

Human-Building Symbiotic Communication with Voice-based Proactive Smart Home Assistants

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ABSTRACT

The IoT-embedded smart homes have a high level of home automation and could change many aspects of the residents' daily lives, such as control, convenience, comfort, and energy-saving. The rise of voice-based virtual assistants like Amazon's Alexa and Google assistants in the past five years has brought new potentials to provide occupants with a convenient and intuitive interface to interact with smart homes through conversations. However, the one-way communications in the form of user commands to control building systems does not result in the optimal course of actions. As such, in this thesis, we proposed the concept of proactive smart home assistants and explored the occupants' perception towards smart home assistants proactively providing suggestions for adaptive energy-saving behaviors. We also investigated the impact of occupants' personal features on their intention in taking energy-saving behaviors. A comprehensive data collection was conducted through online surveys, in which 307 valid responses with participant's personal profile information, their perceptions of smart home assistants, and their feedback to our designed messages were collected. The first manuscript compared participants' responses to traditional plain-text energy-saving suggestions and suggestions provided by smart home assistants. The nudging effect of smart home assistants was justified to be significant in affecting occupant's energy-saving behaviors. Occupant's thermal comfort range, smart home device previous experience, values and beliefs were then proved to have significant impact on their intention in taking the smart home assistant's suggestions. The second manuscript presents the investigation on developing machine learning models (SVM, Random Forest, Logistic Regression) by using 21 personal characteristic features to predict occupant's intention and attitude towards energy-saving suggestions. After training, the developed models could predict participant's intention with high accuracy. The results indicated that occupant's beliefs about interests in taking actions and beliefs about energy expenses, occupant's education level, residence occupancy type, thermal comfort ranges, and smart home device experiences are important features in occupants' energy-saving behavior intention prediction. This research demonstrates the effect of proactive smart home assistants on human-building interaction as well as the impact of personal characteristic features on occupant's energy-saving behaviors, paving a path to the future development of bi-directional human-building communication.

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GENERAL AUDIENCE ABSTRACT

With the technology development in the fields of the Internet of Things (IoT), smart homes have made it possible to help occupants conserve energy in an efficient way without sacrificing the occupants' comfort. The rise of voice-based virtual assistants like Amazon's Alexa, Google assistants accompany the proliferation of smart speaker products in the past five years has brought new potentials to provide occupants with a convenient and intuitive interface to interact with smart homes through conversations. Based on IoT, the virtual assistants are able to control a broad range of Wi-Fi connected home devices like thermostats, lighting systems, and security systems. As such, through the simple wake words (e.g., "Alexa", "Hey, Google"), occupants can easily control the home environment with their voice commands. However, the one-way communications in the form of user commands to control building systems do not result in the optimal course of actions. Therefore, in this study, we have envisioned that these virtual assistants, coupled with their corresponding smart home ecosystems could act proactively as a bridge to facilitate human-building interaction and achieve goals like nudging occupants to adopt sustainable and healthy behaviors. A comprehensive data collection was conducted through online surveys, in which 307 valid responses with participant's personal profile information, their perceptions of smart home assistants, and their feedback to our designed messages were collected. The first manuscript compared participants' responses to traditional plain-text energy-saving suggestions and suggestions provided by smart home assistants. The nudging effect of smart home assistants was justified to be significant in affecting occupant's energy-saving behaviors. Occupant's thermal comfort range, smart home device previous experience, values and beliefs were then proved to have significant impact on their intention in taking the smart home assistant's suggestions. The second manuscript fitted 21 personal characteristics features in machine learning models (SVM, Random Forest, Logistic Regression) to predict occupant's intention and attitude towards energy-saving suggestions. The results indicated that occupant's beliefs about interests in taking actions and beliefs about energy expenses, occupant's education level, residence occupancy type, thermal comfort ranges, and smart home device experiences are important features in occupants' energy-saving behavior intention prediction. This research demonstrates the effect of proactive smart home assistants in human-building interaction as well as the impact of personal characteristic features on occupant's energy-saving behaviors, paving a path to the future development of bi-directional human-building communication.

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INTRODUCTION

With the technology development in the field of the Internet of Things (IoT), smart homes have made it possible to help occupants conserve energy in an efficient way without sacrificing the occupants' comfort. The rise of voice-based virtual assistants like Amazon's Alexa and Google assistants accompanied with the proliferation of smart speaker products in the past five years has brought new potentials to provide occupants with a convenient and intuitive interface to interact with smart homes through conversations. Leveraging IoT technologies, the virtual assistants are able to control a broad range of Wi-Fi connected home devices like thermostats, lighting systems, and security systems. As such, through the simple wake words (e.g., "Alexa", "Hey, Google"), occupants can easily control the home environment with their voice commands.

Despite the potentials brought by these voice-based virtual assistants, it has been shown that users might not know about all the supported features and limit their interaction with smart home assistants to simple daily tasks. The one-way communications in the form of user commands to control building systems does not result in the optimal course of actions. Therefore, in this study, we have envisioned that these virtual assistants, coupled with their corresponding smart home ecosystems could act proactively as a bridge to facilitate human-building interaction and achieve goals like nudging occupants to adopt sustainable and healthy behaviors.

With the vision of developing human-building symbiotic communication through voice-based proactive smart home assistants, we would like to explore if the proactive smart home assistants, coupled with IoT-based smart home ecosystem, can nudge occupants and improve occupants' intention in taking energy-saving adaptive behaviors. Also, we would like to investigate what personal features of the occupants could affect their acceptance level to the adaptive behavior suggestions raised by the proactive smart home assistants. A comprehensive data collection was conducted through online surveys, in which we collected 307 valid responses with participant's personal profile information, their perceptions of smart

home assistants, and their feedback to our designed messages. Based on these data, we conducted two studies to evaluate the hypotheses and answer research questions.

In the first study, comparison between the study group (energy-saving suggestions with nudging from smart home assistants) and the control group (traditional plain-text energy-saving suggestions) were conducted to justify the positive influence of smart home assistants on occupant's energy-saving behavior intention. We also investigated how the occupant's thermal comfort range, previous experiences with smart home devices, values and beliefs affect their intention in taking the smart home assistant's suggestions. T-tests and ANOVA analysis were conducted to evaluate the difference between the control group and the study group, and to identify the impact of influential factors.

To further investigate the important features of individual characteristics that could affect the participants' intention in taking the energy-saving suggestions, in the second study, We developed machine learning models (SVM, Random Forest, Logistic Regression) by using 21 features to predict occupant's intention and attitude towards the energy-saving suggestions provided by proactive smart home assistants. Accuracy and F-measure of the models were computed to compare the model performance. We also calculated the feature importance scores to identify the most critical features in occupant's energy-saving behavior prediction.

Findings in this study will fill the gap of limited previous studies in the interaction between the occupants and the smart home assistants and pave the path to the future development of bi-directional human-building communication. With the advancement of IoT technologies and the smart home ecosystems, there will be more interactions between the occupants and the smart home assistants. Further exploration is needed to better understand how conversational proactive smart home assistants can tailor energy-saving suggestions according to occupant's characteristics, efficiently nudging occupants to adopt energy efficient behaviors one day in the future.

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1.1 Abstract

With the advancement of the Internet of Things (IoT) technologies, smart homes have promoted human-building interaction and sustainability in occupants' daily life. Aiming at enhancing the human-building symbiotic communication, we proposed the concept of proactive voice-based smart home assistants. After collecting 307 responses through online surveys, we justified that proactive smart home assistants can improve occupants' intention in taking energy-saving adaptive behaviors by nudging. The influential factors from occupant's personal features on their acceptability to the virtual assistants were also identified, including occupant's thermal preference, experience with smart home devices, values and beliefs. Findings in this study will provide a valuable reference for the academic researchers and the industry practitioners in the development of proactive smart home systems and the human-building interaction.

Key words:

Human-Building Interaction, IoT, Smart Home, Smart Home Assistant, Virtual Assistant

1.2 Introduction

About 40% of the world's energy consumption is associated with buildings (Costa et al., 2013). Over the past decade, the residential sector accounts for about 22% of the total energy consumption in the United States (Biswas et al., 2016). It was estimated in previous studies that the potential energy saving by systematic building management can range from 5% to as high as 30% (Costa et al., 2013). With the technology development in the fields of Internet of Things (IoT), smart homes have made it possible to help occupants conserve energy in an efficient way without sacrificing the occupants' comfort (Alaa et al., 2017). Smart home is an automated residence equipped with Internet of Things (IoT) that link sensors, domestic devices, appliances, and indoor environment systems (e.g., lighting, HVAC systems) to respond to the occupants' needs (Balta-Ozkan et al., 2013). Supported by IoT technologies, smart homes can not only provide the smart power management with energy demand forecasts and different load strategies (Pawar and TarunKumar, 2020), but also bring convenience and health care to the occupants with ambient assisted living systems (Nižetić et al., 2020). Traditionally, occupants would interact with smart homes through a

display-based central hub like smartphones, smart home dashboards. However, in the past five years, the rise of voice-based virtual assistants like Amazon's Alexa, Google assistants, has brought new potentials to provide occupants with a convenient and intuitive interface to interact with smart homes through conversations (Gnewuch et al., 2018). Based on IoT, the virtual assistants are able to control a broad range of Wi-Fi connected home devices like thermostats, lighting systems, and security systems (Morris and Thompson, 2020). As such, through the simple wake words (e.g., "Alexa", "Hey, Google"), occupants can easily control the home environment with their voice commands.

As a major carrier of the voice-based virtual assistants, smart speakers play a significant role in the application of smart homes. The report from Voicebot (Figure 1.1.1) indicates that the smart speaker market is booming with a rapid annual growth rate of 37% in the domestic market. In 2020, nearly 90 million adults, which is 34.4% of the U.S. adults, have owned at least one smart home device in their home and about 50% of these owners are daily active users (Bret and Ava, 2020). Many companies in the industry have produced various kinds of virtual personal assistants based on their own areas and needs, like Microsoft's Cortana, Apple's Siri, Amazon Alexa, and Google Assistant (Kepuska and Bohouta, 2018). In the current U.S. smart speaker market (Figure 1.1.1), Amazon takes over half of the market share (53%), then followed by Google (30.9%), Sonos (4.7%), and Apple (2.8%). These smart speaker devices equipped with far field microphone that supports voice recognition from anywhere in the house makes it possible for many hand-free operations (Noda, 2018). Apart from the common commands from users like playing music, checking weather, setting alarms, 24.5% of the smart speaker users utilize it to control smart home devices (Bentley et al., 2018; Bret and Ava, 2020). As these virtual assistants' intelligence advances, users will interact with the smart home devices more naturally, more conveniently, and more automatically. For example, with commands and control presetting, users will be able to create scenes that control various devices simultaneously with simple words.

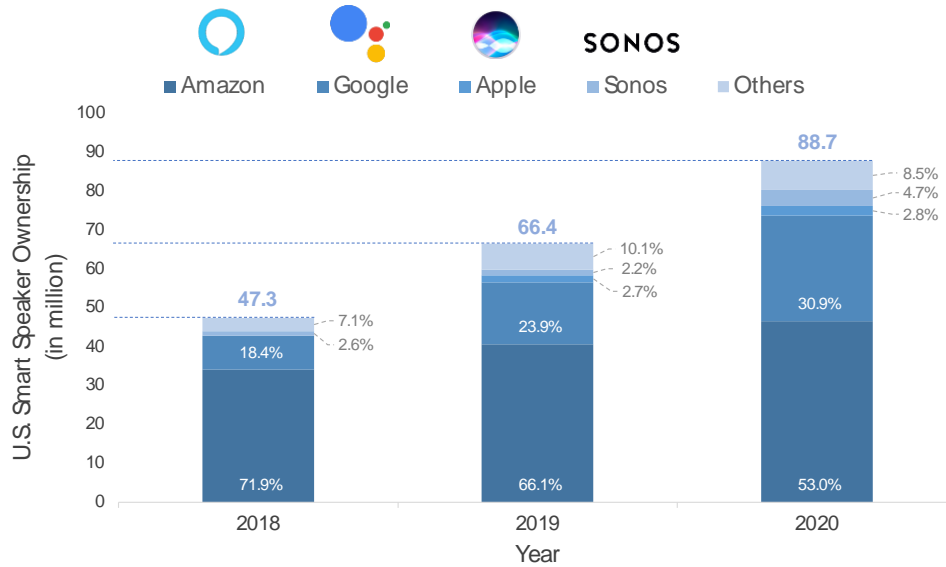


Figure 1.1. U.S. Smart Speaker Market Development (Bret and Ava, 2020)

Despite the great convenience and potential brought by these voice-based virtual assistants, some problems remained in this area. One significant problem identified in previous studies is that the agents from smart speaker are not capable to comprehend complicated commands (Handosa et al., 2020). Sometimes commands have to be repeated in different ways to accomplish a task (Pyae and Joelsson, 2018). Another problem is that it's often the case that users are uncertain about the system features (Bentley et al., 2018; Luger and Sellen, 2016), i.e., they are not aware of the broad capabilities of these smart home devices and limited their usage to simple daily tasks. Originally the smart home devices like smart speakers should perform as a bridge to facilitate human-building interactions. However, the barriers from both sides (virtual assistants and the users) made this goal difficult to achieve. At this point, a natural hypothesis is raised: Is it possible that we solve this problem from a new perspective? *Instead of passively receiving commands from the users, the voice-based virtual assistants can proactively give suggestions to occupants about smart home operations, helping occupants to conserve energy while providing comfort.* As such, occupants won't need to explore the capabilities of the smart home devices by themselves as the virtual assistants would help guide the users to explore, and the users no longer need to repeat their commands accomplishing their goals as they just need to provide direct binary feedback to the suggestions from the agents.

With the vision of developing human-building symbiotic communication through voice-based proactive smart home assistants, in this paper, we explored the users' perception towards smart home assistants proactively providing suggestions to adapt them into energy-saving behaviors. Through online surveys to general public, we aimed to collect their attitude towards the designed messages raised by the smart home assistants, and their acceptance level to the proactive smart home systems. We believed that with the help of proactive smart home assistants, occupants will be more willing to take adaptive behaviors to conserve energy given that the smart home automation eco-system provides a nudging effect. As it learns more about the occupants' preferences and habits during the bi-directional communications, smart home assistants can further provide personalized suggestions to fit occupants' comfort while saving energy. As such, we also investigated how the occupant's thermal comfort range, smart home device previous experience, values and beliefs affect their intention in taking the smart home assistant's suggestions. In the following sections of this paper, we will introduce the prior studies related to the smart home assistants, how we designed and distributed the surveys, and the major findings from the collected data.

1.3 Background

1.3.1 Smart Building / Smart Home with IoT

The ongoing technological developments in society have brought new possibilities to the traditional industries and made significant changes. The heterogeneous network composing of smart devices or objects, referred to as the Internet of Things (IoT), is an example that brings a completely new perspective on the development of building and construction industry (Nižetić et al., 2020; Stojkoska and Trivodaliev, 2017). To fulfill the demands of occupants like improving the energy efficiency or automation level, digitalized IoT endows the "smart" features to the buildings. Smart buildings are automated buildings installed with detection and control devices that are capable of communication and computation, ranging from the sensor nodes to home appliances and systems like HVAC (heating, ventilation, and air conditioning) systems, lighting systems, and security systems (Alaa et al., 2017). Compared with the traditional building system with no cooperation or communication among appliances, IoT-based smart building enables the

interoperability of these devices and thus the occupants would be able to control and manage all the devices through a single central hub (Vashi et al., 2017). Apart from bringing convenience to the users, IoT-based smart building can also benefit occupants in terms of energy conservation, cost reduction, healthcare, entertainment and comfort (Alaa et al., 2017). With the overall goal of improving the occupants' life quality, smart buildings with the IoT technologies help simplify the processes in our daily life fields, and optimize the efficiency of the systems (Nižetić et al., 2020).

As a residential sector of the smart building, smart homes can be viewed as an environment in which occupants' convenience and comfort are improved by the connected IoT (Feng et al., 2017). Based on the smart home device control system proposed by Guamán et al. (2018) and the smart home management model raised by Stojkoska and Trivodaliev (2017), here we propose a smart home ecosystem framework that presents the role of smart home assistants in the smart home with IoT (Figure 1.2). The smart home central hubs perform the raw data collection and data processing from various home appliances and then forward them to the cloud, reducing the redundancy of direct cloud-appliances data flow (Viani et al., 2013). After receiving the commands from occupants, the central hubs can operate the various third-party smart home appliances simultaneously, reducing occupants' effort of operating the devices separately (Stojkoska and Trivodaliev, 2017). The smart home assistants are the central part of this ecosystem, building the bridges between the occupants, cloud, and the third-party home appliances. Although broad studies have investigated the control systems and networks between the central hubs and smart devices, how can these central hubs interact with the occupants and help them make the best use of IoT-embedded smart homes need to be further explored.

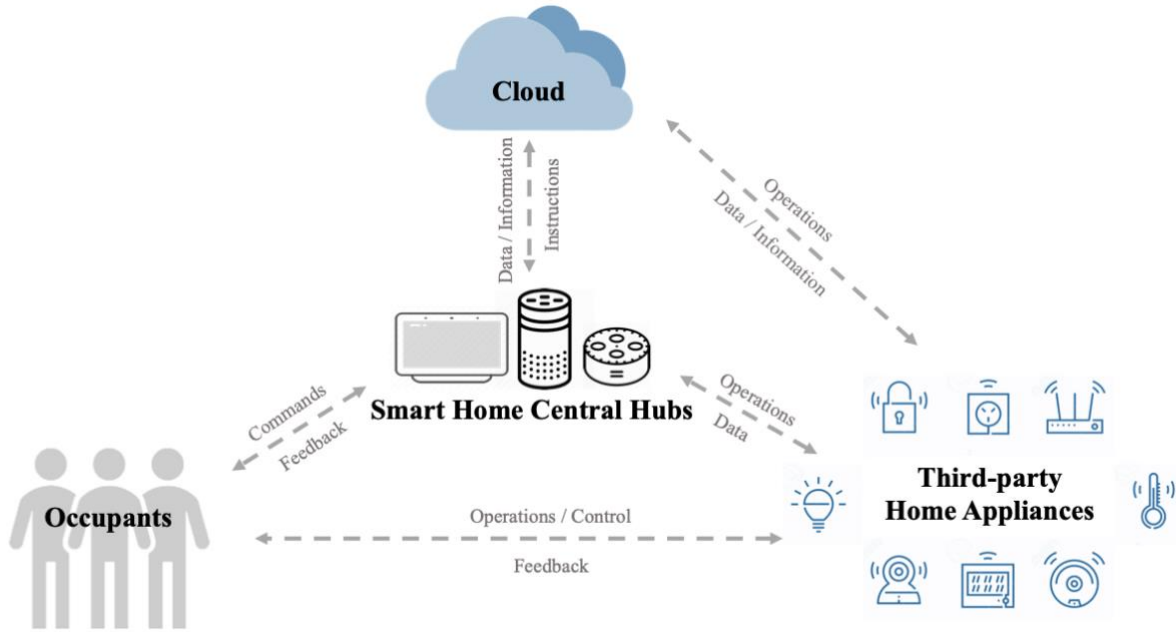


Figure 1.2. Smart Home Assistant Centric Smart Home Ecosystem

1.3.2 Human-Building Interaction

The IoT technologies bring great potential to the performance of smart buildings in sustainability. However, the optimized mechanical system itself cannot guarantee the efficiency improvement of the buildings. Occupants' behavior like their preferences and habits also have a major impact on the building operational strategies. Human-Building Interaction (HBI) has been introduced to build an adaptive building control system to account for the complexities of occupants and reduce the inefficiency of traditional conservative operations (Jazizadeh et al., 2014). Compared with the conception of Human-Computer Interaction (HCI) in which the user interacts with the machine through a circumscribed modality, HBI considers occupants to be completely immersed in an interactive environment (Nembrini and Lalanne, 2017). As such, occupants are involved of the consequences of their behaviors and operations on the building systems. Nevertheless, occupants have a general lack of awareness of their energy consumption and ability to optimize it, so there is a need for building systems to provide easily accessible services and personalized feedback to occupants for energy efficiency (Hsu et al., 2010). Previous studies have broadly investigated the efficacy of the various content and form of feedback and interventions that are designed to

encourage occupants to adopt energy efficient behaviors. For instance, building information model-based energy visualizations raised by Francisco et al. (2018), historical comparison and incentives form justified by Jain et al. (2012), and personalized eco-feedback explored by Petkov et al. (2012). However, these studies mainly have focused on a one-way interaction in which the building systems cannot further learn from the occupants' responses of the feedbacks. The advent of advanced and ubiquitous information-communication technologies has paved the way for a bi-directional communication between human and building systems, in which intelligent building agents or virtual assistants and occupants could cooperate for a mutual adaptation to form an overall better decision. This new form of mutual interaction calls for the exploration of an active communication between the virtual assistants of the building systems and the occupants.

1.3.3 Choice Architecture

In the context of mutual interaction between smart home assistants and occupants, the implementation of choice architecture interventions is a promising approach to help occupants make beneficial decisions for both energy efficiency and their own comfort. The concept of choice architecture is actually using known deviations from rational behavior to design choice situations that 'nudge' decision makers toward more beneficial options (Szasz et al., 2018). The nudge theory, which was popularized by Thaler and Sunstein (2009), introduces generally inexpensive and less invasive solutions compared with traditional direct interventions. Review of the literature shows that the theory has already been applied on various domains (e.g., consumer choices, finance, health, sustainability) in different intervention forms, such as changing choice defaults, providing reminders, and providing social reference points (Landais et al., 2020; Szasz et al., 2018). Lehner et al. (2016) compiled the related literature and summarized four common nudge mechanisms used in the intervention of residential energy consumption, including simplification and framing of information like customized consumption feedback (Podgornik et al., 2016), changes to the physical environment like the design of home and appliances with intent (Bhamra et al., 2011), changes to the default option like the opt-out of green electricity offers (Ölander and Thøgersen,

2014), and use of descriptive social norms like the social comparative energy feedback (Delmas et al., 2013). Specifically, in terms of the framing of information, Gnewuch et al. (2018) have explored the impact of text-based proactive conversational agent on the occupant's sustainable energy use. In terms of default option, there is a behavioral intention of occupants to take the default option that requires least effort (Thaler and Sunstein, 2009), like setting the thermostat as the original preferred setpoints without any adjustment in different outdoor weather conditions. Smart home assistants have the potential of acting as choice architects to indirectly influence the behavior choices the occupants make. However, there is still a lack of studies on nudging when it comes to the interaction between the voice-based smart home assistants and the occupants, which requires further exploration.

1.3.4 Study Objectives and Design

Lying in the intersection of Smart Building / Smart Home with Internet of Things (IoT), Human-Building Interaction (HBI), and Choice Architecture, in this study, we are seeking to investigate the requirements for human-building symbiotic communication with voice-based virtual intelligent agents in smart home to proactively provide efficient and unobtrusive solutions so that it can nudge occupants in cooperative decision making for their comfort, well-being, and energy efficiency. According to the Energy Information Administration, almost half of the building energy consumption (47.7% of energy use in residential buildings) is consumed to meet thermal conditioning demands (Meir, 2013). As such, in this research, we are specifically exploring the smart home assistants for energy efficiency of thermal conditioning. Example scenarios of the smart home assistants communicating with the occupants could include: When the occupant wake up in the morning with the alarm from smart home assistant, the agent would also give the suggestion for occupant's comfort and energy saving - "Good Morning, John! It's rather cool outside now, would you like me to turn off the thermostat and help you open the window to let some fresh air in?"; As the occupant come back home from work and turn the thermostat on with its default setpoint, the home assistant would try to provide tips of adaptive behavior for the occupant: "Hey, Jessica, would you like me to reset the thermostat setpoint higher? We will potentially save our energy expenses.

Meanwhile, I can turn the fan on to help you stay cool.”. In this study, with the goal of moving towards the personalized proactive smart home systems with the capabilities in our pictured scenarios, we are exploring to answer the following research questions:

- **RQ1:** How could proactive smart home assistants, coupled with IoT-based smart home systems improve occupants’ intention in taking energy-saving adaptive behaviors?

- **RQ2:** What personal features of the occupants could affect their acceptance level to the adaptive behavior suggestions raised by the proactive smart home assistants?

In answering the **RQ1**, we will evaluate the following hypothesis:

- **H1:** Compared with traditional forms of text-based eco-feedback, the bi-directional communication created by smart home assistants will result in improving occupants’ intention in taking energy saving behaviors.

In order to answer the **RQ2**, we have identified three potential influential features based on previous studies, and posed the following hypotheses:

- **H2:** Occupants’ thermal preferences, ranges and sensitivities have a major impact on their acceptance level to suggestions about energy-saving adaptive behaviors (specifically, increasing thermostat setpoint).

- **H3:** Occupants’ experience and familiarization with smart home devices will affect their perceptions of the proactive smart home assistants.

- **H4:** Occupants’ values and beliefs will affect their attitude towards the energy-saving suggestions provided by the smart home assistants.

1.4 Methodology

1.4.1 Survey Design

With the goal of testing the hypotheses and answering the research questions, we designed a survey to collect occupants’ feedback to the energy-saving suggestions raised by the smart home assistants. The

survey was distributed online through Qualtrics platform to collect data from the general public. With the capability of obtaining information from large samples of the population, online surveys are well suited to gathering objective feedback and demographic data in this study (Glasow, 2005; Kelley et al., 2003). Analysis of the data collected from the survey was used to evaluate the hypotheses on the smart home assistants’ personalized communication content development and their efficacy. The survey is designed to be divided into three different sections: feedback to designed messages, participants’ profile, and perceptions to smart home assistants (Figure 1.3).

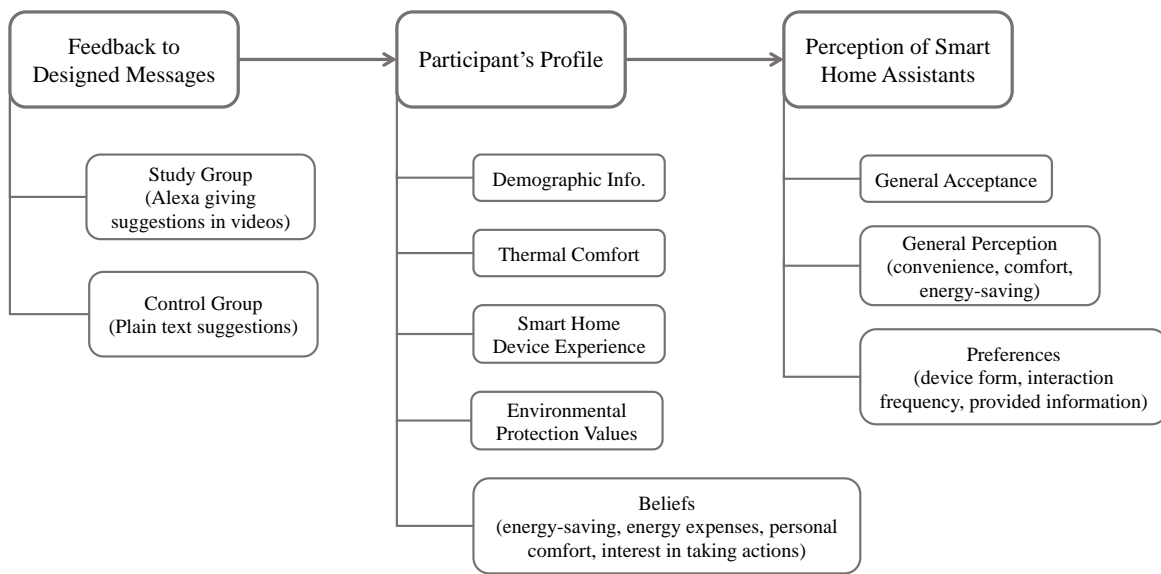


Figure 1.3. Structure of the Online Survey

1.4.1.1 Feedback to Designed Messages

The first section of the survey, feedback to designed messages, was separated into study group and control group with the intention of testing *H1*. The participants in the study group would receive suggestions on changing thermostat setpoint for energy saving in the forms of video with virtual smart home assistant ‘Alexa’ from the Amazon Echo (Figure 1.4), while participants in the control group would only receive plain text of the energy saving suggestion, which is a traditional eco-feedback form. Participants’ intention in accepting the suggestions will be reflected on the agreeable scale from “Definitely No” to “Definitely Yes”. We intentionally set this section at the front part of the survey, so that participants won’t be biased

by other related questions. Appropriate questionnaire sequence is critical to the success of a survey and the first few questions are particularly important as they can affect respondents' attitude in seeking his desired cooperation (Roopa and Rani, 2012). In the case of this study, if the participants were asked about the values and belief on environmental protection first before being asked about their intention to accept the energy saving suggestions, they were likely to be influenced to offer positive responses.

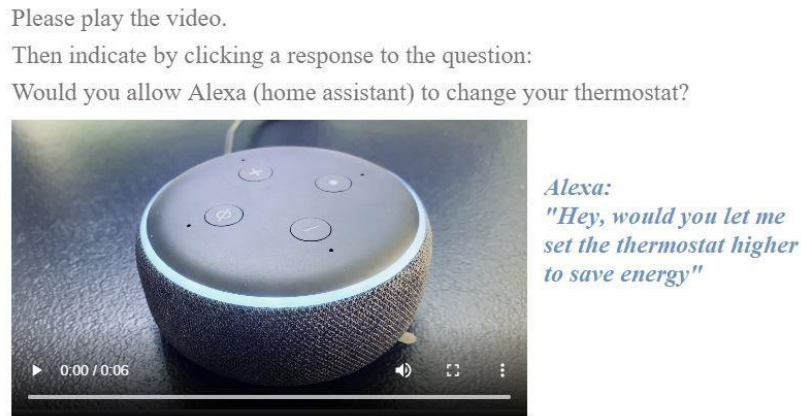


Figure 1.4. Example of the Designed Message from Alexa (Study Group)

Before giving the suggestions, we describe a scenario to the participants that the indoor temperature is set as they preferred, i.e., the participants are in a comfortable thermal condition, so that we can get closer to the participants' natural responses in the real-world cases. We would like to differentiate the study group and the control group with the consideration that the smart home with IoT improves the building automation level. As such, the content of the message from Alexa in the study group is designed to be "Hey, would you *let me set* the thermostat higher to save energy?", while the content of the text message in the control group is "Would you be willing to *go reach your thermostat and reset* the setpoint higher? In this way, you will save energy". We hypothesized that as the smart home assistants brings convenience of control through IoT-based smart home and human-like communications to occupants, it will nudge the occupants to be more acceptable to taking the adaptive behaviors in energy-saving.

In this study, we want to develop proactive smart home assistants that can nudge occupants in adapting energy saving behaviors. As such, we have also designed a suggestion (nudging) flow from Alexa in the study

group (Figure 1.5). If the participant shows a positive attitude towards the suggestion, he/she will be asked about the raising temperature. However, if he/she shows a neutral or negative attitude to the suggestion, we will further nudge them with additional information about savings in energy expenses and tips of other operations to help the respondents keep comfort. For participants in the control group, after answering the plain text questions, they will be further questioned with the settings the same as the study group. Based on the comparison between the participants' attitude before and after nudging, we would like to investigate if the choice architecture will be effective in smart home assistants affecting the occupant's decision making.

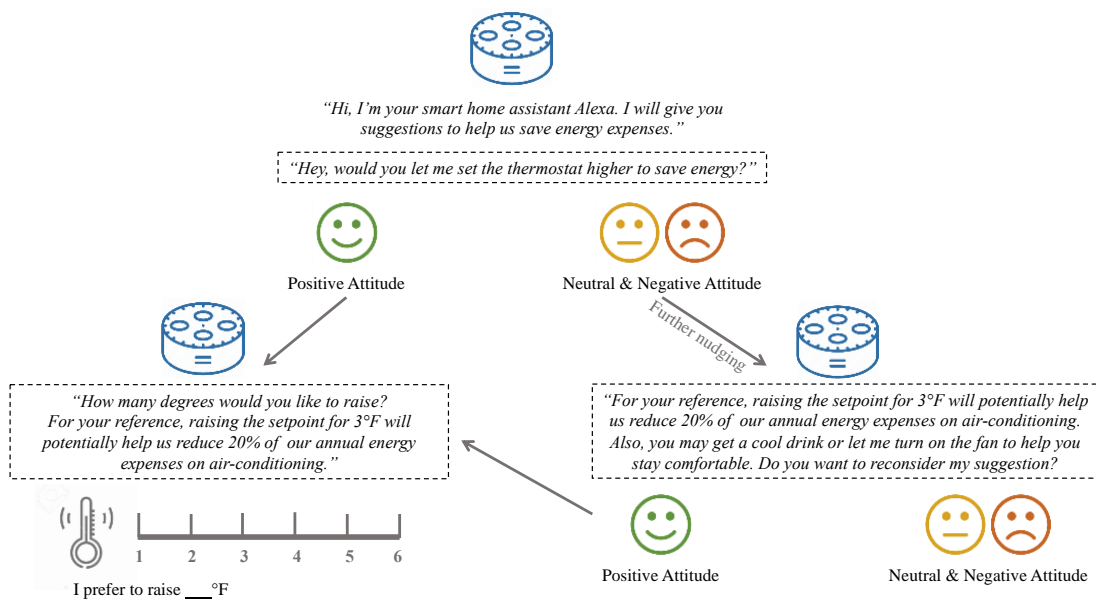


Figure 1.5. Suggestion (Nudging) Flow of the Smart Home Assistant Alexa

1.4.1.2 Participant's Profile

The survey questions in the participant's profile section will collect their demographic information, thermal comfort range and sensitivities, smart home device experiences, values and beliefs (Figure 1.3). Data collected in this section will be utilized to test the **H2-4** to answer the **RQ2**. The demographic information of the participants would include their gender, age, education, residence type, and employment status. Previous studies have justified that these socio-demographic characteristics are determinants of the differences of their energy-saving behavior (Yue et al., 2013). For example, Wang et al. (2019) proved that there is a gender difference when it comes to energy-related behaviors, where thermal preferences have

more noticeable influence on cooling energy consumption for males than females. The thermal preference range questions would collect two attributes of the occupants' thermal need: comfort range (Jazizadeh et al., 2014) and sensitivity (Jung and Jazizadeh, 2019). We will ask participants about their preferred thermostat setpoints and acceptable ranges with upper and lower limits, which would reflect their personal sensitivities to the changes in an environment – e.g., heat-sensitive means feeling discomfort for a slight increase in temperature while accepting a wider range reduction in the temperature setpoints. In **H2** we assumed that occupants' thermal preferences, ranges and sensitivities will affect their decisions in accepting the suggestions from smart home assistants. We also assumed that the occupants' familiarization with smart home devices would affect their attitude towards the proactive smart home assistants (**H3**), so we collected this information in the survey and specifically we would ask about their previous experience with smart home devices and IoT-based smart home appliances. The questions in the survey will collect participants' previous experience with smart home devices (e.g., Amazon Echo, Google Home) including holding period, using frequency, common commands, connected home appliances and systems.

It has been found in previous studies that occupants' values and beliefs are significant factors in their pro-ecological behavior (Dalvi-Esfahani et al., 2020). Previous study has also proved that there is a strong association between environmental attitudes and behaviors (Gadenne et al., 2011). As such, we collected participants' environment-related values (unity with nature, respecting the earth, protecting the environment, preventing pollution) with importance level scale from “Opposed to my values” to “Of supreme importance”. We also will utilize Likert scale in different options (Table 1.1.1) from “Strongly Disagree” to “Strongly Agree” to collect the participants' beliefs in environmental protection, energy expenses saving, personal comfort, and interests in taking actions. These options will be shown to the participants in random sequence to avoid potential biasing.

Table 1.1. Options Reflecting Participant's Beliefs

| Beliefs | Survey Options |
|--|--|
| Environmental Protection / Energy Savings | <ul style="list-style-type: none"> • Home energy use has an impact on global energy saving. • If I reduce my own home energy use it will have a positive impact on the environment. • I believe it is my personal responsibility to take action to reduce problems related to energy saving. |
| Energy Expenses | <ul style="list-style-type: none"> • Changing Home energy use considerably affects individuals' expenses. • If I reduce my own home energy use I can save money. • I pay close attention to how much money is spent on energy for my home every month. • I don't think that changing the thermostat temperature settings at home affects my energy bills much. |
| Personal Comfort | <ul style="list-style-type: none"> • I pay more attention to my personal comfort than how much energy I use. |
| Interest in Taking Actions | <ul style="list-style-type: none"> • I think I need more guidance on how to adapt my daily behavior in order to use less energy in my home. • I am interested in adapting my daily behavior in order to save money on energy if proper guidance is provided. |

1.4.1.3 Perception of Smart Home Assistants

Apart from the participants' feedback to our designed messages and their personal profile, we would also collect their perceptions towards smart home assistants. First, we will ask them about their general acceptance to the form of proactive smart home assistants, i.e., how do they feel about smart home assistants starting the conversation and giving suggestions. We would like to know if the users will feel intrusive or unsuited with the systems that we proposed, and if the participants believe that the proactive system can help them in terms of convenience, comfort, and energy saving. Then we will further acquire preference information like the participants' preference on the form of smart home devices (Display-based or Voice-based), the proper interaction frequency that won't make the participants feel bothered, and their preference on the information provided from the smart home assistants (energy expenses, environment impact, or adaptive behavior tips). These perceptions of the smart home assistants will provide valuable reference for the future implementation of the proactive smart home assistants providing tailored contents of communication.

1.4.2 Data Collection and Analysis

Before the full launch of online survey and data collection, we ran a pilot study with 60 participants involved. Based on the initial analysis of the pilot test results, a prior power analysis was conducted with G*Power 3 software (Faul et al., 2007). The prior power analysis is an effective approach to estimate the minimum sample size required for an experiment before a study is actually conducted (Faul et al., 2007). A desired significance level, effect size, and statistical power is needed to estimate the required sample size N . With data from the 60 participants in pilot test, we estimated the mean difference between the control group and the study group to be in the range 0.3-0.6, and the standard deviation of both groups to be around 1, thus lead to the effect size d to be in the range 0.3-0.6. With the consideration of power in the range from 0.8-0.95 and the significant level of 0.05, we ran the power analysis and got the results (Figure 1.6). Taking the time and cost of data collection into consideration, eventually we decided to include 300 valid responses in the full data collection.

Apart from determination of the sample size, the comments from the pilot test also helped us to slightly modify the survey to make it easier for the participants to understand. Through the Qualtrics platform, we distributed the survey and collected more than a thousand of responses from general public in the U.S. After data cleaning and unfinished surveys excluded, 307 valid responses were collected as the base of this study for further statistical analysis.

After data collection, we tested the above-mentioned hypotheses through descriptive statistics, and visualization of the collected data with bar charts and box plots. T-tests and ANOVA analysis were conducted to evaluate the difference between the control group and the study group, and to identify the impact of influential factors on the participant's intention in accepting the suggestions from smart home assistants. K-means clustering technique were also implemented during the classification of participants with regard to the influential factors. Details of the findings from the data analysis will be discussed in the following sections.

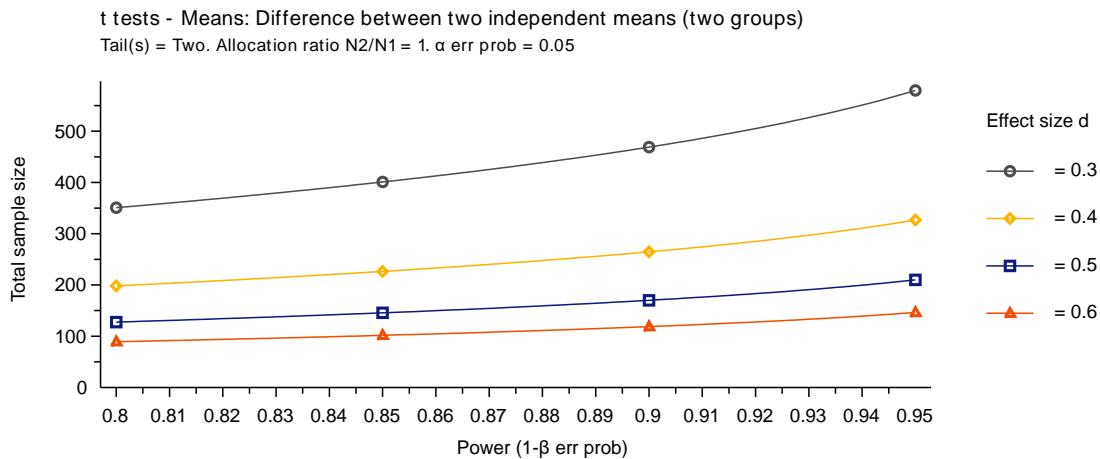


Figure 1.6. Power Analysis for Sample Size Estimation

1.5 Results and Findings

1.5.1 Sample Characteristics

After data collection and the basic validation process, 307 valid responses were retained for further analysis. Table 1.2 shows the general sample characteristics. The gender, age, and the education level of the respondents were basically uniformly distributed. Of the 2010 census population, the male and female proportions in the actual population were 49.2% and 50.8%, respectively (Howden and Meyer, 2011). The sample of 144 male (47%) and 161 female (52%) respondents shows almost equal distribution as we have 2 participants (1%) identified themselves as non-binary. In terms of the age distribution, as the survey was distributed online, the percentage of the younger generation and the middle age was comparatively higher, and the percentage of the older generation was comparatively lower in the sample. The distribution of education level was also a reflection of the actual population in 2015 with 33% reported with bachelor's degree or more and 12% with advanced degree (Ryan and Bauman, 2016). Of the 307 participants, half were full-time employee, and the other half consisted of various employment status including student (7%), half-time employee (13%), self-employed (4%), retired (12%), and unemployed (13%). Almost two-third of the respondents lived in single-family homes and one third lived in apartments, the remaining live in townhouses (7%) and studios (1%). About 16% of the participants live by oneself, 29% live with

roommates or friends, and 55% live with family including parents or children.

The feedback of participants' intention in taking the suggestions both in the study group and the control group are also presented in Table 1.2. Through basic descriptive analysis, it can be seen of how the demographic background affect the participants' attitude towards the energy saving suggestions. Compared with males, more females hold a neutral or negative attitude to the suggestions, especially in the control group. This finding is contrary to some of the previous studies on the impact of gender to energy saving attitudes and behaviors, which identified that females are more likely to express positive attitude towards energy saving (Aktamis, 2011; do Paço et al., 2015; Yang et al., 2016). This may be explained by the work from Karjalainen (2007) that when it comes to thermal comfort, females are more sensitive and easier to feel uncomfortable than males. As such, more females are reluctant to accept the suggestions and change the thermostats compared with males. In terms of the age, younger generations are more likely to respond positively to the suggestions than the old, which is reasonable as the younger generations are more receptive to the new technologies like smart home assistants in this study. This is also the case with education level, where more respondents with higher education are showing a positive attitude to the energy saving suggestions. This finding aligns with what previous studies have found that higher education background would lead to more conduct of energy saving behaviors (Yang et al., 2016). When it comes to employment status, full-time employees with stable income and the responsibility to pay the bills are more likely to show a positive attitude to the suggestion compared with the unemployed participants (students, homemakers, retired people). We did not find clear differences among participants from different residence types, but we did find that in terms of residence occupancy, respondents that live with family are more likely to accept the energy saving suggestions. Although these initial findings support the previous studies about the influence of the demographic background on the energy saving attitudes and behavior tendencies, further statistical analysis is needed to evaluate the findings in the future studies.

Table 1.2. Sample Characteristics and Feedback to Designed Messages

| Demographic Category | | Total Sample | | Study Group | | Control Group | |
|----------------------------|---|--------------|-------|-------------|--------------------|---------------|--------------------|
| | | Num. | Perc. | Positive | Neutral & Negative | Positive | Neutral & Negative |
| Gender | Male | 144 | 47% | 53 | 13 | 52 | 26 |
| | Female | 161 | 52% | 53 | 26 | 36 | 46 |
| | Non-binary | 2 | 1% | 1 | 1 | 0 | 0 |
| Age | 18-29 | 103 | 34% | 48 | 10 | 20 | 25 |
| | 30-39 | 102 | 33% | 38 | 10 | 37 | 17 |
| | 40-49 | 52 | 17% | 13 | 6 | 21 | 12 |
| | 50 + | 50 | 16% | 8 | 14 | 10 | 18 |
| Education Level | Less than high school | 16 | 5% | 5 | 3 | 2 | 6 |
| | High school graduate | 72 | 23% | 13 | 23 | 17 | 19 |
| | Some college | 31 | 10% | 9 | 7 | 5 | 10 |
| | Bachelor's degree | 121 | 39% | 52 | 9 | 36 | 24 |
| | Master's degree | 48 | 16% | 18 | 4 | 17 | 9 |
| | Other advanced degree | 6 | 2% | 1 | 0 | 4 | 1 |
| Employment | Doctorate Degree | 13 | 4% | 3 | 0 | 7 | 3 |
| | Student | 22 | 7% | 7 | 10 | 1 | 4 |
| | Part-time employee | 39 | 13% | 11 | 6 | 9 | 13 |
| | Full-time employee | 157 | 51% | 60 | 9 | 60 | 28 |
| | Self-employed | 13 | 4% | 4 | 1 | 3 | 5 |
| | Retired | 37 | 12% | 6 | 13 | 9 | 9 |
| Residence Type | Unemployed | 39 | 13% | 10 | 10 | 6 | 13 |
| | Single-Family Home | 184 | 60% | 66 | 23 | 50 | 45 |
| | Apartment | 98 | 32% | 31 | 12 | 34 | 21 |
| | Townhouse | 21 | 7% | 9 | 5 | 4 | 3 |
| Residence Occupancy | Studio | 4 | 1% | 1 | 0 | 0 | 3 |
| | Live by oneself | 50 | 16% | 14 | 11 | 10 | 15 |
| | Live with roommate/friends | 89 | 29% | 27 | 12 | 27 | 23 |
| | Live with family including children/parents | 168 | 55% | 66 | 17 | 51 | 34 |

1.5.2 Efficacy of Voice-based Smart Home Assistants

As we proposed the proactive voice-based smart home assistant, we assumed that the form of voice-

based humanlike virtual assistant and the improved automation control in the smart home scenario would have a positive effect on the participants' acceptance level to the energy saving suggestions. In other words, we assumed that with the help of smart home assistants, occupants' intention to accept the suggestions will be higher. In order to evaluate the assumption and *HI*, we quantified the Likert scale of participants' feedback from "Definitely No" (=1) to "Probably Yes or Probably No (Neutral)" (=3) to "Definitely Yes" (=5). Then we compared the mean value of different groups and utilized t-test to indicate the difference and its significance level (Table 1.3). As mentioned in the survey design (Figure 1.5), the participants would first receive the simple question asking about their intention in taking the energy saving behavior, and their first feedback are labeled as "Study Group - Initial" in Table 1.3. If the participants show a neutral or negative attitude, he/she will be further nudged with additional information and tips, and their second feedback are labeled as "Study Group - Nudged". Also, for the control group, participants will first provide their feedback to the plain text questions ("Control Group - Initial") and then their feedback to the video questions ("Control Group - Nudged").

As shown in Table 1.3, all the feedback after nudged are performing better than before nudged with higher mean values based on Comparison 2-4, which indicates that the framework we proposed is efficient in nudging occupants to take energy saving behaviors. However, the initial feedback between the study group and the control group are not differentiated much nor statistically significant (Comparison 1). This may be due to the limitation of online survey compared with the in-person experiments, that the participants can't actually feel and interact with the smart home assistants in an IoT-based smart home environment, and thus the difference between the voice-based assistant and the plain text is not clearly introduced to the participants. Further studies with experiments are needed to investigate the differences.

The difference of participants' attitude between before and after nudged within the study group (Comparison 3) or control group (Comparison 4) are also not statistically significant. This can be explained in Figure 1.7. It can be seen that most of the changes are made in the "Neutral" and "Probably Yes" intention, while the "Definitely No" and "Probably No" are barely changed. This finding indicates that the proactive smart home assistants are actually working on the occupants who hold a neutral attitude towards energy

saving behavior, nudging them to a positive intention. However, the smart home assistants can't change the mind of the people who hold a negative attitude to the energy saving suggestions. It can be of reference to the frequency of the smart home assistants reaching to the occupants. If the occupant constantly declines the suggestions, the smart home assistants should record that and reduce the suggestion frequency to avoid bothering the occupants with only minor positive effect.

Table 1.3. T-Tests for Different Groups of Comparisons

| Comparisons | Number | Mean | Std. Deviation | t (Sig.) | |
|--------------|-------------------------|------|----------------|----------|----------|
| Comparison 1 | Study Group - Initial | 147 | 3.54 | 1.11 | 0.722 |
| | Control Group -Initial | 160 | 3.45 | 1.17 | (0.335) |
| Comparison 2 | Study Group - Nudged | 147 | 3.72 | 1.06 | 2.123 |
| | Control Group - Initial | 160 | 3.45 | 1.17 | (0.035*) |
| Comparison 3 | Study Group - Initial | 147 | 3.54 | 1.11 | -1.397 |
| | Study Group - Nudged | 147 | 3.72 | 1.06 | (0.163) |
| Comparison 4 | Control Group - Initial | 160 | 3.45 | 1.17 | -1.265 |
| | Control Group - Nudged | 160 | 3.61 | 1.13 | (0.207) |

* Significant level < 0.05.

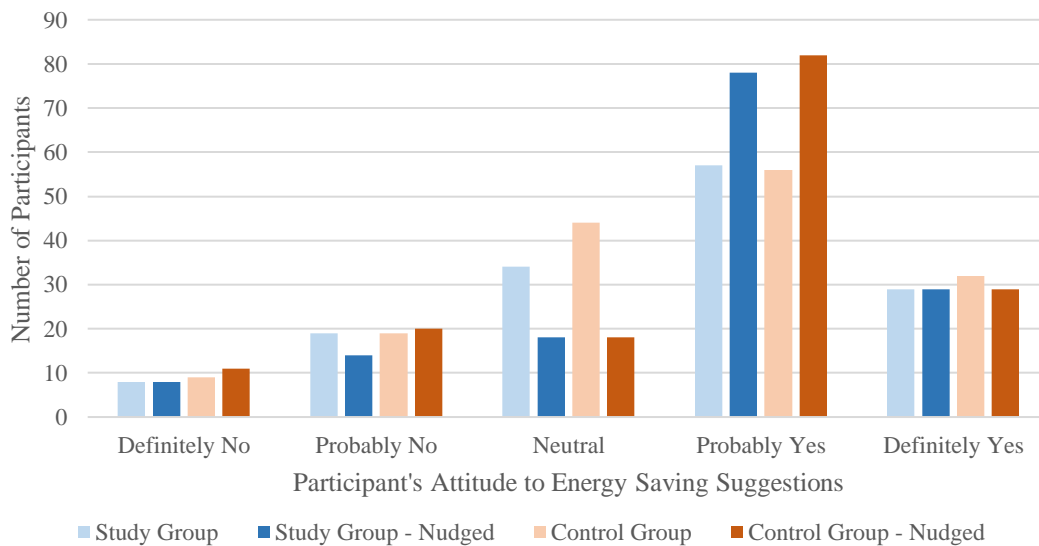


Figure 1.7. Difference of Participant's Attitude Between Before and After Nudging in Study and Control Group

1.5.3 Participant's Intention Influential Factors

1.5.3.1 Thermal Comfort Range and Sensitivity

In the survey, we have asked participants to provide their preferred thermostat setpoints and thermal comfort range with upper and lower limits. Before justifying the impact of the participants' thermal comfort range and sensitivity on their intention in taking the energy-saving suggestions, the collected data were further cleaned as some of the thermal comfort responses were invalid with comfort range larger than 15 degrees Fahrenheit, or upper limit below the lower limit. 203 valid responses of thermal comfort were included for data analysis. Note that the participants' thermal comfort range and sensitivity here are based on their thermostat setpoints, which is their self-reported subjective feedback, and may have deviation with their physical thermal comfort perception. We further divided these participants into different groups based on their thermal comfort range and thermal sensitivities to investigate their impact on the participants' intention in accepting suggestions and temperature setpoint changes.

The acceptable thermal comfort region for residential building is ± 1.5 °C for ISO 7730 and ± 2.5 °C for prEN 15251 (Peeters et al., 2009). Based on that, in this study we set 5°F (± 2.5 °F) as a boundary. With 5°F as a boundary, the participants' thermal comfort range are divided into large thermal comfort range group and the small comfort range group. It can be seen from the T-test results (Table 1.4) that the two groups are significantly different in terms of the intention in accepting suggestions. It can be seen from the box plot (Figure 1.8) that the people with larger thermal comfort range are more willing to accept the suggestions raised by the smart home assistants, while people with smaller thermal comfort range tend to hold a neutral attitude to raising the thermostat setpoints. In terms of the temperature setpoint change (Figure 1.8), the larger thermal comfort range group would agree to raise the temperature higher (2.61°F) compared with the smaller comfort range group (1.83°F).

Table 1.4. T-Test for Different Thermal Comfort Ranges

| | Thermal Comfort Range | N | Mean | Std. Deviation | t (Sig.) |
|------------------------------------|-----------------------|-----|------|----------------|----------|
| Intention in Accepting Suggestions | Large (> 5°F) | 89 | 3.74 | 0.99 | 2.321* |
| | Small (<= 5°F) | 114 | 3.37 | 1.24 | (0.021) |
| Temperature Setpoint Change | Large (> 5°F) | 89 | 2.61 | 1.74 | 3.086** |
| | Small (<= 5°F) | 114 | 1.83 | 1.79 | (0.002) |

* Significant level < 0.05.

** Significant level < 0.01.

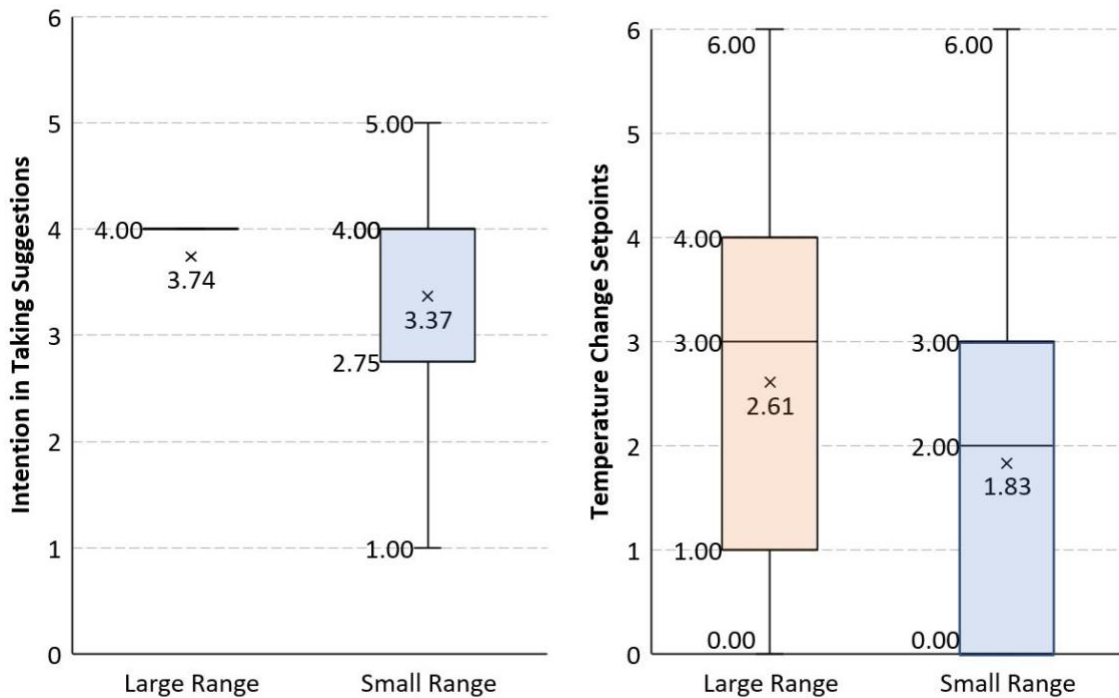


Figure 1.8. Effects of Thermal Comfort Range on Participants' Intention in Taking Suggestions (Left) and Temperature Change Setpoints (Right)

The occupant's thermal sensitivity could significantly affect their thermostat setpoints during the operation of the HVAC systems (Jung and Jazizadeh, 2018). We segment the participants based on their feedback to the thermal comfort range. If the participant's thermal comfort upper range (Upper limit – Preferred setpoint) is smaller than the lower range (Preferred setpoint – Lower limit), then it indicates the participant is sensitive to the hot or warm thermal conditions and more tolerable to the cold or cool thermal conditions. Vice versa, cold sensitive (hot tolerant) means that the participant has a wider comfort range in

the hot/warm thermal conditions compared with the cold/cool conditions. The ones with equal range on the warm side and cool side would be grouped with label “Neutral”.

The ANOVA test for three groups of thermal sensitivities (Table 1.5) shows that the thermal sensitivity does have a statistically significant impact on the people’s intention to accept the energy-saving suggestions and thermostat setpoint changes. Data results indicate that people who are cold sensitive (hot tolerant) have a higher intention to accept the suggestions and willing to raise the temperature higher compared with other groups (Figure 1.9). On the contrary, the hot sensitive (cold tolerant) group shows lower score in intention and temperature setpoint changes. The neutral group shows a relatively negative attitude to the raising temperature setpoint suggestion compared with the other groups. This might be due to the limitation of the online survey, where participants can’t really experience the thermal condition and their feedback are based on their previous experience and own judgement. As such, the thermal comfort sensitivity may be too subjective and requires further in-person experiments.

Table 1.5. ANOVA Test for Different Thermal Sensitivities

| | | N | Mean | Std. Deviation | F (Sig.) |
|--|----------------------------------|----|------|----------------|--------------------|
| Intention in Accepting Suggestions | Hot Sensitive (Cold Tolerate) | 81 | 3.56 | 1.06 | 5.916** (0.003) |
| | Neutral | 68 | 3.21 | 1.25 | |
| | Cold Sensitive (Hot Tolerate) | 54 | 3.91 | 1.03 | |
| Temperature Setpoint Change | Hot Sensitive (Cold Tolerate) | 81 | 2.25 | 1.90 | 3.462* (0.033) |
| | Neutral | 68 | 1.75 | 1.82 | |
| | Cold Sensitive (Hot Tolerate) | 54 | 2.59 | 1.56 | |

* Significant level < 0.05.

** Significant level < 0.01.

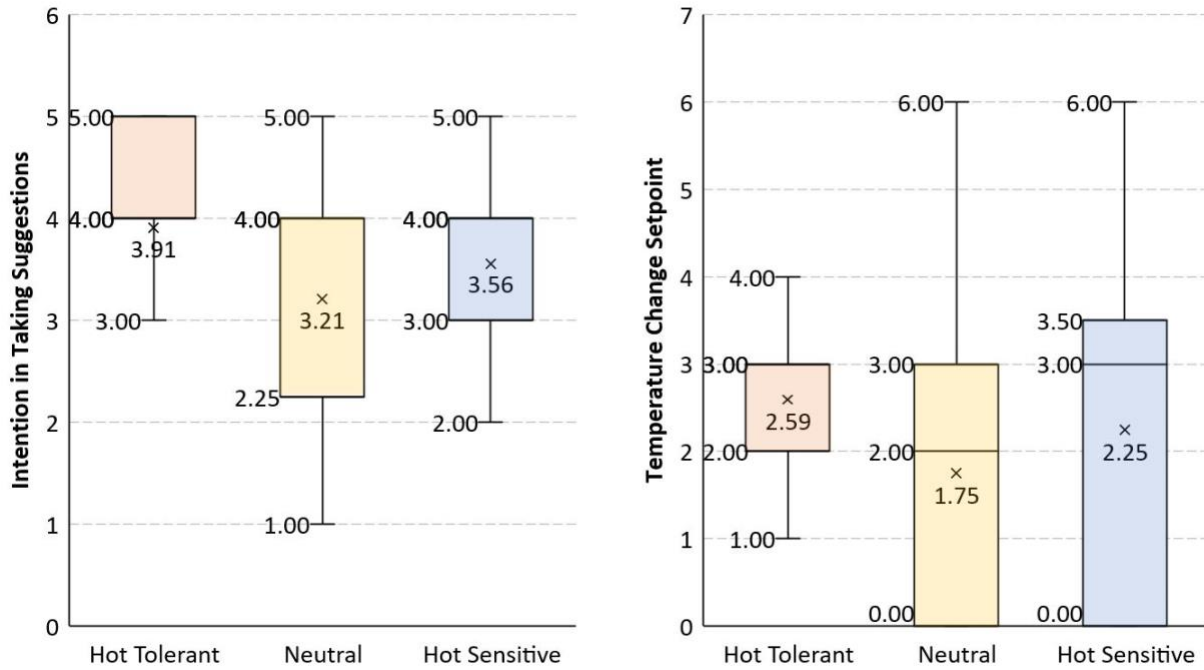


Figure 1.9. Impact of Participants' Thermal Sensitivity on Participants' Intention in Taking Suggestions (Left) and Temperature Change Setpoints (Right)

Apart from T-tests and ANOVA tests, we also conducted Pearson correlation tests to evaluate the correlation between the participants' thermostat setpoints, thermostat ranges and their intention in accepting suggestions, temperature setpoint change. As shown in Table 1.6, the upper limit setpoint has a significant correlation with participants' intention and temperature change, while the lower limit setpoint and the preferred setpoint don't have significant correlation. In terms of the thermostat ranges, the total range and the upper range both show significant correlation. It can be seen from the correlation results that compared with occupants' lower thermal comfort range (thermostat lower limit), their upper thermal comfort range (thermostat upper limit) has a closer and more significant correlation with their intention in taking the energy-saving suggestions and acceptance in raising higher temperature setpoints (Table 1.7). This may be due to the air conditioning difference in different seasons. In this study we conducted the survey in the summer scenario, when occupants are using the cooling system and would be more sensible to the hot ambient environment, so the participants' thermostat upper limit setpoint acquires more attention. We assume that in the winter scenario, the situation may differ, when the thermostat lower limit setpoint

may have a significant correlation with occupants' intention and temperature setpoint change. Further experiment and analysis are needed to evaluate this assumption in the future.

Table 1.6. Pearson Correlation Analysis Results (Thermostat Setpoints)

| | Lower Limit | Preferred Setpoint | Upper Limit |
|------------------------------------|--------------------|--------------------|--------------------|
| Intention in Accepting Suggestions | 0.067 (0.341) * | 0.121 (0.085) | 0.210** (0.003) |
| Temperature Setpoint Change | 0.013 (0.853) | 0.067 (0.344) | 0.147** (0.036) |

* Pearson correlation r value (Significance (2-tailed))

** Significant level < 0.01.

Table 1.7. Pearson Correlation Analysis Results (Thermostat Ranges)

| | Range (Upper-Lower) | Upper Range (Upper-Preferred) | Lower Range (Preferred-Lower) | Upper Range- Lower Range |
|------------------------------------|------------------------|----------------------------------|----------------------------------|-----------------------------|
| Intention in Accepting Suggestions | 0.197** (0.005) * | 0.213** (0.002) | 0.109 (0.120) | 0.087 (0.215) |
| Temperature Setpoint Change | 0.189** (0.007) | 0.191** (0.006) | 0.118 (0.094) | 0.061 (0.388) |

* Pearson correlation r value (Significance (2-tailed))

** Significant level < 0.01.

1.5.3.2 Experience with Smart Home Devices

In **H3**, we assumed that occupant's previous experience with the smart home devices (e.g., Amazon Echo, Google Nest) would have a positive effect on their intention to accept the suggestions brought by the smart home assistants. As such, in order to evaluate the hypothesis, we collected information about participant's previous experience with the smart home devices with five factors, including Number (the number of smart home devices that the participant has used before), Holding Period (the time that the participant has owned the smart home devices), Command Frequency (the frequency that the participant gives commands to the smart home devices), Command Types (the number of the frequently used command types that the participant give to the devices, with five command types in total), and Connected Devices/Systems (the number of connected devices/systems to the smart home central hubs).

After normalizing the original scores of five factors with z-score standardization, we utilized k-

means clustering technique to distinguish the participants into three different groups: No/Limited experience users, Some experience users, and Rich experience users (Figure 1.10). For people in the no/limited experience group, the majority of them (134 out of 140) didn't have any former experience with the smart home devices, and the remaining ones (7) had only used the devices for short period of time with limited interaction. The main difference between some experience group and the rich experience group is that the rich experience users have interacted with more than one type of smart home devices, including the voice-based (e.g., Amazon Echo, Apple Home pod) and the display-based (e.g., Google Nest Hub, Facebook Portal) forms. In addition, the rich experience users have interacted with the devices more frequently and more broadly.

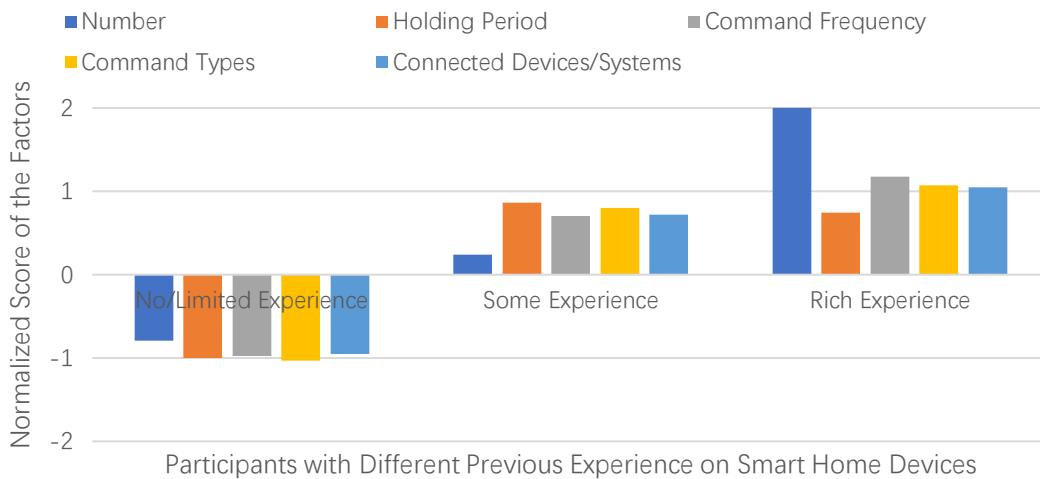


Figure 1.10. Clusters of Participants with Different Previous Experience on Smart Home Devices

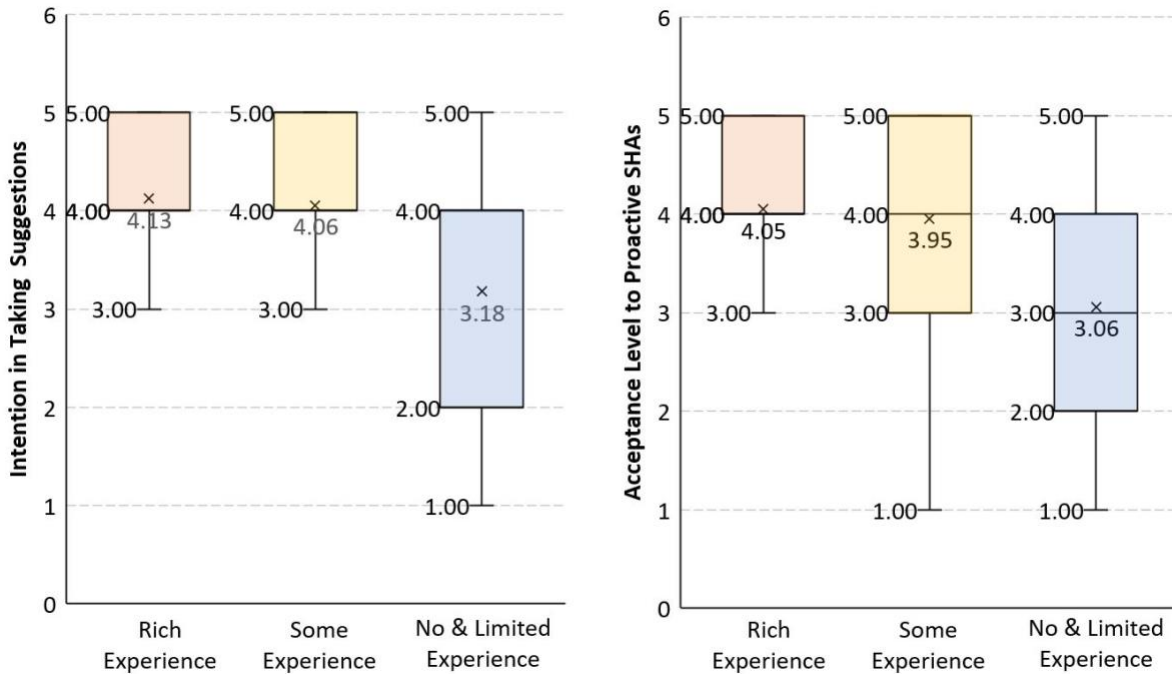


Figure 1.11. Impact of Participants' Experience with Smart Home Devices on Participants' Intention in Taking Suggestions (Left) and Acceptance Level to Proactive SHAs (Right)

In the perception of smart home assistant section, we have a question asking the participants to indicate their acceptance level to the form of proactive smart home assistants raising suggestions for energy saving. The feedbacks from the participants are counted here as an evaluation criterion of the impact of participants' experience with smart home devices on their perceptions (Figure 1.11). The ANOVA Post-hoc test results (Table 1.8) indicates that the difference of the intention and acceptance level are both significant, which quantitatively justified the impact of previous experience. It can be seen from **Error! Reference source not found.** that whether or not have previous experience with smart home devices have a significant impact on the participant's intention to accept the suggestions, while there's not much difference between some experience group and the rich experience group. In terms of the acceptance level to proactive smart home assistants, rich experience users show highest acceptability, then followed by some experience users. No/limited experience users show the lowest acceptability to the concept of proactive smart home assistants.

Table 1.8. ANOVA Tukey Post-hoc Test Results (Smart Home Device Experience)

| Groups | | Intention (Mean Difference) | Acceptance Level (Mean Difference) |
|-------------------------|-------------------------|--------------------------------|---------------------------------------|
| No & Limited Experience | Some Experience | -0.088* | -0.896* |
| | Rich Experience | -0.095* | -0.993* |
| Some Experience | No & Limited Experience | 0.877* | 0.896* |
| | Rich Experience | -0.070 | -0.097 |
| Rich Experience | No & Limited Experience | 0.946* | 0.993* |
| | Some Experience | 0.070 | 0.097 |

* The mean difference is significant at the 0.05 level.

1.5.3.3 Value and Beliefs

After collecting the information of participants' environment-related values (unity with nature, respecting the earth, protecting the environment, preventing pollution) and their beliefs in environmental protection, energy expenses saving, personal comfort, and interests in taking actions, we would like to evaluate **H4** to prove that people's value and beliefs can affect their perception of smart home assistants. As such, based on the collected variables, we normalized the scores and utilized the standardized scores to segment the participants with k-means clustering technique. The clustering result shows two different groups with distinguish characteristics: occupants with a positive attitude towards environmental protection (Positive group) and occupants with a general negative attitude (Negative group) (Figure 1.12).

For the Negative group, people are not paying attention to environmental protection or energy saving. They show no interests in taking actions to save energy and would like to conserve their personal comfort. Generally, the people in this group hold a negative attitude to sustainability. On the contrary, the Positive group hold a positive attitude to sustainability, with great attention on energy saving and environmental protection, willing to sacrifice personal comfort for taking actions. Through the T-test (Table 1.9), we found that the difference among two groups is statistically significant, and we identified that the positive group shows higher acceptance level to the form of proactive smart home assistants offering suggestions, compared with the negative group (Figure 1.13). The difference aligns with findings in

previous studies that the association between environmental attitudes and behaviors is very strong (Gadenne et al., 2011).

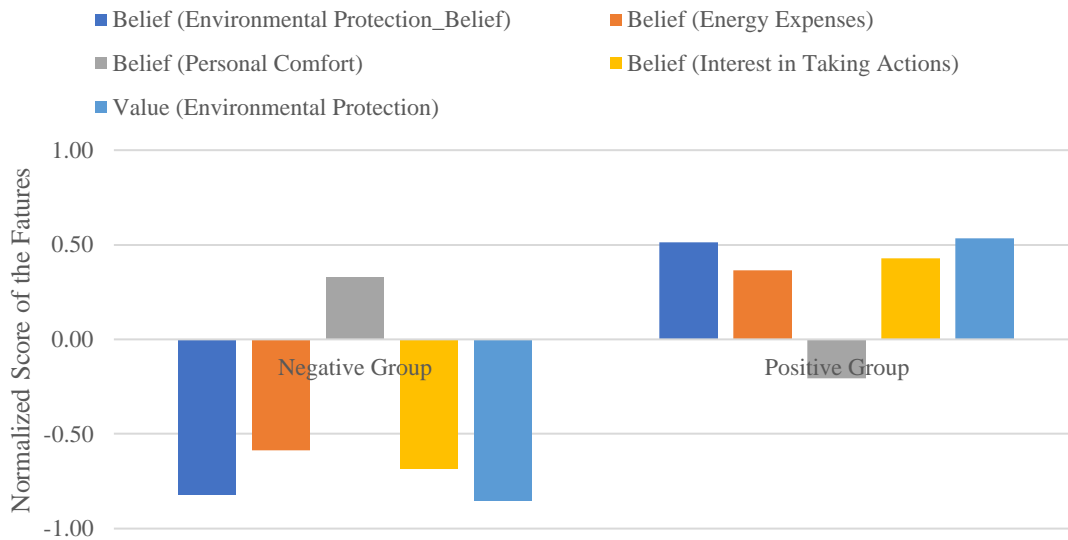


Figure 1.12. Groups of Participants with Different Value and Beliefs

Table 1.9. T-Tests for Two Groups with Different Values and Beliefs

| | Groups | N | Mean | Std. Deviation | t (Sig.) |
|------------------------------------|----------|-----|------|----------------|-------------|
| Intention in Accepting Suggestions | Negative | 118 | 3.08 | 1.04 | 34.41** |
| | Positive | 189 | 3.81 | 1.06 | (0.000) |
| Acceptance Level to Proactive SHAs | Negative | 118 | 2.92 | 1.11 | 63.44** |
| | Positive | 189 | 3.95 | 1.05 | (0.000) |

** The mean difference is significant at the 0.01 level.

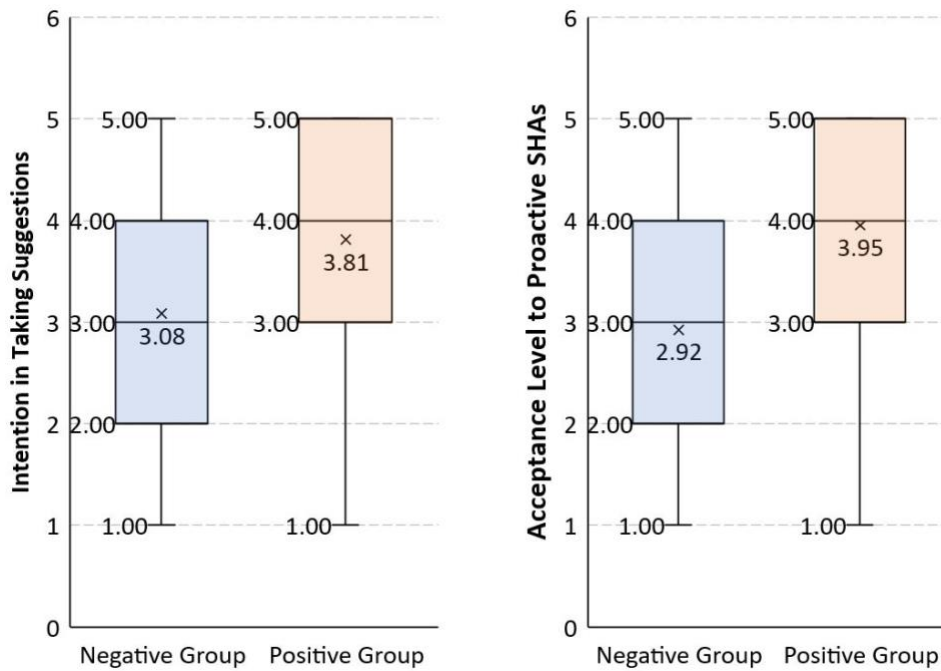


Figure 1.13. Impact of Participants' Value and Beliefs on Participants' Intention in Taking Suggestions (Left) and Acceptance Level to Proactive SHAs (Right)

1.5.4 Perception of Proactive Smart Home Assistants

Apart from identifying the participant's intention influential factors, we would also like to explore the participant's perception of the concept of proactive smart home assistants. As such, we asked the participants: "How do you feel about receiving suggestions from your Home Assistant System to help you with energy-saving? (i.e., instead of you starting a conversation or giving a command, Home Assistant starts a conversation)". Figure 1.14 shows the participants' feedback to this question and their general acceptability to the proactive smart home assistants. Above half of the respondents (57%) show a positive attitude towards the concept, while 27% hold a neutral attitude and 16% show a negative attitude.

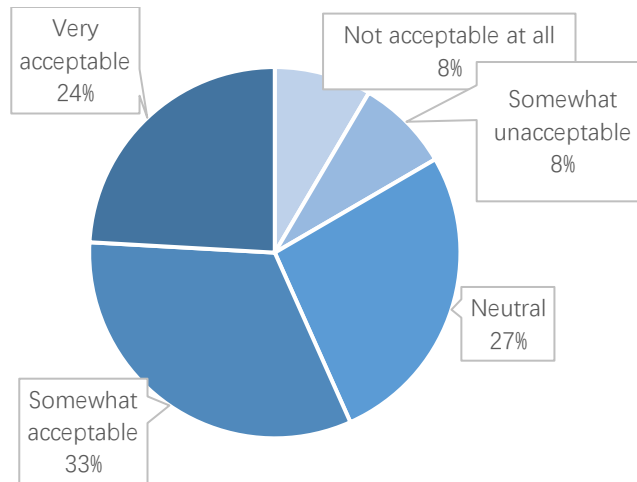


Figure 1.14. Participants' General Acceptance Level to Proactive Smart Home Assistants

We further asked the participants to compare between the passive smart home assistants and the proactive smart home assistants. In both scenario occupant can use their voice commands to control the home appliances, with the only difference that the proactive one can give energy-saving suggestions while the passive one can only receive commands. It can be seen from the results (Figure 1.15) that although more people feel that the proactive assistant can help them save energy, they also feel that the proactive assistants would lower the convenience and their comfort level compared with the passive assistants. Participants' uncertainty about the proactive smart home assistants' concept may be the reason for this difference.

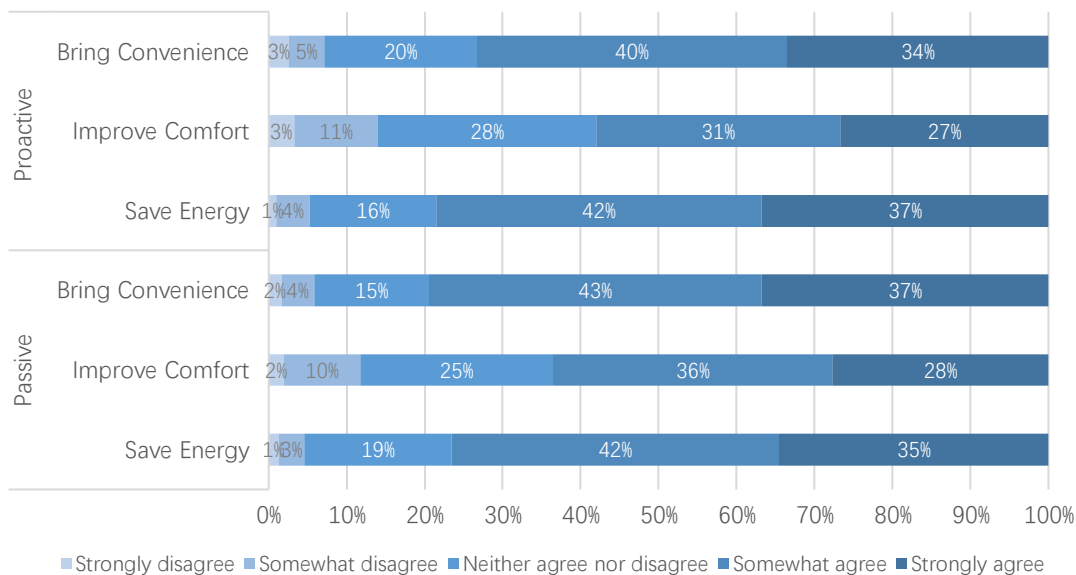


Figure 1.15. Participant's Perception of Passive and Proactive Smart Home Assistants

In terms of the participant's preference on the smart home assistants, we collected information about their preferred form (Figure 1.16), suggestion frequency (Figure 1.17) and suggestion contents (Figure 1.18). One fifth (62) of the participants prefer not to use any kinds of smart home assistants, while the rest have picked their preferred forms. Participants like smartphone assistant more than the smart display, as the smartphone may be more reachable and convenient for users that have no previous experience with the smart displays. A large proportion of the participants prefer the use smart speaker (i.e., voice-based device) as their smart home assistants, this might be due to the broad market penetration and application of smart speakers, or the participants might be nudged by the previous video questions in the survey with Amazon Echo giving energy-saving suggestions. There is a need in the future studies to objectively explore user's preference on the form of smart home assistants.

In terms of how frequent the participants want their smart home assistants give energy-saving suggestions, the data results (Figure 1.17) indicate that about half of the participants (47%) would prefer the assistants not to bother them too often, while 30% of the participants prefer to regularly hear from the smart home assistants. In terms of the contents in the messages brought from the smart home assistants (Figure 1.18), participants prefer tips with information about energy saving and energy expenses saving. However, comparatively participants show less interest in tips with the savings in carbon footprints and the tips with adaptive behavior suggestions.

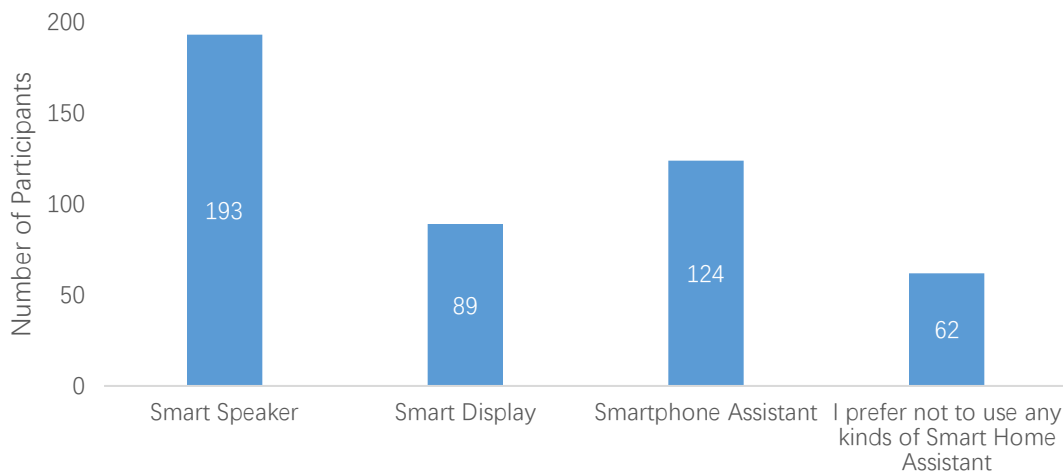


Figure 1.16. Participant's Preference on the Form of Smart Home Assistants

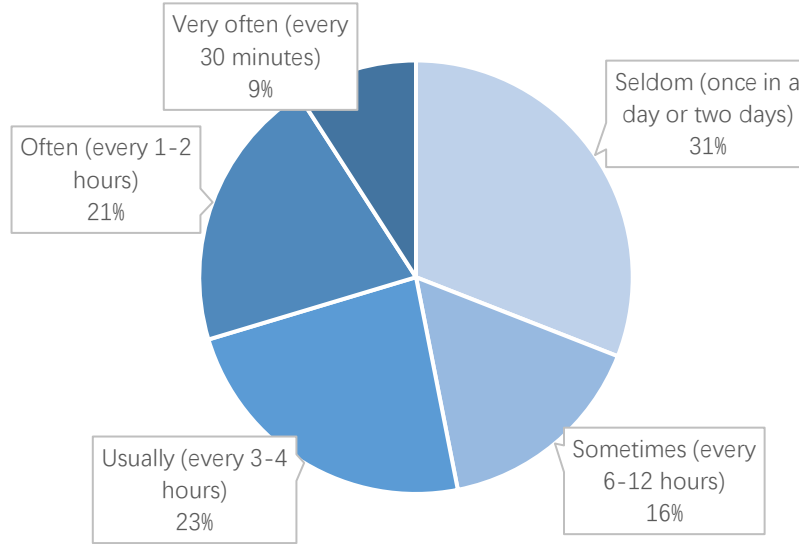


Figure 1.17. Participant’s Preference on SHAs Raising Suggestions Frequency

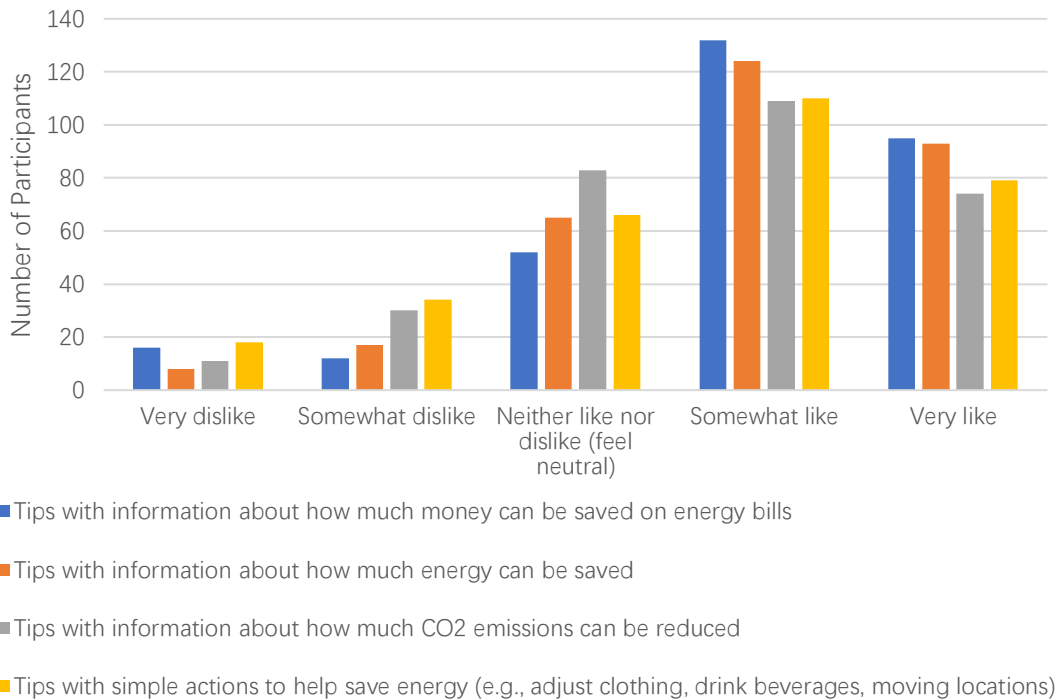


Figure 1.18. Participant’s Preference to the Information Provided by the SHAs

1.6 Discussion and Conclusion

In this study, with the aim of promoting the bi-directional human-building interaction, we proposed the concept of proactive voice-based smart home assistants. In our vision, embedded by IoT-based smart home, the virtual assistants could proactively raise suggestions to occupants and nudge them to form

energy-saving habits with choice architecture. We assumed that through nudging, the smart home assistants can improve occupants' intention in taking energy-saving adaptive behaviors. In order to evaluate it, we distributed an online survey and collected 307 valid responses. The comparison between the control group (plain text suggestions) and the study group (suggestions from virtual assistant Alexa) proved that the smart home assistant can nudge the people who originally hold a neutral attitude to a positive attitude towards energy-saving behavior.

This study also explored the influence of occupant's personal features on their acceptance level to the suggestions raised by the smart home assistants. These personal features include their thermal preferences, experience with smart home devices, values and beliefs. We justified that people with a larger thermal comfort range ($> 5^{\circ}\text{F}$) would be more acceptable to the suggestions of raising the temperature setpoint for energy-saving and agree to raise the setpoint higher, compared with the people with a smaller comfort range ($\leq 5^{\circ}\text{F}$). In terms of smart home device experience, compared with people with no or limited experience with smart home devices (e.g., Amazon Echo, Google Nest Hub), people who have some or rich experience show considerable higher acceptability to the proactive smart home assistants and the suggestions that the assistant propose. Last but not least, based on the values and beliefs in environmental protection and energy-saving, occupants can be clustered into two groups: Negative group and Positive group. The Positive group holds a positive attitude to sustainability and driven by their values and belief, these people show a high intention to accept the adaptive behavior suggestions from smart home assistants, even if that might sacrifice their personal comfort. Comparatively, the Negative group show lower intention in accepting the energy-saving suggestions.

The investigation on the participants' perception of the proactive smart home assistants shows that 57% of the respondents hold a positive attitude towards the concept, while the remaining ones are still skeptical about it. The uncertainty about the benefits that can be brought by the smart home assistants may be the reason. Two-third of the respondents indicate that they prefer a smart speaker as the carrier of the virtual assistant, and many of the respondents prefer not to be bothered a lot in a day by the proactive suggestions from the assistant. Tips with information about how much money can be saved on energy bills

are the most popular ones in terms of the contents provided with the suggestions. These above-mentioned findings of people's perceptions will provide a valuable reference for the future implementation of proactive smart home assistants and human-building interactions.

However, limitation still exists in this study. The online survey is collecting the participants' subjective perceptions and views towards the concept of smart home assistants, which may not be their final actions or behavior in the real-world scenarios. People's decision to the suggestion from the assistants may be different when they are in the smart home environment and when they are experiencing the actual thermal conditions. As such, an in-person user study is needed in the future to observe the interactions between the proactive smart home assistants and the occupants.

In summary, the findings in this study fill the gap of limited previous studies in the interaction between the occupants and the smart home assistants and pave the path to the future development of bi-directional human-building interaction. The academic researchers and the industry practitioners can both refer to this study when they are developing the conversational proactive smart home assistants.

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Journal Paper 2: Occupants' Characteristics-based Energy-saving Behavior Prediction with Machine Learning Techniques in Smart Home Scenarios

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2.1 Abstract

AI-powered smart homes bring high-quality intelligent services to occupants with digital virtual assistants. Through interactions with occupants, smart home assistants can build occupant's profile with their personal characteristics. In this study, we explored to identify the most important characteristic features in occupants' energy-saving behavior prediction. After comprehensive data collection through online surveys, we fitted 21 participants' personal characteristics features in machine learning techniques (SVM, Random Forest, Logistic Regression) to predict occupant's intention and attitude towards the energy-saving suggestions provided by proactive smart home assistants. The Logistic Regression model with 3 variables as input was proved to have the best performance with an accuracy of 0.803 and an F-measure of 0.867. Important features in occupant's attitude prediction were identified, including occupant's beliefs about interests in taking actions and beliefs about energy expenses, occupant's education level, residence occupancy type, thermal comfort ranges, and smart home device experiences. Findings in this study will support the future development of smart home assistants providing personalized energy-saving suggestions to nudge occupants taking adaptive behaviors.

Key words:

Occupant Characteristics, IoT, Smart Home Assistant, Energy-saving Behavior, Machine Learning

2.2 Introduction

With the rapid development of the Internet of Things (IoT) technology, the smart home has already become part of the high-quality life across the world (Shahjalal et al., 2020). The IoT in smart home is a network consists of detection and control devices that provide the infrastructure to exchange household appliance information and services, which includes the heating, ventilation and air conditioning (HVAC), lighting, and security systems (Alaa et al., 2017). The IoT-embedded smart homes have a high level of home automation and could change many aspects of the residents' daily lives, such as control, convenience, comfort, and energy-saving. Residents usually interact with the smart home environment through a central hub, a user interface in the forms of mobile phone, computer, tablet, or smart speaker. The cloud-connected

central hub acts as a digital virtual assistant, enabling the residents to easily operate and control all the devices at home. The implementation of artificial intelligence (AI) in the hub further optimize the services that the residents can get from the smart home environment. Through the AI techniques like machine learning or energy consumption prediction, the digital virtual assistant can learn from the historical data and help improve the residents' well-being from various application levels, including energy management and healthcare (Zaidan and Zaidan, 2020).

The adaptation of IoT and AI technologies have made smart home services and products rapidly developed and proliferated in the past five years (Yang et al., 2018). The AI-based intelligent virtual assistants have been made suitable for the public market by the large technology companies like Apple, Amazon, Microsoft, and Google (Maedche et al., 2019). For example, through the Amazon Echo, users can easily control the lights or thermostats with voice commands to the intelligent virtual assistant "Alexa". Google Assistant can also provide similar services with a matured ecosystem that contains broad compatible smart devices. Users can even trigger group actions in the Apple HomeKit, which means controlling multiple appliances simultaneously with single "wake" words. When a user get home and say "Siri, I'm home.", then the lighting, indoor temperature, and devices like television, would be automatically operated as desired by the smart home virtual assistant.

Building occupant's behaviors have a significant impact on the indoor environment and the energy efficiency. The adaptive behaviors like thermostat adjustment, window opening, lights on and off, can be triggered and influenced by the eco-feedback system (Paone and Bacher, 2018). Traditional eco-feedback systems provide occupants with information like energy consumption or energy saving reports, environmental impacts (e.g., CO₂ emissions), energy usage comparison with peers/neighbors, to affect occupant's daily behaviors and thus help reduce energy consumption (Paone and Bacher, 2018). A balance between the energy efficiency and occupants' comfort perception needs to be kept for the long-term effect of the eco-feedback systems. Also, if occupants don't have effective control over the environment, their discomfort level would increase and the user satisfaction will be negatively affected (Hoes et al., 2009). The AI-powered smart homes not only enable occupants to have convenient control over the household

appliances, but also can learn the occupants' preferences based on their daily activities (Jivani et al., 2018). The energy-saving suggestions and responsive notifications provided by the digital virtual assistants can help simplify the users' decision making process and nudge them into taking energy efficient behaviors (Singla and Sharma, 2020).

Based on previous studies, we know that the targeted or tailored eco-feedback can be much more efficient than the uniform eco-feedback in regards to the individual differences and the variability of occupants' behaviors (Khosrowpour et al., 2016). Many conventional eco-feedback studies focused on the contents or formats of the communication and treated the occupants uniformly as the users of the designed system. However, the occupants' characteristics can be varied, and their demographic background, previous experiences, values and beliefs can all considerably affect their responses to the eco-feedback. In the smart home ecosystem, the AI virtual assistants should be able to learn from the collected data and information from occupants and optimize their interaction with occupants through personalized services.

In this study, we would like to explore the feasibility of the smart home assistants learning occupant's characteristics and intentionally providing suggestions to nudge them to take energy-saving behaviors. Through an online survey, we collected 307 participants' information about their demographic background, thermal comfort perceptions, smart home device experience, values and beliefs. And we also collected their feedback to the energy-saving suggestions raised by the smart home assistant "Alexa" from Amazon Echo Dot in the survey. By implementing the machine learning algorithms (Support Vector Machine, Random Forest, Logistic Regression), we identified the important features of individual characteristics that could affect the participants' intention in taking the energy-saving suggestions and built models to predict occupant's attitude towards the proactive smart home assistants. This study will provide a comprehensive analysis about the effects of the individual characteristics on the occupant's interaction with the AI-powered smart home ecosystem. The related work, research methods, results and statistical findings of this study will be further introduced in the following sections.

2.3 Related Works

2.3.1 Human-centric Smart Home Ecosystem

Broad review studies have summarized the state of the art of smart home ecosystem development (Alaa et al., 2017; Gaikwad et al., 2015; Marikyan et al., 2019; Moser et al., 2014; Samuel, 2016; Stojkoska and Trivodaliev, 2017). The smart home ecosystem is a human-centric environment where IoT technologies are employed for the automatic control and management of various home appliances to improve the occupant's life quality (Feng et al., 2017). The sensors and actuators are interconnected in a network, and within the network the devices can communicate with each other and the occupants through the central hubs to create an interactive ecosystem (Alam et al., 2012). Stojkoska and Trivodaliev (2017) summarized the IoT-based framework for smart home with five major components: smart home equipped with smart devices, a cloud that store and process the data, utility with smart grids, third party applications, and user interfaces that deliver messages to the occupants. Through the form of ambient intelligence or home automation, the smart home ecosystem can provide occupants with context-aware automated or assistive services (Alam et al., 2012).

Design proposals and research studies on the smart home applications justified the great benefits that the human-centered ecosystem can bring to the occupants, including the benefits related to healthcare, environmental protection, cost reduction, and psychological wellbeing (Alaa et al., 2017; Marikyan et al., 2019). In terms of healthcare, the strengths of the smart home ecosystem are maximized when it is utilized to support the people in need, including the vulnerable group like the elderly and the disabled (Das et al., 2015; Hussein et al., 2014). Elderly people and people with diseases need long-term support services in case of health inconsistency (Czaja, 2016). The smart home ecosystem can provide sufficient support to the people in need with sensor-based health monitoring systems (Finch et al., 2008) and smart devices that can enhance their connection to the home appliances (Das et al., 2015). For the general public, smart homes can improve the occupant's comfort through the automation of daily routines and remote home control (Marikyan et al., 2019). The benefits of environmental protection and energy efficiency are brought by

human-centered energy management in smart homes. The detection and monitor of home occupancy can help reduce energy consumption (Nag and Mukhopadhyay, 2015; Zimmermann et al., 2017). The consultancy from smart homes like eco-feedback or adaptive behavior suggestions can also guide occupants to use their energy efficiently (Zhou et al., 2016). The cost reduction or the financial benefit is usually closely related to the environmental benefits, since from the long-term perspective smart homes can bring sustainability and energy saving in the whole life cycle of the building (Marikyan et al., 2019). In the short run, transparency of the energy consumption in smart homes contribute to a higher occupant's awareness of their energy-related behaviors and thus lead to the reduction of energy expenses (Balta-Ozkan et al., 2013). For the psychological wellbeing, smart home ecosystem can help users overcome isolation feeling with services related to support and assistance (Chan et al., 2008). The smart home assistants can act as a companion of the occupants to ease their social isolation burden.

2.3.2 Tailored Eco-feedback

Apart from the advanced technologies implemented in the smart home ecosystem, the building energy efficiency also heavily relies on the occupant's behaviors. Occupant's habitual behaviors have a considerable impact on energy consumption. Eco-feedback was therefore introduced as a way to provide energy consumption related information to occupants and hence guide the occupants to save energy (Ma et al., 2017). Conventional eco-feedback studies cover a wide range of feedback forms including the paper-based approaches, computer-based and smartphone-based feedback, in-home smart devices like smart displays or smart speakers feedback (Bartram, 2015; Khosrowpour et al., 2016). Various content to motivate occupant's energy-saving behaviors have also been broadly investigated, including historical consumption data, social norms (e.g., peer comparison), goal settings, and many other methods (Khosrowpour et al., 2016). The efficacy of these methods on energy conservation has also been evaluated in previous studies. Some of the traditional eco-feedback methods lack active response from the feedback system users because the occupants are treated uniformly and get non-differentiated eco-feedback. Occupants with different characteristics and habits have different levels of susceptibility to the eco-

feedback messages (Petkov et al., 2012). As such, tailored or targeted eco-feedback was further explored to optimize the motivation of feedback messages on occupant's energy-saving behaviors (Gamberini et al., 2012; Khosrowpour et al., 2016; Petkov et al., 2012). The variability of occupant's characteristics (e.g., demographic, social and economic background) was incorporated in the eco-feedback design and then generated personalized feedback information with different psychological motivators (Khosrowpour et al., 2016). For example, Petkov et al. (2012) found different occupant's environmental concerns and values (egoistic, altruistic, and bio spheric) can determine the efficiency of different information in promoting energy-saving behavior. A tailored eco-feedback platform named EnergyLife was developed in another study (Gamberini et al., 2012) to provide customized advice to households based on their historical energy consumption behavior. Bartram (2015) also justified that personalized visualization of energy consumption in eco-feedback design is the key to residential energy use improvement.

Despite the broad separate investigation in the fields of tailored eco-feedback and the human-centric smart home ecosystem, scarce studies have implemented the tailored eco-feedback concept into the smart home ecosystem. The advancement of AI technologies enables occupants to interact with smart homes through digital virtual assistants, and based on the communication with the occupants, smart home assistants can learn the occupant's characteristics, building occupant's profiles to provide personalized eco-feedback. As such, we hypothesized that based on occupant's characteristics (demographic background, thermal preferences, experience with smart home products, values and beliefs), models can be developed to predict occupant's intention in taking energy-saving behavior suggestions provided by the smart home assistants. A further goal in this study is to identify the important characteristic features in the model that have a significant impact on the occupant's decision-making process. To achieve these goals, online surveys were distributed to collect data and information about participant's characteristics and their feedback to the energy-saving suggestions. The survey design and model development will be discussed in the following sections.

2.4 Methodology

2.4.1 Survey Design and Data Collection

In order to investigate the abovementioned hypothesis, we conducted a data collection campaign with online surveys that covers numerous variables with the potential in affecting occupant's behavior. Twenty-one potential influential variables lie in four major categories: demographic background, thermal comfort perceptions, smart home device experience, values and beliefs (Table 2.1).

In the survey, we collected participant's demographic background information including seven related variables: gender, age, cultural background, education level, employment status, residence type, and residence occupancy type. Occupant's social-demographic characteristics have been justified to have considerable impact on the differences of the individual's energy-saving behaviors in previous studies (Yang et al., 2016; Yue et al., 2013). For example, many previous studies investigating the effect of gender on environmental behaviors identified that female usually shows a higher intention in taking energy-saving behaviors compared with male (Shrestha et al., 2020; Wang et al., 2019; Yang et al., 2016). A cross-culture assessment study found that people from different countries show different responses to the eco-feedback and proposed that eco-feedback systems need to adopt to the local cultural context for their effectiveness in energy conservation (Ma et al., 2017). For residence occupancy type, it was identified that households with children under 12 years old or the old over 60 years old conduct more direct and indirect energy-saving behaviors compared with people who don't live with other family members (Yang et al., 2016). Other influencing demographic factors like age, education level, employment status, income have also been broadly investigated and proved to have effect on occupant's environmental behaviors (Ding et al., 2017; Hori et al., 2013; Yang et al., 2016; Zhang et al., 2018).

The questions about participant's thermal comfort perceptions would collect two major components: comfort range and sensitivity. In the survey, participants need to report their preferred thermostat setpoints and acceptable upper and lower limits in a typical summer day. Based on that, we can infer their thermal sensitivities through the comparison between the upper range and the lower range (Jung

and Jazizadeh, 2019). A larger upper range means that the participant is warm-tolerable and less sensitive to increasing the indoor temperature and vice versa, a larger lower range means that the participant is warm-sensitive and tend to feel discomfort for increase of temperature. Previous studies found that occupant's thermal sensations, thermal perceptions, and opinions to the trade-off between thermal comfort and energy saving can all affect their decisions on energy-saving behaviors (Hwang et al., 2009; Jazizadeh et al., 2014; Ming et al., 2020).

Although no study has justified the influence of occupant's smart home device experience on the effectiveness of smart home assistants yet, previous studies did justify that occupant's previous lifetime experiences can contribute to their pro-environmental behaviors (Amador et al., 2013; Forstmann and Sagioglou, 2017). We assumed that occupant's previous experience and familiarization with smart home devices can affect their acceptance level to the energy-saving suggestions from smart home assistants. As such, we collected participant's smart home device experience related information, including the number of smart home devices that they have used, holding period of the smart home devices, the frequency of user giving commands and control appliances, the number of common command types and the number of appliances that have been connected to the participant's smart home devices.

According to the Value-Belief-Norm theory proposed by Stren (2000), people's personal values guide their general beliefs about the human-environment relationship, and thus generate their personal norms (sense of obligation) to reduce the potential threats through behaviors. Occupant's environmental attitudes are closely related to their energy-saving behaviors (Gadenne et al., 2011). Also, environmental concerns and beliefs have been justified to have significant interaction effect on energy-saving attitudes, intentions and behaviors (Aguilar-Luzón et al., 2014). In the survey we collected participant's values about environmental protection (specifically: unity with nature, respecting the earth, protecting the environment, preventing pollution) and their beliefs about environmental protection, energy expenses, personal comfort, interest in taking actions.

Table 2.1. Potential Influencing Variables of Participant's Characteristics

| Categories and Variables | | Variable Types |
|------------------------------|---|----------------|
| Demographic Background | 1. Gender | Categorical |
| | 2. Age | Numerical |
| | 3. Cultural Background | Categorical |
| | 4. Education Level | Ordinal |
| | 5. Employment Status | Categorical |
| | 6. Residence Type | Categorical |
| | 7. Residence Occupancy Type | Categorical |
| Thermal Comfort Perceptions | 8. Preferred Temperature Setpoint | Numerical |
| | 9. Thermal Comfort Range | Numerical |
| | 10. Thermal Sensitivity | Categorical |
| Smart Home Device Experience | 11. Number of Used SH Devices | Numerical |
| | 12. SH Device Holding Period | Categorical |
| | 13. Command Frequency | Ordinal |
| | 14. Number of Common Command Types | Numerical |
| | 15. Control Appliances Frequency | Ordinal |
| | 16. Number of Connected Devices/Systems | Numerical |
| Value and Beliefs | 17. Value (Environmental Protection) | Ordinal |
| | 18. Belief (Environmental Protection) | Ordinal |
| | 19. Belief (Energy Expenses) | Ordinal |
| | 20. Belief (Personal Comfort) | Ordinal |
| | 21. Belief (Interest in Taking Actions) | Ordinal |

Apart from the potential influencing variables from participant's characteristics, in the survey we also collected participant's feedback to designed energy-saving suggestions provided by the smart home assistant "Alexa" from Amazon Echo. We describe a scenario to the participants that they are in a fully connected smart home with smart home assistant "Alexa" having the full control of all the home appliances, and it will give suggestions to participants to guide them save energy. After that, participants would watch a video in which "Alexa" ask them if they allow the smart home assistant to adjust the thermostat temperature setpoint for energy saving (Figure 2.1). Then participants need to provide their intention of accepting the suggestion on a Likert scale from "Definitely No" to "Definitely Yes". The feedback will

show participant’s attitude (positive, neutral and negative) towards the energy-saving suggestions from smart home assistant.



Figure 2.1. Energy-saving Suggestion from Alexa and Participants’ Likert Scale Feedback

The data collection was conducted through the Qualtrics platform, where we distributed the survey and collected responses from the general public in U.S. We specifically pre-set the quota of the survey distribution in terms of gender, age, and education level, so that the sample size of the respondents can be uniformly distributed and be representative to the actual population distribution. After excluding the unfinished responses and cleaning off the feedback that did not pass the verification, we collected 307 valid responses in total. Based on the information and data from these 307 participants, we ran basic statistical analysis and developed machine learning models to investigate the impact of personal characteristics on occupant’s intention in taking energy-saving suggestions from smart home assistants.

2.4.2 Data Pre-Processing and Model Development

As shown in Table 2.1 the data collected from the surveys have three different variable types: numerical, categorical and ordinal. The nominal nature of the categorical variables makes it necessary to pre-process the data before fitting them into the machine learning models (Cerda et al., 2018). For example, the residence type variable includes four different labels (Apartment, Single-Family Home, Townhouse, and Studio) and cannot be encoded by values like Likert scale responses (e.g., value and beliefs). Also, it is improper to standardize some ordinal variables like education levels as the intervals are different inside

the variables (e.g., the interval between “less than high school” and “high school graduate” is different from the interval between “some college” and “bachelor’s degree”) (Cerda et al., 2018). As such, we utilized One-hot encoding, the most widely used encoding method, to pre-process some categorical and ordinal variables. One-hot encoding turn the single variable with x distinct values into x binary variables (Potdar et al., 2017). As shown in Figure 2.2 example, the categorical variable with 4 different categories can be encoded respectively into four feature vectors: [1, 0, 0, 0], [0, 1, 0, 0], [0, 0, 1, 0], [0, 0, 0, 1]. After data pre-processing, seven categorical and ordinal variables (gender, culture background, education level, employment status, residence type, residence occupancy type, thermal sensitivity) were encoded into dichotomous binary variables with only presence (1) or absence (0) values. 21 variables were then turned into 46 variables after transformation.


| Random ID | Residence Type | | Random ID | Residence Type_ Apartment | Residence Type_ Single-Family Home | Residence Type_ Townhouse | Residence Type_ Studio |
|-----------|--------------------|---|-----------|---------------------------|------------------------------------|---------------------------|------------------------|
| 88347 | Apartment | One-Hot Encoding  | 88347 | 1 | 0 | 0 | 0 |
| 90141 | Single-Family Home | | 90141 | 0 | 1 | 0 | 0 |
| 54721 | Townhouse | | 54721 | 0 | 0 | 1 | 0 |
| 13172 | Studio | | 13172 | 0 | 0 | 0 | 1 |

Figure 2.2. Example (Residence Type) of One-Hot Encoding Data Pre-Processing

Participant’s responses to the energy-saving suggestion from smart home assistant in Likert scale were encoded with values from 1 (“Definitely No”) to 5 (“Definitely Yes”). These are the participant’s original intention in taking the energy-saving adaptive behaviors. Taking these original intentions as input, we transformed the original values to Boolean values, which are 0 - neutral & negative attitude (Likert scale 1-3) and 1 - positive attitude (Likert scale 4-5).

The pre-processed data was then analyzed with correlation heatmap and Spearman’s correlation, a nonparametric correlation measure computed from the rank of the observations (Croux and Dehon, 2010). The correlation results helped identified the potential multicollinearity issue of the variables and provided

reference for the variable selection in the later section. Then the data was fed into three machine learning classifier models and their respective accuracy, F-measure, precision and recall was computed. The three models include the linear Support Vector Machine (SVM), Random Forest, and Logistic Regression. We tested the models by Repeated K Fold cross validation with 5 folds repeated 10 times. For the optimization of the machine learning models, we conducted feature selection based on the top variables in Spearman's correlation, Chi² statistical test, Recursive Feature Elimination (RFE) results, and feature importance scores in three models. Two sets of features with 15 and 9 variables were extracted and tested separately and we got fine-tuned models. The variable importance was then investigated in detail. All the above-mentioned data pre-processing and machine learning model developments were conducted through python.

2.5 Results and Findings

2.5.1 Sample Characteristics

307 valid responses were collected after the online survey collection and data validation. Table 2.2 shows the demographic distribution of the collected data. Before data collection, we have set quotas for sampling in terms of gender, age, and education level. As such, these three variables are uniformly distributed. The number of Male and Female participants are basically equal. Since the survey was distributed online, we got more younger generation (34%) and middle-aged generation (50%) participants compared with the elderly (16%), which is different from the general population distribution. As for the educational level, one-third of the participants have a relatively lower educational background and two-third of the participants reported having a bachelor's degree or more. In terms of employment status, half of the participants are full-time employee, and the other half includes student (7%), half-time employee (13%), self-employed (4%), retired (12%), and unemployed (13%) participants. Most of the participants live in the single-family home (60%) or apartment (32%), and the remaining ones (8%) live in townhouses or studios. When it comes to residence occupancy type, 55% of participants live with family including parents or children, others live by themselves (16%) or live with roommates (29%).

Table 2.2. Demographic Distribution of Collected Data

| Sample Demographic Background | | Number | Percentage |
|-------------------------------|--|--------|------------|
| Gender | Female | 144 | 47% |
| | Male | 161 | 52% |
| | Non-Binary | 2 | 1% |
| Age | 18-29 | 103 | 34% |
| | 30-39 | 102 | 33% |
| | 40-49 | 52 | 17% |
| | 50 + | 50 | 16% |
| Culture Background | Asian | 21 | 7% |
| | African American | 25 | 8% |
| | Caucasian | 235 | 77% |
| | Hispanic/Latino | 18 | 6% |
| | Pacific Islander | 2 | 1% |
| | Native American | 2 | 1% |
| | Would like not to specify | 4 | 1% |
| Education level | Less than high school | 16 | 5% |
| | High school graduate | 72 | 23% |
| | Some college | 31 | 10% |
| | Bachelor's degree | 121 | 39% |
| | Master's degree | 48 | 16% |
| | Other advanced degree beyond a master's degree | 6 | 2% |
| | Doctorate Degree | 13 | 4% |
| Employment Status | Student | 22 | 7% |
| | Part-time employee | 39 | 13% |
| | Full-time employee | 157 | 51% |
| | Self-employed | 13 | 4% |
| | Unemployed | 39 | 13% |
| | Retired | 37 | 12% |
| Residence Type | Single-Family Home | 184 | 60% |
| | Apartment | 98 | 32% |
| | Townhouse | 21 | 7% |
| | Studio | 4 | 1% |
| Residence Occupancy Type | Live by oneself | 50 | 16% |
| | Live with roommate/friends | 89 | 29% |
| | Live with family including children/parents | 168 | 55% |

2.5.2 Variable Intercorrelations

The variable intercorrelations are shown in the correlation heatmap (Figure 2.3). Most of the independent variables are not highly correlated with each other. However, variables in the smart home device experience section (SH device holding period, command frequency, number of command types, control appliances frequency, number of connected devices/systems) are significantly correlated with each other with high correlation coefficients. It is reasonable to get high correlations between variables in this section. For example, if a participant is an experienced smart home device user, then he would have a long holding period, a high frequency of giving commands, and a high number of command types, vice versa. However, this might lead to potential multicollinearity issue in the machine learning model fitting. Multicollinearity means that two or more explanatory variables in a regression model are highly linearly related, which would cause wrong signs of the regression coefficients (Alin, 2010). As such, the number of smart home device experience related variables should be considered to be reduced in the later feature selection section.

Apart from the correlation between explanatory variables, we also computed the correlation between explanatory variables and target variable – participant’s intention in taking the energy-saving suggestions (Likert scale 1-5). 28 of the 46 variables have a statistically significant correlation with the intention. 18 of them are positively correlated with intention and 10 of them are negatively correlated with intention (Table 2.3). Value and beliefs related variables as well as the smart home device experience related variables have a strong positive correlation with participant’s intention, which aligns with findings in previous studies that people’s environmental beliefs have a considerable impact on their behaviors. On the other hand, some of the demographic variables are negatively correlated with the participant’s intentions. For example, the education-related variables indicate that people with lower educational backgrounds show lower intentions in taking energy-saving behaviors. In addition, people who are unemployed and people who live by him/herself both don’t have high intention of taking the energy-saving suggestions.

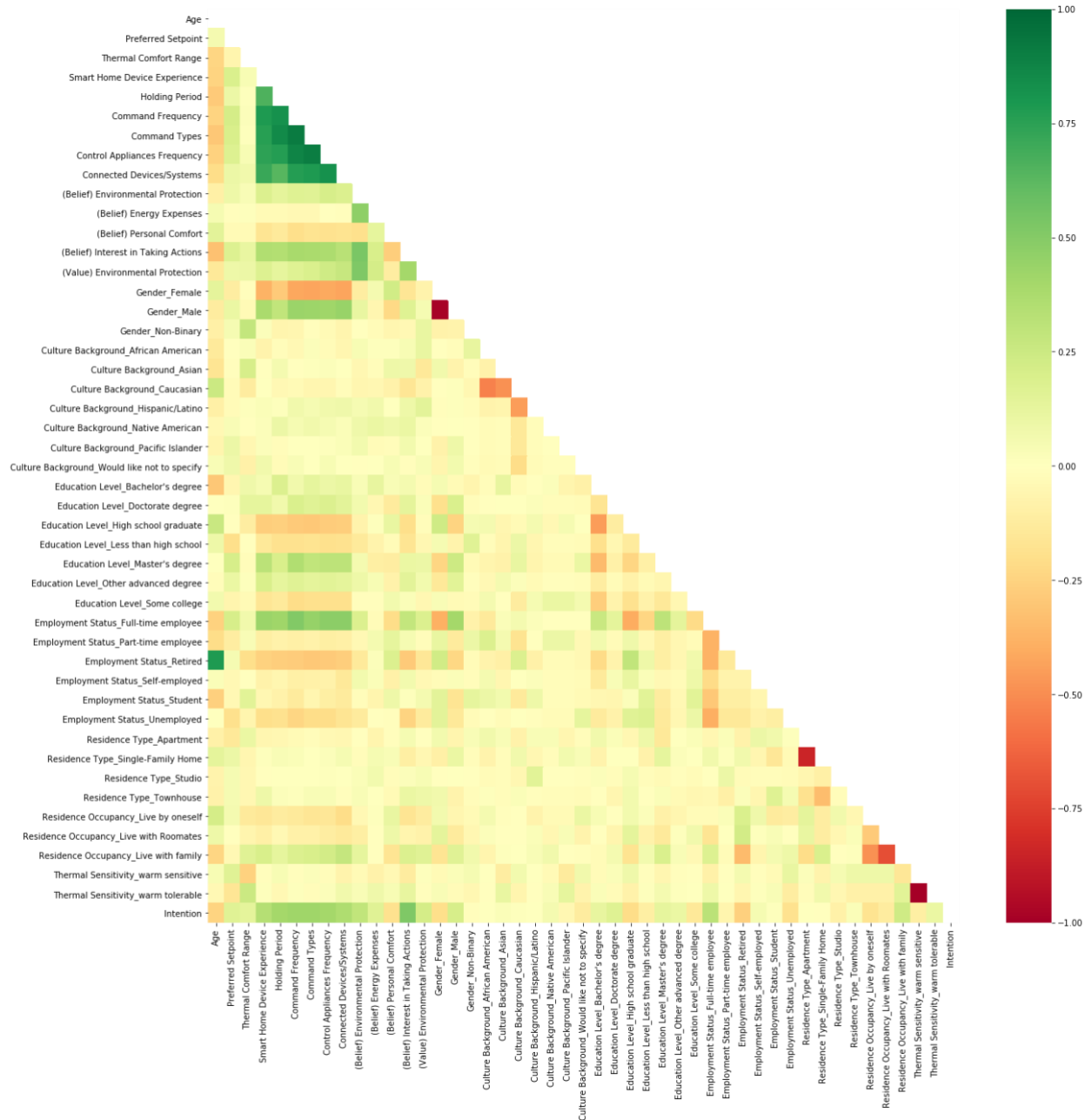


Figure 2.3. Correlation Heatmap Between Study Variables

Table 2.3. Variables that have Statistically Significant Correlation with Participant’s Intention in Taking Energy-Saving Suggestion

| Positively Correlated Variables | Correlation Coefficient | Negatively Correlated Variables | Correlation Coefficient |
|---------------------------------------|-------------------------|--|-------------------------|
| Belief (Interest in Taking Actions) | 0.51** | Employment Status-Retired | -0.27** |
| Command Frequency | 0.42** | Gender-Female | -0.23** |
| Control Appliances Frequency | 0.42** | Belief (Personal Comfort) | -0.23** |
| Command Types | 0.42** | Education Level-Highschool graduate | -0.22** |
| Number of Used SH Devices | 0.41** | Residence Occupancy-Live by oneself | -0.20** |
| Number of Connected Devices/Systems | 0.40** | Employment Status-Unemployed | -0.16** |
| SH Device Holding Period | 0.37** | Culture Background-Would like not to specify | -0.14* |
| Employment Status-Full time employee | 0.33** | Education Level-Some college | -0.12* |
| Belief (Environmental Protection) | 0.33** | Age | -0.12* |
| Value (Environmental Protection) | 0.25** | Education Level-Less than Highschool | -0.11* |
| Residence Occupancy-Live with family | 0.24** | | |
| Gender-Male | 0.24** | | |
| Education Level-Doctorate degree | 0.19** | | |
| Belief (Energy Expenses) | 0.17** | | |
| Education Level-Master’s degree | 0.14* | | |
| Thermal Comfort Range | 0.13* | | |
| Preferred Setpoint | 0.12* | | |
| Education Level-Other advanced degree | 0.12* | | |

* Correlation is significant at the 0.05 level

** Correlation is significant at the 0.01 level

2.5.3 Machine Learning Models

2.5.3.1 Models with All Variables Included

In this study, we would like to predict occupant’s attitude and intention in taking energy-saving suggestions from smart home assistants based on their personal characteristics. We first fitted data with all 46 variables in three machine learning methods and got the models’ performance (Table 2.4). The models that predict the participant’s general attitude with characteristic features performs better than the models that predict participant’s more detailed intentions in taking energy-saving behaviors. In terms of intention

prediction, the Random Forest model outperforms the other two models with an accuracy of 0.527. For attitude prediction, the Logistic Regression model performs the best with an accuracy of 0.772 and an F-measure of 0.844. All models show both high recalls and high precisions, while the recalls are comparatively larger, indicating that the models generate more false-negative predictions than false-positive predictions. It means that when it comes to false predictions, the models with all variables have a relative higher intention to predict people with a positive attitude towards energy-saving suggestions as people with neutral & negative attitude.

Table 2.4. Performance of Models with All Variables Included

| Model Performance | | SVM | Random Forest | Logistic Regression |
|--|-----------|-------|---------------|---------------------|
| Intention (Likert scale 1-5) | Accuracy | 0.521 | 0.527 | 0.492 |
| | Accuracy | 0.765 | 0.750 | 0.772 |
| Attitude (Positive, Neutral & Negative) | F Measure | 0.837 | 0.837 | 0.844 |
| | Precision | 0.821 | 0.806 | 0.817 |
| | Recall | 0.859 | 0.886 | 0.876 |

2.5.3.2 Variable Importance and Selection

After One-hot encoding, the number of explanatory variables in the model reaches 46, which may lead to a feature redundancy problem. As such, we would like to select the important features, simplifying and optimizing the machine learning models. During feature selection, we referred to six sets of observations. Spearman's correlation results show the variables with the highest positive correlation coefficients. Chi² statistical test is a traditional feature selection method and we utilized it to help identify the ten most important variables. Recursive Feature Elimination (RFE) identified the important features by recursively removing variables and building models on those variables that remain. The feature importance scores from three different machine learning models were also computed for important feature selection.

As shown in Table 2.5, some variables are frequently identified as important ones across various methods. Participant's belief about interest in taking actions is the most frequently identified one. If the

occupant shows a high interest in taking actions, then he/she is very likely to show positive attitude towards the energy-saving suggestions from smart home assistants. Two smart home device experience related features number of command types and control appliances frequency are also important in prediction. Other identified important features are age, thermal comfort range, smart home device holding period, command frequency, belief in energy expenses, and environmental protection related values. Based on the variable importance results, we extracted four sets of variables with 15, 9, 5, and 3 variables separately for model optimization (Table 2.5).

Table 2.5. Important Variables Identified by Different Methods (All Variables included in model development)

| Feature | Spearman's Correlation | Chi ² statistical test | RFE | SVM | Random Forest | Logistic Regression | Count |
|--|------------------------|-----------------------------------|-----|-----|---------------|---------------------|-------|
| Age ^{1,2} | | √ | √ | | √ | | 3 |
| Preferred Setpoint ¹ | | | √ | | √ | | 2 |
| Thermal Comfort Range ^{1,2,3} | | √ | √ | | √ | | 3 |
| Number of Used SH Devices | √ | √ | | | | | 2 |
| SH Device Holding Period ^{1,2} | √ | √ | | | √ | | 3 |
| Command Frequency ^{1,2} | √ | √ | | | √ | | 3 |
| Number of Command Types ^{1,2} | √ | √ | √ | | √ | | 4 |
| Control Appliances Frequency ^{1,2,3,4} | √ | √ | | √ | | √ | 4 |
| Number of Connected Devices/Systems | √ | √ | | | | | 2 |
| (Belief) Environmental Protection | √ | | | | √ | | 2 |
| (Belief) Energy Expenses ^{1,2,3} | | | √ | | √ | √ | 3 |
| (Belief) Personal Comfort | | | √ | | | | 1 |
| (Belief) Interest in Taking Actions ^{1,2,3,4} | √ | √ | √ | √ | √ | √ | 6 |
| (Value) Environmental Protection ^{1,2} | √ | | √ | | √ | | 3 |
| Culture Background-Asian | | | | √ | | √ | 2 |
| Culture Background-Caucasian ¹ | | | | √ | | √ | 2 |
| Education Level-Bachelor's degree ¹ | | | | | | √ | 1 |
| Education Level-Doctorate degree | | | | √ | | √ | 2 |
| Employment Status-Full-time employee ¹ | √ | | √ | | | | 2 |
| Employment Status-Retired | | √ | | | | | 1 |
| Employment Status-Self-employed | | | | √ | | √ | 2 |
| Employment Status-Student | | | | √ | | | 1 |
| Residence Type-Apartment ¹ | | | | √ | | √ | 2 |
| Residence Type-Single-Family Home | | | | √ | | | 1 |
| Residence Occupancy-Live by oneself | | | √ | | | | 1 |
| Residence Occupancy-Live with family including children/parents ^{1,3,4} | | | | √ | | √ | 2 |

¹ included in the 15 variables set.

² included in the 9 variables set.

³ included in the 5 variables set.

⁴ included in the 3 variables set.

2.5.3.3 Optimized Models

After testing two sets of selected variables in machine learning models in the prediction of participant’s attitudes towards energy-saving suggestions, we got the results presented in Table 2.6. Both two sets of variables improve the model performance compared with the models that included all variables. Models with 15 variables perform slightly better than models with 9 variables in both accuracy and F-measure, proving that demographic background information can make a difference in predicting occupant’s attitude towards energy-saving suggestions from smart home assistants. Among all optimized models, the Logistic Regression model with 3 variables included performs the best with an accuracy of 0.803 and an F-measure of 0.867.

Table 2.6. Optimized Models' Performance

| Model Performance | | SVM | Random Forest | Logistic Regression |
|-------------------|-----------|-------|---------------|---------------------|
| 15 Variables | Accuracy | 0.788 | 0.778 | 0.785 |
| | F Measure | 0.855 | 0.848 | 0.855 |
| 9 Variables | Accuracy | 0.787 | 0.772 | 0.791 |
| | F Measure | 0.854 | 0.840 | 0.857 |
| 5 Variables | Accuracy | 0.787 | 0.760 | 0.784 |
| | F Measure | 0.856 | 0.833 | 0.853 |
| 3 Variables | Accuracy | 0.796 | 0.754 | 0.803 |
| | F Measure | 0.862 | 0.832 | 0.867 |

We further computed the importance scores of the variables in the machine learning models and ranked the top ten important variables in each model accordingly (Figure 2.4). It can be seen that all three models rank Belief (Interest in taking actions) and Belief (Energy expenses) high with importance scores. Both Support Vector Machine and Logistic Regression attach great importance to demographic background like culture background, education level, and residence occupancy types. Specifically, people with Caucasian culture background, people with bachelor’s degree or higher degrees and people who live with their family including children or parents would tend to show a positive attitude towards energy-saving suggestions. In Random Forest model, thermal comfort perception including thermal comfort range and preferred temperature setpoint are identified as important features in prediction.

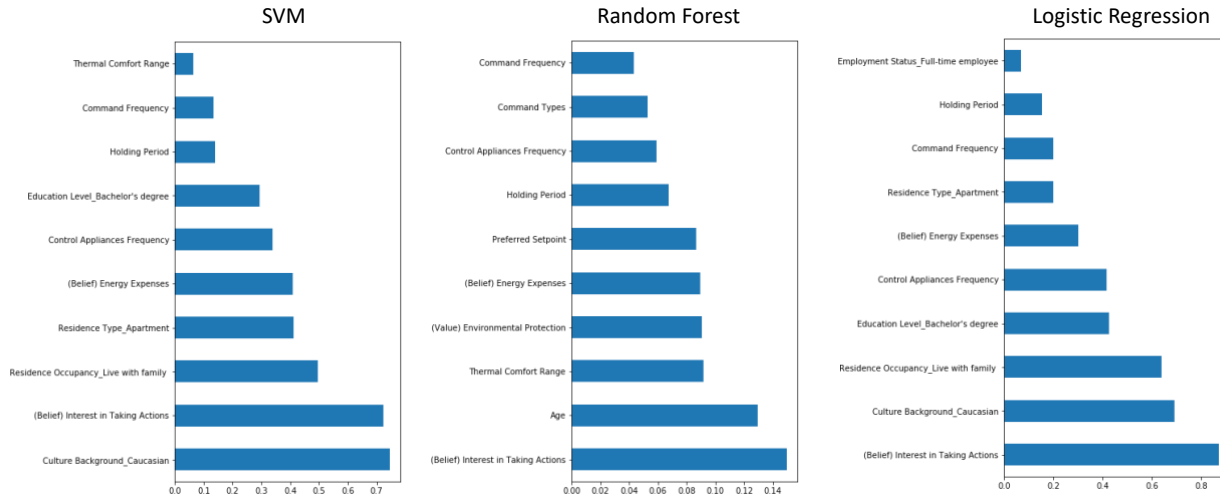


Figure 2.4. Top 10 Important Variables in Three Models (15 variables included in model development)

2.6 Discussion and Conclusion

In this study, we investigated the impact of occupant's personal characteristics on their intentions and attitudes to energy-saving suggestions raised by the smart home assistant. Through online surveys we collected 307 participant's information and feedback to our designed messages. By fitting the data in three different machine learning models (Support Vector Machine, Random Forest, Logistic Regression), we identified the important influencing features in predicting occupant's attitude to energy-saving suggestions. Logistic Regression model with 3 variables (Belief-Interest in Taking Actions, Residence Occupancy, Control Appliances Frequency) as input was proved to have the best performance with an accuracy of 0.803 and an F-measure of 0.867.

Based on the importance scores of variables in the models, values and beliefs show high importance in occupant attitude prediction, especially beliefs of occupant's interest in taking actions and beliefs about energy expenses (Figure 2.5). Occupant's demographic background also plays a critical role in the models. Specifically, cultural background, education level, and residence occupancy type are of vital importance. If the people have bachelor's or higher degree or live with family including children and parents, then he/she would have a high intention in taking the energy-saving suggestions and conduct adaptive behaviors to save energy. Smart home device experiences are also closely correlated with user's attitudes to smart home assistants. An experienced smart home device user is more acceptable to the smart home assistants

proactively raising energy-saving suggestions. In terms of occupant’s thermal comfort perceptions, preferred setpoint and thermal comfort range are proved to be important features in attitude predictions.

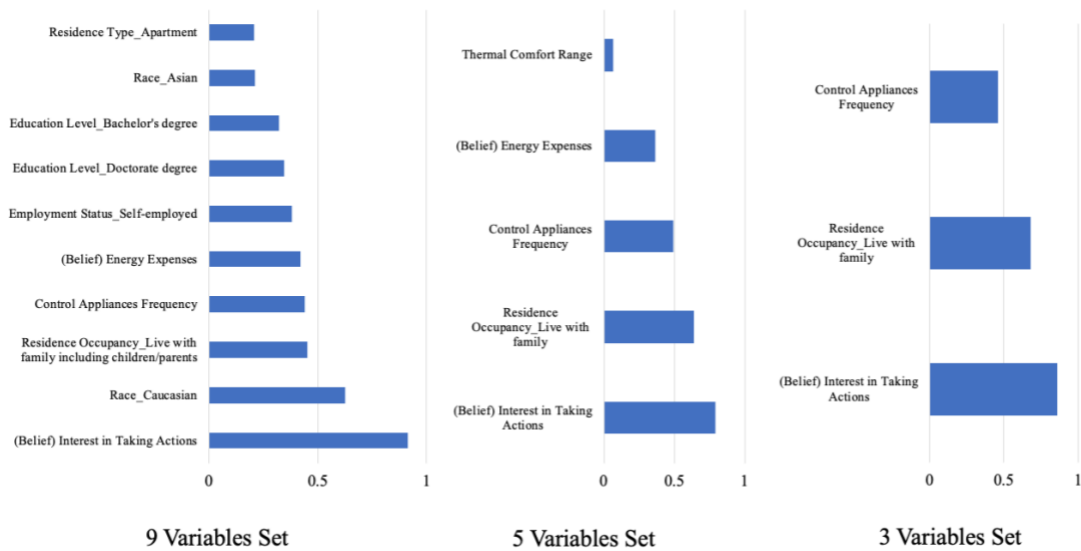


Figure 2.5. Feature Importance Scores in Logistic Regression Models

Findings in this study fill the gap of limited previous studies about the impact of people’s personal characteristics on their energy-saving behavior intentions in smart home scenarios. With the advancement of IoT technologies and the smart home ecosystems, in the future, there will be more interactions between the occupants and the smart home assistants. Further exploration is needed in this field so that the smart home assistants can not only predict occupant’s attitude to taking energy-saving suggestions but also tailored the suggestions according to occupant’s characteristics, efficiently nudging occupants to take energy-saving behaviors.

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CONCLUSION

This research proposes the concept of proactive voice-based smart home assistants with the aim of promoting the bi-directional human-building interaction. In the IoT-embedded smart home ecosystem, the intelligent virtual assistants could proactively raise suggestions to occupants and nudge them to adopt energy-saving behaviors. We hypothesized that through nudging, the smart home assistants can improve occupants' intention in taking energy-saving adaptive behaviors. 307 valid responses with participants' characteristics profiles and feedback to designed messages were collected through online surveys to evaluate the hypotheses and investigate the research questions.

In the first study, comparison between the control group (plain text suggestions) and the study group (suggestions from virtual assistant Alexa) proved that the smart home assistant can nudge the people who originally hold a neutral attitude into a positive attitude towards energy-saving behavior. The influence of occupant's personal features on their acceptance level to the suggestions raised by the smart home assistants was also investigated. We justified that people with a larger thermal comfort range would be more acceptable to the suggestions of raising the temperature setpoint for energy-saving and agree to raise the setpoint higher, compared with the people with a smaller comfort range. Compared with people with no or limited experience with smart home devices, people who have some or rich experience show considerable higher acceptability to the proactive smart home assistants and the suggestions that the assistant proposes. In terms of values and beliefs, we clustered the participants into two different groups: Positive group and the Negative group. The Positive group occupants hold a positive attitude to environmental protection and energy saving, and thus show a high intention to accept the adaptive behavior suggestions from smart home assistants, even if they need to sacrifice their personal comfort. Comparatively, the Negative group occupants show no interest towards sustainability from their values and beliefs, and thus show much lower acceptability to the energy-saving suggestions and attach great importance to their personal comfort.

In the second study, by fitting the 21 personal characteristic features in three different machine

learning models (Support Vector Machine, Random Forest, Logistic Regression), we identified the important influencing features in predicting occupant's attitude toward energy-saving suggestions. The Logistic Regression model with 3 variables (Belief-Interest in Taking Actions, Residence Occupancy, Control Appliances Frequency) as input was proved to have the best performance with an accuracy of 0.803 and an F-measure of 0.867. Beliefs have the highest importance in occupant attitude prediction, especially beliefs of occupant's interest in taking actions and beliefs about energy expenses. Occupant's demographic background also plays a critical role in affecting model performance. Specifically, cultural background, education level, and residence occupancy type are of vital importance. Smart home device experiences are closely correlated with user's attitudes to smart home assistants. In terms of occupant's thermal comfort perceptions, preferred setpoint and thermal comfort ranges are proved to be important features in attitude predictions.

This research justifies the nudging effect of smart home assistants on occupant's energy-saving behaviors and provides a better understanding of the interaction between the occupants and the smart home assistants. The online survey in this study is collecting the participants' subjective perceptions and views towards the concept of smart home assistants, which may not be their final actions or behavior in the real-world scenarios. As such, an in-person user study may be conducted in the future to observe the interactions between the proactive smart home assistants and the occupants with actual thermal conditions in the real-world scenarios.