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AI-powered virtual assistants nudging occupants for energy saving: proactive smart speakers for HVAC control

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ABSTRACT

Virtual assistants powered by Artificial Intelligence (AI) and integrated into the smart home ecosystems facilitate human–building interactions. We have envisioned that the proactive virtual assistant capabilities could be designed to encourage energy conservation behaviours by relying on their nudging effect through conversational interactions, autonomous actuation and guiding users' decision-making. To this end, we investigated how proactive virtual assistants, in a simulated smart home ecosystem, influence occupants to take energy-saving, adaptive actions for Heating, Ventilation and Air Conditioning (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.

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KEYWORDS
Smart home; virtual assistant; Amazon Alexa; 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 buildings' energy management using human-centred operations could result in considerable energy savings (Costa et al., 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 et al., 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 (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 et al., 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). As carriers of voice-based virtual assistants, smart speakers play a significant role in smart home applications. In 2021, nearly 90.7 million adults, which is 35% of the US adults, have owned at least one smart home device in their home and about 50% of these owners were daily active users (Bret & Ava, 2021). A total of 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), and learning to use smart home devices can be time-consuming with little support available (Hargreaves et al., 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 (reactive modality) might not result

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in an optimal outcome, for example, when it comes to energy management. Therefore, we have envisioned smart-home-integrated virtual assistants that act proactively (proactive modality) as a bridge to facilitate users' efforts towards 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 behaviours 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 behaviour for energy-saving. In other words, with prompts initiated by virtual assistants, occupants might be more willing and enabled to take adaptive behaviours to conserve energy due to the nudging effect from smart home intelligent conversations, automation ecosystems and providing guidance for actions. 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 different thermal preferences affected the likelihood of accepting energy-saving suggestions from proactive smart home assistants (SHAs). We conducted this study through an online experiment with members of the general public across the US as detailed in the following sections.

Background, objectives and study design

Smart building/home ecosystem

Smart home ecosystems consist of third-party sensors and smart appliances, cloud services, occupants, and smart home central hubs. Based on example smart home frameworks (Stojkoska & Trivodaliev, 2017), we envisioned an ecosystem, in which virtual assistants play a critical role as shown in Figure 1. Smart home central hubs represented by virtual assistants on smart speakers are at the centre of our envisioned ecosystem. We refer to them as *SHAs* hereafter. SHAs could build bridges between occupants, cloud computing platforms, and third-party home appliances (Figure 1). Prior studies have designed various platforms around voice-activated central hubs in smart home scenarios, including those with Alexa Voice Services, Alexa Skill Sets (Yue & Ping, 2017) and Google Assistant (Isyanto et al., 2020). As an important aspect, interactions between users and virtual assistants have been the subject of investigations. For example, studies have identified the common user commands (e.g. weather checking, media control, and device control) (Lopatovska et al., 2019) or they have compared the differences in interactions for different virtual assistants including Amazon Alexa, Google Assistant, Apple Siri and Microsoft Cortana (Berdasco et al., 2019). Human interactions with SHAs for smart home operations have remained to be further explored (Bylieva et al., 2020). Upon receiving user commands, SHAs can operate various connected appliances, reducing occupants' effort to operate the devices separately (Jabbar et al.,

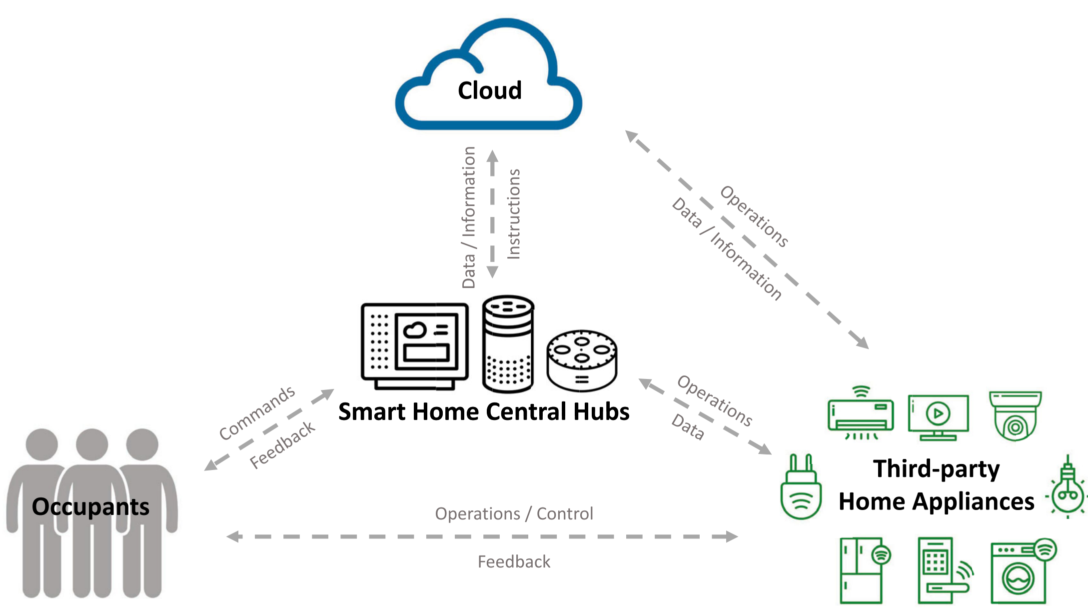

Figure 1. Smart home ecosystem centred around virtual assistants in smart home ecosystems (i.e. SHAs).

2019). However, how SHAs can interact with the occupants and help them make the best use of IoT-embedded smart homes needs to be further explored.

Energy awareness, choice architecture and nudge theory

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 for energy efficiency (Hsu et al., 2010). Studies have broadly investigated the efficacy of various content and forms of feedback and interventions to encourage energy-efficient behaviours (Jain et al., 2012). However, the traditional forms of eco-feedback have been found to have scalability limitations and focused on one-way interactions. The technological advances have enabled bi-directional communications between SHAs and occupants. In this context, choice architecture interventions could be a promising approach to encourage occupants' 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 (Szaszi et al., 2018). Nudge theory introduces generally inexpensive and less invasive solutions compared to traditional direct interventions (Thaler & Sunstein, 2009). The key factor of nudge theory is focused on positive reinforcements that maintain freedom of choice and the feeling of being in control for decision-making (Thaler & Sunstein, 2009). Through data-driven nudges, the choice architects such as policy makers or industry practitioners can arrange decision-making contexts that influence people's daily choices and behaviours in an inexpensive and effective way (Ranchordás, 2020).

In energy efficiency applications, cost-effective nudges have been demonstrated effective in voluntary energy efficiency adoption (Gillingham & Tsvetanov, 2018) and energy consumption reduction (Chang et al., 2016). Five common nudge mechanisms used in interventions related to residential energy consumption include (Lehner et al., 2016): simplification and framing of information (e.g. customized consumption feedback; Podgornik et al., 2016); data visualization of energy consumption (Herrmann et al., 2018); changes of the physical environment (e.g. design of home and appliances with intent; Bhamra et al., 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 et al., 2013). Our envisioned implementation of SHAs draws on providing guidance for users with the potential to influence occupants' energy-saving behaviours through smart home automation by nurturing adaptive actions using proactive conversations.

Influence of individual differences on behaviour and decision-making

In evaluating the nudging effect of the proactive bi-directional communication from SHAs, we have relied on drivers of energy-saving behaviours. Contemporary theories and models that predict environmental (and energy-related) behaviours suggest several influential, personal factors that could affect how people make decisions in response to energy-saving prompts. The value-belief-norm theory of environmentalism (Stern et al., 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 behaviours 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 behaviours (Oreg & Katz-Gerro, 2006). For example, individuals' awareness of/beliefs about environmental consequences of specific behaviours (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 behaviours. The comprehensive action determination model (CADM) of ecological behaviour also identified the impact of habitual influences on environmentally friendly behaviour (Klöckner, 2013). Based on the model, prior actions or habits, such as previous heating or cooling behaviours, predict future actions along with one's sense of whether or not s/he has the ability to take action (perceived behavioural control; Klöckner, 2013).

Another individual difference with an important effect on the energy-saving behaviour and decision-making is the use or adoption of new technologies, such as smart home technologies. The diffusion of innovation theory (Parthasarathy & Bhattacherjee, 1998) predicts that prior experience with the given technology tends to predict future and/or expanded use of the technology. For instance, previous research indicates that the command frequency in user interactions with SHAs was associated with the ownership period and the number of smart home devices a user has (Sciuto et al., 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 et al., 2012). Prior use is an individual difference variable that is common in above-mentioned technology related theory and models, which should also be applied in this study. Based on previous studies about the influence of individual differences on energy-saving behaviour and decision-making, various individual characteristics can be investigated to explore the influence of these features on interactions between proactive SHAs and occupants.

Based on the nudging effect of proactive communications from SHAs and consideration of individual drivers of energy-efficient behaviour and decision-making, we have sought to explore how proactive SHAs guide users toward improved adaptive behaviour for energy-saving. An example scenario of SHAs nudging occupants is as follows. When an occupant wakes up in the morning with the SHA alarm, the agent would also give a suggestion – '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?'. Considering similar scenarios and existing theories that explain energy-related behaviours, 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 nudging effect of 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 aforementioned literature on technology use and personal characteristics of those who engage in pro-environmental behaviours 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 behaviour suggestions from SHAs.

– *H1*: (Based on diffusion of innovation theory (Parthasarathy & Bhattacherjee, 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; Stern et al., 1999) and the CADM (Klöckner, 2013) of pro-environmental behaviour) 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

In this study, 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 participants 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 et al., 2003). Therefore, for communication with users, we used Qualtrics to design an interactive interface (referred to as 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).

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

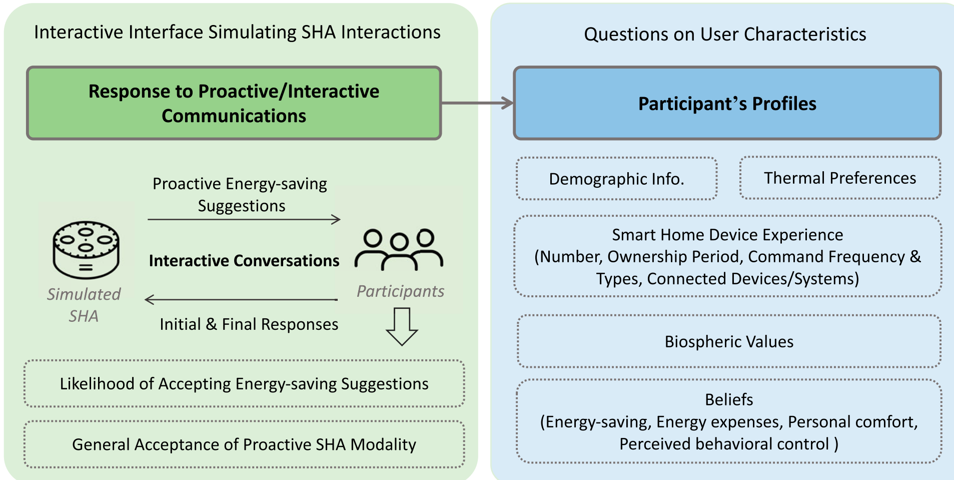

Figure 2. The structure of the online interactive interface/questionnaire.

shown in Figure 3, this scenario was presented through videos showing 'Alexa' initiating conversations – using the Alexa Text to Voice Skill.

The information flow for the suggestions was first evaluated through an empirical assessment in a pilot study of 40 participants on the university campus. Participants' comments from this first pilot study helped us modify the content to facilitate the flow of information and address any ambiguity that participants may have encountered. In the first step, 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 SHA with automatic control of thermostat that could give suggestions for energy-saving and have a conversation with users for follow-up actions. The design goal for this component was to emphasize the characteristics of SHAs' conversational and interactive communication that supports occupants' decision-making in taking adaptive and energy-saving actions. 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'

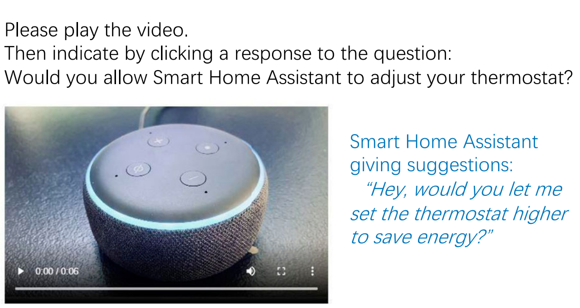

Figure 3. Designed video and audio message from SHA in interactive conversations.

responses to this question were recorded as their initial responses.

Pursuing the proactive communication concept, the next steps of interactions included a conversational suggestion flow from Amazon Alexa as illustrated in Figure 4. These follow-up conversations were centred around providing information that facilitate occupants' decision-making. 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 behaviour 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 mode of interactions from SHAs for energy management – proactive SHA modality (Figure 2). As noted, in this study, we have considered two operational modalities: reactive (only responding to

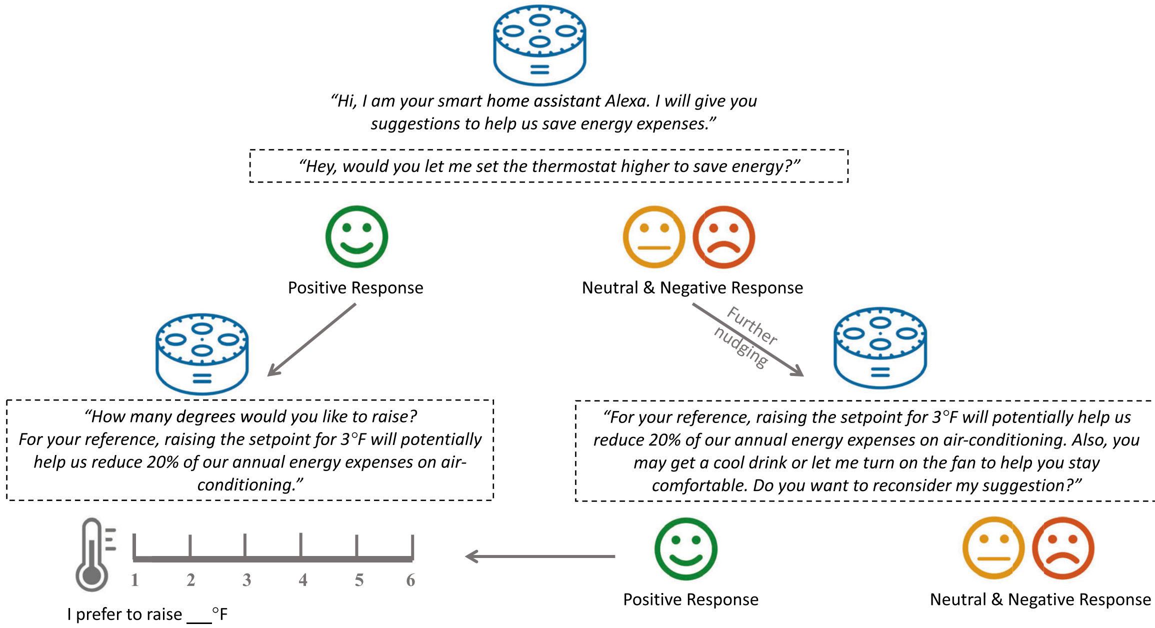

Figure 4. The flow of the suggestions (conversation) from the simulated SHA.

users' commands/questions) and proactive (initiating conversations/suggestions).

Participant's characteristics and profile

As shown in Figure 2, the questions in the *participant's profile/characteristics* component focused on the participants' personal characteristics and individual differences. 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 behaviour (Yue et al., 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 & Bhattacherjee, 1998) and the expanded unified technology acceptance (Venkatesh et al., 2012), 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 (i.e. number of devices, ownership period, command frequency, command types count and number of connected devices/systems) in order to examine the role of prior use of SHAs in influencing responses to SHA suggestions and evaluations of proactive SHAs modality. Table 1 provides the details of the question items used to collect this information. 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 (Jazizadeh et al., 2013). 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 (i.e. a cooling season), using integer scales on sliders. Participants' 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.

Based on existing theories of pro-environmental behaviour (described in the Background, objectives and study design section) that suggest the importance of individual differences/personal traits that predict behaviours, we included question items measuring participants' biospheric values (including their rating of the importance of unity with nature, respecting the earth, protecting the environment and preventing pollution with response categories ranging from 'opposed to my values' to 'of supreme importance') (Steg et al., 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.

Table 1. Questions for features about experience with smart home devices and virtual assistants.

Feature	Questions	Options
Number	Which of the following SHA devices have you used before? (Please check all that you have used)	Apple Home pod, Google Home/Google Nest mini, Amazon Echo, Google Nest Hub, Amazon Echo Show, Facebook Portal, other/value (please specify), none
Ownership period	How long have you owned your SHA device?	Less than a month, one to six months, more than six months, no, I have not owned one, I have only used one from others
Command frequency	How often do you use (talk to or give commands to) your SHA device when you are at home?	Very often (every 30 min), often (every 1–3 h), usually (every 6–12 h), sometimes (once every couple of days), rarely (only use a few times a month)
Command types count[a]	How often do you use the following functions with your SHA device?	Media control, alarm and time, purchasing, control appliances, acquire information, others. Command frequency options: never, seldom, sometimes, often, always
Connected devices/ systems count	Which one of the following household appliances/systems is connected to your SHA device? (Please check all that apply)	HVAC system, lighting system, power-plug, kitchen appliances, audio/ video devices, home security system, I have not connected any of my household appliances with my SHA device

[a]The count is computed based on the participants' frequency of giving different commands. If the participant has never used a specific command (selecting 'never' in the command frequency), then the command will not be counted in this feature.

Table 2. Individual beliefs and values with potential impact on energy-related behaviour.

Belief/value groups	Survey options
Environmental protection belief	• 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 belief	• 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 do not 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 behavioural control belief[b]	• I think I need more guidance on how to adapt my daily behaviour in order to use less energy in my home[a] • I am interested in adapting my daily behaviour in order to save money on energy if proper guidance is provided
Biospheric values	• Unity with nature (fitting into nature)[a] • Respecting the earth (harmony with other species)[a] • Protecting the environment (preserving nature)[a] • Preventing (pollution protecting natural resources)[a]

[a]These options were selected as clustering variables for participants segmentation based on an internal consistency test further described in the following sections.
[b]Because of the way the question item for perceived behavioural control/ capacity was worded, a high score indicates a greater perceived need for assistance to take actions (low perceived control/capacity)

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 behavioural 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 2. These questions were presented in a random sequence to avoid the potential biasing of question order.

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 using different constraining factors. Before the full data collection, we conducted a second pilot study with 60 participants, recruited through Qualtrics, to estimate the minimum sample size through *a priori* power analysis with G*Power 3 software (Faul et al., 2007). The *a 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 fulfil 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 in the range of 0.3–0.6, we estimated the representative sample size to be 300 for effect size = 0.4, $p < .05$ and power = 0.95. Furthermore, we used this second 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%) and 40+ (40%); (3) uniform geographic distribution of participants among all states; (4) matching the educational background of participants with the distribution of the US population; (5) requiring participants to respond using a desktop/laptop computer only and (6) requiring at least 8 min for completing the questionnaire. Through the second pilot study, we found that participants who completed the questionnaire using mobile devices or who completed the questionnaire in less than 8 min typically did not provide complete and accurate responses. Starting in August 2020, the participants were recruited through the Qualtrics platform to participate in the online experiment and were provided with monetary compensation for qualified responses based on our pre-determined quotas and constraints. Upon completion of the data collection in September, and after data cleaning and excluding unfinished responses, 307 valid responses were included in the statistical analyses. We recorded the state-level location of the participants and identified that they were uniformly distributed across the nation.

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.

Table 3. Sample characteristics and feedback to designed messages.

Demographic category		Total sample Num.	Total sample 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%
	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%

Results and findings

Sample characteristics

Table 3 shows the general sample characteristics with a sample size of 307 in total. The gender, age and education level of the participants were uniformly distributed due to specified constraints during the data collection. The sample of 144 male (47%) and 161 female (52%) participants shows almost equal distribution with 2 participants (1%) identifying themselves as non-binary, which is similar to the gender distribution within the US population (49.2% male and 50.8% female) (Bureau, 2019). Based on the US demographic distribution by age (Bureau, 2019), we constrained the participants of the study to be above 18, and equally distributed among younger, middle-aged and senior participants. The final sample distribution by age is similar with pre-set quotas with 34% in 18–29, 33% in 30–39 and 33% in 40+ age groups (Table 3). The distribution of education level was similar to that in the US 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 3.

Efficacy of SHAs nudging effect

RQ1 asked if the proactive SHAs would have a positive nudging 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.

We further investigated if participants with different initial responses would react differently in their final

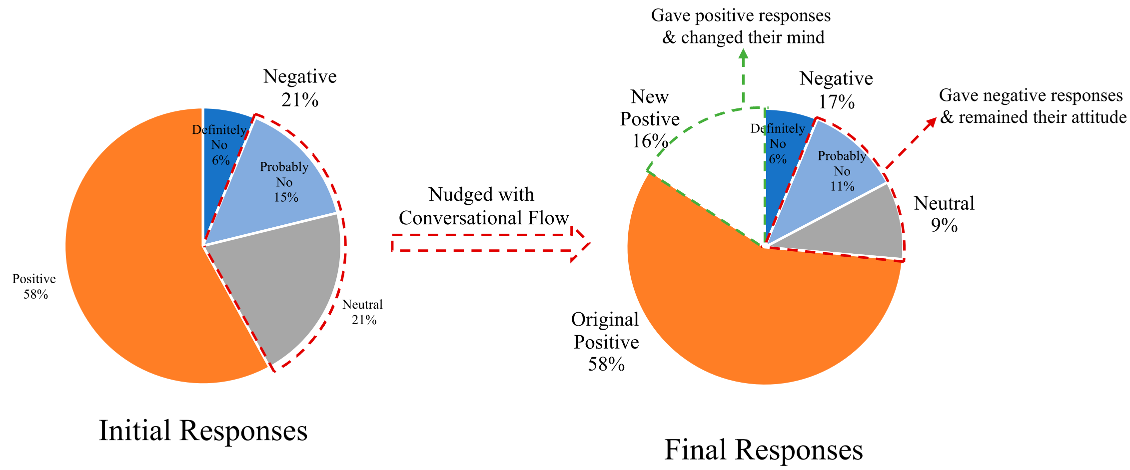

Figure 5. Comparison of participants' responses to energy-saving suggestions from SHAs.

responses after interactive conversations. As shown in Figure 5, we recorded participants' initial responses and final responses through the flow of conversations from SHAs. Participants with initial neutral and negative responses were both provided with further nudges including energy-saving information (Figure 4). To compare the effect of SHA interactive conversations on participants with different initial responses, a Chi-square test was conducted. The results ($\chi^2 = 3.61$, $p < .05$) showed a statistically significant difference in participants' final responses between the group with an initial neutral response and the group with an initial negative response as shown in Table 4. More participants with an initially neutral response towards the energy-saving suggestions changed their response (36 out of 64) after interactive conversations, compared with the participants who initially had a negative response (12 out of 46). This observation indicates that the proactive SHAs seem to be more effective in nudging occupants with an initially neutral predisposition toward energy-saving behaviour. However, a change for those with an initial negative predisposition could still be possible but less likely.

Table 4. 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: Refused to change Num.	Perc.	Agreed to change Num.	Perc.	χ^2
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 (Parthasarathy & Bhattacherjee, 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) did not 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 or Apple Home pod) and display-based (e.g. Google Nest Hub, Facebook Portal) forms, which resulted in much higher normalized score for the feature representing the number of devices. Although participants in the

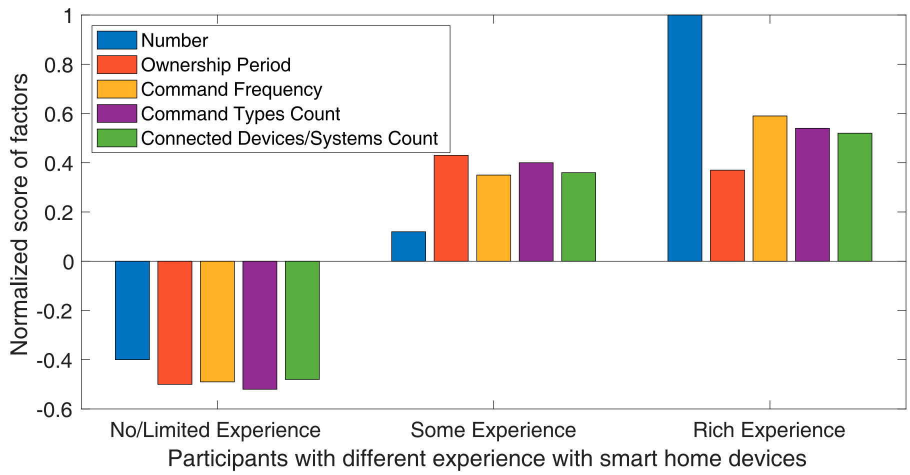

Figure 6. Clusters of participants with different levels of experience with smart home devices and virtual assistants.

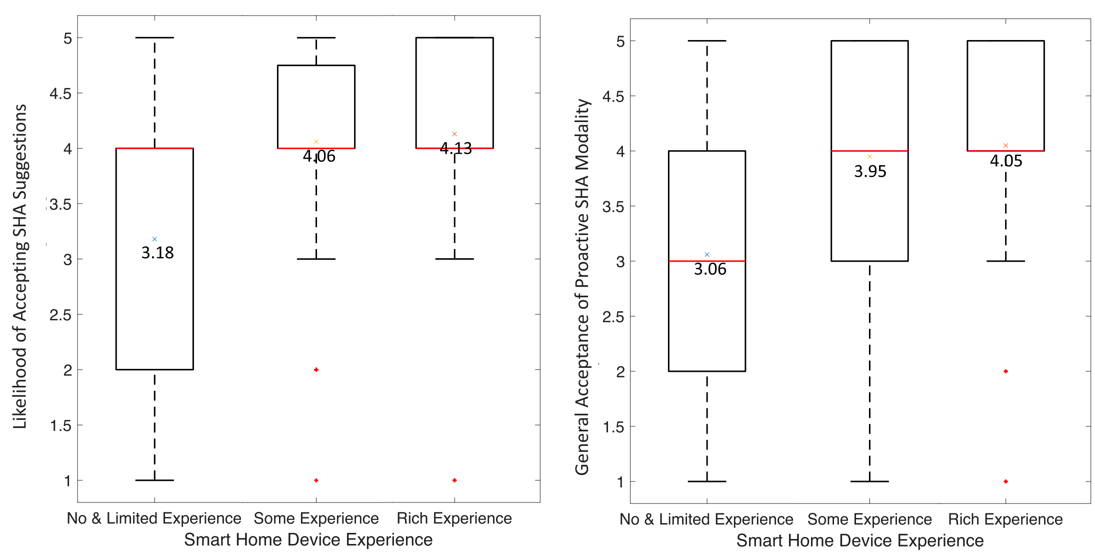

Figure 7. Impact of participants' experience with smart home devices on their responses to proactive SHAs for energy management.

group with some experience showed slightly higher score for the ownership period feature, they had lower normalized scores for other features. In other words, participants with rich experience have used their devices more frequently (higher command frequency) and more broadly (more command types and connected devices/systems).

Figure 7 shows the box plots of participants' responses across different groups. 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 had 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 (honestly significant difference) *post hoc* test results, shown in Table 5, indicate differences in behavioural 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-

Table 5. 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(0.76)[b]	3.95(0.92)[b]
Rich experience	4.13(0.88)[b]	4.05(1.04)[b]

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

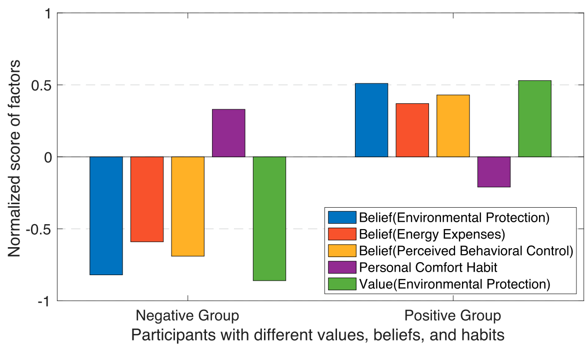

Figure 8. Groups of participants with different values, beliefs and habits

(Note: lower perceived behavioural control indicates high perceived need for assistance).

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.

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 SHAs for energy management and have a more positive perception of proactive SHA modality in general. Based on the CADM (Klöckner, 2013), we also included a measure of perceived behavioural control. 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, values and perceived control. This method was used because examining and contrasting the preferences of individuals in different clusters can help SHAs through 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 2, the responses did not pass the internal consistency tests for two belief items (energy expenses and perceived behavioural control), and therefore, we extracted the

Table 6. *t*-Tests for two groups with different values and beliefs.

	Groups	Num.	Mean	Std. dev.	*t*-value
Likelihood of accepting suggestions	Negative	118	3.08	1.04	−5.87**
	Positive	189	3.81	1.06	
General acceptance of proactive SHA modality	Negative	118	2.92	1.11	−8.15**
	Positive	189	3.95	1.05	

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

most representative option from each of several belief items which were marked in Table 2. The clustering on the normalized variables of beliefs and values showed that two clusters were effective in distinguishing participants with a likely (based on theories discussed above) positive disposition to save energy/take recommended actions (positive group) and those with a likely 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 6, 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.

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 values of participants' preferred thermostat setpoint is 73°F, with a mean upper limit of 75°F and a mean lower limit of 70°F.

We divided these participants into different groups based on thermal preference range and sensitivities in our investigations. The general acceptable thermal comfort region could be considered ±1.5°C for residential buildings (Peeters et al., 2009). By converting from degrees Fahrenheit to Celsius, we estimated ±2.5°F to be the thermal comfort range for occupants. As such, we set 5°F (±2.5°F) as a boundary to divide participants' preference ranges into large and small ranges. The independent samples *t*-test results in Table 7 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 11, show that those with forgiving thermal preferences were more receptive

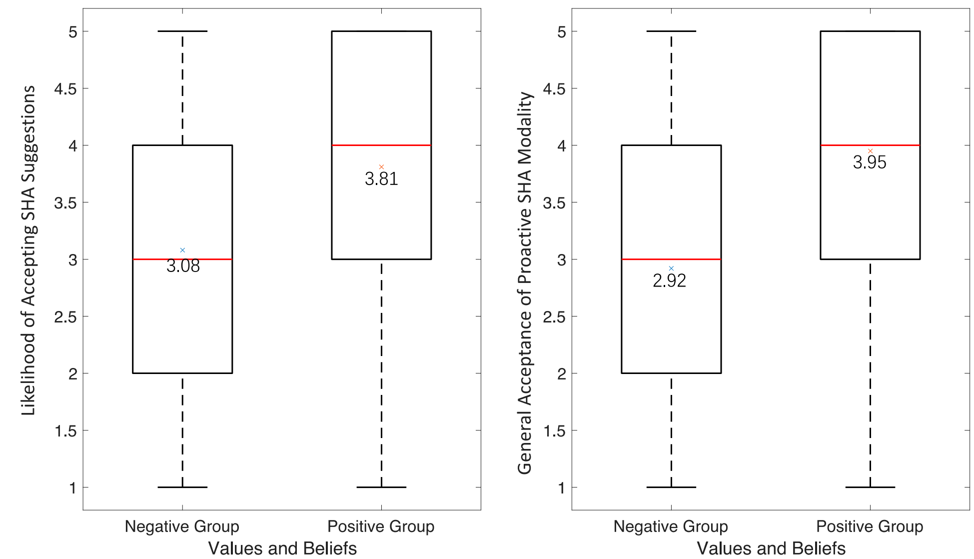

Figure 9. Impact of participants' values and beliefs on their responses to proactive SHAs for energy management.

to the suggestions and indicated tolerance for higher temperature increases (2.61°F versus 1.83°F).

Occupants' sensitivity to temperature change (i.e. thermal sensitivity) has been shown to affect their preferred shift in thermostat setpoint for HVAC operations (Jazizadeh et al., 2013). 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 a *t*-test to identify the difference in responses from two thermal sensitivity groups – heat sensitive and heat tolerant. The results indicated that two groups of participants have significantly different likelihoods of accepting SHA suggestions as shown in Table 8. The box plots, in Figure 12, also show that the heat-tolerant group has a higher likelihood of accepting the energy-saving suggestions. However, for changes in thermostat setpoint, although the box plots show that the heat-tolerant group has a higher mean value (2.29°F) compared with the heat-sensitive group (2.59°F), the *t*-test results, shown in Table 8, indicated that the difference was not significant.

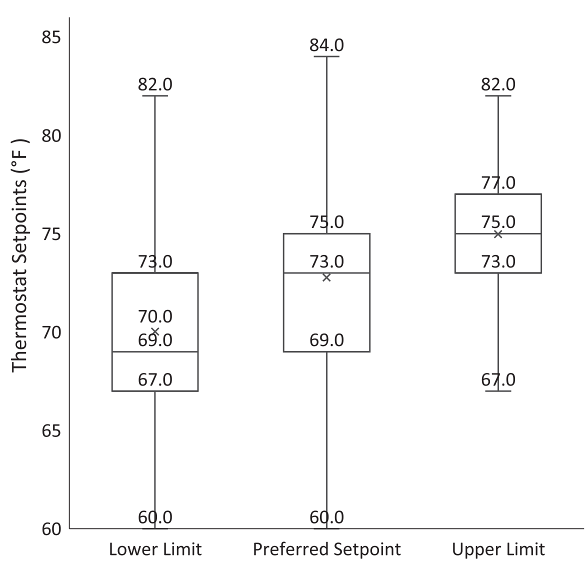

Figure 10. Participants' thermal comfort range distribution (lower limit, preferred setpoint and upper limit)

Discussion

This study explored the extent to which a proactive smart-home-integrated virtual assistant might facilitate users' decision-making to adapt energy-saving behaviours through nudging effects of smart home automation, proactive communication and proper guidance. In evaluating this nudging effect, the online experiment also investigated individuals' different characteristics that could affect users' receptiveness to the SHA suggestions and proactive SHA modality for energy management. Factors such as experience with smart home ecosystems, pro-environmental

Table 7. *t*-Test for different thermal comfort ranges.

Participants' responses	Thermal comfort range	Num.	Mean	Std. dev.	*t*-value
Likelihood of accepting suggestions	Large (>5°F)	89	3.74	0.99	2.321*
	Small (≤5°F)	114	3.37	1.24	
Temperature setpoint change	Large (>5°F)	89	2.61	1.74	3.086**
	Small (≤5°F)	114	1.83	1.79	

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

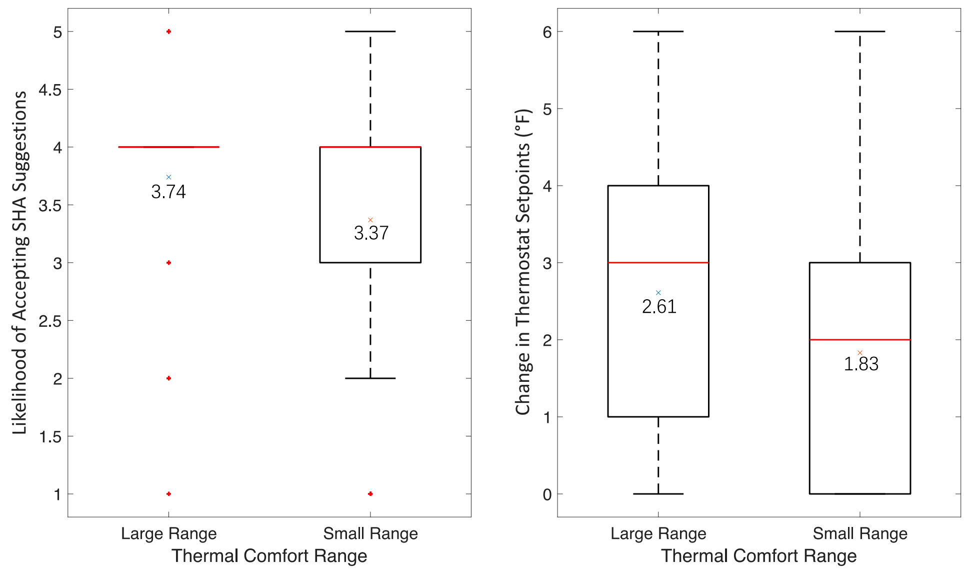

Figure 11. Effects of thermal preference range on participants' responses to adaptive behaviour suggestions (left) and changing temperature setpoints (right).

(biospheric) values and beliefs about environmental and economic consequences of saving energy, as well as thermal preferences were found to have a statistically significant effect on participants' energy efficiency-related decision-making, which is in line with theories and models in previous studies, including the diffusion of innovation theory (Parthasarathy & Bhattacherjee, 1998), the unified theory of acceptance and use of technology (Venkatesh et al., 2012), the value-belief-norm theory (Oreg & Katz-Gerro, 2006) and the personal differences of comfort acceptability (Jung & Jazizadeh, 2020).

Various stakeholders can benefit from consideration of the findings in this study. Findings from this study can provide technology developers with a better understanding of users' preferences for different smart home interactional modalities. For example, by drawing on the findings and the theoretical constructs examined here, developers could design new and adaptive functionalities for AI-powered virtual assistants to optimize the interactions, focusing on the users who are likely to benefit from/respond most positively to assistants' nudging without a blanket use of the proactive interactions. Researchers and developers could refer to the identified influence of individual differences on the energy-saving decision-making process in the future development of efficient personalized communications between smart homes and occupants. The findings also show that end-users are interested in getting guidance from smart home ecosystems to help them with taking actions toward improved operation and sustainable behaviour.

Of course, the findings from this study must be considered in light of its limitations. 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 (Nayak & Narayan, 2019). However, they can be sometimes limited by participant inattentiveness and social desirability of answers/responses and can 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 participants' 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

Table 8. *t*-Tests for different thermal sensitivities.

Participants' responses	Thermal sensitivity	Num.	Mean	Std. dev.	*t*-value
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.

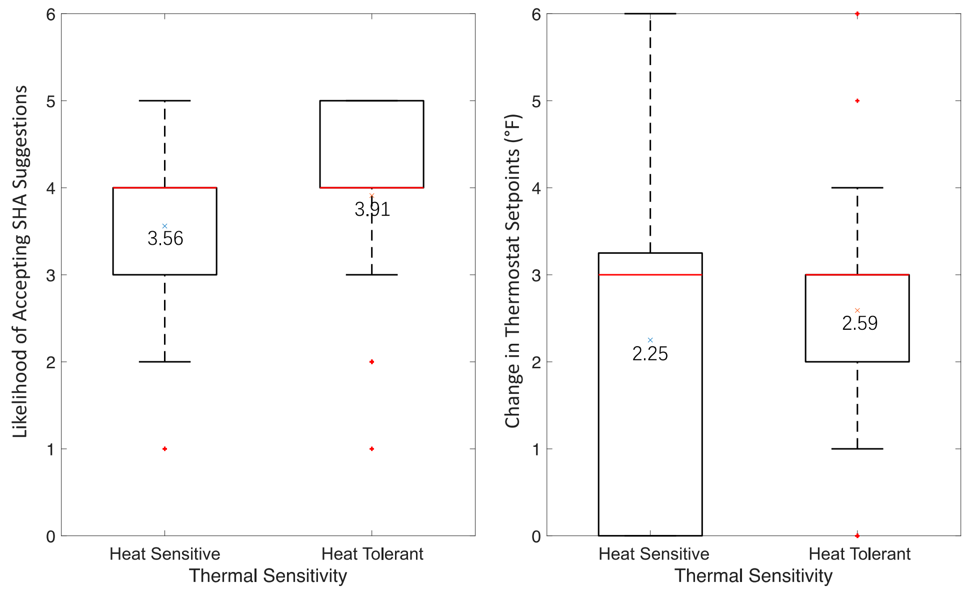

Figure 12. Impact of participants' thermal preference sensitivity on their responses to adaptive behaviour suggestions (left) and changing temperature setpoints (right).

examine the extent to which the predictive models are consistent across research settings and data-gathering approaches.

The quantification and forecast of the energy-saving potentials due to increase in thermostat setpoints could be used by the envisioned proactive SHAs to provide more informed suggestions on adaptive behaviour. In a related note, the variations of climate conditions for different geographical locations were not considered in evaluating participants' response and should be further investigated in the future. With the incorporation of the local climate data into the energy consumption estimation models, proactive SHAs can provide users with suggestions that are based on realistic energy use prediction, and thus initiate more efficient interactive conversations. Moreover, these prediction models could also account for energy-related behaviours based on history of interactions. 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 SHAs and the occupants in daily usage and the long run.

Conclusion

In this study, we investigated the impact of SHAs – proactive voice-based virtual assistants that can be integrated into smart home ecosystems – on user adaptation for energy-saving with a focus on thermal conditioning. In our envisioned system, SHAs could proactively provide guidance through adaptive behaviour suggestions to occupants in order to nudge them toward changing their energy-related behaviours in order to save energy. Through statistical analysis, it was found that conversational interactions had a significantly positive effect on the stated likelihood of accepting suggestions. This study also revealed that not all occupants were open to proactive interactions and that individual differences (such as prior experience with similar technologies, existing values, beliefs and perceived need for assistance) among users can predict positive responses to system nudges. To this end, knowledge of such differences among current or potential users could be leveraged by designers to build predictive models for tailoring interactions specifically in case of AI-powered nudging. The findings suggest that tailoring and implementing proactive modality in the development of smart home virtual assistants to promote human–building interaction has the potential to improve the energy efficiency of smart home ecosystems.

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