related behaviors on cooling energy consumption within each gender group.

3.3. Extraction of typical energy-related behaviors

3.3.1. Ranking the effects of energy-related behaviors for males and females

The ultimate goal of this study is to find out the typical energy-related behaviors influencing cooling energy consumption. After identifying the effects of occupant behavior on cooling energy consumption, grey relational analysis was utilized to further investigate and rank the effects of different types of specific energy-related behaviors on cooling energy consumption. Therefore, the annual room cooling energy consumption was selected as the objective sequence in GRA, and different types of group energy-related behaviors shown in Table 1 were regarded as reference sequences. According to the procedure of GRA described in Section 2**,** the correlation coefficient r_{ij} reflects correlations between group energy-related behavior and cooling energy consumption, which is based on the whole sample. It describes the effects of different types of energy-related behaviors on cooling energy consumption. The results of GRA are showed in Fig. 12 and Fig. 13 for different gender groups, respectively.

As can be seen from Fig. 12, B13 (the daily average hours of air

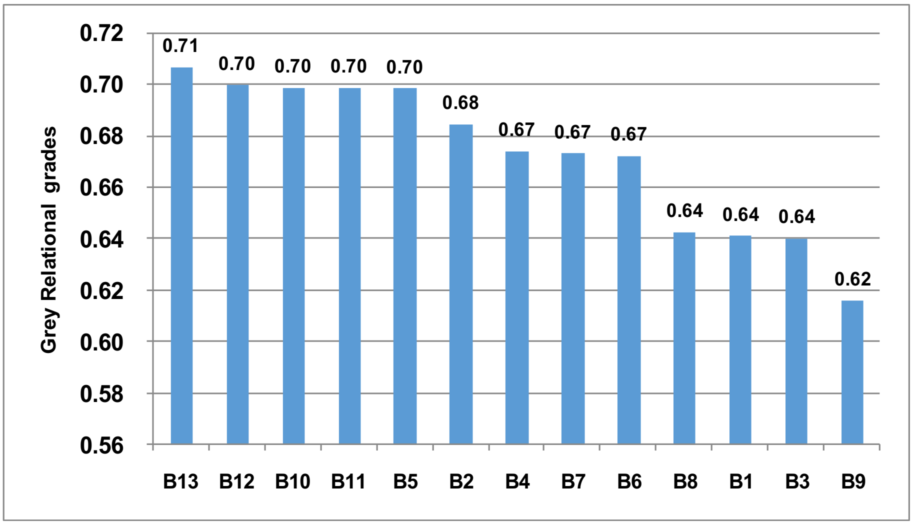

Fig. 12. The influences of cooling energy behavior on energy use (males).

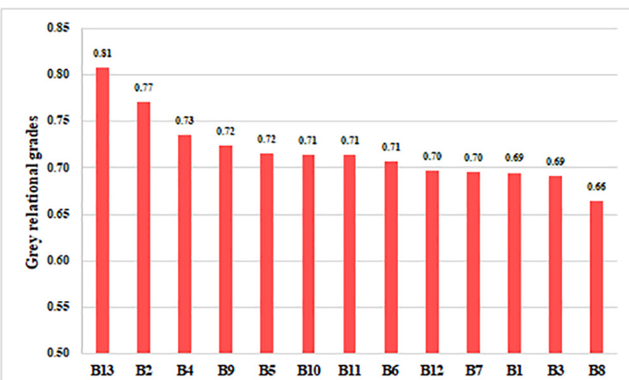

Fig. 13. The influences of cooling energy behavior on energy use (females).

conditioning utilization) influenced cooling energy consumption more significantly than the other energy-related behaviors for males. It's suggested that the daily average hours of air conditioning utilization is the most significant behavior influencing cooling energy consumption. At the same time, B12 (thermal preferences), B10 (the ratio of occupancy in room), B11 (the temperature set points of air conditioning), and B5 (using fans instead of turning on air conditioner) have noticeable impacts on cooling energy consumption for males, since the grey relational grades of these four behaviors all exceed 0.7. As the most typical behavior, the daily average hours of air conditioning utilization has significant differences under different consumption patterns. As presented in Fig. 14, for the over-use pattern, the daily average hours of air conditioning utilization mainly take the values of 10–15 h (50.00%) and 15–20 h (33.30%), but its values are evenly distributed for the austerity, with 29.20% for 5–10 h, 36.20% for 10–15 h, 26.90% for 15–20 h, respectively.

Compared with males, female group behavior seems to have more impact on cooling energy consumption. As shown in Fig. 13, there are a total of eight typical behavior types whose grey relational grades are more than 0.7, the rankings of which are as follows:

$r1(B13) = 0.81 > r2(B2) = 0.77 > r3(B4) = 0.73 > r4(B9) = 0.72 > r5(B5) = 0.72 > r6(B10) = 0.71 > r7(B10) = 0.71 > r7(B11) = 0.71$

It shows that B13 also has the most marked influence on cooling energy consumption for females. As can be seen from Fig. 15, the daily average hours of air conditioning utilization differs significantly under different consumption patterns. For the over-use pattern, most of them spend 15–20 h with air conditioning opened, at the proportion of 77.80%. In contrast, the daily average hours of air conditioner utilization ranged from 10 to 15 h each day for the austerity (61.50%).

Clearly, the daily average hours of air conditioner utilization among males' behaviors ranks top, same as that in females' behaviors. The significant effects of this behavior on cooling energy consumption are also stated in Rinaldi et al. (2018) and Li et al. (2007) that the cooling energy consumption of different apartments varied widely due to the variance in duration with air-conditioning. Furthermore, B2 (turning on air conditionings as long as entering the room) noticeably influences cooling energy consumption, which is similar with the findings in Feng et al. (2016). Moreover, B4 (opening doors and windows for ventilation instead of turning on air-conditioning), B9 (the daily average frequency of utilization of air conditioner), B5 (using fans instead of turning on air conditioner), B10 (the ratio of occupancy in room), B11 (temperature set points of air conditioning), and B6 (adjust clothing to adapt to room temperature) have noticeable influences on cooling energy consumption. It is concluded that these energy-related behaviors of female occupants should be paid more attention.

3.3.2. Comparative analysis between genders

Table 5 presents the rankings regarding the effects of different energy-related behaviors on cooling energy consumption under different genders. Results show that there are certain similarities and differences in the typical specific energy-related behaviors influencing cooling energy consumption between males and females.

On the one hand, it can be found from Table 5 that among the top six energy-related behaviors, three of them are similar, such as

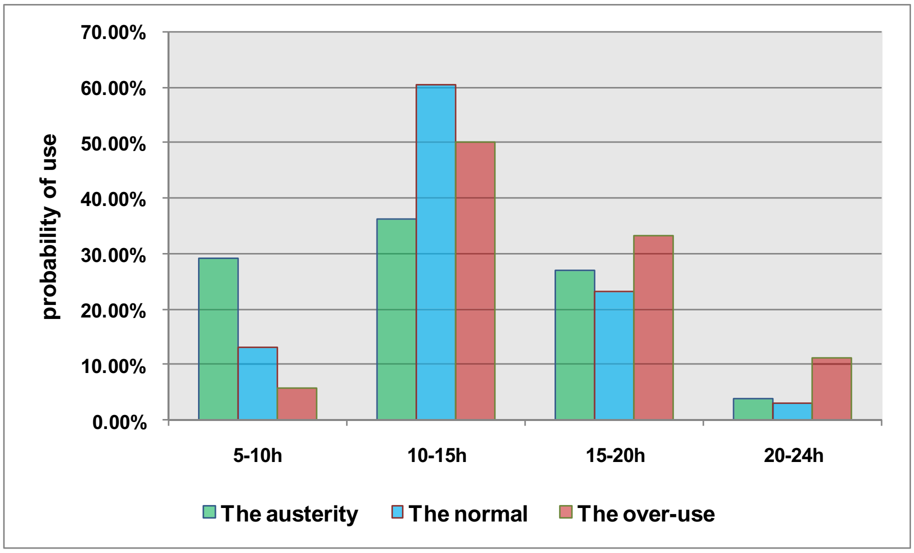

Fig. 14. The probability of the daily average hours of air conditioning utilization under different consumption patterns (males).

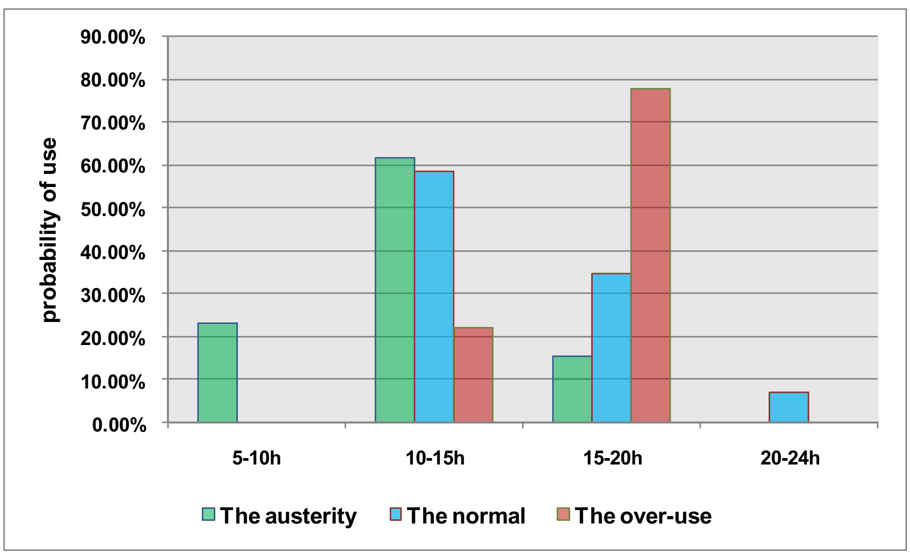

Fig. 15. The probability of the daily average hours of air conditioning utilization under different consumption patterns (females).

B13 (the daily average hours of air conditioner utilization), B5 (using fans instead of turning on air conditioner), and B10 (the ratio of occupancy in room). Particularly, the rank for B13 and B5 are the same for males and females. In other words, regardless of gender, B13, B5, and B10 are the typical energy-related behaviors influencing cooling energy consumption, thus deserving more attention in building energy design and improvement of occupant behavior in operation stage. For B10, the current result is different from the experiments of Ahn and Park (2016) which showed that occupants' presence is not strongly correlated with energy consumption. Yet, behaviors such as B1 (closing the curtain when feeling hot), B3 (closing the doors and windows before turning on air conditioner), and B8 (turning off air conditioner when leaving room) are found with negligible influence on cooling energy consumption in this research. Further statistical analysis shows that these behaviors have no significant differences among occupants. For B6 (adjustment clothing to adapt to room temperature), results show that it is not a significant influencing factor of cooling energy consumption, which is in line with findings in Schweiker et al. (2012).

On the other hand, there are some differences in the grey relational order for B2 (turning on air conditioner as long as entering rooms), B4 (opening doors and windows for ventilation instead of turning on air conditioner), B9 (the daily average frequency of utilization of air conditioner), B12 (thermal preferences), and B11 (temperature set points of air conditioning). The comparative study of different gender indicated that B2, B4, and B9 were typical behaviors influencing cooling energy consumption for females, while these behaviors are untypical for males. As for females, the better their behavior performance is, the less energy they consume. In contrast, B12 and B11 have more significant effects on cooling energy consumption for males than females. Details are discussed as

Table 5
Orders of behaviors influencing cooling energy consumption under different genders.

Code	Items	Ranking results of GRA (male)	Ranking results of GRA (female)
B1	Closing the curtains when feeling hot	11	11
B2	Turning on air conditioner as long as entering rooms	6	2
B3	Closing doors and windows before turning on air conditioner	12	12
B4	Opening doors and windows for ventilation instead of turning on air-conditioner	7	3
B5	Using fans instead of turning on air conditioner	5	5
B6	Adjusting clothing to adapt to room temperature	9	8
B7	Switching off the air conditioner regularly when sleeping	8	10
B8	Turning off air conditioner when leaving room	10	13
B9	The daily average frequency of utilization of air conditioner in summer	13	4
B10	Ratio of occupancy in room	3	6
B11	Temperature set points of air conditioning	4	7
B12	Thermal preferences	2	9
B13	The daily average hours of air conditioner utilization in summer	1	1

following.

Firstly, for B2 and B4, similar performance was found in males' behaviors. Taking B4 as an example, most male occupants prefer opening windows and doors in summer. However, the females varied in B4 due to their different attitudes and behaviors for privacy protection. The variation of females' behavior (B4) leads to their discrepancy of cooling energy use. Partially different from the findings in Fabi et al. (2013) that the opening window behavior has great impact on energy consumption, the current results indicate that the window opening behavior influences noticeably on cooling energy consumption for females rather than males.

Second, for B9, it shows a quite different order between genders. It ranks the last for males, indicating negligible influence on male occupants' cooling energy consumption. It was found that the frequency of utilization of air conditionings in males' room is usually higher than that in females' room. Besides, female occupants vary widely in this behavior, thereby causing dramatic differences in cooling energy consumption.

Another remarkable difference is found in the rank of B12 (thermal preferences). It ranks the second for males while the ninth for females, which suggest that it has a more noticeable influence on males' cooling energy consumption. Considering the rank difference for B11 between genders, it can be deduced that thermal comfort influences behaviors. Data showed that male and female occupants varied in thermal preferences. There are great variations in thermal preferences for males, with the comfortable temperature indoors averagely distributed between 20 °C and 28 °C but only between 24 °C and 26 °C for females. Accordingly, males tend to set the temperature of air conditioning ranging from 17 °C to 28 °C in summer, while females set it from 24 °C to 26 °C. This is because males have more significant individual differences in thermal preferences than females. With respect to temperature set points, both data-driven and simulation-based analysis have indicated that such behavior has a significant influence on cooling energy consumption (Lin et al., 2018; Mauri et al., 2019). In contrast, the results in this study show that the effect of the chosen temperature set points on cooling energy consumption varied in different gender. For males, it has strong correlation with energy consumption, while it is not so important for females. Occupant behavior to meet thermal comfort normally results in high energy consumption. Therefore, there should be a trade-off between human thermal comfort and building energy consumption, and it is necessary to strike a balance between achieving a high comfort level and reducing energy consumption through improving occupant behavior.

3.4. Implications of the study

The main contributions of this study are generally summarized into two aspects. Firstly, the paper proposed a data mining approach to identify the influences of occupant behavior on building energy consumption with empirical data. This study addresses the inadequacies of simulation tools in quantifying the energy use attributable to building occupants. As various factors influence building energy consumption simultaneously, it is difficult to identify the individual effects of occupant behavior. Since determining the parameters in behavior models often requires intensive measurements, it is time and financially consuming to describe each occupant and develop complicated behavioral model as inputs due to users' behavior diversity and complexity. Besides, the energy consumption is largely a group phenomenon as it usually occurs in social systems. As a result of actions by joint group members, it is impossible to determine each occupant's energy consumption. Meanwhile, concerning technical cost and privacy protection, data of occupant behavior is mainly collected by subjective questionnaire based on individuals in this stage. How to quantify the impact of occupant behavior on building energy consumption with empirical data is still a challenge. Based on data mining technique, this study proposed a method to extract group-level behavior based on individual behaviors, and successfully quantify the impact of occupant behavior on building cooling energy consumption by correlating the actual energy performance of similar rooms with different group-level occupant behaviors. Data mining, as an emerging powerful technology in the field of computer science, has great potential to extract knowledge from building-related data. It contributes to studying occupant behavior and building energy consumption for improving building energy performance. Therefore, data mining approach used in this study can provide a new perspective in quantifying the impact of the occupant behavior on building performance.

In addition, when it comes to industry such as building design and code formulation, practical implications of this study cannot be ignored. Findings of this study provide an in-depth understanding of the correlation between occupant behavior and cooling energy consumption. A better understanding of occupant behavior in building energy use can improve not only modeling accuracy of occupant behavior in numerical simulation, but also design efficient and targeted management strategies for behavioral change. The occupants' behaviors arise under complex context including their thermal comfort, physiological phenomena, psychological state, and interaction with others. It may be unrealistic to develop accurate occupant models unless an in-depth understanding of occupants' behavior is achieved. In particular, the derived typical energy-related behaviors for males and females can provide reference for building designers. Occupant behavior can be simplified into several typical behaviors. Further verification studies will be conducted by integrating these typical energy-related behaviors into energy simulation tools, which may contribute to narrowing the performance gap between predicted and actual energy consumption. Besides, this study is conducive to designing effective behavioral change strategies for energy conservation, since the typical energy-related behaviors could be targeted for energy consumption reduction.

4. Conclusions

In order to extract typical energy-related behaviors influencing cooling energy consumption, this study analyzed the effects of different behaviors. Based on empirical data mining, significant differences are found in cooling energy use between genders. Generally, males consume 1.2−1.5 times more cooling energy than females. Occupant behavior causes almost 2−3 times differences in cooling energy consumption within the same gender. Through the comprehensive analysis of various energy-related behaviors for males and females, main findings from this study are summarized as following:

1) Regardless of gender, behaviors such as the daily average hours of air conditioning utilization, using fans instead of turning on air conditioner, and the ratio of occupancy in room are typical behaviors influencing cooling energy consumption. According to DNA's framework and TPB theory, these behaviors are mainly triggered by environment, habit and event. Among the three triggers, habit is found as a vital influencing one based on data analysis. Yet, the behaviors, such as closing the curtain when feeling hot, closing the doors and windows before turning on air conditioner and turning off air conditioner when leaving room have negligible influence on cooling energy consumption;
2) The comparative study between gender indicate that behaviors, like the frequency of utilization of air conditioner, and open doors & windows for ventilation instead of turning on air conditioner are typical behaviors influencing cooling energy consumption for females. However, behaviors including thermal preferences and the temperature set points of air conditioner have more noticeable influence on cooling energy consumption for males than females. Although the typical energy-related behaviors of females and males differ to some extent, the factors affecting these behaviors are both greatly triggered by environment and habit.

There are some similarities and discrepancies in typical energy-related behaviors for males and females. There is a need to consider gender differences in building energy design and behavioral improvement strategies. Findings in this study could help improve modeling accuracy of occupant behavior in numerical simulation. Besides, it helps prioritize efforts at improvement of occupant behavior in order to reduce building energy consumption in operation stage. Moreover, this study identified individual effects of occupant behavior on cooling energy consumption by controlling other influencing factors. Furthermore, it further investigated the influence of occupant behavior on cooling energy consumption for men and women. This study fills the research gap that the influence of only one or two particular behaviors on building energy consumption was investigated by previous simulation studies. The originality of this work is to conduct comprehensive analysis of different energy-related behavior effects on cooling energy consumption, and to extract typical energy-related behaviors influencing cooling energy consumption under different gender with data mining approach.

Particularly, the diversity of occupant behavior was ignored in previous studies. In contrast, this study provides an approach to extract features of group behavior based on individuals. The features have five indicators (Mix, Min, Mean, Mode, and Median), and more indicators need to be found in future study. Further studies should investigate in depth occupant behaviors at a group level. Besides, the energy-related typical behaviors are mainly triggered by environment and habit. Relevant theories and models of behavior such as Self-efficacy, Theory of planned behavior, Theory of reasoned action, etc. should be considered to further study typical energy-related behaviors comprehensively and systematically. Understanding of what typical energy-related behaviors are and how they change could help researchers improve modeling of occupant behavior and design management strategies.

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Appendix A. Measurement Scales in Questionnaire Survey

Please put "√" in the blank for each item according to your own attitudes. Following is listed the connotation of each code:

Code	Items	Always	Often	Occasionally	Rarely	Never
B1	Closing the curtains when feeling hot					
B2	Turning on air conditioner as long as entering rooms					
B3	Closing doors and windows before turning on air conditioner					
B4	Opening doors and windows for ventilation instead of turning on air conditioner					
B5	Using fans instead of turning on air conditioner	**Always**	**Often**	**Occasionally**	**Rarely**	**Never**
B6	Adjusting clothing to adapt to room temperature					
B7	Switching off the air conditioner regularly when sleeping					
B8	Turning off air conditioner when leaving room					
B9	The daily average frequency of utilization of air conditioner	5 times	4 times	3 times	2 times	1 time
B10	Ratio of occupancy in room	90% ≤ B10 ≤ 80%	60% ≤ B10 < 80%	40% ≤ B10 < 60%	20% ≤ B10 < 40%	B10 < 20%
B11	Temperature set points of air conditioning	26 °C ≤ B11 ≤ 28 °C	24 °C ≤ B11 < 26 °C	22 °C ≤ B11 < 24 °C	22 °C ≤ B11 < 20 °C	17 °C ≤ B11 < 20 °C
B12	Thermal preferences	26 °C ≤ B12 ≤ 28 °C	24 °C ≤ B12 < 26 °C	22 °C ≤ B12 < 24 °C	22 °C ≤ B12 < 20 °C	17 °C ≤ B12 < 20 °C
B13	The daily average hours of air conditioner utilization in summer	24 h ≤ B13 ≤ 20 h	15 h ≤ B13 < 20 h	10 h ≤ B13 < 15 h	5 h ≤ B13 < 10 h	B13<5 h
Room No._________________						

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