Nudging Occupants for Energy-Saving through Voice-based Proactive Virtual Assistants

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ABSTRACT

With the advancement of the Internet of Things (IoT) technologies, smart homes have promoted human-building interaction and sustainability in occupants' daily life. The rise of voice-based AI-powered virtual assistants has brought new potentials to provide occupants with a convenient and intuitive interface to interact with smart homes. Aiming at enhancing the human-building bi-directional communication, voice-based proactive virtual assistants integrated with smart home ecosystems – i.e., Smart Home Assistants (SHAs) – were investigated in this study. A comprehensive data collection was conducted through an online experiment, in which 307 valid questionnaire responses with participant's demographic background information and their feedback to proactive SHAs were collected. Occupants' perception of the proactive SHAs was evaluated among different groups of users with various demographic backgrounds. Five occupants' socio-demographic background features were identified to have a significant impact on their acceptance level to the energy-saving suggestions by proactive SHAs, including gender, age, education level, employment status, and the number of occupants in a residence. By utilizing these demographic features, ensemble learning models can predict occupants' perception of proactive SHAs with good performance (accuracy in the range of 0.69 to 0.75). Findings in this study will provide a valuable reference for academic researchers and industry practitioners in the development of personalized proactive smart home systems for human-building interaction.

INTRODUCTION

The smart home is a residence equipped with the internet of things (IoT) including sensors, devices, and appliances connected by a communication network that can be monitored and controlled by occupants remotely (Balta-Ozkan et al. 2013). Through ambient intelligence and automatic control, smart homes can respond to the occupants' needs and provide services accordingly (De Silva et al. 2012). Smart home technologies can improve the living environment of occupants by providing various kinds of services, such as remote and automatic control of the appliances and systems, healthcare support, home security monitor, and energy management for sustainability (Marikyan et al. 2019). With smart sensors and monitoring systems, smart homes can promote occupants' ecological awareness by providing information about their energy usage, and then help the occupants to save energy as well as to conduct environmental-friendly behaviors (Chen et al. 2017). In the interaction between occupants and smart homes, users usually interact with different systems through an integrated interface or a "Central Hub" to get information and give commands (Stojkoska and Trivodaliev 2017). Traditional interfaces are display-based, such as applications on smartphones or home central control dashboards (Gunge and Yalagi 2016). Nevertheless, the rise of voice-based smart home devices and accompanied artificial intelligence/virtual assistants in recent years, such as Amazon Alexa and Google Assistant, have brought a more convenient and intuitive interface for conversational interactions.

The voice-activated smart home devices like Amazon Echo and Google Home can enable users to conveniently perform daily functions by voice commands, such as requesting information or controlling home appliances or systems (Canziani and MacSween 2021). The integration of smart devices into the smart home ecosystems helps occupants control lights, HVAC (heating, ventilation, and air-conditioning) systems, and other appliances through natural languages. However, previous studies found that users tend to limit their interactions with the smart home devices in simple commands (e.g., turning lights on and off) and rarely try previously unexplored domains (Bentley et al. 2018), which cannot gain the optimal benefits of smart homes, especially in terms of energy efficiency. Therefore, we envisioned smart home devices that can not only react to users' verbal commands but also perform proactive interactions. It has been identified in previous studies that interactions initiated by virtual assistants is effective and can get positive evaluation from the users (Miksik et al. 2020). In this study, we further investigated whether proactive communication from the smart home assistant (SHAs) can affect occupants' adaptive behaviors for energy saving, specifically behaviors associated with thermal conditioning, which accounts for half of the energy consumption in residential buildings (Steemers and Yun 2009). To this end, a number of questions can be explored: How do users perceive the concept of proactive SHAs with automatic control over the thermal conditioning for energy-saving? How do users' demographic background affect their perception of SHAs, and their likelihood of accepting energy-saving suggestions from proactive SHAs?

In order to address the above-mentioned questions, in this study, we conducted an online experiment using questionnaires with members of the general public across the US. In these analyses, we used statistical tests and machine learning models to evaluate predictive power of demographic features. This study is positioned to offer additional insights to practitioners in the industry and the academics regarding the proactive interaction between smart homes and occupants. The research methods, and findings of this study will be further introduced in the following sections.

METHODOLOGY

Online questionnaire design. In this study, questionnaires were distributed online to collect participants' responses to SHAs' proactive interaction for energy-saving. The online data collection enabled us to reach a wide range of respondents across the US and to gain data from members of the general public with varied backgrounds. The questionnaire was in the form of an interactive questionnaire, which consists of three different sections: (1) Information about demographic background, (2) responses to a proactive interaction (energy-saving suggestions) from SHAs, and (3) preference on modes of interactions. Figure 1 shows different sections of the online questionnaire.

The first section of the questionnaire was designed to collect participants' demographic background information, which includes gender, age, ethnicity, education level, employment status, type of residence, and the number of occupants in a residence. Previous studies have identified that socio-demographic features are determinants of occupants' differences in energy-saving behavior (Yue et al. 2013) and their perceptions towards smart home technologies (Singh et al. 2018). For example, McLean and Osei-Frimpong (2019) found that there is a significantly positive relationship between household size (number of occupants in a residence) and the usage of in-home voice assistants.

In the second section of the questionnaire, participants were presented with a scenario, in which they are in a smart home with smart home assistants that have automatic control of the thermal conditioning. Through a number of videos, participants received proactive interactions with energy-saving suggestions related to an automatic change of the thermostat setpoint during a cooling season provided by Alexa from an Amazon Echo, and they needed to provide their likelihood of accepting the suggestions (Figure 1). Participants' responses were collected on an agreement-type scale from "Definitely No" to "Definitely Yes". We designed this section with scenario descriptions and video presentations to create a more realistic simulation of the interactions.

For the last section of the questionnaire, we collected participants' general acceptance to the form of proactive smart home assistants, i.e., how do they feel about smart home assistants starting the conversation and giving suggestions. We explored if the users would find it intrusive or unsuited if the conversations are initiated by smart home assistants. Their preference of the interaction mode can provide valuable reference for the feasibility of implementing proactive SHAs for effective communications.

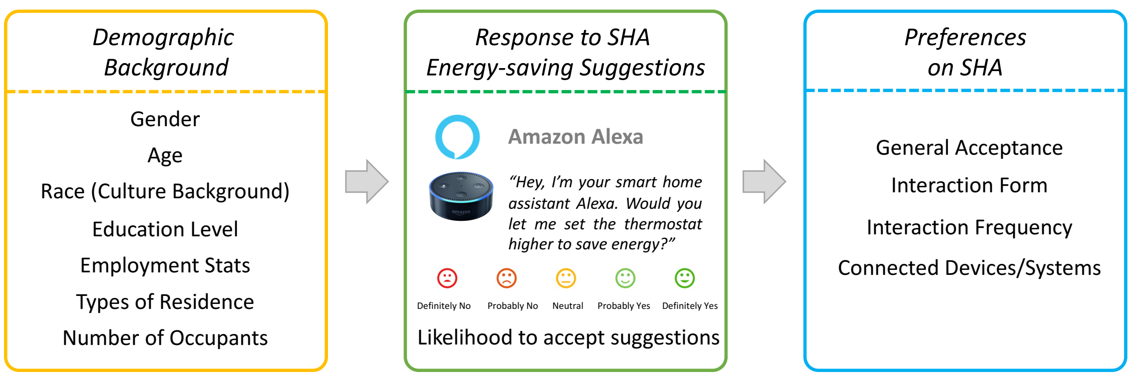

Figure 1. Online Questionnaire Structure

Data collection and analysis. Upon receiving an IRB approval, the questionnaire was distributed online through Qualtrics data collection platform to recruit participants. A validation process was conducted on the collected data based on participants' responses to a pre-set validating question and time to complete the questionnaire. After data cleaning and excluding unfinished responses, 307 valid responses were selected as the database for further investigation. We pre-processed the data by transforming the agreement-type scale responses into numeric values. Specifically, we transformed participants' likelihood of accepting SHA suggestions and acceptance of proactive mode of communication into values in the range between 1 and 5.

The data was then processed through descriptive statistics and Analysis of Variance (ANOVA) tests. Compared with t-tests, ANOVA tests can conduct comparison of more than two groups of means. The method assesses the relative size of between-group variance (variation between group means) compared to the within-group variance (variation within a group) and renders the result of the test - F-statistics (Kim 2014). However, only the significance (p-value) of the F-statistics can indicate if the group means are different or not. To reveal which groups are significantly different from others, Tukey's post-hoc tests were also conducted in this study to perform pair-wise comparisons (Pohlert 2014).

These ANOVA tests can identify the influential features in participants' demographic background that significantly affect their responses to proactive energy-saving suggestions and their preferences on SHAs' proactive mode of interaction. Using these influential features, we also developed ensemble learning classification models to predict users' responses and preferences. The ensemble learning models were utilized to evaluate the predictive power of the influential demographic features and enabled the SHAs to identify user's potential responses to the interactions. Ensemble learning is a method mainly used to improve the performance of a task (e.g., classification or prediction), in which multiple models, such as classifiers, are strategically generated and combined (Polikar 2012). Empirical studies have shown that the ensemble learning technique that contains multiple classifiers can significantly improve the generalization performance of the model (Li et al. 2014). Before training the models, all the dependent variables (e.g., acceptance to proactive SHAs) were transformed into binary classes. For the ensemble learning, two levels of models were built: the base models and the meta model. The base models (classifiers) included Logistic Regression, KNN, Decision Tree, Support Vector Machine, and Naïve Bayes. Then the outputs of these classifiers were combined in the meta model with a stacking fusion strategy (Divina et al. 2018).

RESULTS AND FINDINGS

Sample characteristics. The general sample characteristics of collected data is shown in Table 1. It can be seen from the table that features like gender, education level, employment status, and the number of occupants in a residence were uniformly distributed. In terms of age distribution, the college-level and young adult age groups had a greater number of participants since the questionnaire was distributed online and potentially not so accessible to the older generation. In terms of ethnicity distribution, the majority of the participants were Caucasian (74%). For the type of residence, two-thirds of the participants lived in single-family homes, and the rest lived in apartments.

The responses including both likelihood of accepting SHAs' energy-saving suggestions and perception of proactive mode for SHAs were also presented in Table 1. It can be seen that most of the values of responses were above 3.0 (neutral), which indicated that in general participants were likely to accept the SHAs energy-saving suggestions and had a generally positive perception of proactive SHAs. Compared with females, male participants were more receptive to the concept of proactive SHAs. In terms of different age groups, younger adults were more likely to respond positively to the suggestions than the older participants. For the education level, participants with higher levels of education had higher mean values of responses. The unemployed participants (including students, retired individuals) were more likely to reject the energy-saving suggestions and had a negative perception of proactive SHAs compared to the full-time employee group. Participants' responses were not differentiated from each other in terms of the ethnicity and type of residence. For the number of occupants in a residence, participants who lived with family (including children) were comparatively more receptive to the proactive mode of interactions for energy-saving.

Influence of demographic background. To further investigate the influence of demographic background on participants' responses, we conducted ANOVA tests and Tukey Post hoc tests on seven demographic features. The results are as presented in Table 2. The F-statistics and p-values of the likelihood (of accepting suggestions from SHAs) and acceptance (of proactive of mode interactions) variables indicate a non-significant effect of the ethnicity and type of residence features, which is aligned with the observation from Table 1. The Post hoc test results indicate that the participants' age, gender, education level, number of occupants in a residence can significantly affect participants' responses. We compiled the Tukey test results and listed the identified groups with significant differences as shown in the right-most column of Table 2, in which the dashes separate the significantly different groups. For example, for the gender feature, males and females were significantly different from each other, and for the age feature, the senior age group was significantly different from the other groups.

Table 1. Sample characteristics and participants' responses to proactive SHAs

Demographic Background		Number of Participants	Percentage	Likelihood of accepting suggestions (Mean)	Acceptance of proactive SHAs (Mean)
Gender	Male	161	52%	3.90	3.86
	Female	144	47%	3.45	3.30
	Non-binary	2	1%	3.50	2.00
Age	18-24 (College Age)	43	14%	3.56	3.28
	25-44 (Young Adult)	197	64%	3.86	3.76
	45-64 (Older Adult)	33	11%	3.70	3.58
	65 years and over (Older)	34	11%	2.65	2.71
Ethnicity	African American	25	8%	3.68	3.44
	Asian	21	7%	3.76	3.52
	Caucasian	228	74%	3.64	3.55
	Hispanic/Latino	27	9%	3.78	3.63
	Native American	6	2%	3.83	4.17
Education Level	Less than high school	16	5%	3.19	2.81
	High school graduate	72	23%	3.25	3.01
	Some College	31	10%	3.19	3.52
	Bachelor's degree	121	39%	3.83	3.71
	Master's degree and above	67	22%	4.15	4.06
Employment Status	Full-time employee	158	51%	3.98	3.87
	Part-time employee	39	13%	3.49	3.56
	Self-employed	13	4%	3.92	4.08
	Unemployed	97	32%	3.19	2.98
Type of Residence	Single-Family Home	205	67%	3.68	3.57
	Apartment	102	33%	3.64	3.54
Number of Occupants in a Residence	Live by oneself	50	16%	3.22	3.06
	Live with significant other	71	23%	3.39	3.32
	Live with roommates	18	6%	3.72	3.94
	Live with family including parents	39	13%	3.54	3.26
	Live with family including children	129	42%	4.02	3.91

Table 2. ANOVA tests results on likelihood of accepting SHAs' suggestions and acceptance of proactive SHA modality

Demographic Background	Likelihood F-statistics	Acceptance F-statistics	Post hoc Test (Tukey test significantly different groups)
Gender	6.67**	10.77**	Male - Female
Age	13.46**	9.29**	Seniors - College age/Young adult/Older adult
Ethnicity	0.19	0.49	/
Education Level	9.72**	9.93**	Bachelor - Less than high school/ High school graduate/Some college
			Master and above - Less than high school/ High school graduate/some college
Employment Status	12.44**	13.60**	Unemployed - Full time/Part time/Self employed
			Full time - Part time
Type of Residence	0.09	0.03	/
Number of Occupants in a Residence	7.13**	7.52**	Live with family including children - Live by oneself/Live with significant other/Live with family including parents
			Live by oneself - Live with roommates

** p-value < 0.01; * p-value< 0.05

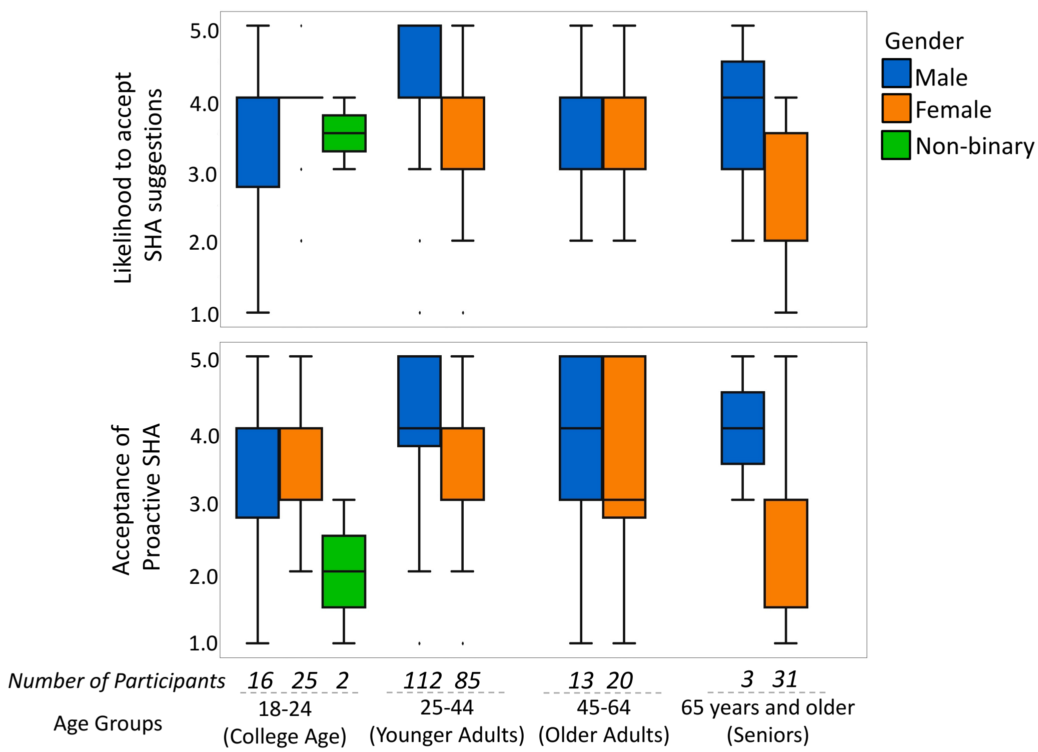

Figure 2. Influence of age and gender on participants' responses to energy-saving suggestions from SHAs and acceptance of proactive SHA modality

The main difference between two genders were shown in the younger adults' and the older adults' groups in Figure 2. Especially, for the younger adults, male users are more likely to accept the energy-saving suggestions from proactive SHAs. The gender difference may also be affected by the age feature as there were more female participants in the seniors' group and more male participants in the younger adults' group (Figure 2). Based on the Post hoc test results, the seniors' group (65 years and older) have significantly lower values of responses compared to the other age groups. This observation is reasonable as the younger generations might be more receptive to new technologies like proactive SHAs with home automation while the seniors might prefer to follow their traditional ways of control.

In terms of education level, participants with post-secondary education (bachelor's, master's, or higher degrees) were significantly more receptive to the proactive SHAs for energy-saving. When it comes to employment status, unemployed participants were more likely to refuse energy-saving suggestions and showed less interest in proactive SHA modality for energy-saving. The participants in the unemployed group included studentsand retirees. The employment status segmentation can also be shown in the age distribution as shown in Figure 3. Most of the full-time employed and the self-employed participants were in the young and older adults' groups, while the unemployed participants were majority in the college age and seniors' group.

For the number of occupants in a residence, we originally assumed that the groups with fewer occupants in a residence would be more receptive to the SHAs' suggestions for energy-saving given that they would be less likely to compromise the majority comfort. However, the post hoc test results indicated that participants living in a residence with more occupants are significantly more receptive to proactive SHAs, especially for the participants who live with family including children as shown in Table 2. For residences with more occupants and more usage of in-home voice assistants, the users are more familiar with the smart home devices and may be more receptive to the interactions with proactive SHAs, which aligns with the findings in previous studies (McLean and Osei-Frimpong 2019).

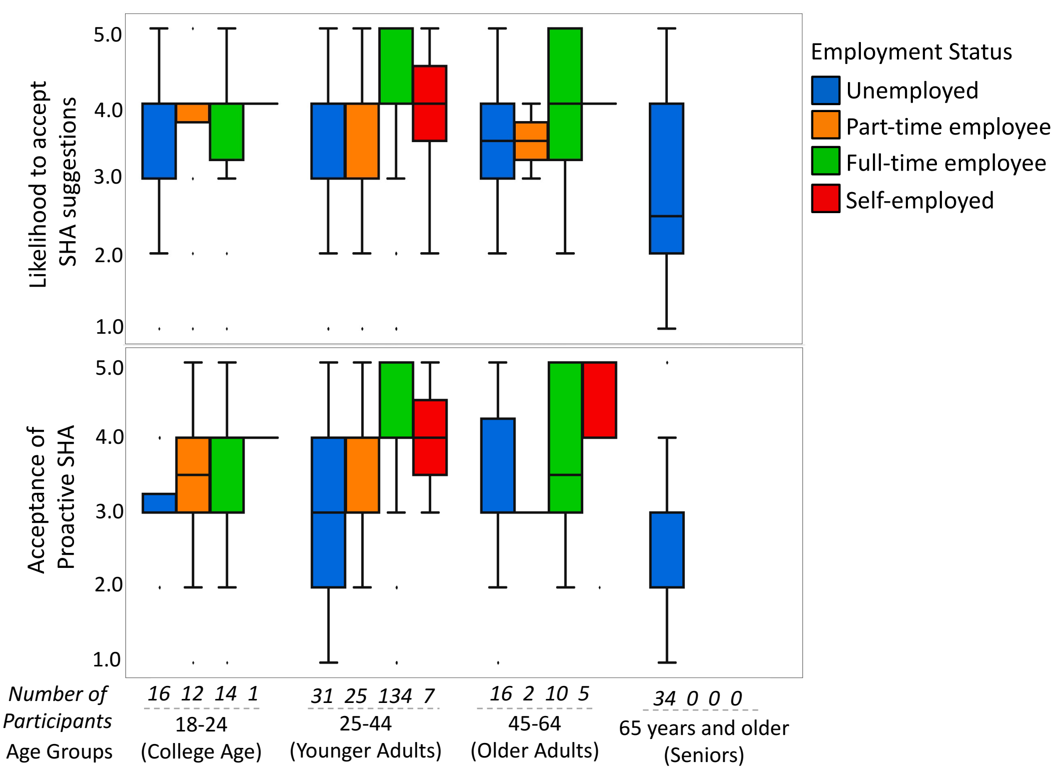

Figure 3. Influence of age and employment status on participants' responses to energy-saving suggestions from the SHAs and acceptance of proactive SHA modality

Ensemble learning models. We utilized ensemble learning modeling for the prediction of users' responses based on their demographic background information to evaluate the predictive power of these features. In previous sections, we identified that the ethnicity and type of residence do not significantly affect users' perception of the proactive SHAs. As such, in the ensemble learning model development, we excluded those two features and utilized the remaining five demographic features (gender, age, education level, employment status, number of occupants in a residence) for model training. To train the base models and meta models, we applied repeated k-fold cross validation (k = 5, repeated times = 3) and computed the classification accuracy as well as the f-score based on the demographic background features. By comparing the base models and the meta model (Table 3), the ensemble learning models reflect the best performance of the underlying base models. In predicting users' likelihood of accepting SHAs energy-saving suggestions, the ensemble learning model can reach an accuracy of 0.75 and a F-score of 0.71. In prediction of users' acceptance of proactive SHAs for energy-saving, the performance was comparatively lower with an accuracy of 0.69 and F-score of 0.68. The prediction models developed in this study can be applied in the future implementation of smart home assistants for personalized energy-saving suggestions based on occupants' background.

Table 3. Comparison among different classification models and ensemble learning model

Models	Likelihood		Acceptance	
	Accuracy	F-Score	Accuracy	F-Score
Logistic Regression	0.75	0.72	0.67	0.66
KNN	0.71	0.69	0.63	0.63
Decision Tree	0.68	0.68	0.65	0.66
Support Vector Machine	0.75	0.71	0.69	0.68
Naïve Bayes	0.72	0.71	0.68	0.68
Ensemble Learning	0.75	0.71	0.69	0.68

CONCLUSION

In this study, with the objective of enhancing the human-building bi-directional communication, proactive voice-based smart home assistants (SHAs) were investigated. We envisioned that the SHAs with smart home automation capabilities can proactively provide suggestions to occupants and nudge them to take energy-saving behaviors. We sought to explore how occupants' demographic background affects their reaction to and perception of proactive SHAs. To this end, we distributed an online questionnaire and collected 307 valid responses. We identified that in general, participants are receptive to the concept of proactive SHAs for energy-saving.

We found that there are five demographic features that could significantly impact (i) occupants' likelihood of accepting energy-saving suggestions from proactive SHAs, and (ii) their acceptance of proactive SHA modality for energy-saving, specifically in the context of thermal conditioning in buildings. These five features, including age, gender, education level, employment status, and number of occupants in a residence, are critical in driving users' response. The impact from some features was predictable according to previous studies, such as age and education level.

The younger age groups (including college age and young adults) were more likely to respond positively to proactive SHAs. Occupants with bachelor's degree and above are more likely to accept the suggestions from proactive SHAs. However, some other variables were beyond our expectation in terms of their impact on perception of proactive SHAs, such as gender, employment status, and the number of occupants in a residence. Through an online experiment, we found that males were more receptive to proactive SHAs compared to females. For the employment status, unemployed occupants (including students, homemakers, and retirees) were more likely to refuse energy-saving suggestions from proactive SHAs. Occupants who live in residences with a larger number of occupants (occupants who live with family including children) were found to be more receptive to proactive SHAs for energy-saving with a significant difference compared to other groups in post hoc tests. The ensemble learning models, developed based on five classical classification algorithms, and by using the five identified important demographic features, were showed to predict occupants' response (reflected in two classes) with relatively high accuracy in the range of 0.69 to 0.75 and F-score in the range of 0.68 to 0.71 for the likelihood of accepting suggestion and acceptance of the proactive SHA modality, respectively. Using such ensemble learning models, personalized proactive SHAs can be built for more efficient interaction with users.

In summary, findings in this study fill the gap of limited previous studies on users' interaction with proactive SHAs, and the impact of occupants' demographic background on such interactions. The academic researchers and the industry practitioners can both benefit from this study when they are developing personalized proactive smart home assistants for energy efficiency. Limitations exist in this study considering that there are several other features that differentiate individual differences when it comes to human-technology interactions such as beliefs, values, experience with technologies, etc. Therefore, more studies are needed to explore other features that have potential predictive power on users' perception of proactive SHAs. In-person field studies are also needed to further investigate how real-world interactions with proactive SHAs will affect users' perception and reactions.

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