Intelligent Agents to Improve Thermal Satisfaction by Controlling Personal Comfort Systems Under Different Levels of Automation

Ashrant Aryal, Burcin Becerik-Gerber, Gale M. Lucas, and Shawn C. Roll

***Abstract*—Heating, ventilation, and air conditioning (HVAC) systems account for 43% of building energy consumption, yet only 38% of commercial building occupants are satisfied with the thermal environment. The primary reasons for low occupant satisfaction are that HVAC operations do not integrate occupant comfort requirements nor control the thermal environment at the individual level. Personal comfort systems (PCSs) enable local control of the thermal environment around each occupant. However, full manual control of PCS can be inefficient, and fully automated PCS reduces an occupant's perceived control over the environment, which can then lead to lower satisfaction. A better solution might lie somewhere between fully manual and fully automated environmental control. In this article, we describe the development and implementation of an Internet-of-Things (IoT)-based intelligent agent that learns individual occupant comfort requirements and controls the thermal environment using PCS (i.e., a local fan and a heater). We tested different levels of automation where control is shared between an intelligent agent and the end user. Our results show that PCS use improves occupant satisfaction and including some level of automation can improve occupant satisfaction further than what is possible with manually operated PCS. Among the levels of automation investigated, inquisitive automation, where the user approves/declines the control actions of the intelligent agent before execution, led to highest occupant satisfaction with the thermal environment.**

***Index Terms*—Building automation, indoor environments, smart buildings, smart systems, thermal comfort.**

I. Introduction

THE Internet of Things (IoT) has opened the possibilities of real-time data acquisition and analysis for making decisions in a diverse range of applications. In the context of smart buildings, these advancements have opened the possibilities of improving occupant comfort, satisfaction, health and productivity while improving energy efficiency, performance monitoring, fault diagnosis and predictive controls of building systems [1]–[3]. Indoor environmental quality (IEQ) parameters (i.e., air quality, ventilation, thermal environment, lighting, and acoustics) are associated with comfort, productivity, creativity, physiological and psychological health, and well-being of building occupants. Among different IEQ parameters, occupants in commercial buildings ranked their thermal environment to be poorer than other IEQ parameters, such as air quality and noise [4]. ASHRAE 55, which provides guidelines for the control of the thermal environment requires building systems to satisfy more than 80% of building occupants [5]. However, heating, ventilation, and air conditioning (HVAC) systems fail to maintain satisfactory indoor conditions for the majority (62%) of building occupants [6], despite consuming about 43% of total building energy [7]. Dissatisfaction with the indoor environment in commercial buildings results from the mismatch between occupant requirements and the actual indoor conditions. Specifically, the "one size fits all" operation of centralized HVAC systems and the inability of these centralized systems to control the environment at a more granular level than building zones, do not account for individual occupant requirements [8]. Personalizing the environment by controlling IEQ parameters to match occupant requirements has the potential to improve comfort, productivity, and well-being. It has been estimated that potential productivity increase in the range of 0.5% to 5% is possible by improving the thermal and lighting conditions, which translates to an annual productivity increase of \$19 billion to \$190 billion in the U.S. alone [9]. Among different aspects that are influenced by the indoor thermal environment, this study primarily focuses on improving occupant satisfaction because avoiding dissatisfaction can lead to improved productivity [10], occupants are generally satisfied with the thermal environment when they are comfortable [5], and the associated energy costs are relatively small compared to potential gains from improved occupant satisfaction [9].

In our previous study, we developed a framework for an intelligent agent (a smart desk) to personalize different environmental conditions (thermal, visual, ergonomics, etc.) around each occupant by using different IoT sensors to monitor the environment, machine learning (ML) algorithms to learn occupant requirements and preferences, and artificial intelligence (AI)-based decision making to control the environment using local actuators [11], [12]. In this article, we describe the development of an IoT-based intelligent agent that can personalize the thermal environment around each occupant

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using different levels of automation. We also present results from a 15-week field study, in which we deployed our intelligent agent in 14 different offices to answer the question: How does occupant satisfaction vary among different levels of automation for personal comfort system (PCS) devices?

II. Related Work

At the most basic level, an intelligent agent is capable of perceiving its environment through sensors, deciding the right action, and acting upon the environment through actuators [13]. In the context of thermal environmental control, perceiving the environment involves understanding the comfort state of occupants, deciding the right action involves understanding what action will improve occupant satisfaction based on their comfort state, and actuation involves controlling the thermal environment. In the subsequent paragraphs, we present a brief overview of the literature relevant to the development of an intelligent agent from the perspective of the agent perception, decision making, and actuation of the indoor thermal environment.

Thermal comfort models currently adopted by international guidelines, such as ASHRAE 55 [5], include the predicted mean vote/predicted percent dissatisfied (PMV/PPD) models developed by Fanger [14] and adaptive model developed by de Dear *et al.* [15]. The PMV/PPD model was developed based on heat balance of the human body, and the adaptive model improved the PMV/PPD model by considering different adaptive opportunities (e.g., opening windows or changing clothing levels) that occupants have in some buildings. Both the PMV/PPD model and adaptive model do not accommodate for individual differences in thermal comfort requirements, which has led researchers to focus on developing personalized comfort models [16].

Personalized comfort models typically map environmental and/or physiological sensor measurements to thermal sensation, satisfaction, or preference obtained from direct feedback from occupants via participatory sensing using different ML algorithms. Thermal sensation is typically assessed on a 7-point Likert Scale ranging from -3 (cold) to $+3$ (hot), reflecting how occupants feel in their thermal environment. Thermal satisfaction is typically assessed on a similar scale ranging from -3 (very dissatisfied) to $+3$ (very satisfied) and reflects how satisfied occupants are with their thermal environment. Some commonly used sensing methods for building personalized comfort models involve environmental sensing of ambient temperature, humidity, radiant temperature, and air speed [17], [18], and physiological sensing of skin temperature from different regions of the body [19], [20]. Other sensing methods, such as electroencephalogram (EEG), heart rate, heart rate variability have also been shown to be useful in personal comfort modeling [21], [22]. Different ML algorithms, such as the Bayesian networks, support vector machines, random forest (RF), K-nearest neighbors (KNNs), linear discriminant, and artificial neural networks [23]–[25] have been utilized for personal comfort modeling. A detailed review of personal comfort models can be found in [16], and a comparison of some common sensing methods and ML algorithms for personal comfort modeling can be found in [23] and [24]. Sensing and ML-based approaches enable the intelligent agent to perceive occupant comfort.

Actuation for the thermal environment consists of either changing the temperature setpoint of the HVAC system, controlling windows, and shading systems or use of PCSs, such as local fans and heaters. Although the control of HVAC systems based on occupant requirements can improve occupant satisfaction from around 38% to 63%, HVAC systems are usually unable to control the thermal environment at a granular level around each occupant, which leads to lower satisfaction when multiple occupants are in the same HVAC zone [8]. Several studies have shown that PCS devices can provide small adjustments to the thermal environment at an individual level and improve occupant satisfaction [26]–[28]. The corrective power of PCS devices, which is defined as the difference between two ambient temperatures at which the same thermal sensation is achieved—one with PCS and one without PCS [27]—varies based on the PCS devices used. Previous studies have shown that air jets have a corrective power of -2 °C to -4 °C depending on the air speed and ambient temperature [27]–[29]; whereas, a small desk-fan has a corrective power of -1.5 °C [28]. The corrective power of a heated chair is about 1.25 °C, a foot and leg heater is about 7 °C–10 °C, a heated wrist pad is about 0.75 °C, and a heated shoe insole is about 0.26 °C [28], [30]. The actual ability to correct for thermal discomfort of the PCS devices depends on the type and size of device, the perception of the user, and the ambient conditions. However, previous studies provide strong evidence that PCS, especially fans and heaters, can be successfully used in cool to warm environments in the range of 18 °C–28 °C to maintain comfortable conditions for occupants [27], [28].

From a decision-making perspective, evaluating the right action by an intelligent agent depends on the objective of the control logic design. Most of the work in building automation has focused on completely automating the control of building services, such as HVAC systems, lights, blinds, and shades [1], [31], [32]. For control of the thermal environment, efforts to evaluate different control strategies have mostly focused on HVAC systems. Different HVAC control strategies have been developed and evaluated in field studies to reduce energy consumption while maintaining comfortable conditions based on the PMV model occupant's adjustment to thermostats, and direct occupant setpoint selection by participatory sensing [33]–[36]. Approaches to select temperature setpoints based on comfort requirements of multiple occupants in the same zone have also been explored, for example to maximize consensus [37] or minimize aggregate occupant discomfort plus energy cost [38]. A review of field implementations of occupant-centric HVAC, lighting, and shading systems control is available in [36]. To the best of our knowledge, field studies that used PCS devices for controlling the thermal environment have left the PCS devices to be manually controlled by the occupant. There is a need to develop and explore automated controls for PCS devices to remove the burden of control from the end user, improve user satisfaction, and reduce inefficiencies caused by the manual operation of PCS devices.

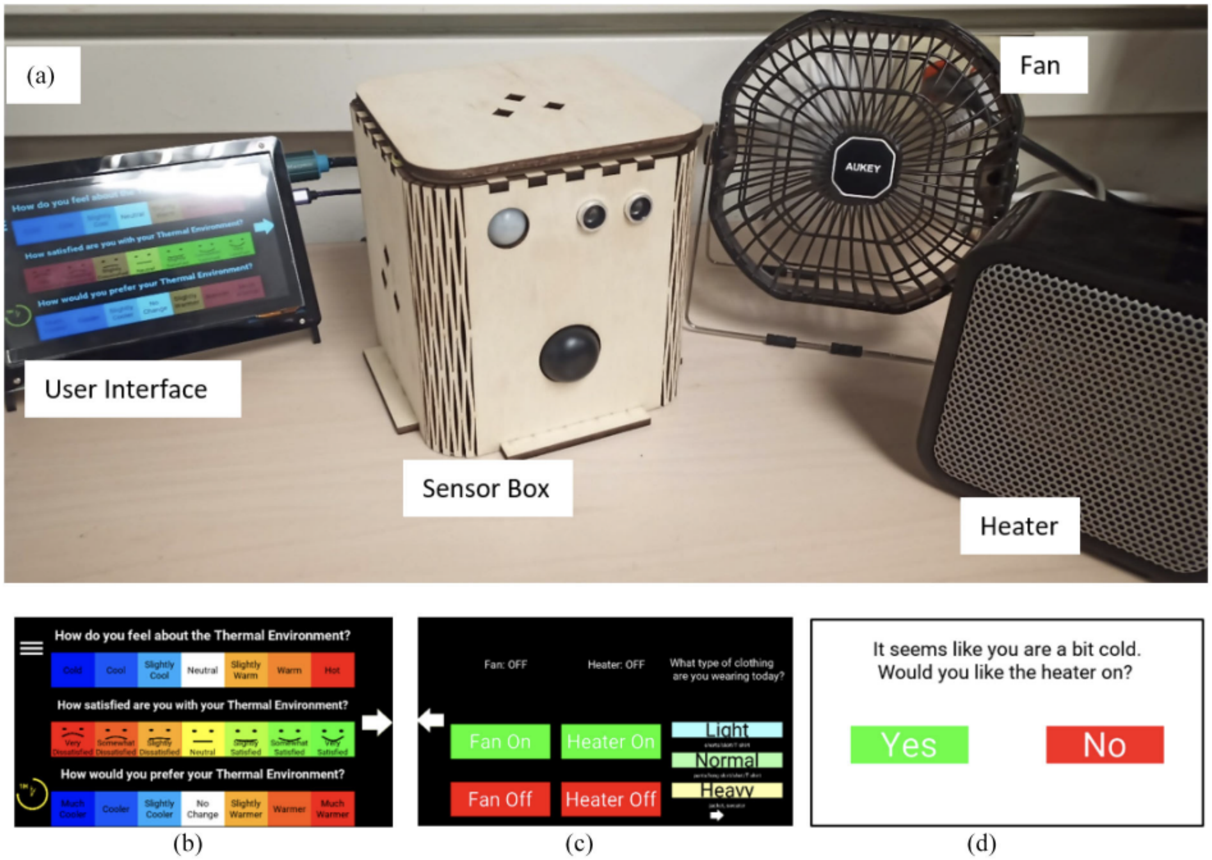

Fig. 1. System setup. (a) Image of different hardware components. (b) UI screen for providing comfort ratings. (c) UI screen for manually controlling fan/heater and providing clothing information. (d) UI screen where system seeks user approval.

In addition to the physical conditions that affect thermal comfort, psychological expectations of the occupant also play a crucial role in occupant satisfaction and need to be considered during decision making by an intelligent agent. Studies have shown that occupants with a higher perception of control over their thermal environment have a higher satisfaction in both indoor [39] and outdoor environments [40] even when the physical conditions were the same. Providing actual control over the environment leads to a larger improvement in thermal satisfaction compared to only having perceived control [39]. Furthermore, occupants with greater perceived control over the environment are likely to tolerate greater levels of discomfort [39]. In field studies where shading systems were fully automated, most of the occupants switched off the automatic mode [41] or corrected the control actions made by the automation system nearly half the time [42]. A potential reason for low acceptance could be that completely automated systems take away an occupant's control over the environment, leading to lower satisfaction [43]. A possible solution to overcome the drawbacks of full automation could be providing adjustable autonomy, where decision making is shared between an intelligent agent and the user [44]. Levels of automation vary across a continuum between fully manual and fully automated conditions, and different taxonomies ranging from 4 to 12 distinct levels of automation have been proposed [45]. One study that focused on automation preferences for appliance controls in residential homes found that although occupant preferences toward automation of different appliances varied depending on the context, personality, and demographic characteristics, no automation could be identified as the least preferred option [46]. These studies suggest that there is no single solution that is likely to satisfy all users, and automation systems should be designed to operate under multiple levels of shared control between the intelligent agent and the end user.

III. System Description

The prototype system includes a sensor box containing different sensors to monitor environmental parameters and control the PCS devices as shown in Fig. 1. The sensor box is connected to an Arduino Uno and Raspberry pi, a small desk fan and a small heater that can be wirelessly controlled using a smart plug, and a touchscreen with a custom interface where users can provide feedback regarding their comfort and can control the connected fan or heater. The intelligent agent, implemented on the Raspberry pi, can also control the fan and heater. Levels of automation were adopted based on Ahmadi-Karvigh *et al.* [46] where user preference toward different levels of automation is applied to building systems and appliances, as compared to automation taxonomies developed for avionics, manufacturing, and other domains [45]. Specifically, our agent used four levels of automation.

1) *No Automation (Manual Control):* The agent does not perform any control actions and PCS devices are controlled manually by the user.

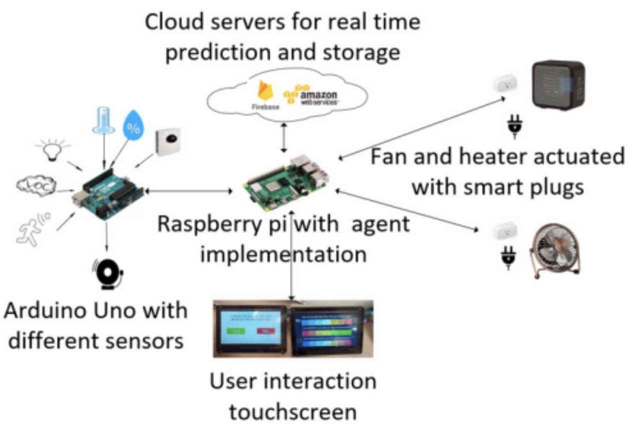

Fig. 2. Illustration of the hardware architecture.

2) *Inquisitive Automation:* The agent predicts the user's comfort state, computes an appropriate PCS control action, and asks for the user's approval before executing the control action.
3) *Adaptive Automation:* The agent learns the user's patterns over time of approving/declining control actions. The agent automatically executes the control actions when it predicts that the user will approve/decline the control action and asks for user's approval when it is not certain.
4) *Full Automation:* The agent computes appropriate control action and automatically executes the control action without any input from the user.

A. System Architecture

The system consists of a sensor box with sensors to monitor ambient temperature, relative humidity, radiant temperature, motion, distance, volatile organic compounds (VOCs) concentration, and lighting levels. These sensors are connected to an Arduino Uno that relays the sensor measurements to a Raspberry pi, which then sends the sensor data to a cloud server every 30 s. ML models on the cloud server use these data to predict the comfort and satisfaction of the user while the thermal environment and control algorithms evaluate the appropriate actions to adjust the thermal environment. These control actions are transmitted back to the Raspberry pi which can actuate the local fan or heater or ask the user for approval using a custom user interface (UI). The custom UI runs on a 7-inch touchscreen where the agent can place requests to the user, thereby enabling bidirectional communication, as well as allowing users to provide comfort ratings or manually control the fan/heater. The entire system is built using open-source hardware combined with custom software developed in Python, which provides a high degree of flexibility to modify and update the system as needed. The overall system architecture is shown in Fig. 2. It is important to note that the desk fan and heater used in this study had only one level of operation when turned on. The fan was a low voltage USB fan capable of producing air speeds of 1.2 m/s at a distance of 1 m. The heater was a fan-forced 500-W ceramic space heater that provided heat by both radiation and convection.

B. Training of Personal Comfort Models

The agent uses personal comfort models trained using ML algorithms for each user to predict thermal sensation and thermal satisfaction separately. Even though it is typically assumed that occupants are satisfied under a neutral thermal sensation, it is important to predict thermal sensation and satisfaction separately for controlling the thermal environment because it is possible for an occupant to be satisfied under cool or warm sensation or dissatisfied under neutral sensation. Users report thermal sensation and thermal satisfaction on the 7-point Likert scales ranging from -3 to $+3$ through the UI; these ratings are used to create training labels. Thermal sensation votes (TSVs) are grouped into three classes: 1) cold (TSV $\in \{-3, -2\}$); 2) comfortable (TSV $\in \{-1, 0, +1\}$); and 3) hot (TSV $\in \{+2, +3\}$), and thermal satisfaction ratings are grouped into two classes: 1) satisfied (satisfaction rating $\in \{0, +1, +2, +3\}$) and 2) dissatisfied (satisfaction rating $\in \{-1, -2, -3\}$). These groupings are based on ASHRAE 55 suggestions for determining thermal satisfaction and acceptability from the Likert scales [5]. Different features that capture the average value of sensor measurements and changes in sensor measurements (first derivative) in the last 1, 5, 10, and 30-min time windows prior to each comfort rating are extracted from the indoor temperature, humidity, and radiant temperature measurements. In addition to the indoor measurements, clothing level, heater and fan states (on or off), time of day, outdoor temperature, humidity, and apparent temperature (which combines the effects of temperature, humidity, and air speed) are included. Due to the large number of extracted features, feature selection is performed using chi-squared statistic between the features and the training class to select the 15 most useful features. The ML comfort models map the extracted features to user ratings of thermal sensation and thermal satisfaction.

RF and KNNs models are trained using fivefold cross validation for predicting thermal sensation and thermal satisfaction separately for each participant. The models with the highest accuracy between the two algorithms are selected for each participant. RF and KNN algorithms were selected based on their usefulness in predicting thermal sensation and satisfaction in our previous studies [23], [24]. The overall model training approach is similar to our previous studies and the detailed procedure for model training can be found in [23] and [24]. Although the users can also indicate their thermal preference on the UI (whether they would prefer to have a warmer or cooler environment), the current implementation of the agent does not use a preference-based model because this study focuses on improving thermal satisfaction. A similar model training approach could be used to train preference-based models if needed.

C. Control Logic

Because this study focuses on improving thermal satisfaction, and people can be satisfied even if they feel warm or cold based on their preference, the agent first predicts thermal satisfaction for all levels of automation. If the user is predicted to be satisfied, the agent does not take any action. If the user is predicted to be dissatisfied, the agent predicts

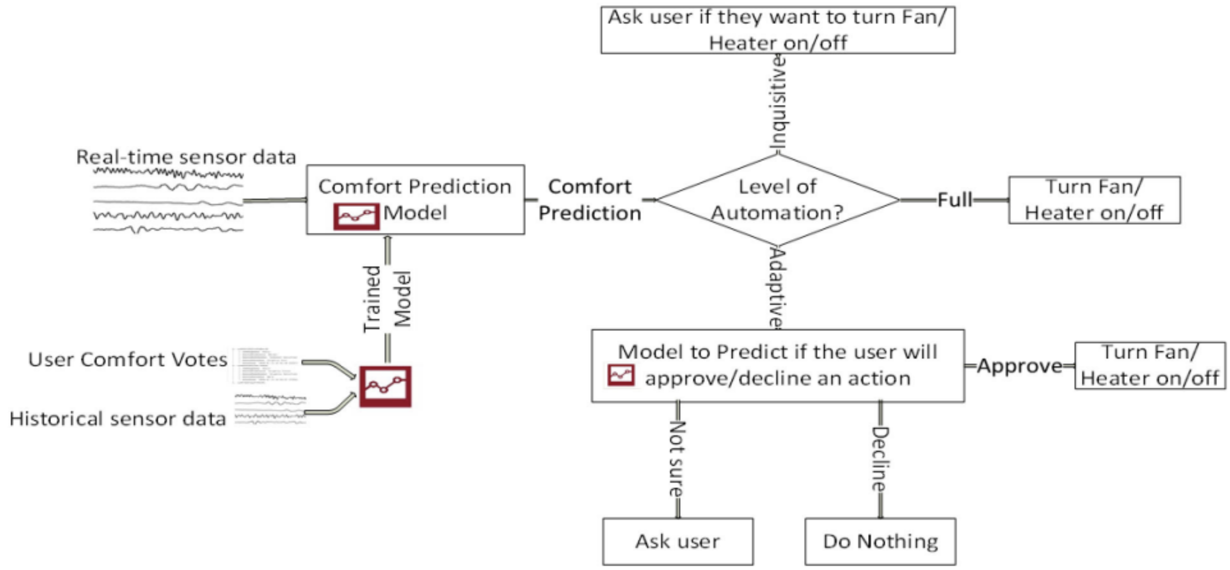

Fig. 3. Control scheme for different levels of automation.

the user's thermal sensation and selects an appropriate control action based on thermal sensation and the current state of the fan and heater as shown in Table I. The training duration for each model was less than 2 min per participant. It is important to note that since the models were only updated between phase 1 and phase 2 rather than continuously, the duration for model training was not a key consideration in this study. The agent then follows the control logic in Fig. 3 to determine if interaction with the occupant is necessary or not, depending on the level of automation.

A new prediction is made by the agent every 30 s. The agent needs to be able to predict changes that might occur in a continuous fashion and take an action before the user decides to make manual adjustments. A shorter time interval increases the chances of the agent being able to take control actions before the user does but also increases the communication costs to the cloud server. A longer time interval reduces the communication costs but also reduces the chances of the agent being able to take control actions before the user does. Therefore, the time interval of 30 s was deemed reasonable where the agent would be able to take a control action before the user does so in a relatively continuous way without incurring high communication costs.

For each level of automation, the control scheme is slightly different. Fig. 3 provides a high-level overview of the control logic for each level of automation. For inquisitive automation, the agent always asks the user if they would like to turn the fan/heater on/off based on the state transitions shown in Table I. For full automation, the agent automatically executes the control actions based on state transitions in Table I. For adaptive automation, a clustering-based model is used to classify if the user is likely to approve or decline the control action based on all of their previous approve/decline interactions with the agent under inquisitive and adaptive automation. For the adaptive action model, the cluster center and radius are calculated for each approved/declined action based on the possible comfort states and state transitions shown in Table I with the

TABLE I
CONTROL ACTIONS BASED ON COMFORT AND PCS STATES

Comfort State	Fan On	Heater On	Both Off
Satisfied	No Change	No Change	No Change
Dissatisfied, Cold	Fan Off, Heater On	No Change	Heater On
Dissatisfied, Warm	No Change	Heater Off, Fan On	Fan On
Dissatisfied, Neutral	No Change	No Change	No Change

Euclidian distance as the distance metric. The clustering model uses the same features used for thermal sensation prediction. If a new observation falls within 75% of the cluster radius of a cluster center and does not overlap with another cluster, then the new observation is classified with the same label as the corresponding cluster and the control action is automatically executed without asking the user in the Adaptive Automation control scheme. The threshold of 75% cluster radius for determining membership to a cluster is used to reduce the influence of any single data point on changing the cluster center and radius, making the model more stable. If the new observation overlaps with two or more clusters or does not belong to any cluster, then the agent asks the user to approve/decline the control action similar to Inquisitive Automation.

IV. Implementation and Validation

To validate the agent and to answer the research question: "how does occupant satisfaction vary among different levels of automation of PCS devices?" we conducted a study with a 15-week deployment of the PCS prototype in 14 offices to evaluate each of the levels of automation. The study was conducted from October 2019 to March 2020 with breaks in data collection during official holidays. The study was approved by the university's institutional review board, and an informed consent was obtained from each participant prior to enrolling them in the study.

TABLE II
TECHNOLOGY READINESS OF PARTICIPANTS

Scale	Average	Standard Deviation
Optimism	4.3	0.6
Innovativeness	3.3	1.1
Discomfort	2.7	1.0
Insecurity	3.4	0.8
TRI 2.0 score	3.4	0.5

A. Participants and Location

Participants were administrative staff (9), research staff (3), faculty (1), and a graduate student (1) at the University of Southern California (USC). Four participants were male and ten were female. The age of the participants ranged from 23-years to 56-years old with an average age of 39 ± 10 years. Participants completed the technology readiness index (TRI) 2.0 [47] to identify the propensity to adopt and embrace technology at home and work on a scale of 1 (low) to 5 (high) with 3 being a neutral score. The TRI 2.0 evaluates four dimensions of optimism, innovativeness, discomfort, and insecurity toward technology. Our participants scored slightly higher than neutral in the overall TRI 2.0 scale and were generally very optimistic as shown in Table II.

Eight participants worked in a private office and six participants worked in private cubicles within a shared office space. The sensor box, UI and the fan shown in Fig. 1 were placed on the participants' desks and the heaters were placed on the floor close to the participants' feet. The participants were free to choose the exact placement of the system components on their desks. The participants were distributed in four different buildings located in three separate USC campuses in Los Angeles, California. According to the Koppen–Geiger climate classification [48], Los Angeles has a warm-summer Mediterranean climate and has relatively small fluctuations in outdoor weather conditions. During the data collection period, the average daily temperature was 16.5 ± 2.2 °C, with an average daily maximum of 20.8 ± 2.8 °C and average daily minimum of 12.6 ± 1.8 °C. The average indoor temperature recorded by the system was 26.4 ± 2.2 °C. The minimum and maximum recorded indoor temperatures were 22.5 ± 1.9 °C and 30.1 ± 1.8 °C, respectively.

B. Data Collection

The study consisted of two phases, phase 2 where the level of automation was gradually increased and phase 2 where the level of automation was randomized. Phase 1 began with a baseline condition lasting about three weeks where no PCS devices were used by the participants, followed by two weeks for each level of automation sequentially increased from no automation to full automation as described in Section III, totaling 11 weeks. Phase 2 consisted of one week for each level of automation, totaling four weeks. In phase 2, the order of the level of automation was randomized for each participant to avoid potential biases resulting from changes in outdoor thermal conditions or order effect from gradually increasing the level of automation. Phase 2 did not include a baseline condition because taking away PCS devices from the participants might have caused a biased response in occupant satisfaction due to the loss of control rather than the physical aspects of the thermal environment.

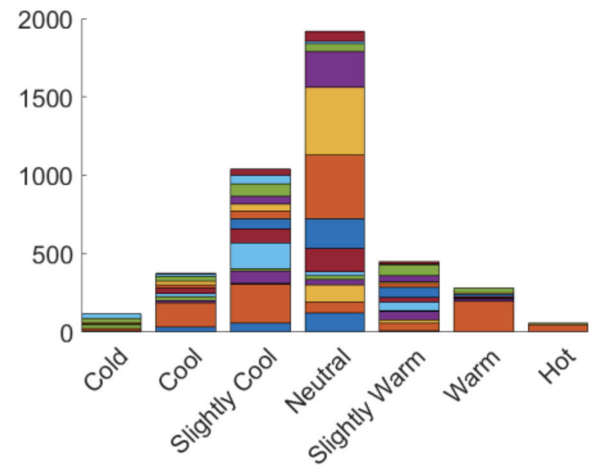

Fig. 4. Distribution of TSVs collected during the study from all participants. Colors indicate different participants.

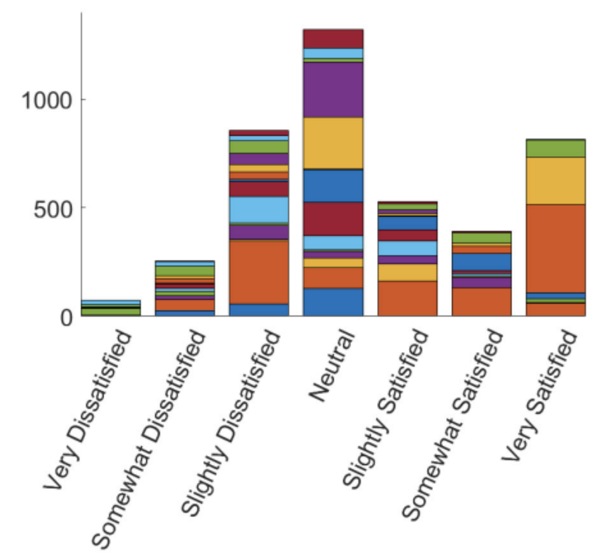

Fig. 5. Distribution of thermal satisfaction votes collected during the study from all participants. Colors indicate different participants.

For each level of automation, the participants were asked to periodically rate their thermal sensation (cold to hot), thermal satisfaction (very dissatisfied to very satisfied) and thermal preference (want much cooler to want much warmer) on the 7-point Likert scales using the UI at their convenience. Figs. 4 and 5 show the overall distribution of thermal sensation and thermal satisfaction votes collected during the entire study. It is important to note that even though the 7-point Likert scales were used to collect comfort votes, the model training and prediction were done by grouping the comfort votes as described in Section III-B. The system used a gentle vibration of the sensor box to remind the participants to rate their comfort every hour when the motion sensor detected that the participant was present. Participants were also asked to report their clothing information in the morning when they

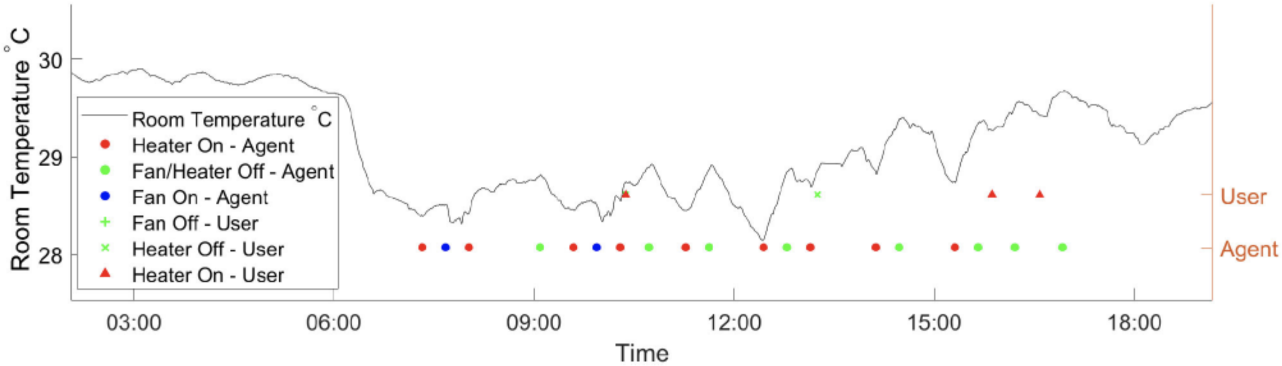

Fig. 6. Illustration of system and user interactions over a day under the full automation level.

arrived at the office and during the day if their clothing level changed (e.g., putting on a jacket). At the end of each level of automation in phase 1 and phase 2, participants were asked to rate their overall satisfaction for the level of automation used. One of the participants did not complete the Full Automation level in Phase 2 because of University shutdown due to COVID-19 but completed all other levels of automation. All other participants completed the entire study.

For phase 2, the comfort models were trained using the data from the baseline and No Automation period. The comfort models were then used to predict thermal satisfaction and thermal sensation for inquisitive, adaptive, and full automation levels. Before starting the data collection for phase 2, we updated the models using data from all levels of automation in phase 1. The inquisitive automation, adaptive automation, and full automation used the same comfort prediction models in each phase to ensure an equivalent comparison across the levels of automation. For each participant, average accuracy of the fivefold cross validation is taken as the participant's model's prediction accuracy. The accuracies are based on the two-class classification for thermal satisfaction (satisfied or dissatisfied), and three-class classification for thermal sensation (cold, comfortable, or hot) as described in Section III-B. The satisfaction prediction models had an accuracy of 0.81 ± 0.15 in phase 1 and 0.86 ± 0.11 in phase 2. The sensation prediction models had an accuracy of 0.74 ± 0.15 in phase 1 and 0.77 ± 0.12 in phase 2. The average number of training labels (satisfaction and sensation ratings) was 125.1 ± 49.9 in phase 1 and 224.8 ± 120.8 in phase 2. For both thermal sensation and satisfaction models, adding more data resulted in more accurate ML models as expected.

The cluster-based model used to predict users' approval/decline patterns for adaptive automation was initially trained using approve/decline interactions from inquisitive automation. The clusters were updated at the end of every day by adding new approve/decline actions during the adaptive automation period, while retaining older interactions in the model. Since the adaptive model evolved with each new approval/decline by the user, model accuracy using training and testing set were not evaluated and all available data were used for model training.

In all levels of automation, participants were still able to override the agent's actions and manually control the fan/heater. An example of control actions by the agent and manual actions by the user during one day in full automation is shown in Fig. 6 for illustration. For adaptive automation and full automation, the system recorded the overrides when the participants manually overrode a control action by the agent within 5 min of the automatic control action execution. Because the agent made predictions every 30 s, 5 min was deemed a reasonable length of time for the participants to override the agent's control actions if they were not satisfied. A shorter time window (1–2 min) for counting overrides might not have given enough time for the participant to take an action, and a longer time window (10–15 min) might not have been reflective of the participant's reaction to the control action as their comfort state could have changed due to the agent's control action.

C. Data Analysis

To answer the research question, "How does occupant satisfaction vary between different levels of automation of PCS devices?" we compared the thermal satisfaction obtained in the baseline condition and in each level of automation in phase 1 and phase 2, as well as combined satisfaction across both phases. Since phase 2 did not include a baseline condition where PCS devices were not used, the baseline from Phase 1 was also used in phase 2 analyses. Thermal satisfaction was evaluated using two metrics: 1) UI-based thermal satisfaction was the average thermal satisfaction across all the ratings provided by the users using the UI under each level of automation and 2) survey-based thermal satisfaction was an overall rating reported by the participants at the end of each level of automation.

A within-subject analysis of variance (ANOVA) F-test was performed to compare thermal satisfaction across the five levels of automation (i.e., baseline, manual, inquisitive, adaptive, and full). When comparing more than two groups, the omnibus ANOVA shows whether significant differences are present between different groups or not but does not show which groups are significantly different. If the omnibus ANOVA test showed that significant differences were present, a *post hoc* analysis with multiple comparison of means was performed using Tukey's range test to identify which levels of automation had significantly different thermal satisfaction. The

TABLE III
AVERAGE SATISFACTION UNDER EACH LEVEL OF AUTOMATION

Phase	Source	Baseline	Manual	Inquisitive	Adaptive	Full
Phase 1	**UI**	0.113	0.383	0.546	0.007	0.135
	Survey	-0.643	0.500	1.214*	0.500	0.929*
Phase 2	**UI**	0.394	0.604	0.333	0.288	0.152
	Survey	-0.770	0.923*	0.923	0.692	0.692
Combined	**UI**	0.113	0.363	0.521	0.020	0.193
	Survey	-0.643	0.679	1.143*	0.679	0.893*

* denotes significantly different from Baseline (p-value $\leq$ 0.05)

results from the ANOVA are reported as [F-statistic (degrees of freedom), p-value], and the results from the multiple means comparison are reported as [Group Mean (M), standard error of the mean (SEM), p-value when compared to baseline]. If the p-value is less than 0.05, a commonly used threshold, then it is concluded that significant differences are present.

The satisfaction ratings from phase 1 and phase 2 were combined to compare the overall satisfaction under each level of automation. For both the survey-based satisfaction and UI-based satisfaction, the combined satisfaction rating is the average of all recorded satisfaction ratings from phase 1 and phase 2 for each level of automation. One participant did not complete the full automation level in phase 2, so the satisfaction rating under full automation from phase 2 was used as the combined satisfaction for full automation. One additional participant did not complete all levels of automation in phase 2; this participant was omitted from phase 2 analyses.

To understand how the accuracy of thermal satisfaction prediction models influenced the actual system performance, we evaluated the correlations between the accuracy of satisfaction prediction models with different performance metrics using the Pearson correlation coefficients. Phase 1 and phase 2 were analyzed separately. For inquisitive automation, the performance metric was the percentage of requests that were declined, calculated as the number of control requests that were declined by a user divided by the total number of requests placed for that user. For full automation, because the control actions were automatically executed, we used the number of overrides as the performance metric. For adaptive automation, we used both the percentage of declined requests and the number of overrides as performance metrics because the agent automatically executes the control request when it predicts the user will approve/decline the request, and asks the user before executing the control action when it is not certain. A Pearson correlation coefficient was also calculated between the accuracy of thermal satisfaction prediction with UI-based satisfaction for each phase. Along with correlation results, the average and standard deviation of different performance metrics are reported as mean $\pm$ standard deviation to indicate the variability among the participants.

V. RESULTS

Table III shows the average satisfaction obtained under each level of automation. Overall, the results show that having local control with PCS devices leads to higher occupant satisfaction compared to not having PCS devices, and having some automation leads to higher occupant satisfaction compared to the manual control. In phase 2, the comparison of survey-based thermal satisfaction with ANOVA showed that significant differences were present [F (4, 52) = 3.922 and p = 0.0074] between thermal satisfaction under different levels of automation. The multiple means comparison showed that occupant satisfaction was significantly higher for inquisitive automation (M = 1.214, SEM = 0.366 and p-value = 0.021) and full automation (M = 0.929, SEM = 0.412, and p-value = 0.024) compared to the baseline (M = −0.643 and SEM = 0.307) in phase 1. When comparing the UI-based satisfaction in phase 1, the ANOVA test showed that none of the groups was significantly different from each other (F = 1.032 and p-value = 0.400). Even though significant differences were not present when comparing the UI-based satisfaction, Inquisitive automation also led to the highest satisfaction followed by manual control in phase 1.

In the phase 2 survey-based satisfaction comparison, the ANOVA test showed that significant differences [F (4, 48) = 2.922 and p-value = 0.030] were present between thermal satisfaction under different levels of automation. The multiple means comparison showed that manual control (M = 0.923, SEM = 0.500, and p-value = 0.035) was significantly higher, and adaptive automation (M = 0.692, SEM = 0.414, and p-value = 0.070) was marginally higher compared to the baseline (M = −0.769 and SEM = 0.3023). When comparing the UI-based satisfaction in phase 2, the ANOVA test did not show any significant differences (F = 0.462 and p-value = 0.763) among different levels of automation. However, it is important to note that since phase 2 involved only one week of data for each level of automation, the chances of seeing significant effects were smaller.

When comparing the combined survey-based satisfaction ratings from both phases, the ANOVA test showed that significant differences (F = 5.70 and p-value = 0.0007) were present in thermal satisfaction under different levels of automation. The multiple means comparison showed that Inquisitive Automation (M = 1.143, SEM = 0.337, and p-value= 0.028) and full automation (M = 0.893, SEM = 0.320, and p-value= 0.026) were significantly higher, and adaptive automation (M = 0.679, SEM = 0.391, and p-value= 0.093) was marginally higher than the Baseline (M = −0.643 and SEM = 0.308). The ANOVA test showed that none of the groups were significantly different (F = 1.014 and p-value = 0.410) when comparing the combined UI-based satisfaction from both phases. Although

TABLE IV
CORRELATIONS BETWEEN ACCURACY OF SATISFACTION PREDICTION AND DIFFERENT PERFORMANCE METRICS

Automation Level	Performance Metric	Phase 1 Satisfaction Accuracy	Phase 2 Satisfaction Accuracy
Inquisitive	**Percent Declined**	-0.813*	-0.59*
Adaptive	**Percent Declined**	-0.671*	-0.51
Adaptive	**Overrides**	0.119	0.149
Full	**Overrides**	-0.284	-0.557*
Inquisitive	**Satisfaction-UI**	0.5405*	0.528
Adaptive	**Satisfaction-UI**	0.436	0.491
Full	**Satisfaction-UI**	0.449	0.500

The reported values are Pearson correlation coefficients.
* indicates significance at p-value $\leq$ 0.05

significant differences were only observed for some conditions due to the small number of participants, the results overall strongly support that having PCS devices for local control of the thermal environment leads to higher satisfaction compared to the baseline condition, and having some level of automation, especially inquisitive automation, led to a higher satisfaction than manual control.

The accuracy of the comfort models also had a direct correlation with the performance of the agent. The performance is evaluated based on the percent declined for inquisitive and adaptive automation, the number of overrides for adaptive and full automation, and UI-based thermal satisfaction for all levels of automation. For inquisitive automation, the percent declined averaged 55.8% $\pm$ 26% in phase 1, and 23% $\pm$ 30% in phase 2. For adaptive automation, the percent declined averaged 46.7% $\pm$ 34% in phase 1, and 22% $\pm$ 29% in phase 2. The number of overrides under adaptive automation averaged 2.9 $\pm$ 4.9 in phase 1, and 0.14 $\pm$ 0.36 in phase 2. For full automation, the number of overrides averaged 1.7 $\pm$ 3.2 in phase 1, and 3.3 $\pm$ 4.5 in phase 2. The UI-based satisfaction averaged 0.55 $\pm$ 1.09 for inquisitive automation, 0.01 $\pm$ 0.96 for adaptive automation, and 0.12 $\pm$ 1.35 for full automation in phase 2, 0.27 $\pm$ 1.68 for inquisitive automation, 0.12 $\pm$ 1.42 for adaptive automation, and 0.12 $\pm$ 1.56 for full automation in phase 2 on the 7-point thermal satisfaction scale [-3 to $+3$]. In general, we observed a large variation across different participants as evidenced by the relatively large standard deviation compared to the mean.

Table IV shows the correlations between different performance metrics and accuracy of satisfaction prediction models in each phase. We observed moderate to strong negative correlations between the accuracy of thermal satisfaction models and the percent declined in inquisitive automation and adaptive automation in both phase 1 and phase 2. We observed a weak negative correlation between the accuracy of thermal satisfaction models and the number of overrides in the full automation for phase 1 and a moderate negative correlation in phase 1. We also observed moderate positive correlations between accuracy of thermal satisfaction models and UI-based thermal satisfaction in the inquisitive, adaptive, and full automation levels for both phases. These correlations indicate that if the prediction accuracy of thermal satisfaction models is increased, then overrides and percent declined are likely to decrease, and thermal satisfaction is likely to increase. The overall results show that the accuracy of thermal satisfaction prediction models have a direct influence on the system performance and developing new ways to improve comfort prediction could lead to even higher occupant satisfaction.

VI. DISCUSSION

In this study, we developed and evaluated intelligent agents capable of controlling PCS devices under different levels of automation. Our objective was to improve occupant satisfaction with the thermal environment. We observed that the use of PCS devices improved occupant satisfaction compared to a baseline condition where PCS devices were not used. We also observed a significant improvement in end of condition survey-based satisfaction for inquisitive automation and full automation compared to the baseline condition. General trends of improved satisfaction were also observed in average daily UI-based satisfaction ratings obtained across these conditions, although significant differences were not observed.

Although the same 7-point Likert scale was used to assess thermal satisfaction, survey-based satisfaction was represented by one rating at the end of each level of automation. This rating more likely represented the participant's satisfaction with how the automation condition managed the thermal environment overall. Alternatively, the UI-based satisfaction was reported periodically and then averaged over a long period of time. Since participants were likely to report both satisfaction and dissatisfaction based on the agent's control actions and changes in the thermal environment throughout the study period, UI-based satisfaction ratings had a higher potential for regression toward the neutral mean. The resulting near neutral averages across all four conditions indicates that either the participants were primarily in a neutral state of thermal satisfaction regardless of the PCS use or that none of the automation levels continuously created either a highly satisfactory or highly unsatisfactory thermal environment across time.

In addition to regression to the neutral mean, there is also potential for anchoring bias in repeated sensorial assessments, which can cause a current assessment to be based on past assessment of comfort or satisfaction [49]. This potential anchoring bias could have also resulted in participants not utilizing the full scale from -3 to $+3$ when their thermal satisfaction improves or declines during different time periods, thereby leading to reduced differences in UI-based satisfaction under different levels of automation. As a collective rating of overall satisfaction under each level of automation, the survey-based results were less subject to anchoring bias. Therefore, significant findings from the survey supporting the inquisitive and full automation conditions may most closely represent levels of automation preferred by the occupants.

In addition, we observed strong to moderate correlations between the accuracy of thermal satisfaction models and actual performance of the agent assessed by the percent declined in inquisitive and adaptive automation, and the number of overrides in full automation. However, the correlations between model accuracy and percent declined were weaker in phase 2 compared to phase 2 even though the offline accuracy of thermal satisfaction models on the test set were higher in phase 2. This suggests that the comfort requirements of participants might have changed due to seasonal variations that were not completely reflected in the satisfaction prediction models.

We also noted a gradual decrease in the number of comfort votes over time, which could have lowered the accuracy of the comfort models. For instance, the average number of votes was 26.1 in week 1, 12.4 in week 8, and 13.1 in week 15. The reduction in number of comfort votes could have been caused by a decline in interest of participants periodically providing comfort votes. Future studies could conduct paired comparisons to understand the underlying factors behind gradual decline and develop ways of maintaining regular interactions with such systems or design systems that do not rely heavily on continuous interaction with the user. Although we updated our comfort models between phase 1 and phase 2 to account for seasonal variations, this reduction in the number of comfort votes over time could have reduced the ability of comfort models to reflect the changes in occupant requirements even though they were periodically updated. In addition, adaptive automation also depended on the adaptive behavior of prediction models. It is difficult to isolate the separate impact of the different prediction models on occupant satisfaction. However, the adaptive model for predicting approve/decline behavior seems to have improved in phase 2 because of the addition of new data and daily updates to the adaptive model as seen by improvements in thermal satisfaction along with a reduction in overrides and percent declined.

In this study, we utilized supervised learning-based comfort prediction models that rely on direct comfort ratings from the occupants. Alternative ways of inferring occupant comfort could reduce the biases in self-reported comfort assessments and potentially improve the accuracy of comfort prediction models. A previous study showed an average accuracy of 68% in inferring thermal preference from manual control actions of PCS devices in a *post-hoc* analysis [50]. The significant correlations observed in this study between the accuracy of thermal satisfaction prediction models and performance metrics (manual overrides, percent declined) supports the concept that occupant satisfaction can be inferred from the usage patterns. Alternate ways of inferring occupant comfort could accommodate for changes in seasonal variations by removing the reliance on direct assessment from occupants. Further studies are needed to evaluate the usefulness of indirect measures of occupant satisfaction or preference based on user control actions.

A within-subjects design was used in this study where each participant experienced all levels of automation. Due to the nature of within-subjects design, there might have been some biases due to carryover effects, such as participants getting habituated with the system and decline in interest to interact with the system over time. Although the order of the levels of automation was randomized in phase 2, the carry-over effects might not have been completely eliminated. Future studies can explore other experimental designs, such as between-subjects designs to eliminate some of the carryover effects that are possible due to within-subjects design of this study.

Costs associated with the prototype development (about $500) and the long duration of the study, resulted in a small number of participants. Despite being limited to a small number of participants, our sample included individuals of varied gender, age, job type, and office building setting, together reducing potential for sample bias that could occur with a more homogenous participant sample. Additionally, since all data were obtained from workers in one geographic location, our findings may not be representative of findings for individuals in other regions or climates. Finally, we did not consider the energy implications of using PCS devices or the costs and benefits across different levels of automation.

Previous studies have shown improvement in occupant satisfaction with manually controlled PCS. To the best of our knowledge, this is the first study to consider different levels of automation of PCS devices. Despite the limits of this study, our findings provide preliminary support for the use of intelligent systems for personalizing indoor environmental conditions to improve occupant satisfaction further than what is possible with manual control. Such intelligent systems could be linked with centralized HVAC systems to provide information about each occupant's comfort requirements and operational states of PCS devices. Further research is required to validate our findings in larger populations and across different regions. These studies will inform the development of HVAC control schemes accounting for occupant comfort and PCS operations while maintaining energy efficient operations.

VII. Conclusion

Current HVAC systems, which operate under a "one size fits all" approach, are unable to accommodate for individual occupant requirements due to a lack of solutions to integrate real-time occupant comfort requirements in their operation, and the inability to control the thermal environment at a granular level. PCS devices provide the ability to control the environment around each occupant and enable local control of the thermal environment. Previous studies have mostly left the burden of PCS control to the end user, which can lead to inefficient operation and lack the necessary intelligence that could be integrated into HVAC operations. In this study, we developed and implemented an IoT-based intelligent agent that can personalize the thermal environment around each occupant by use of a PCS device. The agent is capable of learning individual comfort preferences and controlling the PCS devices using multiple levels of automation to improve occupant satisfaction. We conducted a 15-week field study to evaluate the impact on occupant satisfaction under four different levels of automation for controlling PCS devices.

The overall results from this study support the use of PCS devices, as we observed higher thermal satisfaction under all levels of automation compared to the baseline condition where PCS devices were not used. Furthermore, our results support that some level of automation is useful, as significantly higher thermal satisfaction was observed for Inquisitive Automation and Full Automation of PCS devices than with

Manual Control alone. We also observed significant correlations between the accuracy of comfort prediction models and actual performance based on the percentage of declined requests and number of user overrides. The observed correlations point toward the need for more accurate comfort models. Current comfort prediction models, including the one used in our study, rely on direct comfort ratings from the end user for model training. In our field study, we observed a gradual decline in the number of comfort ratings over time, which suggests a need for alternate approaches to model occupant comfort without the need of periodic input from the end user for long-term real-world deployment of such systems.

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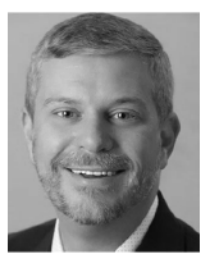

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He is an Associate Professor and the Director of the Ph.D. program in the Mrs. T.H. Chan Division of Occupational Science and Occupational Therapy with the University of Southern California, Los Angeles, CA, USA. He is a licensed occupational therapist and registered musculoskeletal sonographer. To date, he has received nearly $4M in funding on individual and collaborative research grants. His research is focused on the advancement of assessment, prevention, and rehabilitation for work-related injuries, as well as understanding the relationships among the person, the environment, and participation in activities (e.g., daily occupations) to promote health and well-being within the adult working population.

Dr. Roll is a member of numerous professional organizations, including the American Occupational Therapy Association (AOTA), American Institute of Ultrasound in Medicine (AIUM), American Society of Hand Therapists, Association of Rheumatology Professionals, Society of Diagnostic Medical Sonography, and the Society for the Study of Occupation. He has been named a Fellow of the AOTA and the AIUM. He is an Associate Editor for the *Journal of Diagnostic Medical Sonography*.