Impact Analysis of Customized Feedback Interventions on Residential Electricity Load Consumption Behavior for Demand Response

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Keywords: demand response, energy policy, questionnaire design, consumption behavior, residential electricity load, customized feedback

Abstract:

Considering the limitations of traditional energy-saving policies, a kind of energy conservation method called the Information Feedback to Residential Electricity Load Customers, which could impact the demand response capacity, has increasingly received more attention. However, most of the current feedback programs provide the same feedback information to all customers regardless of their diverse characteristics, which may reduce the energy-saving effects or even backfire. This paper attempts to investigate how different types of customers may change their behaviors under a set of customized feedback. We conducted a field survey study in Qinhuangdao (QHD), China. First, we conducted semi-structured interviews to classify four groups of customers of different energy-saving awareness, energy-saving potential, and behavioral variability. Then, 156 QHD households were surveyed using scenarios to collect feedback of different scenarios. Social science theories were used to guide the discussion on the behavior changes as a result of different feedback strategies and reveal the reasons for customers' behaviors. Using the Chi-Square test of independence, the variables that have strong correlations with the categories of residents are extracted to provide references for residents' classification. Finally, the practical implications and needs for future research are discussed.

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Abstract: Considering the limitations of traditional energy-saving policies, a kind of energy conservation method called the Information Feedback to Residential Electricity Load Customers, which could impact the demand response capacity, has increasingly received more attention. However, most of the current feedback programs provide the same feedback information to all customers regardless of their diverse characteristics, which may reduce the energy-saving effects or even backfire. This paper attempts to investigate how different types of customers may change their behaviors under a set of customized feedback. We conducted a field survey study in Qinhuangdao (QHD), China. First, we conducted semi-structured interviews to classify four groups of customers of different energy-saving awareness, energy-saving potential, and behavioral variability. Then, 156 QHD households were surveyed using scenarios to collect feedback of different scenarios. Social science theories were used to guide the discussion on the behavior changes as a result of different feedback strategies and reveal the reasons for customers' behaviors. Using the Chi-Square test of independence, the variables that have strong correlations with the categories of residents are extracted to provide references for residents' classification. Finally, the practical implications and needs for future research are discussed.

Keywords: customized feedback; residential electricity load; consumption behavior; questionnaire design; energy policy; demand response

1. Introduction

A substantial increase of the global energy consumption has taken place over the past 40 years due to the rapid increase in population and the rapid economic development around the world [1]. Considering the environmental consequences of thermal power plant operation, the main way of electricity generation, reducing electricity consumption has been an urgent task for sustainable development of any society [2,3]. According to the statistics from International Energy Agency (IEA) [4], residential electricity consumption possesses enormous energy-saving potentials due to energy efficiency appliances and appropriate energy choices [5,6], which has been responsible for an estimated 31% of global electricity usage [1,7] and the share of residential sector in total electricity demand will keep on increasing with the development of economy in the future. Therefore, residential electricity conservation plays a significant role in energy-saving and environmental protection.

As the main factor impacting the residential electricity consumption behavior, energy policy has always been the key issue to promote energy conservation. Many policies for residential electricity conservation, including economic incentives and promotion of new energy-saving technologies, have been launched. Technical changes are indispensable and it's undeniable that the development of high-efficiency electrical appliances lowers the electricity consumption. But the limited investments and barriers in understanding and acceptance of advanced technology reduce the energy-saving effects. Similarly, for traditional economic incentive policies, there are also some gaps between the expectation and the implement results. The disparity may be caused by various factors. First, electricity consumption for some people usually shows low price elasticity on the basis of previous studies [8,9]. Second, as results of the low proportion of household budgets, electricity consumption bills may not get adequate attention from users. Moreover, due to the hysteresis of electricity consumption bills (e.g., users usually receive monthly or weekly bills, not real-time bills), the impact to consumption behaviors is time lagged which weakens the effects of the policies [10].

Considering the limitations of traditional policies, another kind of energy conservation method called information provision has been increasingly gaining attention. Information provision, also known as "information feedback" [11], enable people to recognize their electricity usage. This method has been proved to be useful for promoting behavioral changes from individual to group level based on detailed electricity bills [8], self-reading of meters, interactive tools [12], and In-Home Displays (IHDs) [13]. A successful program on information feedback that has been carried out by a company called OPOWER (city, state abbrev if USA, country). OPOWER provides Home Energy Report Letters (HERLs) that include the comparison results between households' electricity usage and that of similar neighbors as well as energy conservation tips. The program results show that approximate 2% to 4% aggregate electricity saving is achieved through information provision, the effect of which equals to that of a short-run electricity price increase of 11% to 20%, and its cost effectiveness was comparable to traditional energy conservation programs [14].

There is a substantial amount of literature covering the discussion over the electricity conservation effectiveness of different feedback types. The feedback can be classified into two categories: direct feedback and indirect feedback [15]. Direct feedback refers to the immediate provision of residential electricity consumption data via a meter or other display monitors [15]. First, raw electricity usage data promotes rational consumption behaviors to a certain extent, such as turning off lights or unplugging appliances when no one is in the room [15]. For example, residents who clearly know their variation of electricity usage are more responsive to demand response programs, thus realizing successful load-shifting and affecting peak consumption [15,16]. Second, decomposition of total power consumption data helps households identify heavy energy equipment, further affecting appliance purchasing decisions such as consider replacing them with more efficient ones. Third, with the proper software to manipulate data, real-time direct feedback can present residential load patterns that make individual households better understand the distribution of electricity consumption in the different time slot. According to reviews of direct feedback experiments, findings reveal that direct feedback interventions can reduce electricity consumption in homes by 5% to 15% [15]. However, their lasting impacts on residential behavior are much less certain [16,17]. A 15 month study carried out by Van Dam and his colleagues [18] has indicated that initial electricity conservation of 7.8% after four months could not be further maintained in the medium to longer term.

Indirect feedback tends to present the electricity consumption related information that has been processed in some way [15], e.g., more detailed electricity expenses, comparison messages or household-specific tips for the curtailment of electricity usage [14,19]. Compared to direct feedback, indirect feedback provides more understandable and feasible messages for an individual household to better manage their home electricity usage. For instance, through intelligent hardware device in the house, Nilsson et al. [20] provided direct feedback (i.e., daily electricity consumption, week electricity consumption, and electricity consumption trend) to residents, but found no significant impact on electricity consumption. The researchers attributed this phenomenon to households' lack of ability to understand and utilize the messages from the intelligent device.

As for specific electricity saving tips, they are always provided alone in feedback or along with other kinds of direct or indirect messages. Carroll et al. [21] have studied the role of electricity saving tips in feedback and the results showed that residents could curtail the electricity usage by 2.9% when received such an indirect feedback once a month. Similarly, with the electricity consumption monitoring system in the individual house, Matsui et al. [22] not only provided householders with electricity consumption information per 15 min through the web page but also give them some useful energy-saving tips. After conducting a feedback intervention for one year, residential electricity consumption is decreased and individual's knowledge of energy saving also improved.

For the comparison message-based feedback, there are two main types investigated in the literature, namely historic feedback and normative feedback. Historic feedback refers to electricity consumption, which is relative to the usage of the same household from a similar time period in the past. One example where historic feedback was implemented for the first time showed that a 10% reduction in electricity consumption occurred in treatment groups and such an energy-saving behavior was maintained for more than three years [23]. In general, it is approved in most literature that historic feedback is readily understandable, relevant and useful for consumers, and the historic standard is also one of the main features of some of the most effective studies for overall electricity conservation. Normative feedback refers to consumption of a household reported in comparison to the consumption of some other similar group of households [15]. It is said that electricity comparison among households in neighbor will elicit social pressure on residents to understand why consumption levels differ, thus stimulate competition and ambition for electricity saving. The OPOWER program we mentioned above is a successful application of normative feedback. The HERL feedback contains social-normative messages that compare resident's electricity use to that of average neighbors, as well as to that of their most efficient neighbors. In the OPOWER's program, researchers [14] conducted a randomized natural field experiment of 600,000 treatment and control households, where residents could receive social normative feedback of electricity. The results exhibit the cost effectiveness of non-price energy conservation programs.

However, in some cases, feedback aiming at energy saving may not perform well, or even backfire. For example, low understanding of or interest in the provided feedback information could bring barriers [13]. The response to the feedback differs from person to person, which is related to the understanding level of information and individual performance [24]. Thus, taking the characteristics of various households into consideration when designing the feedback programs may increase the effects of information feedback. Nevertheless, most of the previous reports usually ignore the differences among various users. With this in mind, it would be significant for policy makers to design feedback programs more carefully. Moreover, the effectiveness of feedback intervention in electricity saving has been frequently discussed in many studies, but the underlying reason behind the change of electricity load consumption behavior (ELCB) is less investigated.

In addition, in order to better maintain the balance between supply and demand in power system, demand response (DR), which can be classified into two categories: price-based and incentive-based, has emerged as a tool to engage in the grid operation [25,26] and improve the flexibility of power system [27]. It is the most important task to estimate the demand response capacity (DRC) of all participants before the implementing process of DR programs and the customer baseline load after that. The DRC is highly related to the load patterns and due to the uncertainties of residential users' ELCBs, the load patterns are influenced by a variety of factors such as information feedback, weather conditions that have a significant effect on distributed photovoltaic systems [28,29], etc. However, with the introduction of information feedback, electricity load consumption behavior of users will be affected and the changes may bring difficulties for the existing DRC estimation models and baseline load estimation to obtain accurate results [30]. Hence, the research on reactions of people under various information feedback will provide supports to improve accuracy of the models under the impact of wildly applied information feedback policies in the future.

In order to fill this gap, a field survey carried out in Qinhuangdao (QHD) is presented in this paper to explore three concrete problems:

1. What kind of feedback information will have a significant impact on the residential customers?
2. How to classify the residential customers according to their response to the information feedback?
3. How does the feedback information influence the electricity load consumption behavior (ELCBs) of customers?

Based on the field survey results, we develop an in-depth investigation into behavioral changes of different residential user types upon various information feedback, as well as willingness degree to implement certain ELCBs in the specific scenarios. Compared to the aforementioned literature, the major contributions of this research are summarized as follows.

First, a detailed designing scheme of the questionnaire is proposed, which consists of four parts namely interview design, questionnaire design, pilot survey and questionnaire modification. The questionnaire design process ensures the quality of the results. Second, based on the particular issues set in our questionnaire, social science theories are applied to frame the study design and to explain the statistical analysis results of the study. It helps provide a unique insight into why a certain type of residents is more willing than the others to perform specific ELCBs. Third, Curve fitting was introduced to show and validate the means of quantifying users' behaviors influenced by feedback information, which is fundamental for the establishment of the residential demand response models. Last and most importantly, the experimental results will guide the policy makers to design customized policies, namely to offer different types of users feedback information according to their characteristics in order to achieve the optimal benefits. In addition, it should be noted that we only conduct the analysis based on data collected by questionnaire due to the lack of electricity consumption data. Also, the sample size is relatively small. These problems will be solved in the future.

In what follows, Section 2 briefly introduces the methodology of the study. Section 3 describes the data processing, and Section 4 presents the data analysis. Empirical analysis of survey data is conducted from three aspects: (1) classification of residential users; (2) effects of information feedback on residential ELCBs; (3) correlation analysis between basic information and residential user types. The applications and future work are shown in Section 5. Section 6 concludes the paper.

2. Methodology

The framework of our study includes three parts: study design; data collection; data processing, and results analysis. The details are illustrated in this section.

2.1. Study Design

2.1.1. Interview Design

In order to figure out what kind of feedbacks have the significant influence on customers' behaviors and how people response to different feedback information, interviews were conducted using face-to-face or telephone methods. Nineteen interviewees were recruited using snowball sampling technique to select evenly distributed sample according to age, and gender of the interviewees. The sample distributions are shown in Figure 1.

During the interview, interviewees were asked several open-ended questions circumfusing the three key problems mentioned in Section 1. We started the interview with basic information questions and their energy utilization questions including energy-saving attitude, perceptions of electricity bill, energy-saving potential, and so on. Subsequently, one of the core questions "What kind of feedback information will have a significant impact on you" was presented to them. A small number of respondents have never thought about this question but others shared their thoughts with us.

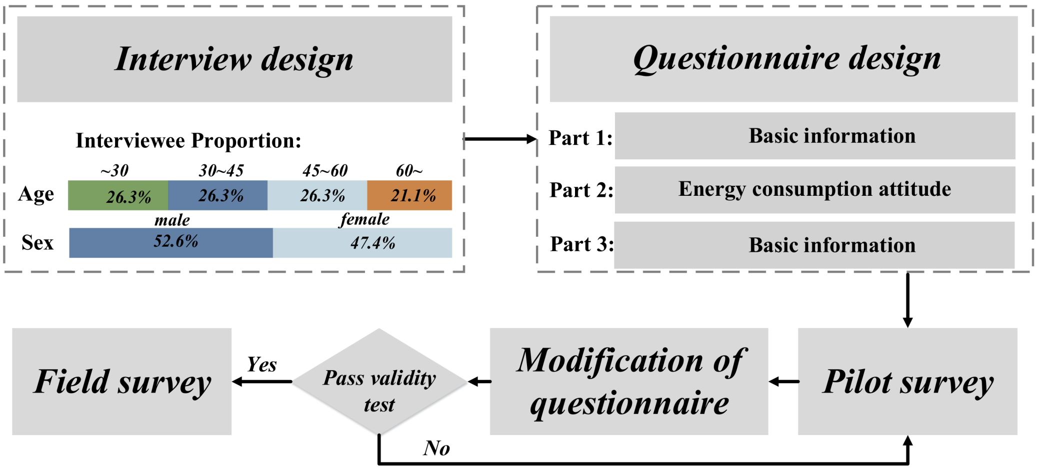

Figure 1. The procedures of study design.

Table 1 captures a summary of three of the interviewees' answers that were relevant to the first question and demographic information of the interviewees. By using qualitative thematic analysis method, a number of themes emerged. The feedback information alone like "Your electricity consumption information" may not have significant influence on people's consumption behaviors. Nevertheless, most of the interviewees are desirous to learn their own electricity consumption as well as the average usage of their neighbors. The comparative results between the two information may have large impacts on their behaviors according to our finding. This conclusion provides support for the selection of the feedback types in our questionnaire. Then another question "How does the feedback information influence your ELCBs?" collected the reactions of respondents to the feedback in various scenarios such as "your electricity consumption is higher than/ lower than/ equal to the average usage of their neighbors in a period time, what will you do?" and the results of this question are regarded as the design bases of the feedback experiments, which will be elaborated in Section 4.2.

Table 1. A summary of partial interview relevant to "What kind of feedback information will have remarkable impacts on customers?" and the basic information of the corresponding interviewees.

Interviewees	Basic Information of the Interviewees	The Actual Replies to the Question
Mr. Qiu	26 years old; well educated; working in a company; living alone	"It doesn't make sense to look at my own electricity, and I feel that the average amount of electricity consumed by people around me may have a certain impact on me"
Mrs. Wang	42 years old; medium education; office worker; two people living in a 110 m^2 apartment	"I may not be affected by other information usually. But once I get a high rate of electricity, I will ask about the electricity bills of others and the comparison results of our electricity bills may have impact on me"
Mr. Wang	78 years old; medium education; retired; two people living in a 110 m^2 apartment	"Sometimes I will talk about the electricity bills with others. If most of my neighbors' bills are lower than mine, I'll check if there's anything wrong and I try to lower the electricity bill."

2.1.2. Questionnaire Design

Based on the findings from the interview study, a questionnaire was designed to include three sections: demographic information (Question 1 to 14); energy consumption attitude (Question 15 to 17) and feedback experiment (Question 18 to 21). The final version of the questionnaire is shown in Appendix A. The demographic information describes the characteristics of the respondents including social demographics, dwelling characteristics, appliance ownership and usage, electricity billing information. Several questions about energy saving potential and attitude constitute the second part of the questionnaire. And feedback experiment is the core content of the questionnaire including people classification and feedback scenario generation.

- People classification

On the basis of the reactions to various feedback scenarios and the energy saving potential of the interviewees obtained from the interview, we find that the people can be grouped into four categories. Thus one question in the questionnaire is designed to place respondents into the classification using the option A-D with descriptive characteristics of the four types. Option A describes people who show weak energy-saving awareness and are not easily influenced by others. There is large energy-saving space in their house. The description in option B is totally opposite to that in option A. As for option C and D, they both describe the people with moderate energy-saving awareness. But for people described in option C will not save energy at the cost of forging comfort. The characteristics described in option D emphasize the non-fixed living habits of people. Option E "others" is also included to provide respondents with an opportunity to add their own characteristics if they don't belong to the four types provided. The detail characteristics of the four classifications will be presented in Section 4.1.

- Feedback scenario generation

In order to obtain reactions of people under various feedback information incentives, we generate several feedback scenarios with two kinds of information: "Your electricity usage (YEU)" and "Average electricity usage (AEU) in your neighbors". The map of feedback scenario generation is shown in Figure 2. In each scenario, people are required to decide to "Maintain their usage", "Decrease their usage" or "Increase their usage" according to their personal preference. Then for scenario 1 and scenario 3, if respondents choose to alter usage behaviors, a concrete integer number should be selected from 1 to 10 to represent the willingness of changing their behaviors. "1" represents the lowest willingness to change and "10" is opposite. In addition, it's important to note that there isn't any sub question for scenario 2. Owing to few people changing their behavior in this scenario according to the interview, we don't add any sub questions in consideration of the conciseness and readability of the questionnaire.

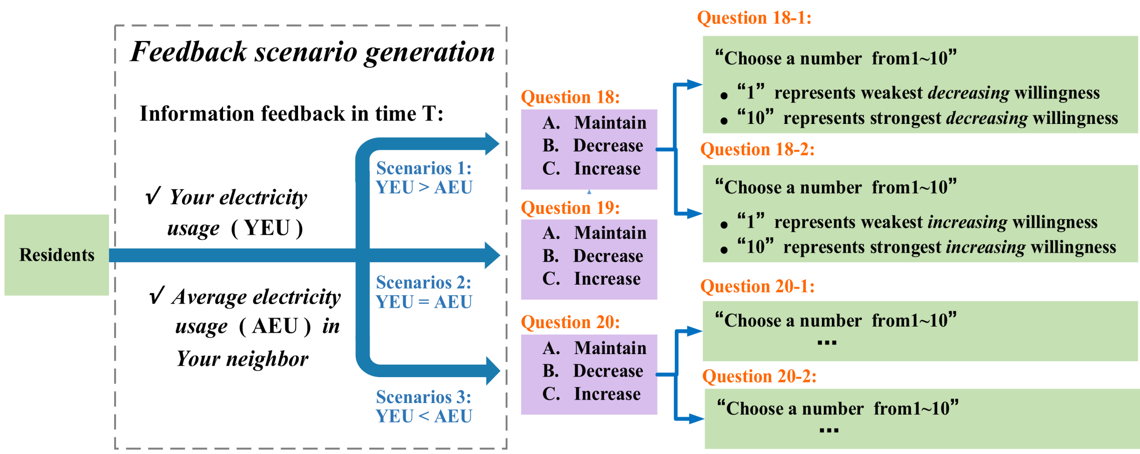

Figure 2. The sketch map of feedback scenario generation.

2.1.3. Pilot survey and Questionnaire Modification

In order to test the validity and reliability of the questionnaire, a 30-person pilot was carried out and the items in the questionnaire were modified based on the feedback of the pilot. We repeated the pilot and modification until the questionnaire pass validity test [31]. The validity test here focuses on the content validity using the Content Validity Index (CVI) methodology. Four researchers including two experts and two researchers in related fields are invited to review the questionnaire and each person gives a judgement on each item (essential or not). Then Content Validity Ratio (CVR) for each item, which is widely used to quantify validity of an assessment instrument, is calculated using the equation shown in the following:

$$\mathrm{CVR} = \frac{n_e - N/2}{N/2} \tag{1}$$

where n_e is the number of reviewers identifying an item as "essential" and N is the total number of reviewers, which equals 4 in this paper. Then CVI can be calculated by averaging the CVRs of all items. According to previous studies [32], if the CVI value exceeds 0.80, we consider it to be preferred or items in the questionnaire should be modified until the value reaches the decision threshold. After that the completed questionnaire was used in the field survey. The procedures of the study design are shown in Figure 2.

2.2. Data Collection

Using the questionnaire, a field survey was carried out in Qinhuangdao, Hebei Province, China. Volunteer sampling method was adopted to distribute questionnaires and we tried to cover the public places of the city as much as possible. So we selected shops, parks, squares, several restaurants, and train station to carry out the survey. The questionnaire results and corresponding analysis are introduced in Section 4, respectively.

3. Data Processing

As mentioned above, a survey questionnaire is designed and delivered to 220 households in Qinhuangdao, in order to collect the data needed for subsequent statistical analysis. Finally, 174 valid questionnaires are obtained after removing invalid questionnaires. The response rate was 79.09%. To better utilize and understand the detailed household information in the questionnaire, the collected survey data is processed with discretion presented as follows.

3.1. Questionnaire Coding

There are two sub-steps in the first step, one is questionnaire numbering and the other is survey question coding.

Firstly, for the total 174 questionnaires filled by residential participants, and they are randomly numbered by consecutive Arabic digits from 1 to 174, and then a serial number of each questionnaire is used as the ID number of corresponding residential interviewees who fills the questionnaire.

Secondly, for the convenience of later statistical correlation analysis, answers to each survey question in the questionnaire are further coded. For example, the question 4 in questionnaire asks the residential interviewees about the educational level of their householders, and five options for this question are respectively "Without formal education", "Primary school level", "Junior middle school level", "High school level" and "University level and above, the answer was coded from 1 to 5 respectively, in other words, if an interviewee chooses the option "Without formal education", then the answer is coded as 1. Same coding process was used for answers to other questions as well.

3.2. Invalid Questionnaire Identification

Invalid questionnaire identification is a common approach to ensure the validity of collected survey data [33]. The traditional recognition method of invalid questionnaires is qualitative analysis, we used the following criteria to measure invalid questionnaires:

- The questionnaires with two thirds of the questions unanswered;
- The questionnaires could not pass the consistency check, namely contradiction in answers.

In this paper, the questionnaires could not pass the consistency check, namely contradiction in answers of interviewees to the items. This phenomenon is mainly caused by their bad attitude to randomly fill the questionnaire. Such responses are invalid and will not pass the consistency check. So based on the first evaluation criteria, the sample size is curtailed to 165, and then it is further reduced to 156 according to the second criteria.

3.3. Missing Data Completion

In this step, different methods are applied to complete the missing quantitative data and non-quantitative data (i.e., ordinal data or category data) in the questionnaire.

- Completion of missing quantitative data

The data of a question in the questionnaire that asks about floor area of the residential house is considered quantitative data, so multiple regression imputation is applied to complete this kind of missing quantitative data [34]. As indicated in the previous literature, floor area is closely related to household income and the number of family members [35]. Therefore, we utilize the available survey data of household income and the number of family numbers, together with non-missing floor area data to estimate a regression model based on regression algorithm, where household income and the number of family numbers are regarded as explanatory variables while floor area is perceived as response variables. Fitted values from the established regression model are then used to impute the missing floor area data.

- Completion of missing non-quantitative data

Methods in two cases of missing non-quantitative data are respectively given as follows:

Case 1: Mode imputation is usually used to complete the missing category data. In our questionnaire, the data in question 7 that asks about dwelling type is the example of category data. This question has two options namely terrace and apartment. Thus if option "apartment" has higher chosen frequency than option "terrace" among remained 156 questionnaires, option "apartment" is used to complete all the missing data in this question.

Case 2: Zero imputation is usually used to complete the missing ordinal data. In our questionnaire, missing data of questions that ask about the number of people over and under 15 years old as well as the number of domestic appliances is completed by digit zero.

4. Results and Discussion

In the following section, the results of our study are described. Using data from a sample of 156 QHD households collected through questionnaires, we aim to examine the effect of information feedback on residential ELCBs. Then the findings in current experiment are interpreted from the perspective of social behaviors. The social norm is generally defined as what the individuals are expected to share in the group, which can be divided into descriptive norms and injunctive norms [36]. The descriptive norm is to point out what most people are doing, and the injunctive norm is to point out the behavior that others disapproval of [36]. The data analysis consists of three parts: classification of residential users, correlation analysis between basic information and residential user types as well as the effects of information feedback on residential ELCBs.

4.1. Classification of Residential Users

Question 21 is utilized to classify Qinhuangdao households participated in our study into four main groups, which concludes from the interview content. Because the proportion of other residential user types in Table 2 is low (2.56%) so was not included in the data analysis. The classification results indicate that Type 3 accounts for the largest share in 156 households, while there is not much difference among the proportions of other three types (i.e., Type 1, Type 2 and Type 4). In addition, Table 2 lists detailed characteristic information of different residential user types, including the energy-saving awareness, energy-saving space and behavioral variability of residents. It is clear that Type 1 and Type 2 are completely different in the above three aspects while Type 3 and Type 4 has the similarly moderate energy-saving awareness and space. The most obvious difference between Type 3 and Type 4 is that the ELCBs of Type 4 are more easily to change due to the non-fixed living habits.

Table 2. Proportion and description of four residential user types.

Residential User Types	Proportion	Description of Characteristics
Type 1	17.95%	(1) Weak energy-saving awareness (2) large energy-saving space (3) Less care about other people's electricity consumption, their ELCBs are almost unaffected by others.
Type 2	11.54%	(1) Strong energy-saving awareness (2) very small energy-saving space (3) The electricity consumption of friends or neighbors has great influence on their ELCBs.
Type 3	53.85%	(1) Moderate energy-saving awareness (2) Moderate energy-saving space (3) The electricity consumption of friends or neighbors has a certain influence on their ELCBs, but they more care about living comfort.
Type 4	14.10%	(1) Moderate energy-saving awareness (2) Moderate energy-saving space (3) Their ELCBs are easily affected by others, together with non-fixed living habits and frequently fluctuating monthly electricity bill.
Other types	2.56%	Written by participants

4.2. Effects of Information Feedback on Residential ELCBs

Feedback intervention has been increasingly perceived as a hot topic, possessing considerable potential for achieving effective reduction of electricity demand through improved occupant behaviors in residential sectors [37]. According to the feedback experiment related questions in the questionnaire, our research builds on social psychology theories in an attempt to shed light on the effects of normative comparison based feedback on residential ELCBs. Further, social norm, an important element of social psychology [36], has been employed to give an in-depth explanation for the behavioral change of different residential user types upon various information feedback, as well as willingness degree to implement certain ELCBs in a specific scenario.

4.2.1. Residential Behavioral Response under Information Feedback

As mentioned in Section 2.1.2, questions 18–20 are respectively designed to ask interviewees about how they will adjust their ELCBs when their electricity usage is higher than (YEU > AEU), equal to (YEU = AEU) or below (YEU < AEU) the average electricity consumption and question 21 is used to classify interviewees into four groups. According to the survey data collected by questions 18–21, this subsection begins with statistical analysis to study the behavioral change direction of different residential user types under the interference of normative comparison feedback, which is clearly presented in Figure 3.

In Figure 3, there are "3 (row) × 4 (column)" subplots, where each column represents residential user type and each row represents feedback experiment. Every subplot gives a clear description of the proportion distribution and total sample size of option A, B, and C in specific question filled in by certain type of user. Then a comprehensive and explanatory analysis of residential behavioral response under information feedback is given via vertical comparison and horizontal comparison as follows:

- ELCB analysis of the same residential user type under different information feedback

The vertical comparison is given in part to analyze the influence of information feedback on ELCB for each residential user type. Three diagrams of the first column all show that option A accounts for a large share in each question, with the mean percentage of 61.91%. It means that a big part of residents in Type 1 are unsusceptible to the feedback based incentive and prefer to remain the original ELCB due to their weak energy-saving awareness and uneasily affected behaviors.

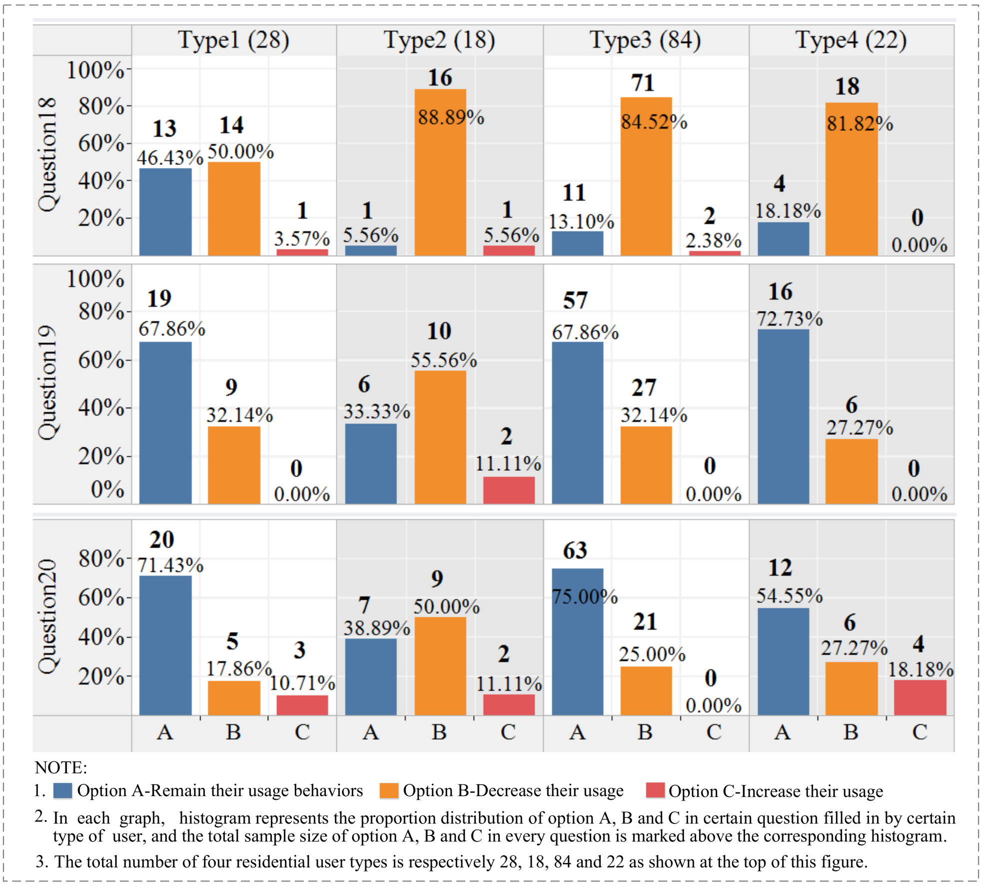

Figure 3. Proportion distribution and sample size of option A, B, C in question 18–20 filled in by four residential user types.

Further, the percentage of choice A increases from 46.43% to 71.43% and that of choice B decreases from 50.00% to 17.86% from the top to down, indicating that part of residents in Type 1 switch from saving electricity to maintaining ELCB if they receive "YEU = AEU" or "YEU < AEU" feedback. However, in the last diagram of the first row, the proportion of choice C is high to 10.71%, which can be inferred that some Type 1 users may increase electricity upon "YEU < AEU" feedback. This undesired phenomenon is called boomerang effect, referring to the fact that low consuming households tend to use more electricity in order to conform to the average consumption level.

In the three diagrams of the second column, choice B has the largest proportion with a mean percentage of 64.82%, showing that whatever the comparison feedback is, a large number of people in Type 2 will save as much as possible electricity because of their strong energy-saving awareness and high concern about others electricity consumption. Similar to Type 1, part of the households in Type 2 are also induced by "YEU = AEU" and "YEU < AEU" feedback to no longer save electricity, as is shown in the variation tendency from the top down that the percentage of choice A increases from 5.56% to 38.89% and that of choice B decreases from 88.89% to 50.00%.

As for the top first diagram in the third column, choice B accounts for the highest proportion of 84.52% while the proportion of choice A is much higher in the second and third diagrams, respectively 67.86% and 75.00%. The results show that residents in Type 3 prefer to reduce electricity under "YEU > AEU" feedback, but once their electricity usage is below or equal to the average level, part of them are less likely to adjust the consumption behavior. It should also be noticed that the percentage of choice C in the second and third diagram is low to 0.00%, indicating that this kind of residents will not increase electricity use even if receive "YEU < AEU" feedback. Such response may be motivated by the internalized injunctive norm that electricity conservation is a pro-environmental behavior accepted by most people.

However, there is no much difference between the three images in the fourth column and the third column. Because both Type 4 and Type 3 users have moderate energy-saving awareness and space, thus generating similar behavioral response under certain feedback. The most obvious difference is the boomerang phenomenon that the proportion of choice C in the third diagram of the fourth column is higher to 18.18%, indicating that Type 4 uses are more likely to increase their electricity usage under "YEU < AEU" feedback due to their easily affected behaviors and unfixed living habits.

- ELCB analysis of different residential user type under the same information feedback

Horizontal comparison is given based on Figure 3 to compare the different behavioral response of four residential user types under the same information feedback. First of all, in the first row, the proportion of choice A in the leftmost diagram is highest (i.e., 46.43%) than that in other three diagrams. This shows that almost half of users in Type 1 will not adjust their previous consumption behavior even if receive "YEU > AEU" feedback due to their weaker energy-saving awareness and lower concern about others ELCB when compared to Type 2–4 users. In contrast, the higher orange bars in 2–4 diagrams indicate that Type 2–4 residents tend to curtail electricity under the influence of such comparison feedback. In addition, few residents will increase electricity in "YEU > AEU" scenario, as the percentage of choice C is rather small in all the four diagrams.

In the second row, the blue bar of the second diagram is obviously lower than that of other three diagrams, but the orange bar of the second diagram is much higher compared to the remained three diagrams. This indicates that Type 2 users have a greater likelihood than other user types to save electricity although the electricity use has already conformed to the average level of their community, because residents (i.e., Type 2) with stronger energy-saving awareness receive more "moral utility" from electricity conservation such as reducing the emission of greenhouse gas. In "YEU = AEU" scenario, boomerang phenomenon does not occur to most kinds of users except for Type 2 who has comparatively strong energy-saving awareness, which needs to be further studied in future work via larger sample size.

The height difference between blue and orange bars in the third row is similar to that in the second row, which indicates that the strong energy-saving awareness makes the Type 2 users more likely to curtail electricity usage even if their consumption is much lower to the average electricity usage in community. In addition, boomerang effect under "YEU < AEU" feedback is more severe than that under other kinds of feedback as the mean percentage of Option C in four diagrams of the fourth row is high to 13.33%.

4.2.2. Analysis of the Willingness Degree Implementing ELCBs under Information Feedback

This subsection begins with the statistical analysis of survey data collected by Question 18-1, 18-2, 20-1 and 20-2, exploring the difference of willingness degree among various residential user types to implement certain ELCB under different scenarios. The above four questions refer to four different ELCBs in turn, that is saving electricity when "YEU > AEU", using more electricity when "YEU > AEU", saving electricity when "YEU < AEU", using more electricity when "YEU < AEU". Figure 4 with "4 (row) × 4 (column)" subplots gives a detailed summarize of related survey information.

In Figure 4, each column represents residential user type and each row represents the above four questions in turn. In every subplot, the histogram in the upper half of the diagram presents total sample size of willingness degree from 1 to 10 in specific question filled in by certain type of user, and the histogram in the bottom half of the diagram describes the proportion distribution of weak willingness and strong willingness in specific question filled in by certain type of user.

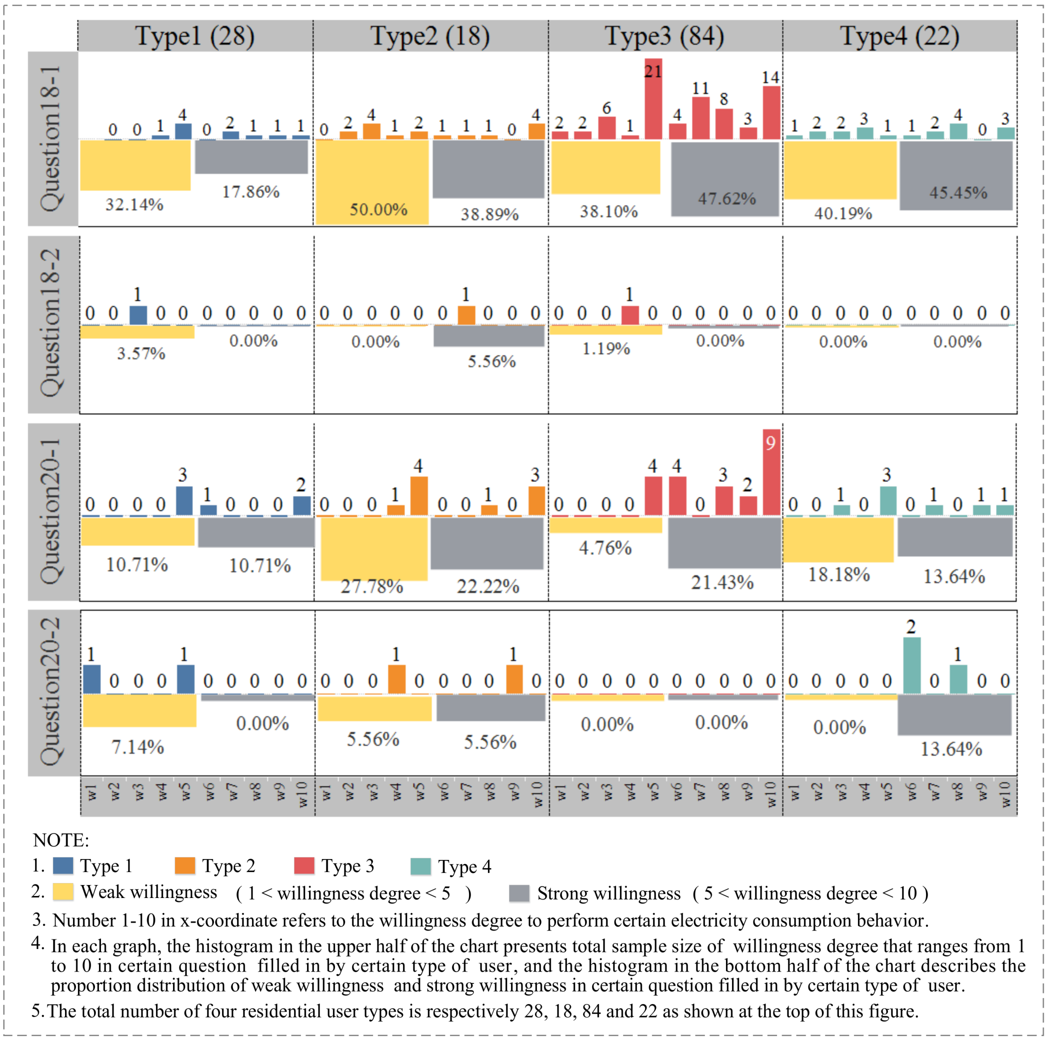

Figure 4. The proportion distribution of weak and strong willingness.

Then a comprehensive and explanatory analysis of the willingness degree implementing ELCBs under information feedback is given via vertical comparison and horizontal comparison as follows:

- Willingness degree comparison of the same residential user type to implement different ELCBs

A vertical comparison is described in this section to respectively analyze the willingness degree to implement four aforementioned ELCBs for the same residential user types. In the first column of Figure 4, the first diagram shows that 32.1% of the Type 1 users have weak willingness degree to save electricity when "YEU > AEU" and only 17.9% of them have strong willingness degree to implement such behavior. This means that the number of Type 1 user, who tend to reduce electricity if "YEU > AEU", is very small (i.e., lower than 50%) and their willingness degree of doing this is not strong (i.e., mean willingness degree is 3.5 < 5). Furthermore, in the third diagram, although 21.4% of Type 1 users tend to save energy when "YEU > AEU" (illustrated by Figure 3), only three residents among them have the strong willingness to do it. As shown in the second and fourth diagrams, few Type 1 users tend to use more electricity when their usage is higher or lower than the mean level, and the corresponding willingness degree is also very weak. These results can be interpreted by the characteristics that people in type 1 emerge weak energy-saving awareness and they are almost unaffected by other people's electricity consumption.

In the second column of Figure 4, the first diagram points out that total 88.9% of Type 2 users will save electricity when "YEU > AEU" and the mean willingness degree is 5.7. In other words, the high energy-saving awareness and easily affected behavior together make most Type 2 users eagerly learn about their personal-optimal level through "YEU > AEU" feedback and willing to reduce electricity usage. According to the third diagram, although the percentage of Type 2 users who want to save electricity decreases to 50%, the average willingness degree of them is high to 6.9. It reveals that comparison of electricity consumption between neighbors does affect ELCBs, especially for the people in type 2.

From the third column, similar results are presented in the second and fourth diagram that almost no one in Type 3 has the strong willingness to increase electricity usage as the response to "YEU > AEU" or "YEU < AEU" feedbacks. In contrast, the first diagram shows that 85.7% of Type 3 users have the mean willingness degree of 6.6 to save energy when "YEU > AEU", and the third diagram indicates that 26.2% of Type 3 users with strong mean willingness degree (high to 8) try to lower their consumption even though their consumption level is lower than the average. In addition, diagrams in the fourth column describe the similar results to that in the third column, because both of Type 3 and 4 users have analogous inner characteristics so as to generate similar behavioral change under feedbacks. A little difference occurs in the bottom diagram of the fourth column that Type 4 users tend to have relatively serious boomerang effect motivated by the "YEU < AEU" feedbacks. This is because residents in Type 4 with weaker behavioral variability are easy to be affected by others and further increase usage to move toward mean level.

- Willingness degree comparison of different residential user type to implement the same ELCBs

A horizontal comparison is given based on Figure 4 to compare the different willingness degree of the same ELCB among four residential user types. According to the diagrams in the first row, the mean willingness degree of Type 2-4 users (i.e., respectively 5.7, 6.6 and 5.8) is much higher than that of Type 1 (i.e., 3.5). Similarly it can be inferred from the diagrams in the third row that for Type 2–4 users, their percentages of high willingness degree to save energy when "YEU < AEU" are also higher that of users in Type 1. The above results can be explained by the fact that Type 2–4 users have relatively stronger energy-saving awareness so that they are more likely to save energy whatever "YEU > AEU" or "YEU < AEU" under the same comparison feedback. Furthermore, we find that residents with weaker behavioral stability (i.e., Type 2 and 4) may be easy to cause boomerang effect.

- The curve-fitting process for willingness degree

The distribution of willingness in various scenarios can reflect the characteristics of different type users, which is able to quantify the user's behaviors, providing support for the establishment of residential ELCB response models. To determine the distribution that best fits the collected data, a curve-fitting process is performed. In this paper, the willingness of Type 3 for saving energy when "YEU > AEU" (SEYLA) is taken for an example. Figure 5 shows the frequency of willingness for Type 3 to perform SEYLA in over five bins (i.e., 1~2, 3~4, 5~6, 7~8, 9~10.). Then it overlays the curve that resulted in the fit. For the case, Gaussian demonstrates the best performance with a considerable goodness-of-fit (R^2 = 0.8221, adjusted R^2 = 0.8221). The expression of the fit model is described by following Equation (2):

$$y = a \cdot e^{[-((x-b)/c)^2]} \tag{2}$$

where a = 0.325, b = 3.723, c = 1.926. In this paper, we merely discuss the fitting results for Type 3 in this scenario considering its largest number of samples. But the remarkable fitting results indicate the feasibility of this method on the premise of enough samples, which is also validated by [38], so we plan to continue this work in the future based on a larger data sample size.

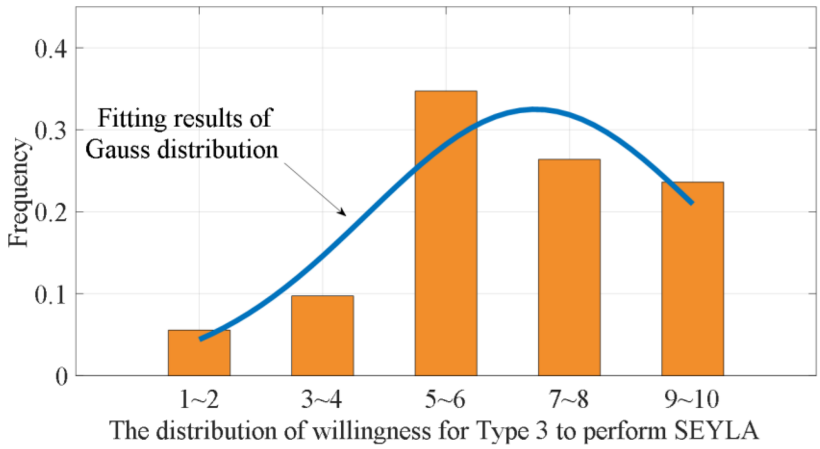

Figure 5. The curve fitting for Type 3 in scenario SEYLA.

4.3. Correlation Analysis between Residential User Types and Basic Information

It is unpractical to judge the type of user through interview every time. So how to classify users in practical applications is a problem. Usually, we can obtain the type information utilizing the relationship between users' types and corresponding basic information. However, too much information may influence the classification for users. Thus, finding just the right amount of the information that associated with the user types is a key problem to be solved.

Then, the correlation between impact factors (IFs) and residential user types is further figured out by statistical analysis methods, namely Chi-Square test of independence. The Chi-Square test of independence is used to determine if there is a significant relationship between two nominal (categorical) variables and a 95% confidence level was used to judge it. The χ^2 values as well as corresponding p-values of various basic information are shown in the "Chi-Square Test of Independence" column of Table 3 respectively. After that, in order to quantify the correlation degree of the two categorical variables, the Contingency Coefficient (CC) is introduced. Contingency coefficients can be used to estimate the extent of the relationship between two variables, or to show the strength of a relationship. It can be calculated as follows:

$$\mathrm{CC} = \sqrt{\frac{\chi^2}{N+\chi^2}} \tag{3}$$

where N represents the total number of participants. Higher CC values indicate higher degree of correlation. The Consistency Coefficient values of basic information variables which are verified to be associated with the user types through the Chi-Square test of independence are shown in the "CC" column of Table 3. The results in Table 3 indicate that there are six IFs (mark in colors) which are associated with the user types and four of them show significant relationships (mark in purple).

In order to analyse the similar socio-economic characteristics people shared in the same group and the differences of them in different groups, the different distributions of answers to basic information for the four groups are explored. We take the "Variation degree of monthly electricity bills", which show the highest relevance to user types, for an example. The distributions of answers to it are presented in Figure 6. We can see that most people in type 4 consider that their electricity bills vary from month to month, which is consistent with their characteristics ("more easily to change due to the non-fixed living habits").

For users in type 1, they have less care about their or other people's electricity consumption. This characteristic results in the variation of their answers to this question. As for people in type 2 and type 3, they have common in this aspect with relatively stable bills. Other significant impact factors can also be analysed through this method and the differences of four group in corresponding aspects emerge along with the discussion.

Table 3. Overview of Chi-Square Test of Independence and consistency coefficient values between basic information and residential user types.

Basic Information (Including Various Impact Factors)	Residential User Type		
	Chi-Square Test of Independence		CC
	χ^2	Sig. (2-Tailed)	
Social-demographics			
Number of permanent residents over 15 years old	4.477	0.877	——
Number of permanent residents under 15 years old	9.141	0.912	——
The age of householder	4.279	0.639	——
The occupation of householder	8.701	0.465	——
The occupation of householder	9.190	0.42	——
Family income	11.91	0.218	——
Dwelling characteristics			
Dwelling age	21.205	0.012 *	0.350
Dwelling type	7.671	0.053	——
Floor area	14.448	0.107	——
Dwelling heating method	8.490	0.204	——
Drinking water heating method	7.878	0.247	——
Cooking method	10.562	0.103	——
Appliance ownership and usage			
Number of air conditioning	8.063	0.528	——
Number of water heater	8.191	0.224	——
Number of washing machine	4.277	0.892	——
Number of induction cooker	9.048	0.433	——
Number of refrigerator	15.617	0.075	——
Number of television	17.113	0.047 *	0.318
Number of computer	27.261	0.001 **	0.390
Number of water dispenser	11.784	0.226	——
Using frequency of washing machine in summer	3.247	0.945	——
Using frequency of washing machine in winter	13.323	0.149	——
Using frequency of induction cooker	33.703	0.001 **	0.426
Working hours of induction cooker every time	34.580	0.000 **	0.431
Working hours of television	4.007	0.911	——
Working hours of computer	13.446	0.143	——
Monthly electricity bills	15.441	0.080	——
Variation degree of monthly electricity bills	53.276	0.000 **	0.509

* The values of χ^2 are significant at the 0.05 level (2-tailed). ** The values of χ^2 are significant at the 0.01 level (2-tailed).

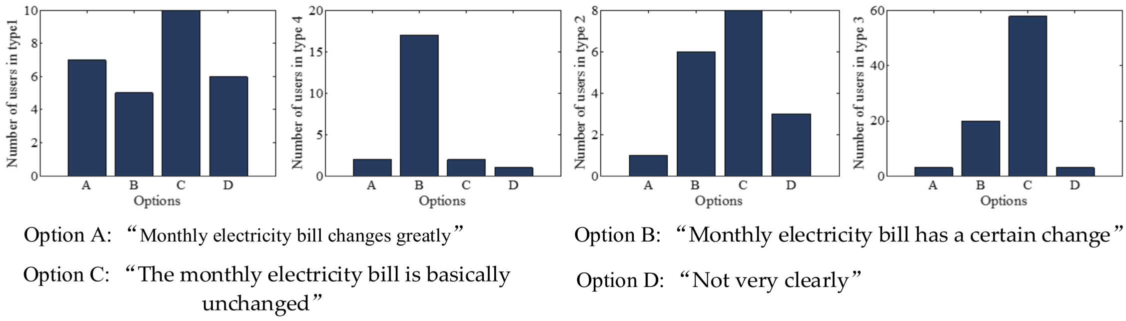

Figure 6. Distributions of answers to "Variation degree of monthly electricity bills" for users in the four groups.

5. Applications and Future Work

The classification results of users obtained in this paper will provide information for policy makers to design customized energy conservation programs, which is more cost-effective. For instance, as we discussed above, people in type 1 exhibit high energy saving potential but not easily affected by normative feedback we provide. For these users, we can consider to carry out economic incentive policies as well as energy conservation tip to increase their energy saving consciousness. As for the people belonging to type 4, decreasing the interval of information provision may improve their energy saving level. Generally, it takes great manpower and material resources to carry out a large program focusing on energy conservation. Thus, preliminary work of the program is necessary. The research framework proposed in the paper, which includes sampling, face to face interview, etc., may be suitable for the pre-work due to its scientific nature and practicability. The distribution of willingness obtained in various scenarios can reflect the characteristics of different type users, which is able to quantify the user's behaviors, providing support for the residential ELCB response models. The model to be established may help people to estimate the demand response (DR) capacity under the incentive of feedback.

Although some meaningful and reasonable results are concluded in this paper, we cannot deny there are still some deficiencies and limitations in our research. First, our field study only focuses on the survey data collected in QHD, which may lead to lack the representativeness of conclusions. Second, the sample scale of this survey is not big enough either. It would be more reasonable to do the survey over a bigger area and involve more participants. Third, our research is established based on a hypothesis that the ELCBs exacted from the survey are the same as their response in real life. But some previous researches indicate that there are some differences between what people want to do and what they actually do. Hence, to solve these problems, a program with more participants from various cities combining actual measurement electricity consumption data maybe make up the deficiencies in this paper.

6. Conclusions

This paper describes and analyzes a field study carried out in QHD in order to investigate the impact of feedback interventions on residential ELCB. According to the interview results, four residential user types with different characteristics are recognized and six type-related questions are selected by the Chi-Square test of independence to provide references for the customer classification. Then the ELCB changes of different type people in various feedback scenarios are discussed. The analysis results show that all kinds of residents prefer saving electricity to maintaining the original ELCB when their REU gradually close to AEU in neighbors. Furthermore, residents with strong sense of energy saving tend to use less electricity when YEU is large than or equal to AEU. As for the willingness degree, residents who have relatively stronger energy-saving awareness and weaker behavioral variability, generally have higher willingness to perform electricity conservation under

"YEU > AEU" and "YEU < AEU" feedback. Despite the appearance of boomerang effect, the number of residents who choose to use more electricity under "YEU < AEU" feedback is very small and their willingness degree are also low. And these results can be used for the designing of the customized feedback policies later. Then taking the willingness of Type 3 for performing SEYLA for example, we introduce curve fitting to show and validate the means of quantifying users' behaviors influenced by feedback information, which is the basic work for the establishment of residential ELCB response models. In addition, a larger sample size collected from various regions combining corresponding actual electricity consumption data may be used to make up for deficiencies of this study in the future work.

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Appendix A

The questionnaire about the influence of residential electricity consumption related information feedback on their electricity consumption behavior.

Note: This questionnaire is only used as academic research and will not be used for any commercial purposes. Thank you for your cooperation and support!

Question 1

How many people in your household are over 15 years of age? ____________

How many children are under 15 years of age? ____________

A 0
B 1
C 2
D 3
E 4
F More than 4

Question 2

How old is your householder? ____________

A Less than 40 years old
B 40–60 years old
C More than 60years old

Question 3

What is the occupation of your householder? ____________

A Ordinary office worker
B Liberal professions
C Farmer
D Unemployed
E Retiree

Question 4

What is the educational level of your householder? ____________

A Without normal education
B Primary level
C Junior high school level
D High school level (Secondary level)
E University level and above

Question 5

What is the approximate annual income of your family? ____________

A Less than 50 thousand yuan
B 50–100 thousand yuan
C 100–300 thousand yuan
D More than 300 thousand yuan

Question 6

How many years have your house been bought (or built)? ____________

A Less than 5 years old
B 5–10 years old
C 10–20 years old
D More than 20years old
E The house is rent

Question 7

What is your dwelling type? ____________

The floor area is approximately ____________ square meters. (Note: There is no corresponding option for this space and you need to fill in it yourself)

A Detached house
B Apartment

Question 8

Which of the following methods does your family use to heating the house? ____________

Which of the following methods does your family use to heating water used to drink or shower? ____________

Which of the following methods does your family use to cook? ____________

A Electricity (e.g., electric heating, air conditioning)
B Non-electrical methods (e.g., natural gas, biogas, central heating)
C Both of them

Question 9

Please write down the number of appliances you use regularly in your house (click "√" at the number below)

Air conditioning: 0/1/2/3 Water heater: 0/1/2/3

Washing machine: 0/1/2/3 Induction Cooker: 0/1/2/3

Refrigerator: 0/1/2/3 Television: 0/1/2/3

Computer: 0/1/2/3 Water dispenser: 0/1/2/3

Question 10

How often do you use the washing machine at home in summer? ____________

How often do you use the washing machine at home in winter? ____________

A One day

B 2–3 days

C One week

D Almost not used or there is no washing machine at home

Question 11

Your home use induction cooker 0/1/2/3/more than 3 times per day? (click "√" at the number below)

How long is the use of induction cooker each time? ____________

A Less than 30 min or there is no induction cooker at home

B 30–60 min

C 1–2 h

D Over 2 h

Question 12

How long do you use your television every day? ____________

A Almost not used or there is no TV at home

B 1–3 h

C 3–5 h

D Over 5 h

Question 13

How long do you use your computer every day? ____________

A Almost not used or there is no computer at home

B 1–3 h

C 3–5 h

D Over 5 h

Question 14

How much is your monthly electricity bill? ____________

A Less than 50 yuan

B 50–100 yuan

C 100–150 yuan

D More than 150 yuan

What is the change in your monthly electricity bill in your home? (click "√" at the option below)

Monthly electricity bill changes greatly/Monthly electricity bill has a certain change

The monthly electricity bill is basically unchanged/Not very clearly

Question 15

Do you think there is room for you to reduce your monthly electricity consumption? ____________

A Basically impossible

B Can be reduced a bit

C Can be reduced a lot.

Question 16

If there is a power-saving measure that can help you reduce your electricity bills, but this measure may change your lifestyle habits. Do you think you might stick to it? ____________

A Basically impossible
B Can stick for a while
C Can stick all the time

Question 17

Do you think that there is a relationship between electricity saving and environmental protection? ____________

A Almost no relationship
B There is a certain relationship
C There is a big relationship

Question 18

If you know that your home's electricity bill is higher than the average electricity bill of the residents in your community for a period of time, what would you do next? ____________

A Keep the original electricity habit
B Take certain energy-saving measures to further reduce electricity expenses
C Relaxed the control of electricity usage and electricity bills may increase

Note: If you select "B" in question 18, please answer question 18-1; if you select "C", please answer question 18-2; if you select "A", then skip question 18-1 and question 18-2!

Question 18-1

If you choose "B" in question 18, then how strong is your willingness to reduce the electricity bill? Please select a number from 1 to 10 to represent your willingness degree. The number 1 indicates week willingness degree and the number 10 indicates strong willingness degree.

Question 18-2

If you choose "C" in question 18, then how about the likelihood that your electricity bills will increase in future? Please select a number from 1 to 10 to indicate the likelihood of the increase of your electricity bill. The number 1 indicates the lowest likelihood and the number 10 indicates the highest likelihood.

Question 19

If you know that your home's electricity bill is not much different from the average electricity bill of the residents in your community for a period of time, what would you do next? ____________

A Keep the original electricity habit
B Take certain energy-saving measures to further reduce electricity expenses
C Relaxed the control of electricity usage and electricity bills may increase

Question 20

If you know that your home's electricity bill is lower than the average electricity bill of the residents in your community for a period of time, what would you do next? ____________

A Keep the original electricity habit
B Take certain energy-saving measures to further reduce electricity expenses
C Relaxed the control of electricity usage and electricity bills may increase

Note: If you select "B" in question 20, please answer question 20-1; if you select "C", please answer question 20-2; if you select "A", then skip question 20-1 and question 20-2!

Question 20-1

If you choose "B" in question 20, then how strong is your willingness to reduce the electricity bill? Please select a number from 1 to 10 to represent your willingness degree. The number 1 indicates week willingness degree and the number 10 indicates strong willingness degree.

Question 20-2

If you choose "C" in question 20, then how about the likelihood that your electricity bills will increase in future? Please select a number from 1 to 10 to indicate the likelihood of the increase of your electricity bill. The number 1 indicates the lowest likelihood and the number 10 indicates the highest likelihood.

Question 21

Which of the following options is the best similar to you?

A weak energy-saving consciousness; there is a lot space to save electricity; do not care about the electricity consumption of others; not easily affected by others

B Strong energy-saving awareness; there is only small energy-saving space in your house; the electricity consumption of friends or neighbors has great influence on you.

C moderate energy-saving awareness; easily affected by others; save energy at the cost of forging comfort.

D moderate energy-saving awareness; easily affected by others, together with non-fixed living habits.

E not belong to the four types above and want to add my own profile:

____

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