

Voice-based Proactive Smart Home Assistants Nudging Occupants for HVAC Energy-Saving Behaviors: A Smart Speaker Case

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Abstract

AI-based virtual assistants integrated into the smart home ecosystems facilitate human-building interactions. We have envisioned that proactive virtual assistant capabilities could be designed to encourage energy conservation behaviors by relying on their nudging effect through conversational interactions and autonomous actuation. To this end, we investigated how proactive virtual assistants, in a simulated smart home ecosystem, influence occupants to take energy-saving, adaptive actions for HVAC operations and how participants' personal characteristics affect their responses. Through an interactive online experiment, we collected data from 307 participants from diverse backgrounds across the United States. It was found that proactive communications with follow-up conversations can significantly increase the likelihood of accepting virtual assistance recommendations. This improvement was reflected in an increased number of participants (by 16%) who accepted energy-saving suggestions by comparing initial versus final responses during proactive conversations. Characterizing groups of participants based on their personal features and individual differences showed that user experience (with ~30% increase), pro-environmental values/beliefs (with ~24% to 35% increase), and forgiving thermal preferences (with ~12% increase) had a significant influence on participants' stated likelihood to accept virtual assistants' recommendations and their evaluation of the general concept of proactive communication from virtual assistants.

Keywords:

Smart Home; Virtual Assistant; Amazon Alexa; User Interface; Eco-feedback; Energy Saving, Conversational AI

Introduction

Buildings account for 28% of the total energy consumption in the United States (EIA, 2020). Studies have shown that building energy management using human-centered operations could result in considerable energy savings (Costa, Keane, Torrens, & Corry, 2013). With advances in the Internet of Things (IoT) technologies, smart homes provide the opportunity for occupants to conserve energy by accounting for their convenience and comfort (Alaa, Zaidan, Zaidan, Talal, & Kiah, 2017). Smart homes are IoT-enabled residences that link sensors, devices, appliances, and building systems (e.g., lighting and HVAC systems) to support occupants' needs (Balta-Ozkan, Davidson, Bicket, & Whitmarsh, 2013; Darby, 2018). Traditionally, occupants interact with smart homes through display-based user interfaces, such as smartphones and dashboards. However, in the past five years, the rise of voice-based virtual assistants, such as Amazon Alexa and Google Assistant have brought new potentials to provide occupants with a convenient and intuitive interface for interactions through conversations (Gnewuch, Morana, Heckmann, & Maedche, 2018). By leveraging IoT-enabled technologies, virtual assistants can control a broad range of connected

devices, such as thermostats, lighting systems, and security systems (Morris & Thompson, 2020). Through simple wake words (e.g., “Alexa” and “Hey Google”), occupants can easily control the home environment with voice commands. As carriers of voice-based virtual assistants, smart speakers play a significant role in smart home applications. 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 were daily active users (Bret & Ava, 2020). 24.5% of the smart speaker users utilize it to control smart home devices (Bret & Ava, 2020). The prevalence of the smart home ecosystems and their learning capabilities facilitate human-building cooperation with virtual assistants providing more personalized suggestions.

Despite this potential, it has been shown that users might not know about all the supported features when interacting with virtual assistants (Bentley et al., 2018; Luger & Sellen, 2016), and learning to use smart home devices can be a very time-consuming task with little support available (Hargreaves, Wilson, & Hauxwell-Baldwin, 2018). In this case, users might limit their usage to simple daily tasks. Moreover, one-way communication in the form of user commands for control of building systems might not result in an optimal outcome, for example, when it comes to energy management. Therefore, we have envisioned smart-home-integrated virtual assistants that act proactively as a bridge to facilitate users to achieve energy and sustainability goals. Interactions initiated proactively by virtual assistants have been found to be effective and evaluated positively by users in previous studies (Miksik et al., 2020). In this study, we investigated whether proactive communication from virtual assistants could be leveraged to affect occupants’ adaptive behaviors for energy saving in thermal conditioning, which accounts for almost half of the energy use in the residential sector (Meir, 2013). To this end, we have studied how the adaptation and flexibility in intelligent communication with users according to their characteristics and responses could result in improved adaptive behavior for energy saving. In other words, with prompts initiated by virtual assistants, occupants might be more willing to take adaptive behaviors to conserve energy due to the nudging effect from smart home intelligent conversations and automation ecosystems. While examining this objective, we have investigated how occupants’ experiences with smart home devices, pro-environmental values, beliefs about environmental and economic effects of energy saving, and thermal preference range affected the likelihood of accepting energy-saving suggestions from proactive smart home assistants. We conducted this study through an online experiment with members of the general public across the US as detailed in the following sections.

1. Background, Objectives, and Study Design

1.1. Smart Building/Home Ecosystem

Based on example smart home frameworks ((Guamán, Calvopiña, Orta, Tapia, & Yoo, 2018; Stojkoska & Trivodaliev, 2017)), we envisioned a smart home ecosystem framework that accounts for the role of virtual assistants as shown in Figure 1. A major direction of smart home research focuses on the design, architecture, and communication protocols of the IoT in ecosystems (Solaimani, Keijzer-Broers, & Bouwman, 2015). For example, local network communication technologies for third-party sensors and home appliances’ integration have been broadly explored (Almusaylim & Zaman, 2019). On the other hand, leveraging higher reliability and scalability of cloud computing, some studies investigated cloud services in smart home frameworks (Singh, Ra, Meng, Kaur, & Cho, 2019).

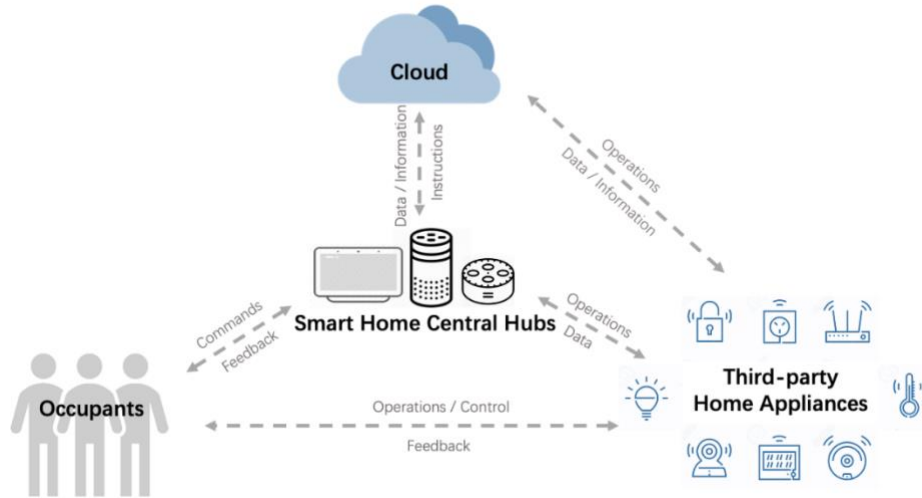


Figure 1. Smart home ecosystem centered around virtual assistants in smart home ecosystems (i.e., smart home assistants)

Smart home central hubs represented by virtual assistants on smart speakers are at the center of our envisioned ecosystem. We refer to them as *smart home assistants* (SHA) hereafter. SHAs could build bridges between occupants, cloud computing platforms, and third-party home appliances (Figure 1). Prior studies have designed various platforms to implement voice-activated central hubs in smart home scenarios, including the systems built with Alexa Voice Services, Alexa Skill Sets (C. Z. Yue & Ping, 2017), and Google Assistant (Isyanto, Arifin, & Suryanegara, 2020). As an important aspect, the interactions between occupants and SHAs have also been widely investigated. Studies have evaluated the interactions between users and virtual assistants and identified the common user commands (e.g., weather checking, media control, and device control (Lopatovska et al., 2019)). Comparisons among different virtual assistants (Amazon Alexa, Google Assistants, Apple Siri, Microsoft Cortana) have also been made to examine various interactions between users and virtual assistants (Berdasco, López, Diaz, Quesada, & Guerrero, 2019). However, there is a lack of research on human interactions with SHAs when it comes to smart home operations (Bylieva, Bekirogullari, Lobatyuk, & Anosova, 2020). Upon receiving the commands from occupants, SHAs can operate various connected appliances simultaneously, reducing occupants' effort to operate the devices separately (Jabbar et al., 2019). How the SHAs can interact with the occupants and help them make the best use of IoT-embedded smart homes needs to be further explored.

Human-Building Interaction

IoT technologies have improved sustainable performance in smart buildings. However, the optimization of mechanical systems cannot guarantee efficiency improvement. Occupants' preferences and habits also have a major impact on building operational strategies (Heydarian et al., 2020). Human-Building Interaction (HBI) has been introduced to build an adaptive building control system to account for the complexities of occupants' behavior and reduce the inefficiency of traditional conservative operations (Alavi et al., 2019). Compared to Human-Computer Interaction concepts, in which users interact with a machine through a circumscribed modality, HBI considers occupants to be completely immersed in an interactive environment and aware of the outcome of their behaviors and building operations (Alavi et al., 2019). Nevertheless, occupants generally lack an awareness of their energy consumption and the ability to optimize it, so there is a need for building systems to assist and provide personalized feedback for energy efficiency (Hsu et al., 2010).

Several studies have broadly investigated the efficacy of various content and forms of feedback and interventions to encourage energy-efficient behaviors. Some examples include historical comparison and incentives investigation (Jain, Taylor, & Peschiera, 2012), personalized eco-feedback (Fotopoulou et al., 2017; Inyim et al., 2018), and building information model-based energy visualizations (Francisco, Truong, Khosrowpour, Taylor, & Mohammadi, 2018). Specifically, some studies investigated methods of offering occupants personalized recommendations or awareness services for energy efficiency with the data collected from IoT in the smart buildings (Fotopoulou et al., 2017; Sardanios et al., 2021). However, these traditional forms of eco-feedback have been found to have scalability limitations. Moreover, they have mainly focused on one-way interactions, which prevents building systems from further learning from the occupants' responses to the feedback. The technological advances have paved the way for bi-directional communications, in which intelligent building agents (e.g., SHAs) and occupants can cooperate for a mutual adaptation to lead to overall better decisions. This new form of mutual interaction calls for the exploration of active forms of communication between SHAs and occupants.

Choice Architecture and Nudge Theory

In the context of two-way communication, choice architecture interventions could be a promising approach to encourage occupant's adaptation at the intersection of energy efficiency and comfort. The concept of choice architecture relies on designing choice situations that 'nudge' decision-makers toward more beneficial options (Szasz, Palinkas, Palfi, Szollosi, & Aczel, 2018). Nudge theory introduces generally inexpensive and less invasive solutions compared to traditional direct interventions (Thaler & Sunstein, 2009). Through nudging, the choice architects such as policy makers or industry practitioners can arrange decision-making contexts to influence people's daily choices and behaviors in a cheap and effective way (Hansen & Jespersen, 2013). Nudge theory has been applied in many domains (e.g., consumer choices, finance, health, and sustainability) in different intervention forms, such as changing choice defaults, providing reminders, and providing social reference points/social comparisons (Landais et al., 2020). In terms of energy efficiency applications, cost-effective nudges have been tested effective in voluntary energy efficiency adoption (Gillingham & Tsvetanov, 2018) and energy consumption reduction (Chang, Huh, & Lee, 2016). Four common nudge mechanisms used in interventions related to residential energy consumption include (Lehner, Mont, & Heiskanen, 2016): Simplification and framing of information (e.g., customized consumption feedback (Podgornik, Sucic, & Blazic, 2016), data visualization of energy consumption (Herrmann, Brumby, Oreszczyn, & Gilbert, 2018)); changes of the physical environment (e.g., design of home and appliances with intent (Bhamra, Lilley, & Tang, 2011)); changes to the default option (e.g., a required opt-out of green electricity offers (Ölander & Thøgersen, 2014)); and use of descriptive social norms (e.g., comparative energy feedback (Delmas, Fischlein, & Asensio, 2013)). SHAs have the potential to influence the choices occupants make. However, there is a lack of studies on nudging concerning the interaction between voice-based smart home assistants and residential occupants, so further exploration is called for.

Influence of Individual Differences on Decision-Making

Contemporary theories and models that predict environmental (and energy-related) behaviors suggest several influential, personal factors that could influence how people make decisions to energy-saving prompts. The value-belief-norm theory of environmentalism (Stern, Dietz, Abel, Guagnano, & Kalof, 1999) proposes that people's personal values predict their beliefs about environmental issues and these beliefs predict their actions related to the environment. A primary driver of such behaviors in this and related models is biospheric values, or the extent to which people consider environmental protection as a guiding principle in their lives and decisions. Previous studies have also found a consistent association between beliefs about the positive and/or negative consequences of pro-environmental or energy-related actions and

engagement in related behaviors (Oreg & Katz-Gerro, 2006). For example, individuals' awareness of/beliefs about environmental consequences of specific behaviors (e.g., a belief that the use of fossil fuels contributes to global warming; a belief that reducing energy use can help mitigate climate change) can be predicted by biospheric values and can, in turn, predict motivation to practice the given behaviors. The comprehensive action determination model (CADM) of ecological behavior also identified the impact of habitual influences on environmentally friendly behavior (Klöckner, 2013). Based on the model, prior actions or habits, such as previous heating or cooling behaviors, predict future actions along with one's sense of whether or not s/he has the ability to take action (perceived behavioral control (Klöckner, 2013)).

Another individual difference that has an important effect on the energy efficiency related decision-making is the use of adoption of new technology. When it comes to use or adoption of new technology, such as smart home technology, diffusion of innovation theory (Parthasarathy & Bhattacharjee, 1998) predicts that prior experience with the given technology tends to predict future and/or expanded use of the technology (Hou et al., 2020). For instance, previous research indicates that the command frequency in user interactions with smart home assistants was associated with the ownership period and the number of smart home devices a user has (Sciuto, Saini, Forlizzi, & Hong, 2018). Additionally, the expanded unified technology acceptance model (UTAUT2) also indicates that past use of a technology (habit) is one of the strongest predictors of motivation to use a technology in the future (Venkatesh, Thong, & Xu, 2012). Based on previous studies about the influence of individual differences on energy efficiency related decision-making process, various individual's characteristics can be investigated to explore the influence of these features on the interactive communications between proactive SHAs and the occupants.

On the basis of previous studies in smart home ecosystem, human-building interaction, choice architecture and nudge theory, and influence of individual differences on decision-making, we tried to explore how the adaptation and flexibility in proactive SHAs and their interactive communication with users could result in improved adaptive behavior for energy saving. Example scenarios of SHAs communicating with occupants for smart control are as follows. When an occupant wakes up in the morning with the SHA alarm, the agent would also give a suggestion according to occupants' comfort and energy-saving - "Good Morning, John! It's rather cool outside now, would you like me to adjust the thermostat and help you open the window to let some fresh air in"? Occupant(s) are at home, and the thermostat is on its default setpoint, the SHA tries to provide tips for adaptive behavior for the occupant(s): "Hey, Jessica, would you like me to set the thermostat setpoint higher? We will save on our energy expenses. Meanwhile, I can turn the fan on to help you stay cool". Considering similar scenarios and existing theories that explain energy-related behaviors, with the goal of moving toward proactive SHAs, we posed one research question and three hypotheses as described below.

Study Objectives and Design

Given the paucity of existing research on the influence of SHAs on residential occupants' energy use, we first posed and tested a research question to examine general, potential effects of nudging by proactive SHAs on participants' likelihood of accepting energy-saving suggestions from SHAs:

- **RQ1:** How does nudging via bi-directional communication from proactive SHAs affect participants' stated likelihood of responding positively to energy-saving suggestions?

Based on existing literature on technology use and personal characteristics of those who engage in pro-environmental behaviors and energy-saving, we proposed and tested the following hypotheses related to how personal characteristics of occupants/research participants would influence their responses to adaptive behavior suggestions from SHAs.

- **H1:** (Based on Diffusion of Innovation theory (Parthasarathy & Bhattacharjee, 1998) and the extended Unified Technology Acceptance Model (Venkatesh et al., 2012)) Occupants with more experience and familiarity using smart home ecosystems will be more receptive to SHA adaptation suggestions and have a more positive perception of proactive SHA modality.

- **H2:** (Based on Value-Belief-Norm theory (Oreg & Katz-Gerro, 2006) and the Comprehensive Action Determination Model (Klöckner, 2013) of pro-environmental behavior) Occupants' beliefs related to energy use, their pro-environmental values, and energy-related habits will be associated with their responses to SHA adaptation suggestions and their general perceptions of proactive SHA modality.

- **H3:** (Based on personal thermal comfort models (Jung & Jazizadeh, 2020)) Occupants' thermal preferences and sensitivities will be associated with their responses to SHA adaptation suggestions for energy-saving.

Methodology

To answer the research question and test the hypotheses, we used an online experiment to collect end users' responses to simulated proactive communications from SHAs for energy-saving objectives. The online data collection approach enabled us to reach a wide range of respondents across the US and to collect data from members of the general public with varied backgrounds and personal characteristics. Interactive online platforms for data collection support different multimedia and questionnaire elements that are well-suited for the intended simulation, as well as gathering objective feedback and data on personal characteristics for a large group of participants (Kelley, Clark, Brown, & Sitzia, 2003). Therefore, for communication with users, we used Qualtrics to design an interactive interface (the questionnaire hereafter) with two components addressing different objectives of the study: (i) An interactive process that simulated smart and bi-directional communications between a user and an SHA, and (ii) questions regarding the influence of participants' personal characteristics on responses (Figure 2).

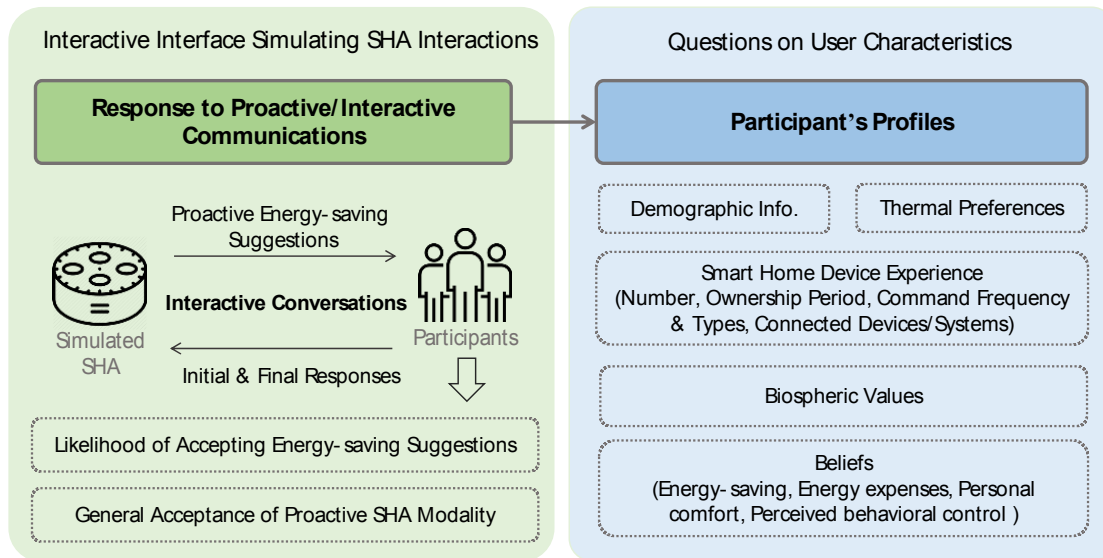


Figure 2. The structure of the online interactive interface/questionnaire

Response to Proactive Communications

The first component of the questionnaire was designed to collect participants' initial and subsequent/final responses in the conversational flow from SHAs. In the simulated interactions between users and SHAs, participants were presented with a scenario, in which energy-saving suggestions related to an automatic

change of the thermostat setpoint during a cooling season were provided by “Alexa” on an Amazon Echo. As shown in Figure 3, this scenario was presented through videos showing “Alexa” initiating conversations - using the Alexa Text to Voice Skill.

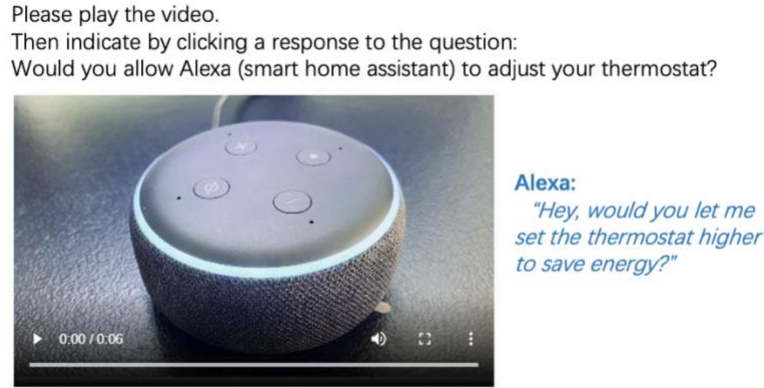


Figure 3. Example of the designed video and audio message from smart home assistant

The information flow for the suggestions was evaluated through an empirical assessment in a pilot study of 60 participants on the university campus. Participants’ comments from the pilot study helped us modify the content to facilitate the flow of information. In the first step of the full study, participants were provided with a context-based scenario, in which imagined they were at home during a summer day (i.e., cooling mode), the indoor temperature was set as they preferred, and there was a smart home assistant with automatic control of thermostat that could give suggestions for energy-saving. The design goal for this component was to emphasize the characteristics of SHAs’ conversational and interactive communication. The initial energy-saving suggestion message from “Alexa” was worded as “Hey, would you let me set the thermostat higher to save energy?” and participants’ responses to this question were recorded as their initial responses.

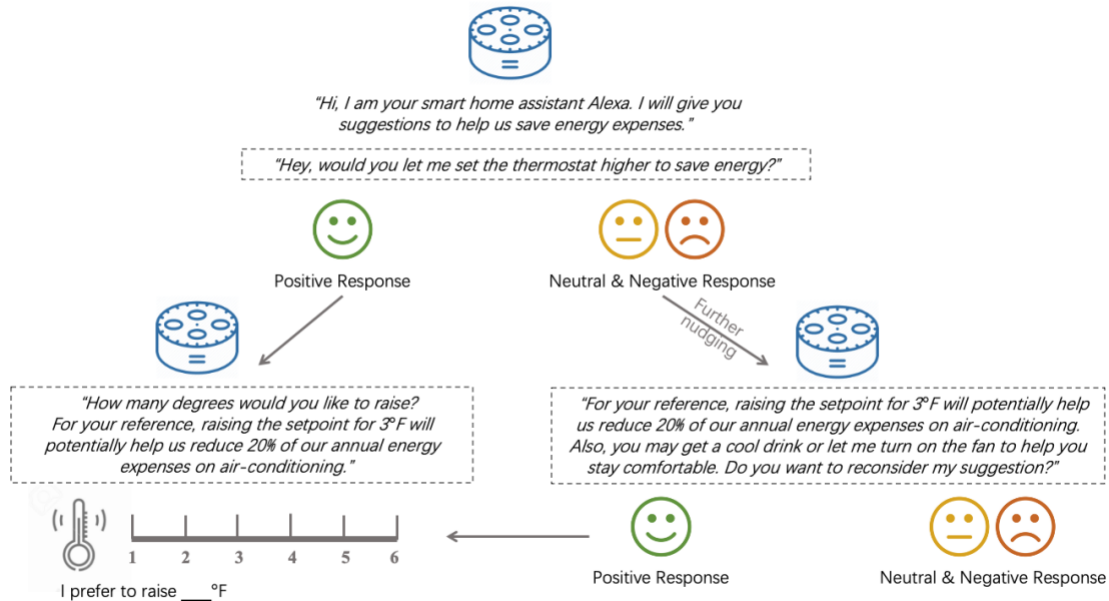


Figure 4. The flow of the suggestions (conversation) from smart home assistant

Following the proactive communication concept, the next steps of interactions included a conversational

suggestion flow from “Alexa” as illustrated in Figure 4. If participants responded positively (“probably yes,” or “definitely yes”) to the initial suggestion, they were asked about how much they would be willing to raise the thermostat setpoint. However, if they indicated a neutral (“might yes/might no”) or negative response (“probably not”) to the initial suggestion (not willing to accept), “Alexa” followed up with additional information about savings on energy expenses and tips for alternative operations to preserve comfort (e.g., turning on a fan). Participants’ responses to follow-up suggestions were recorded as their final responses. Participants who responded “definitely not” to the initial suggestion were not asked a follow-up question about changing the thermostat nor were they asked to reconsider their response. Participants’ responses to these questions were utilized to analyze the nudging effect of bi-directional communication from SHAs and the impact of personal characteristics on participants’ stated likelihood of accepting proactive communications and adaptive behavior suggestions. In addition to measuring participants’ direct responses to SHA suggestions in the simulated scenario, we also asked a separate set of questions for participants to indicate the extent to which they would generally accept proactive forms of interactions from SHAs for energy management - proactive SHA modality (Figure 2).

Participant’s Characteristics and Profile

As shown in Figure 2, the questions in the *participant’s profile/characteristics* component focused on the background and personal characteristics. We collected demographic information, information about previous experience with smart home ecosystems, participants’ environmental/energy-related values and beliefs, and their thermal preference range and sensitivities. The following rationales were used in identifying the collection of different data attributes.

The demographic information included gender, age, level of education, residence type, and employment status. Previous studies have shown that these socio-demographic characteristics are determinants of differences in energy-saving behavior (T. Yue, Long, & Chen, 2013). Therefore, the demographic information was used to ensure that the participants’ diversity was preserved during the data collection. According to the diffusion of innovation theory (Parthasarathy & Bhattacharjee, 1998) and the expanded unified technology acceptance (Venkatesh et al., 2012), the past experience with/prior use of a technology can also play an important role. Considering the significant effect of this feature, we collected data on various indicators of participants’ previous experience with smart home devices (e.g., Amazon Echo, Google Home), and examined the role of prior use of SHAs in influencing responses to SHA suggestions and evaluations of SHAs in general. Given the focus of the study on energy-saving for thermal conditioning, the thermal preference range questions focused on two attributes: occupants’ thermal preference range and sensitivity (Jung & Jazizadeh, 2019). Participants were required to provide their thermostat preferred setpoint (normal setpoint), their acceptable upper limit, and their acceptable lower limit on a typical summer day (cooling season), within the range between 60°F and 86°F using integer scales. Respondents’ thermal preference range and sensitivity can be computed based on the collected data. As an example, a heat-sensitive user should have a relatively small acceptable upper limit and a larger acceptable lower limit, and may feel uncomfortable due to a slight to moderate increase in temperature while accepting a wider range of temperature reduction.

Based on existing theories of pro-environmental behavior (described above) that suggest the importance of individual differences/personal traits that predict behaviors, we included question items measuring participants’ on biospheric values (including unity with nature, respecting the earth, protecting the environment, and preventing pollution with an importance level scale from “Opposed to my values” to “Of supreme importance”) (Steg, Perlaviciute, Van der Werff, & Lurvink, 2014). In order not to bias participants toward offering positive responses, we also asked participants about their other core values (such as benevolence and self-enhancement values) as a distraction. These other core value items were mixed in with items measuring biospheric values. Items measuring participants’ beliefs about environmental protection consequences of energy use, financial consequences of energy-saving, their habit of using energy to enhance personal comfort, and perceived behavioral control (measured as perceived

capacity to save energy) were also included with Likert-type response options ranging from “Strongly Disagree” to “Strongly Agree,” with higher scores indicating greater agreement. The specific question items for each category/variable are shown in Table 1. These questions were presented in a random sequence to avoid the potential biasing of question order.

Table 1. Individual beliefs and values with potential impact on energy-related behavior

Beliefs and Values	Survey Items
Environmental Protection	• 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. ^a • I believe it is my personal responsibility to take action to reduce problems related to energy-saving.
Energy Expenses	• Changing home energy use considerably affects individuals’ expenses. • If I reduce my own home energy use, I can save money. ^a • 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 Habit	• I pay more attention to my personal comfort than how much energy I use. ^a
Perceived Behavioral Control ^b	• I think I need more guidance on how to adapt my daily behavior in order to use less energy in my home. ^a • I am interested in adapting my daily behavior in order to save money on energy if proper guidance is provided.
Biospheric Values	• Unity with nature. • Respecting the earth. • Protecting the environment. • Preventing pollution.

^a These options were selected as clustering variables for participants segmentation based on an internal consistency test further described in the following sections.

^b Note: because of the way the question item for perceived behavioral control/capacity was worded, a high score indicates a greater perceived need for assistance to take actions (low perceived control/capacity)

Data Collection and Analysis

The data collection was conducted through Qualtrics upon approval from Virginia Tech’s Institutional Review Board (IRB#20-297). The platform enables to recruit and monitor the progress of data collection by using different constraining factors, such as the geographical location, education level, age, type of device used for responding to the questions, time for completing the study, etc. Before the full data collection, we conducted a pilot study with 60 participants involved to estimate the minimum sample size through *a priori* power analysis with G*Power 3 software (Faul, Erdfelder, Lang, & Buchner, 2007). The *priori* power test can utilize the estimated effect size, significance criterion, and prospective (before-the-fact) power to compute the required sample size that can fulfill the specific significance criterion (e.g., 0.95) and power with the same effect size (O’Keefe, 2007). Based on the pilot study results with effect size of 0.38, we estimated the representative sample size to be 300 under the pre-settings (effect size = 0.4, $p < .05$, Power > 0.90). Furthermore, we used the pilot study data to identify the constraints for data collection and ensure a high-quality dataset. The study questionnaire also included validating questions to ensure that participants were paying attention to the questions. For the full data collection, to secure a group of participants from diverse backgrounds and data with sufficient reliability and validity, six quotas and constraints were set: (1) even gender distribution of participants; (2) balanced age distribution of

participants - 18-29 (30%), 30-39 (30%), 40+ (40%); (3) uniform geographic distribution of participants among all states; (4) matching the educational background of participants with the distribution of the U.S. population; (5) requiring participants to respond using a desktop computer only; (6) requiring at least 8 minutes for completing the questionnaire. Through the pilot study, we found that participants who completed the questionnaire using mobile devices or who completed the questionnaire in less than 8 minutes typically did not provide complete and accurate responses. From August to September (thermostat cooling seasons) in 2020, the Qualtrics team invited the volunteers on the platform to participate in the online experiment and provided monetary compensation for qualified responses based on the quotas and constraints. We recorded the state-level location of the respondents and identified that the participants were uniformly distributed across the nation. After data cleaning and excluding unfinished responses, 307 valid responses were included in the statistical analyses.

In addition to basic descriptive statistics and visualizations such as bar charts and box plots, Chi-square tests, *t*-tests and Analysis of Variance (ANOVA) tests were used for evaluation of the research question and hypotheses. K-means clustering, coupled with feature analysis, was implemented in order to segment participants into groups with regard to their individual differences and personal characteristics.

Results and Findings

Sample Characteristics

Table 2 shows the general sample characteristics with a sample size of 307 in total. The gender, age, and education level of the respondents were uniformly distributed due to specified constraints during the data collection. The sample of 144 male (47%) and 161 female (52%) respondents shows almost equal distribution with 2 participants (1%) identifying themselves as non-binary, which is in parallel with the U.S. population distribution by gender (49.2% Male and 50.8% Female) (Bureau, 2019). Given the online distribution of the study questionnaire, the percentage of younger (18-29) and middle-aged (30-49) individuals was comparatively higher than the senior individuals (50+). The distribution of education level was similar to that in the U.S. population in 2015, with 33% reporting completion of bachelor's degree or more and 12% with an advanced degree (Ryan & Bauman, 2016). Half of the participants were full-time employees, and the rest included students (7%), part-time employees (13%), retirees (12%), and unemployed (13%). The residential status of the participants is also shown in Table 2.

Table 2. Sample characteristics and feedback to designed messages

Demographic Category		Total Sample	
		Num.	Perc.
Gender	Male	144	47%
	Female	161	52%
	Non-binary	2	1%
Age	18-29	103	34%
	30-39	102	33%
	40-49	52	17%
	50 +	50	16%
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	6	2%
	Doctorate Degree	13	4%
Employment	Student	22	7%
	Part-time employee	39	13%
	Full-time employee	157	51%

Demographic Category		Total Sample	
		Num.	Perc.
	Self-employed	13	4%
	Retired	37	12%
	Unemployed	39	13%
Residence Type	Single-Family Home	184	60%
	Apartment	98	32%
	Townhouse	21	7%
	Studio	4	1%
Residence Occupancy	Live by oneself	50	16%
	Live with roommate/friends	89	29%
	Live with family (including children/parents)	168	55%

Efficacy of Smart Home Assistants with Conversational Flow

RQ1 asked if the medium of a voice-based, humanlike virtual assistant and the bi-directional conversational flow would have a positive effect on participants' acceptance of the energy-saving suggestions. Participants' responses to the energy-saving suggestions from SHAs were grouped into positive, neutral, and negative responses. About one-third of the participants (110 out of 307) provided neutral (specified on the questionnaire as might yes and might no) or negative (probably no) responses in their initial feedback and were further nudged with interactive conversations (Figure 4), after which they provided their final responses (negative or positive). We compared the participants' initial and final responses and found a 16% increase in positive responses – i.e., 4% increase for those with “Probably No” initial responses and 12% increase for those with neutral initial responses.

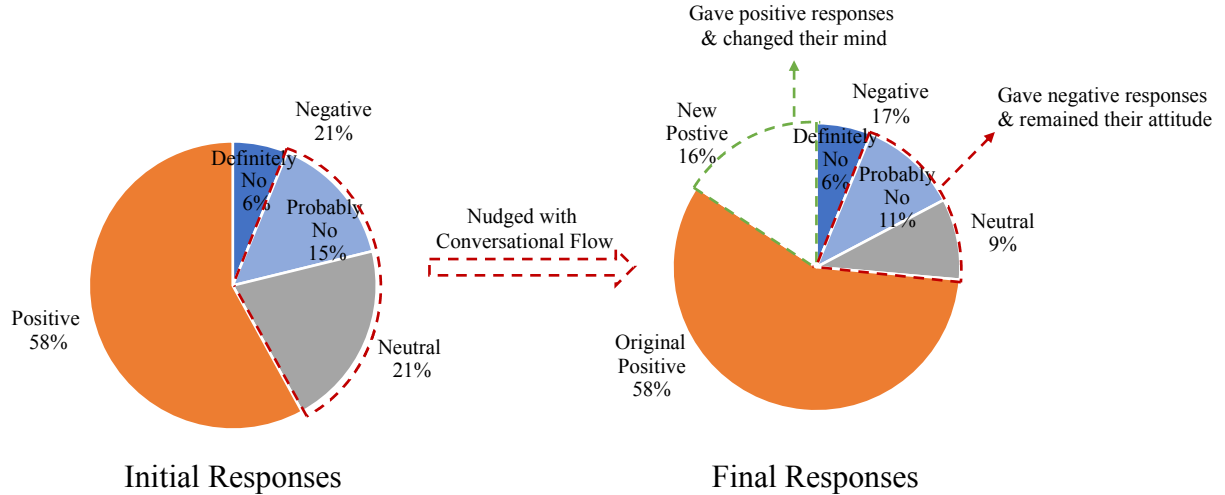


Figure 5. Comparison of participants' responses to energy-saving suggestions from SHAs

In order to compare the effect of SHA interactive conversations on participants with different initial responses (i.e., to investigate if participants' with different initial responses would react differently in their final responses after interactive conversations), a Chi-square test were conducted. The results ($\chi^2=3.61$, $p < .05$) identified that there is a statistically significant difference in participants' final responses between the initial neutral response group and the initial negative response group (Table 3). More participants who initially held a neutral attitude towards energy-saving suggestions agreed to change their idea after interactive conversations compared with the participants who initially held a negative attitude. This observation indicates that the proactive SHAs seem to be more effective among occupants with an initially neutral predisposition toward energy-saving behavior. However, a change for those with an initial negative

predisposition could still be possible but less likely. These observations could be referenced in designing proactive communications by leveraging an initial screening of the users' intention toward energy-saving efforts.

Table 3. Chi-square test results for the nudging effect of SHA interactive conversation

Initial Response to SHA Suggestions	Number of Initial Responses	Final Responses After SHA Interactive Conversations				χ^2
		Refused to change Num.	Perc.	Agreed to change Num.	Perc.	
Probably No (Negative)	46	34	73.91%	12	26.09%	3.61*
Maybe/Might Yes or Might Not (Neutral)	64	28	43.75%	36	56.25%	

* One-tailed significant level < .05

Influence of Participants' Individual Differences

Experience with Smart Home Systems

H1 predicted that occupants' previous experience with smart home devices (e.g., Amazon Echo, Google Nest) would have a positive effect on accepting the suggestions offered by the SHAs and on their perceptions of proactive SHAs in general (Hou et al., 2020; Parthasarathy & Bhattacharjee, 1998). To test the hypothesis, we first converted the Likert-type final responses to SHAs energy-saving suggestions into numeric values: "Definitely No" (=1) to "Definitely Yes" (=5). Then we evaluated five factors including the number of smart home devices that a participant has used before (Number), the duration that a participant has owned the smart home devices (Ownership Period), the frequency of giving commands to virtual assistants (Command Frequency), the number of frequently used command types (Command Types Count) with a total of five types, and the number of connected devices/systems to the smart home central hubs (Connected Devices/Systems Count).

Upon normalizing these factors with z-score standardization, through *k*-means clustering, we segmented the participants into three groups: No/Limited Experience, Some Experience, and Rich Experience, as shown in Figure 6. In the first group, the majority (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 a short period of time with limited interactions. Between the other two groups, participants with rich experience reported that they had interacted with more than one type of smart home device, including voice-based (e.g., Amazon Echo, Apple Home pod) and display-based (e.g., Google Nest Hub, Facebook Portal) forms, which resulted in much higher normalized score for the number feature. Although participants in some experience group showed slightly higher score in ownership period feature, they had much less normalized score for other features. Participants with rich experience have used their devices more frequently (higher command frequency) and more broadly (more command types and connected devices/systems).

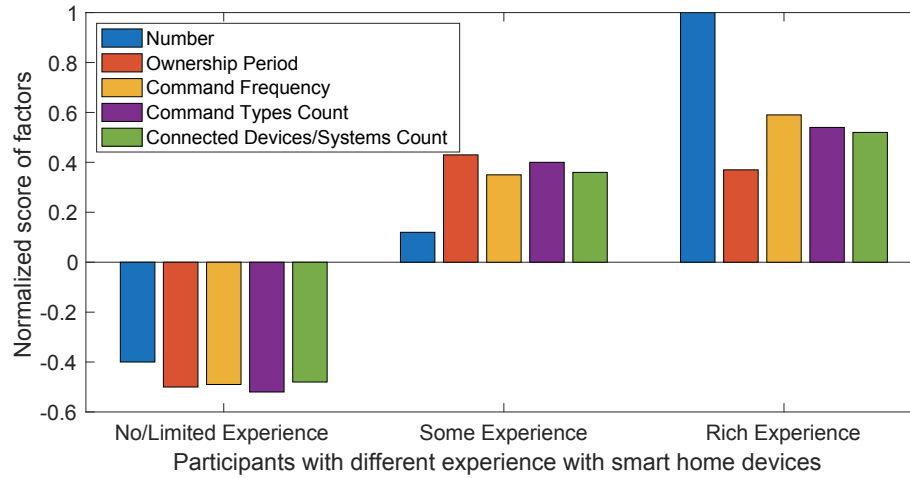


Figure 6. Clusters of participants with different levels of experience with smart home devices and virtual assistants

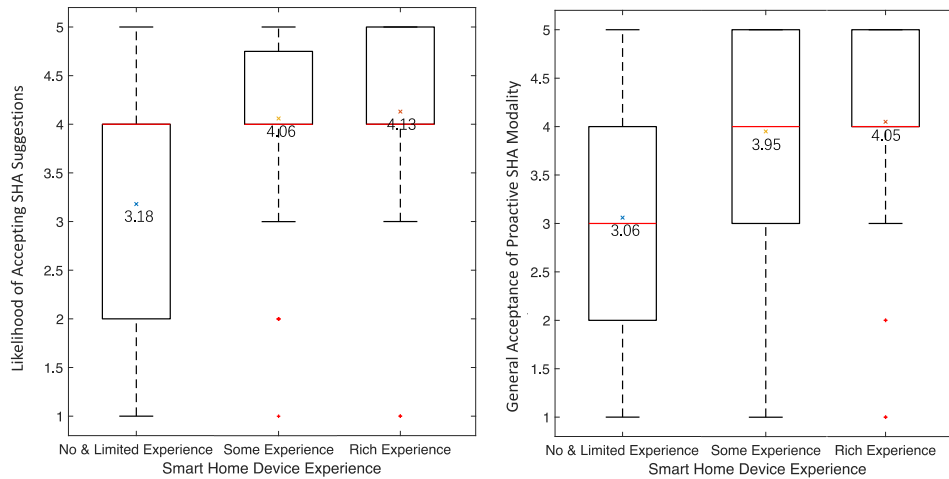


Figure 7. Impact of participants' experience with smart home devices on their responses to proactive smart home assistants (SHAs) for energy management

Figure 7 shows the box plots of participants' responses across different groups. Red lines show the median value and the markers with numbers are the average scores for participants in each group. The general ANOVA tests indicate that the participants' experience with smart home devices has a significant impact on their likelihood of accepting SHA suggestions with F-statistics of 30.31 ($p < .05$, $df = 306$) and their acceptance of proactive SHA modality in general with F-statistics of 26.89 ($p < .05$, $df = 306$). The ANOVA Tukey HSD post-hoc test results, shown in Table 4, indicate differences in behavioral intention and acceptance levels across the groups. It can be seen from Figure 7 that those with at least some previous experience with smart home systems (either some experience or rich experience) had significantly greater likelihood of accepting the suggestions than those with no or limited experience, while there was not a significant difference in likelihood between the some-experience and rich-experience groups. The same pattern emerged for general acceptance of proactive SHA modality, users with some or rich experience reported higher acceptance levels than those with no experience. Again, there was not a significant difference between those with some experience or rich experience. These findings indicate that users with

more experience will likely be more receptive to suggestions from virtual assistants for energy management of thermal conditioning.

Table 4. ANOVA Tukey Post-hoc test results on the impact of experience with smart home devices

Comparison Cases	Likelihood Mean (Std. Dev.)	Acceptance Mean (Std. Dev.)
No/Limited Experience	3.18(1.21) ^{a,*}	3.06(1.25) ^a
Some Experience	4.06(.76) ^b	3.95(.92) ^b
Rich Experience	4.13(.88) ^b	4.05(1.04) ^b

* Means with differing superscripts within each column differ at $p < .05$.

Value and Beliefs

In *H2*, we predicted that users with greater pro-environmental values and with stronger beliefs regarding positive consequences of energy-saving would be more receptive to suggestions from smart home assistants for energy management and have a more positive perception of proactive SHA modality in general. In testing this hypothesis, we also included the measure of perceived behavioral control, because prior research indicates those with less perceived capacity to take action might be less likely to do so, even if they have strong, conducive values and other beliefs. In testing this hypothesis, we used *k*-means clustering to group participants according to their beliefs and values. This method was used because examining and contrasting the preferences of individuals in different clusters can help SHAs as a machine learning approach to perform initial screening of the users' intention toward energy-saving efforts. For responses to the four items intended to measure biospheric values, Cronbach's Alpha, a measure of scale reliability, was 0.89, indicating a good internal consistency (>0.7) of the scale. Thus, we used mean values for participants' responses to those four items. However, for the belief groups in Table 1, the responses did not pass the internal consistency tests for two items (energy expenses and perceived behavioral control), and therefore, we extracted the most representative option from each of the four belief items which were marked in Table 1. The clustering on the normalized variables of beliefs and values showed that two clusters were effective in distinguishing participants with a positive disposition to save energy/take recommended actions (Positive Group) and those with a negative disposition to save energy/take action (Negative Group) as illustrated in Figure 8.

Compared to the Negative Group, the Positive Group included participants with stronger biospheric values, more positive beliefs about the environmental and economic consequences of saving energy, lower perceived control/capacity (indicating a greater perceived need for additional assistance in saving energy) and a weaker habit of preferencing personal comfort over energy-saving. An independent samples *t*-test, as shown in Table 5, indicated those in the Positive Group had significantly higher mean values both with respect to accepting SHA's suggestions and perceptions of proactive SHA modality in general as shown in Figure 9.

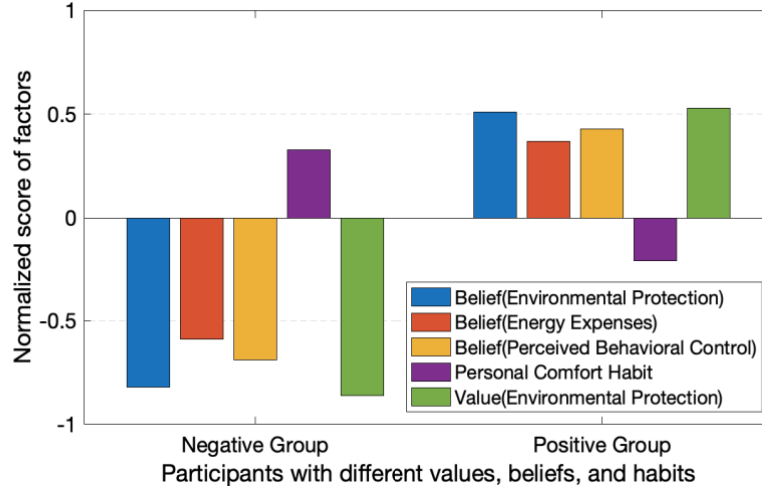


Figure 8. Groups of participants with different values, beliefs, and habits (Note: low perceived behavioral control indicates high perceived need for assistance)

Table 5. T-tests for two groups with different values and beliefs

	Groups	Numbers	Mean	Std. Deviation	<i>t</i> values
Likelihood of Accepting Suggestions	Negative	118	3.08	1.04	34.41**
	Positive	189	3.81	1.06	
General Acceptance of Proactive SHA Modality	Negative	118	2.92	1.11	63.44**
	Positive	189	3.95	1.05	

* One-tailed significance level < .05. ** One-tailed significance level < .01.

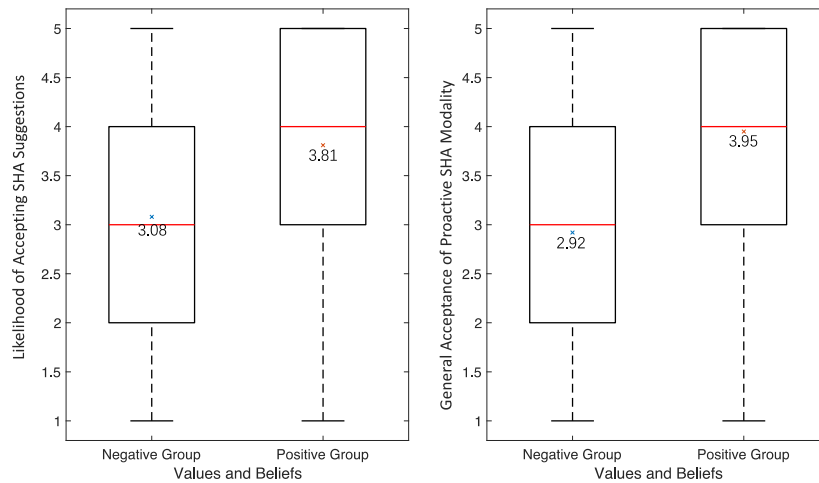


Figure 9. Impact of participants' value and beliefs on their responses to proactive smart home assistants (SHAs) for energy management

Thermal Preference and Sensitivity

To test *H3*, we also collected participants' self-reported preferred thermostat setpoints and their preferred range with upper and lower limits. As shown in Figure 10, the mean and median value of the participants' preferred thermostat setpoint is 73°F, with a mean upper limit of 75°F and a mean lower limit of 70°F. Participants' preferred setpoint mainly lies in the range between 69°F and 75°F.

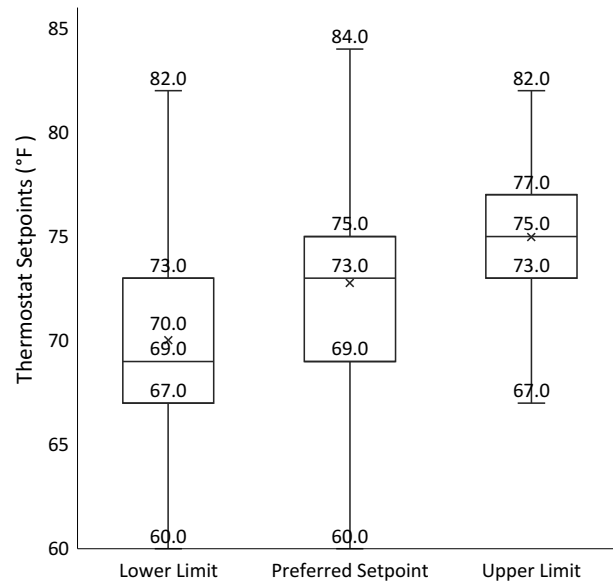


Figure 10. Participants' thermal comfort range distribution (lower limit, preferred setpoint, upper limit)

We divided these participants into different groups based on thermal preference range and sensitivities in our investigations. The acceptable thermal comfort region for occupants is $\pm 1.5^{\circ}\text{C}$ for residential buildings (Peeters, De Dear, Hensen, & D'haeseleer, 2009). Through the Fahrenheit degree to Celsius degree conversion, we estimated $\pm 2.5^{\circ}\text{F}$ to be the thermal comfort range for occupants. For example, if someone's preferred thermostat setpoint is 24°C (75.2°F) and have a $\pm 1.5^{\circ}\text{C}$ of comfort range, then his/her comfort range would be 22.5°C (72.5°F) to 25.5°C (77.9°F). As such, we set 5°F ($\pm 2.5^{\circ}\text{F}$) as a boundary to divide participants' preference ranges into large and small ranges. The independent samples *t*-test results in Table 6 show that the two groups were significantly different in accepting the SHA's suggestions. The box plots of the responses from the two groups, in Figure 10, show that those with forgiving thermal preferences were more receptive to the suggestions and indicated tolerance for higher temperature increases (2.61°F versus 1.83°F).

Table 6. T-Test for different thermal comfort ranges

Participants' Responses	Thermal Comfort Range	Number	Mean	Std. Deviation	<i>t</i> -value
Likelihood of	Large ($> 5^{\circ}\text{F}$)	89	3.74	0.99	2.321*
Accepting Suggestions	Small ($\leq 5^{\circ}\text{F}$)	114	3.37	1.24	
Temperature Setpoint	Large ($> 5^{\circ}\text{F}$)	89	2.61	1.74	3.086**
Change	Small ($\leq 5^{\circ}\text{F}$)	114	1.83	1.79	

* One-tailed significance level $< .05$. ** One-tailed significance level $< .01$.

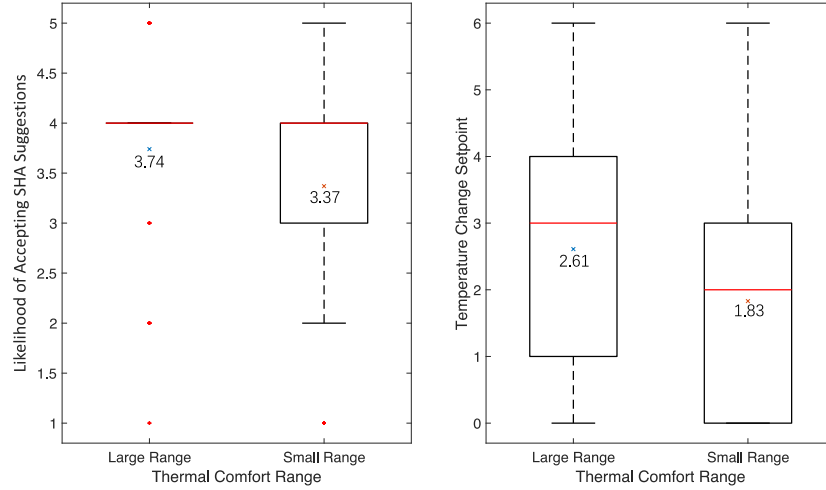


Figure 11. Effects of thermal preference range on participants' responses to adaptive behavior suggestions (left) and changing temperature setpoints (right)

Occupants' sensitivity to temperature change (i.e., thermal sensitivity) has been shown to affect their preferred shift in thermostat setpoint for HVAC operations (Jung & Jazizadeh, 2019). To investigate its impact, we grouped participants accordingly. If their preference upper range (Upper limit – Preferred setpoint) was smaller than their lower range (Preferred setpoint – Lower limit), they were classified as less tolerant of warmer conditions and more receptive to cooler conditions and vice versa.

We utilized *t*-test to identify the difference of responses from two varied thermal sensitivity groups (heat sensitive and heat tolerant group). The results indicated that two groups of respondents are significantly different from each other in the likelihood of accepting suggestions (Table 7). The box plot (Figure 11) also shows that the heat tolerant group respondents have higher likelihood to accept the energy-saving suggestions raised by SHA. However, in terms of temperature change setpoint, although the box plot shows that the heat tolerant group have higher mean value and more respondents willing to raise their thermostat setpoint for 2°F to 3°F, the *t*-test results (Table 7) indicates that the two different thermal sensitivity groups do not significantly different from each other.

Table 7. T-tests for different thermal sensitivities

Participants' Responses	Thermal Sensitivity	Number of participants	Mean	Std. Deviation	T values (Sig.)
Likelihood of Accepting Suggestions	Heat Sensitive	81	3.56	1.06	1.91*
	Heat Tolerant	54	3.91	1.03	
Temperature Change Setpoint	Heat Sensitive	81	2.25	1.90	1.11
	Heat Tolerant	54	2.59	1.56	

* One-tailed significance level < .05.

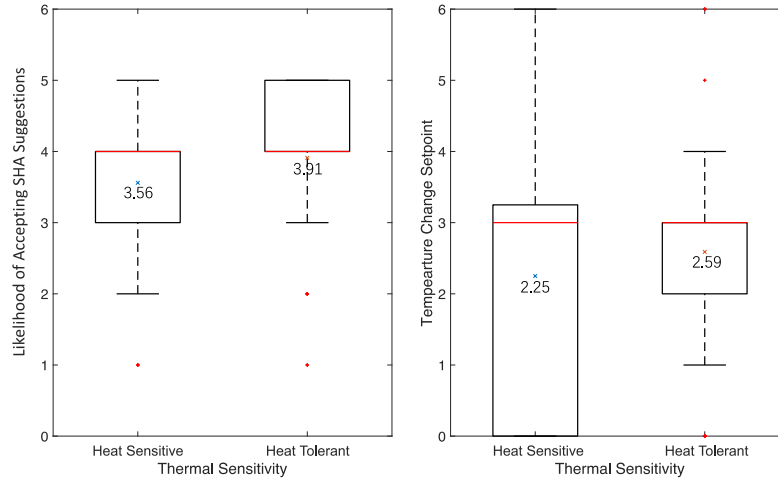


Figure 12. Impact of participants' thermal preference sensitivity on their responses to adaptive behavior suggestions (left) and changing temperature setpoints (right)

Discussion

Implementation of AI-based virtual assistants in the smart home ecosystem has introduced occupants with a more interactive interface to enjoy the comfort, convenience, and energy efficiency brought by the IoT-based home automation. However, the one-way passive communication between the users and the smart home virtual assistants has limited its usage, despite its great application potentials. This study provides empirical evidence that a proactive smart-home-integrated virtual assistant can facilitate users to achieve energy-saving and sustainability goals. The online experiments also investigated individuals' different characteristics that could affect users' receptiveness to the SHA suggestions and the proactive SHA modality for energy management. Factors such as experience with smart home ecosystems, pro-environmental values, and beliefs about environmental and economic consequences of saving energy, as well as thermal preferences have been identified to have a statistically significant effect on the individual's energy efficiency-related decision-making, which is in line with theories and models in previous studies, including the diffusion of innovation theory (Parthasarathy & Bhattacharjee, 1998), the value-belief-norm theory (Oreg & Katz-Gerro, 2006), and the personal thermal comfort model (Jung & Jazizadeh, 2020).

Various stakeholders can benefit from the findings in this study. Developers of smart home ecosystems should consider implementing the proactive modality of the AI virtual assistants and utilize it to improve the human-building interaction in smart homes. Future researchers should refer to the identified influence of individual differences on the energy-saving decision-making process in the future development of efficient personalized proactive communications between the smart home assistants and the occupants/users. Last but not least, smart home occupants and smart speaker users can also learn about the energy-saving potentials that can be brought from mutual interactions between them and the virtual assistants.

This study is not free of limitations. There are several aspects of this study that should be addressed in future efforts. The online experiment examined participants' subjective perceptions of and views toward the concept of SHAs. Online experiments and surveys are helpful for reaching a large segment of a population in a short period of time for a reasonable cost and for collecting a rich set of information about a diverse group of research participants (Dandurand, Shultz, & Onishi, 2008; Nayak & Narayan, 2019). However, they can be sometimes limited by participant inattentiveness and social desirability of answers/responses and have less external validity (compared to natural or field studies) due to the research setting (Clifford & Jerit, 2014; Keyton, 2014). We attempted to address potential inattentiveness by

screening responses based on the amount of time to complete the study/answer the questions and eliminating data from participants who completed the study too quickly, thus indicating lack of attentiveness. We minimized social desirability effects by including distractor items, randomizing the order of some items, and by keeping the survey respondents' identities anonymous to the research team. The online experiment described here measures responses to a hypothetical situation. Such approaches are common in online or lab-based experiments, especially for more exploratory work such as that reported here. However, replication of work in natural or field settings is encouraged to examine the extent to which the predictive models are consistent across research settings and data-gathering approaches.

Another limitation that requires further investigation in the future is that the climate zones of the participants were not considered in terms of the energy-saving potentials of raising thermostat setpoints. With the incorporation of the local weather data and the energy consumption estimation, proactive SHAs can provide users with more accurate information of energy-saving potential through suggested behaviors, and thus initiate more efficient interactive conversation. In addition, privacy concerns associated with voice-based smart speakers is also a potential factor that may affect user's attitude and usage of the smart home assistants, while this factor was not specifically addressed in this study. Finally, although previous studies have shown that voice-based virtual assistants can be incorporated into households' lives with long-term stability, the long-term efficacy of the proactive SHAs requires further investigation. As such, an in-house long-term user study is needed in the future to observe the interactions between the proactive smart home assistants and the occupants in daily usage and the long run.

Conclusion

In this study, we investigated the impact of smart home assistants (SHAs) – proactive voice-based virtual assistants integrated into the smart home ecosystems – on user adaptation for energy-saving with a focus on thermal conditioning. In our envisioned system, SHAs could proactively give adaptive behavior suggestions to occupants toward changing their energy-related behaviors. This online experiment included 307 responses from participants with diverse backgrounds experiencing proactive/interactive conversation from Alexa (AI virtual intelligence) on a smart speaker. Through the statistical analysis, it was found that conversational interactions have a significantly positive effect on the stated likelihood of accepting suggestions. Compared with the participants' initial responses to the energy-saving suggestions, in their final responses after the conversational flow and further interactions with Alexa, the number of participants who accepted SHAs' energy-saving suggestion of adjusting thermostat setpoint increased by 16%. This study also revealed the significant impact of three individual's characteristics on their receptiveness to the SHA suggestions and the proactive SHA modality for energy management, including experience with smart home ecosystems, pro-environmental values and beliefs, as well as thermal preferences. Future researchers and developers are encouraged to implement the proactive modality and nudge theory in the development of smart home virtual assistants to promote human-building interaction and improved energy efficiency of the smart home ecosystem.

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