Building and Environment 185 (2020) 107316

Contents lists available at ScienceDirect

Building and Environment

journal homepage: http://www.elsevier.com/locate/buildenv

Thermal comfort modeling when personalized comfort systems are in use: Comparison of sensing and learning methods

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ARTICLE INFO

Keywords:
Thermal comfort models
Personal comfort systems
Corrective power
Ambient sensing
Machine learning

ABSTRACT

Centralized HVAC systems are usually unable to cater to individual requirements when multiple occupants are present in the same zone. Personalized Comfort Systems (PCS) such as local fans and heaters, heated/cooled chairs, local ventilation systems, have shown to be useful for maintaining comfortable thermal conditions by creating a microclimate around each occupant. Previous studies have mostly focused on personalized thermal comfort modeling under regular HVAC operations, and there is a lack of work that focuses on personalized thermal comfort modeling when PCS devices are in use. In this study, we compare different sensing and machine learning methods to build personal comfort models when a local fan or heater is in use. The experiment was conducted in a controlled environment with three segments: regular (no fan/heater), fan on, and heater on. Our results indicate that the data from environmental sensors results in 2%–5% higher prediction accuracy compared to using a wearable device to monitor wrist skin temperature or thermal imaging to monitor skin temperature from different regions of the face. Furthermore, environmental sensors are more affordable and have relatively fewer privacy concerns compared to the physiological sensors. Overall, the results of this study support the use of environmental sensors for building personalized thermal comfort models with or without PCS. Furthermore, the results also highlight the need for building separate personalized thermal comfort models when PCS devices are in use, and when PCS devices are not in use.

1. Introduction

Heating, Ventilation, and Air Conditioning (HVAC) systems are responsible for about 43% of total energy consumption in buildings [1]. Despite the large consumption of energy, centralized HVAC systems often fail to meet their primary purpose of maintaining satisfactory thermal environments for most of the building occupants due to poor operation policies and differences in occupants' comfort requirements. ASHRAE 55 guidelines require HVAC systems to satisfy at least 80% of building occupants [2]. However, field studies that surveyed occupants in commercial buildings across North America showed that only about 38% of building occupants were actually satisfied with their thermal environment, and only 8% of the surveyed buildings met the ASHRAE requirement of satisfying more than 80% of building occupants [3]. The poor performance of existing HVAC systems with regard to low occupant satisfaction is caused by two primary reasons: (1) There is a large diversity in occupants comfort requirements and this diversity is not accounted for in existing "one-size-fits-all" HVAC operations and (2) Centralized HVAC systems are usually unable to cater to individual requirements, especially when there are multiple occupants in the HVAC zone with large differences in comfort requirements, because of system limitations in controlling the environment at a more local level than an HVAC zone [4].

Current HVAC systems in most commercial buildings in the U.S. are centralized and rely on the PMV/PPD model to determine the indoor environmental conditions that are necessary for occupancy. The PMV/PPD model does not accommodate for individual differences among occupants, leading to a relatively static indoor thermal environment that is controlled within a narrow range without accommodation for actual occupant requirements. To shift away from the static operation of thermal environments, several researchers have focused their efforts on developing new techniques that can model personalized requirements [5–7]. Such methods mostly rely on different sensors to monitor different environmental and/or physiological parameters and leverage different Machine Learning (ML) algorithms to model occupant's thermal sensation, satisfaction, or preferences [6,8], with the motivation of

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https://doi.org/10.1016/j.buildenv.2020.107316
Received 14 July 2020; Received in revised form 31 August 2020; Accepted 22 September 2020
Available online 24 September 2020

integrating such comfort models into the HVAC operations. A previous study has shown that incorporating occupant comfort into centralized HVAC operations by selecting zone level temperature setpoints based on individual comfort models can improve the occupant satisfaction from around 38%–63% [4].

Centralized HVAC systems are controlled at a room or a zone level. Even when zone temperature setpoints are selected based on the occupant requirements for that zone, the HVAC system alone cannot satisfy all of the occupants in the zone. When there are more than 4–5 occupants in the same zone, it becomes increasingly difficult to satisfy more than 60% of the occupants in the zone [4], failing to meet the ASHRAE requirements of satisfying more than 80% of occupants [2]. One of the possible solutions is to utilize Personalized Comfort Systems (PCS) such as local fans and heaters that are able to control the thermal environment at a more local level. PCS devices can create small microclimates around each occupant and thus provide a more local control of the environment around each occupant. Several studies have shown that PCS devices are able to improve occupant satisfaction beyond what is possible with HVAC systems alone [9,10]. Different PCS devices can provide an effective cooling capacity of 2–3 °C and an effective heating capacity of 7–10 °C, which can help in adjusting the thermal environment to meet individual occupant requirements [10,11].

Although several studies have developed methods to model individual comfort requirements for HVAC operations [5,6,12], there is a lack of research studies that have focused on understanding how individual comfort requirements can be modeled when PCS devices are in operation. In our previous study [6], we investigated the tradeoffs between different sensing and learning methods for modeling individual comfort requirements for centralized HVAC operations. In this study, we investigate the tradeoffs between using different sensing and machine learning methods for modeling individual comfort requirements when PCS devices are in use. We conducted controlled experiments to compare how occupants' thermal sensation and satisfaction changes when PCS devices such as a fan or a heater are in operation and used different sensing and machine learning methods to evaluate the accuracy of thermal sensation and satisfaction prediction under different approaches. The rest of the paper is organized as follows. In section 2, we review the relevant literature on personalized comfort models and PCS devices. We describe our methodology for data collection and analysis in section 3, followed by the results in section 4. We discuss some of the practical considerations and the limitations of this study in section 5 and conclude the study in section 6.

2. Literature review

The current guidelines for HVAC operations in buildings, such as the ASHRAE 55 [2] and ISO 7730 [13], utilize the PMV/PPD model developed by Fanger [14] for fully air-conditioned buildings or the adaptive model developed by de Dear and Brager [15] for naturally ventilated buildings. Both the PMV/PPD model and the adaptive model are based on an averaged response from a large sample, hence do not explicitly accommodate individual occupant requirements [7,16]. With the rise of the Internet of Things (IoT) and ML, several researchers have developed methods to model individual comfort requirements by leveraging different sensors to capture real-time information and different ML algorithms [5–7,17]. The most common sensing methods used in building personalized comfort models include environmental sensors [6,18], wearable devices to monitor skin temperature from different body parts, such as wrist and legs [6,19,20], and thermal imaging to monitor skin temperature from different regions of the face [6,21,22]. Some of the common ML algorithms used for personalized comfort modeling include Random Forest [6,23–25], decision trees [26], Support Vector Machines (SVM) [6,27], and Artificial Neural Networks (ANN) [28], with accuracies ranging from 75% to 95%. A general review of personal comfort models can be found in Refs. [7], and the specific literature review focusing on different sensing and machine learning methods for personalized comfort models can be found in the authors' previous work [6].

Although previously developed personal comfort models help in controlling the HVAC temperature setpoints based on occupant requirements, centralized HVAC systems are unable to control the thermal environment at a local level for each individual occupant. There has been a renewed interest in using PCS devices in recent years to control the environment around each occupant. Several PCS devices, such as heated chairs, hand warmers, local cooling fans have been studied recently and can be used to control the local thermal environment around occupants to improve their comfort and satisfaction [9–11,29]. In a field study, Bauman reported 100% thermal satisfaction from occupants using a desktop-based Task Ambient Conditioning (TAC) system with an air supply nozzle and a radiant heating panel, compared to 80% satisfaction from occupants without TAC system [30]. In another study using ceiling-mounted Personal Ventilation (PV) system, Yang et al. reported 77%–97% satisfaction under ambient temperatures of 26 °C and supply air temperature in the range of 21 °C–26 °C and air speeds of 0.36–0.76 m/s [11,31]. Zhang et al. demonstrated in a field study that the use of a combination of PCS devices which included a heated/cooled chair, foot warmer and leg warmer resulted in increased thermal acceptance from 56% to around 80% when the ambient temperatures were between 20 °C and 25 °C [32]. These studies demonstrate that the use of PCS devices can improve occupants' comfort and satisfaction levels and have the potential to meet the ASHRAE requirements of satisfying 80% of building occupants.

PCS devices perform differently in their ability to provide local heating and cooling. Some studies have attempted to quantify the ability of PCS devices to correct the thermal discomfort in terms of temperature by using the idea of corrective power. Corrective power is defined as the difference between two ambient temperatures at which the same thermal sensation is achieved – one with PCS and one without PCS [11]. Zhang et al. reviewed 41 studies and evaluated the corrective power of different PCS devices that cooled the participant using frontal air jets, ceiling fans, cooling chairs, and heated the participant using heated chairs and foot warmers [11]. Cooling with air jets, directed to the face, had a corrective power equivalent to -2 K to −3 K when air speeds were around 0.4–0.6 m/s, and ambient temperature was around 26 °C–27 °C [30,33]. At a higher ambient temperature of 28 °C–30 °C, air speeds of 0.8–1 m/s had a cooling effect of -2 K to -4 K [11,34], and above 32 °C, high air speeds of up to 2 m/s was needed to maintain comfort [11,35]. Heating PCS devices, such as chairs, foot and leg warmers had a corrective power of 7 K–10 K when the ambient temperature was 14 °C–16 °C [11,36,37]. In another study, Luo et al. found that the corrective power of a small desk fan was 1.5 K, cooling wrist pad was 0.5 K and cooling chair was 2 K when the ambient temperature was 29 °C [10]. In the same study, the corrective power of a heated wrist pad was 0.75 K, heated chair was 1.25 K and heated shoe insole was 0.26 K when the ambient temperature was 18 °C [10]. The actual ability to correct for thermal discomfort of the PCS device depends on the type and size of the device, user perception, 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 building occupants.

Several studies have developed methods to create personalized comfort models for HVAC operations, and many studies have shown the usefulness of using PCS devices to personalize the thermal environment. However, previous studies utilizing PCS devices left the burden of control to the end-user. There is a lack of studies that focus on creating personalized comfort models for PCS operation, which can be useful to automatically control PCS devices or to incorporate the impact of PCS devices on occupant comfort into HVAC operations. In this work, we study the tradeoffs between different sensing and modeling methods for personalized thermal comfort models when PCS devices (i.e., desk fan and heater) are in use. We also provide insights regarding whether existing thermal comfort models that are developed for centralized

HVAC operations can be leveraged for controlling PCS devices by adjusting the existing models with the corrective power of PCS devices. The specific research questions that we attempt to answer in this paper are: (1) What are the most useful sensing and modeling methods for predicting individual thermal sensation and satisfaction when PCS devices are in use? and (2) Can regular comfort models be utilized for comfort prediction when PCS devices are in use by incorporating the corrective power of PCS devices?

3. Methodology

The overall methodology used in this study involves a climate-controlled experiment conducted in three segments where the room temperature was gradually changed using the HVAC system for cooling and space heaters placed more than 3 m away from the participants for heating the room. It is important to note that these space heaters are different from the heater that was used as a PCS device. The three segments are: regular (no fan or heater used), fan (fan is on throughout the segment), and heater (PCS heater is on throughout the segment). The environment was monitored using sensors to measure changes in air temperature, humidity, air speed, and radiant temperature. Physiological changes in skin temperature were monitored using a wearable device on the wrist as well as using a thermal camera directed at participants' faces. The three sensing methods (i.e., environmental, wearable, and thermal imaging) were selected based on their performance in building personal comfort models from previous literature [6]. Thermal sensation and thermal satisfaction votes were collected every 5 min from the participants in the form of self-reported values. The collected data was used to train different ML models to learn individual thermal sensation and satisfaction with and without PCS use. The detailed methodology is described in the following subsections.

3.1. Experiment procedure

The experiments were conducted in a research office at the University of Southern California (USC) in Los Angeles during the summer months of July 2019 and August 2019. Los Angeles falls in a warm-summer Mediterranean climate according to the Koppen-Geiger climate classification [38]. The average outdoor temperature during the data collection period was 23 °C, with average low and high outdoor temperatures ranging from 18 °C to 30 °C, respectively. All the participants were asked to wear trousers and t-shirts to keep the clothing levels consistent. The approximate clothing insulation is 0.57 clo. for the ensemble [2]. Fifteen healthy subjects, 11 males and 4 females participated in the study. The anthropometric details of the study participants are shown in Table 1.

The experiment was conducted in three segments: (1) a regular segment where no fan or heater was in use, (2) a fan segment where the fan was in use, and (3) a heater segment where a heater was in use. In each segment, the room temperature was changed either from cold (approx. 19 °C) to hot (approx. 31 °C) or from hot to cold. All participants participated in all three phases resulting in roughly 6 h of data per participant. The order of segments, regular, fan, and heater were randomized, and the starting temperature (hot or cold) was also randomized for each segment. The randomization was done to avoid any systematic biases in thermal sensation and satisfaction votes in the collected data that could have resulted from the order of the experiments or the direction of temperature change. For example, if the order of data collection was fixed to fan, regular, and heater segments respectively, participants might have compared their current sensation to their sensation in the previous segment and report feeling much cooler or warmer due to their previous thermal experience. Although participants' thermal experience cannot be eliminated, randomization of the data collection order would help to limit any potential systematic bias in the collected data resulting from their previous thermal experience.

Table 1
Anthropometric details of study participants.

Gender	Count	Age (years)	Height (cm)	Weight (kg)
Male	11	21.5 ± 3.5	174.0 ± 5.7	67.3 ± 7.4
Female	4	22.0 ± 3.7	154.9 ± 2.9	60.2 ± 4.0
Overall	15	21.6 ± 3.5	168.9 ± 10.1	65.4 ± 7.3

Each segment lasted between 1.5 and 2 h and was stopped when the participant voted +3 or −3 for three consecutive times or when 2 h was over. This approach was taken to gather data covering different ranges of thermal sensations without causing too much discomfort to the participants. There was at least a 1-h gap between the segments, and some participants completed different segments over multiple days. Participants were asked to stay in the experiment room for at least 15 min to acclimatize the participants to the starting hot or cold condition prior to starting data collection in order to avoid overshoots in thermal sensation. Thermal overshoot is sometimes observed when the body's thermal stress is relieved by local cooling/heating to restore homeostasis and tends to initially exceed their comfort state in a steady-state environment [39]. The room temperature was gradually changed at a rate of 1 °C/10 min to avoid sudden changes in the thermal environment in all segments. For the fan segment, a small desk fan was operated at a distance of 1 m from the participant and directed at their face, which generated an air speed of about 1.2 m/s around the participant's face. For the heater segment, a radiant heater of 1000 W was operated on the ground, approximately 1 m away from the participant's feet. A fan directed to the face and heater directed to the feet were used because the heightened sensitivity of head for cooling and feet for warming creates a bigger comfort effect compared to other local heating or cooling regimens [11,40]. The experimental setup for this study is shown in Fig. 1.

Different sensors were used to monitor changes in air temperature, humidity, radiant temperature, and air speed. DHT22 (accuracy ±0.5 °C and resolution 0.1 °C) sensor connected to Arduino Uno was placed on the desk roughly 0.5 m from the participant to monitor air temperature and humidity every second. A handheld anemometer UT363BT (accuracy ±0.5%rdg), was placed between the fan and the participant to monitor air speed generated by the fan. The anemometer was placed between the participant and the fan at a distance of 0.4 m from the fan to monitor the air speed every second. A black globe temperature sensor, Sper Scientific 800,037, was used to monitor dry globe and wet globe temperatures which capture the radiant heat generated by the heater at the height of 0.5 m (approximately knee height), placed 0.2 m parallel to the knee. The black globe temperature sensor has an accuracy of ±0.6 °C for dry globe temperature. In addition to the environmental sensors, a wearable device with MLX90614 (accuracy ±0.5 °C and resolution 0.02 °C) contact-less infrared temperature sensor fitted on a wristband with the sensor, placed roughly 1 cm from the wrist, was used to monitor changes in skin temperature from the wrist every second. The MLX90614 sensor has been used to monitor skin temperatures in previous studies and has been shown to be useful for monitoring physiological changes [6,41]. A FLIR Lepton thermal camera from Tinkerforge was used to capture thermal images, and a standard web camera was used to capture RGB images of the participants' facial region every second. The FLIR Lepton is a low-cost thermal camera capable of capturing 80 × 60-pixel thermal images with an accuracy of ±5 °C and a resolution of 0.1 °C per pixel. It is important to note that the accuracy of ±5 °C is for measuring absolute temperatures in the worst-case scenario, but in practice the FLIR Lepton provides consistent measurements for monitoring changes in skin temperature over time [24]. FLIR Lepton was previously validated by Li et al. [24]. and used in several previous studies to monitor changes in skin temperature for thermal comfort assessment [6,24,42]. In addition to sensor measurements, participants were asked to rate their thermal sensation and thermal satisfaction on a 7-point scale every 5 min using a web interface shown in Fig. 2. Approximately 28 comfort votes were collected for each participant in each of the three phases, resulting in a total of around 85 thermal

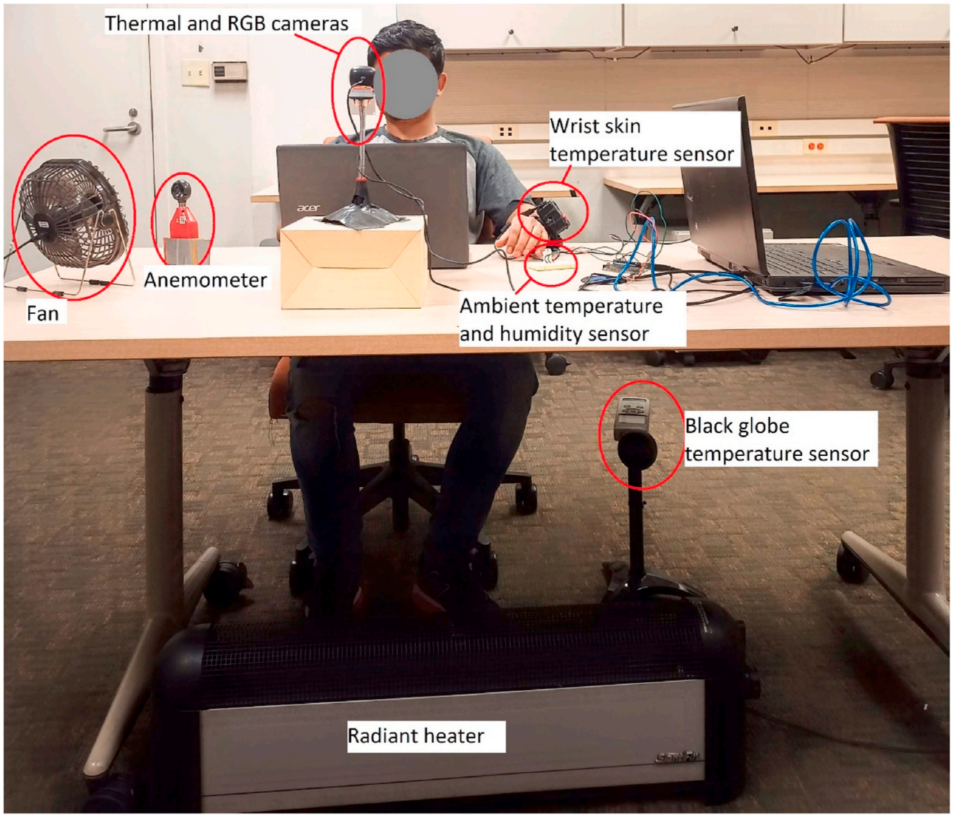

Fig. 1. Experimental setup.

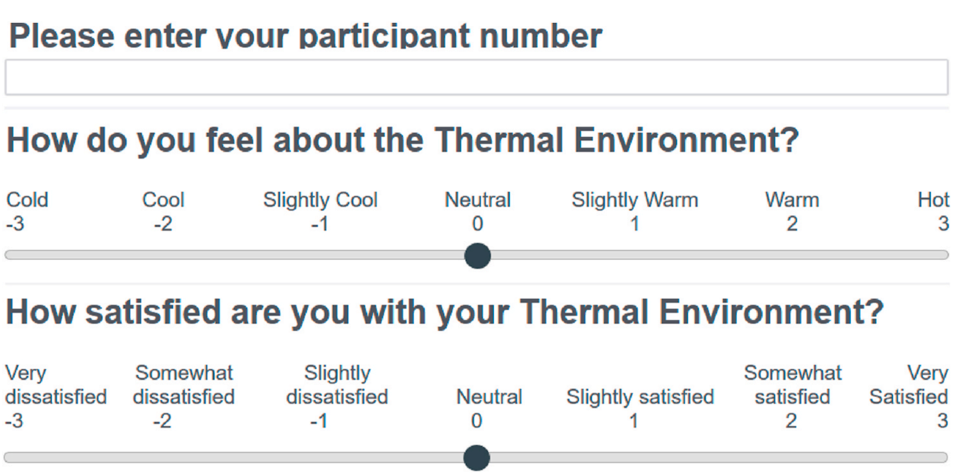

Fig. 2. Web interface to collect participants' thermal sensation and thermal satisfaction.

sensation and thermal satisfaction votes per participant.

3.2. *Data analysis*

The data analysis broadly consisted of three stages for building the thermal sensation and thermal satisfaction prediction models: (1) data cleaning and preprocessing, (2) feature extraction, and (3) training and evaluation of different ML algorithms to predict individual thermal sensation and satisfaction as described in sections 3.2.1 to 3.2.3. Further analysis, described in section 3.2.4, was conducted to evaluate the effectiveness of using corrective power to predict thermal sensation under PCS use by using models built without PCS use.

3.2.1. *Data cleaning and preprocessing*

Skin temperatures from four Region of Interests (ROIs): nose, forehead, right cheek, and left cheek were extracted from the thermal images based on their usefulness identified in previous studies [21,24,43]. To extract temperature measurements from different ROIs, first, the RGB image was overlapped on the thermal image using image registration, then the facial landmark detection algorithm [44] was used to identify different landmarks such as lips, nose, eyebrows and face boundary. The locations of different ROIs were calculated based on their relative location in reference to the landmarks and the corresponding temperature measurements of the ROIs were extracted from the thermal images. For a detailed description of the skin temperature extraction from thermal images, readers are referred to previous work by the authors in Refs. [21].

All of the sensor measurements, including skin temperatures from the thermal camera, were cleaned by passing them through a moving median filter to remove sudden changes in sensor measurements if present. Then, a Savitzky-Golay filter, which removes some noise from the signal without greatly distorting the original sensor signal [45], was used to smooth the sensor measurements and reduce some of the sensor noise. Readers are referred to a previous work by the authors in Ref. [6] for further details on data cleaning and filtering. The sensor measurements were then synchronized to a common time axis for assisting in feature extraction. An example of collected ambient temperature measurements and corresponding thermal sensation and satisfaction from a participant under the three segments is shown in Fig. 3. Other sensor measurements are not shown to keep the figure legible.

3.2.2. *Feature extraction*

Prior to training individual comfort models, several features were extracted from the measurements. The measurements include air temperature, relative humidity, air speed, black globe temperature, wrist skin temperature, and temperatures from the forehead, nose, left cheek, and right cheek. For each Thermal Sensation Vote (TSV) and Thermal Satisfaction (TSat) from the participants, sensor measurements within a 5-min window prior to the TSV was separated. Then, for each 5-min window corresponding to a TSV, seven different features that capture the value of measurements and the rate of change were extracted from each sensor measurement. The extracted features included: the instant measurement at the time of TSV; the minimum, maximum, average, standard deviation of the measurements, the overall change in the measurements between the first and the last values in the time window; and the average of the derivative of the measurements to capture the rate of change. These features were calculated based on their usefulness in previous studies for modeling thermal comfort [6,23,24]. Two binary variables indicating the states of fan and heater (on or off) were also added as features. The final dataset prior to training included a total of 65 features for each corresponding TSV and TSat: 63 extracted from different sensor measurements and 2 features indicating fan and heater states.

3.2.3. *Training and evaluation of ML models*

The ASHRAE 7-point scale, which was used to collect thermal sensation, was grouped into three comfort states: Cold (TSV ε {-3, −2}), Comfortable (TSV ε {-1, 0, +1}) and Hot (TSV ε {+2, +3}). Previous studies have shown that a thermal sensation vote of 0 does not necessarily correspond to satisfaction, and the comfortable condition usually spans a larger range than the neutral sensation [46,47]. The grouping of thermal sensation into thermal comfort states is based on the assumption in ASHRAE 55 that occupants are satisfied in the range of $-1.5 \leq \text{TSV} \leq +1.5$ when the scale resolution is 0.5 or less, or $-2 < \text{TSV} < +2$ when the scale resolution is limited to integers [2]. The Thermal Satisfaction was grouped into two categories, Satisfied (TSat ε {0, +1, +2, +3}) and Dissatisfied (TSat ε {-1, −2, −3}), based on the ASHRAE 55's suggestion of thermal acceptability, although a more generous grouping of TSat ≥ −1 as satisfied is also permitted by the guidelines [2]. The grouped Thermal Sensation and Thermal Satisfaction values were used as target labels to train classification models to predict individual sensation and satisfaction, respectively.

Prior to training the ML algorithms, we performed feature selection to remove the features that were less useful for the classification problem using chi-squared statistics between each feature and the class. The chi-square test measures the dependence between the features and the training class, which enables removing features that are most likely to be independent of the training label and therefore not very useful for training a classification model. Thus, up to 15 best features were selected for each individual thermal sensation and satisfaction model separately using the chi-squared statistics before training each model. Removing unnecessary or redundant features can improve training performance both in terms of speed and accuracy. Furthermore, the feature selection also provides some insight into which features and which sensing methods are more useful than others for predicting thermal sensation and satisfaction.

In order to answer the first research question *"What are the most useful sensing and modeling methods for predicting individual thermal sensation and satisfaction when PCS devices are in use?"*, we trained four different ML algorithms under different combinations of sensor inputs for each segment. For each participant, we trained separate models for each segment (regular, fan, and heater) to understand the differences in prediction accuracies when PCS devices were in use. We also trained general models for each participant with data from all segments to understand the predictive accuracies when separate models are not available. To understand which sensing methods are most useful, we repeated the model training by using features from different categories of sensing methods (environmental, wearable, and thermal imaging), and their combinations to understand the differences in predictive accuracy when only certain sensors are used in data collection. For each segment and combination of sensing methods, we evaluated Random Forest (RF), K-Nearest Neighbors (KNN), Support Vector Machine (SVM) with a cubic kernel, and Decision Trees (DT), based on their performance in previous studies [6,23–27,48]. Each algorithm was evaluated using 5-fold cross-validation, and hyperparameters were tuned with a grid search. In 5-fold cross-validation, the dataset is randomly partitioned into 5 subsets, where 1 subset is held for validation and 4 subsets are used for training the model, and the training and validation are repeated 5 times with each subset acting as the validation set and remaining subsets used for training the models. The k-fold cross-validation is a common strategy to reduce the chances of overfitting the model to the training set and typically leads to a more generalizable model while utilizing the entire dataset [49].

The KNN algorithm makes a prediction for the input features based on a majority vote among k-nearest neighbors in the training set. The

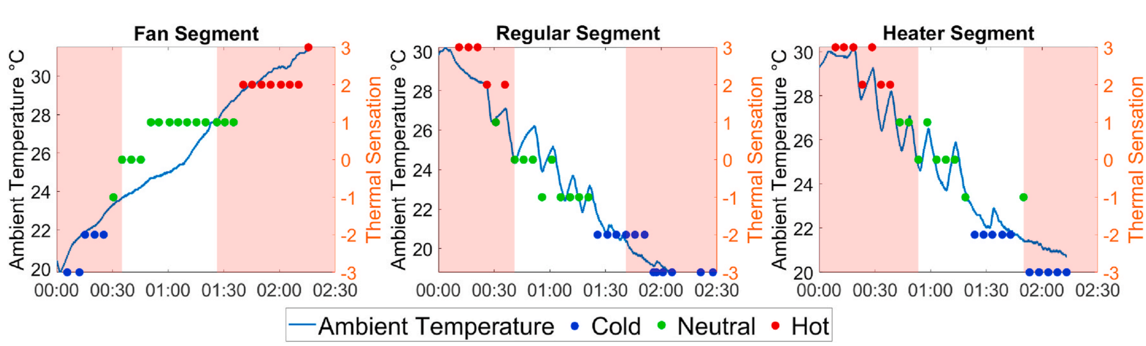

Fig. 3. Ambient temperature measurements with corresponding thermal sensation and satisfaction of a participant under three segments. The red background regions indicate thermal dissatisfaction and white regions indicate thermal satisfaction. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

SVM method determines an optimal hyperplane in the feature space that separates different classes. Using a nonlinear kernel such as the cubic kernel enables the creation of nonlinear decision boundaries or support vectors in the feature space. The Decision Tree method repeatedly partitions the dataset into subsets based on most significant differentiating features until the each of the remaining partitions fall under the same training label, or until the size limits specified for the tree structure are reached. Random Forest is an ensemble method that trains multiple decision trees on a random subset of features, resulting in a group of weak predictors. The Random Forest then combines the output of multiple decision trees using specified consensus criteria resulting in a more robust prediction. All of the algorithms used in this study are standard ML classification algorithms and readers are referred to different ML textbooks for further details about each algorithm [50,51].

3.2.4. Corrective power calculations and model training

In [11], Zhang et al. defined corrective power as the difference between two ambient temperatures at which the same thermal sensation is achieved – one without PCS and one with PCS. In this study, multiple environmental parameters such as relative humidity, dry globe temperature, wet globe temperature were monitored in addition to the ambient temperature. Furthermore, different features extracted from the sensor measurements as described in section 3.2.2 in addition to the direct value of sensor measurements were used for the training of ML models. Therefore, we adopt the idea of corrective power from Ref. [11] and calculate it across the feature space used to train the ML comfort models as explained in section 3.2.3. In the present study, we define corrective power as the average difference between all the variables in the feature space at which the same thermal sensation is achieved – one without PCS and one with PCS. For calculation of corrective power, we calculate the average difference for all the features that resulted in the thermal sensation of cold, comfortable, and hot for each participant between regular, fan, and heater segments. The corrective power of the fan or heater is the average difference among all participants in the feature vectors where the same thermal sensation is achieved between the regular and fan or heater segments, respectively.

To answer the second research question, *"Can regular comfort models be utilized for comfort prediction when PCS devices are in use by incorporating the corrective power of PCS devices?"*, we utilized the thermal sensation prediction models from the regular segment as explained section 3.2.3 to predict thermal sensation during the fan and heater segments. The corrective power is integrated into the thermal comfort models by adding the corrective power of the fan and heater to the original features extracted from the fan and heater segments, respectively. We then compare the difference in prediction accuracies between the models when corrective power is added to the input features against when corrective power is not added to the input features to evaluate the effectiveness of integrating corrective power into thermal sensation prediction models. Since previous studies used environmental measurements for calculating corrective power, we evaluated the effectiveness of integrating corrective power into thermal sensation prediction only when environmental measurements are used.

4. Results

We trained several ML algorithms for predicting thermal sensation for different experiment segments using different combinations of sensor streams as described in section 3.2.3. For each participant, the average accuracy of the 5-fold cross-validation is taken as the prediction accuracy for that participant. We then calculated the average and standard deviation among the 15 participants to compare the prediction accuracy of different approaches in Table 2, Table 3, and Table 5. The average prediction accuracies and standard deviations for thermal sensation predictions are shown in Table 2. From Table 2, we observe that all of the evaluated algorithms performed similarly and there was no statistically significant difference between the evaluated algorithms.

Table 2
Prediction accuracies for cold, comfortable, and hot sensations for each segment.

Segment	Algorithm	Environmental only	Wearable only	Thermal Imaging only	Wearable and Environmental	Thermal Imaging and Environmental	All Sensors
Regular Segment	KNN	0.90 ± 0.07	0.88 ± 0.11	0.87 ± 0.10	0.90 ± 0.07	0.90 ± 0.08	0.90 ± 0.07
	RF	0.89 ± 0.06	0.84 ± 0.12	0.87 ± 0.11	0.89 ± 0.05	0.88 ± 0.08	0.89 ± 0.08
	SVM	0.88 ± 0.11	0.83 ± 0.15	0.86 ± 0.11	0.88 ± 0.10	0.89 ± 0.09	0.90 ± 0.08
	DT	0.88 ± 0.07	0.82 ± 0.13	0.85 ± 0.12	0.89 ± 0.05	0.88 ± 0.12	0.88 ± 0.10
Fan Segment	KNN	0.86 ± 0.10	0.82 ± 0.12	0.86 ± 0.08	0.86 ± 0.10	0.87 ± 0.10	0.88 ± 0.10
	RF	0.84 ± 0.11	0.82 ± 0.13	0.84 ± 0.09	0.84 ± 0.09	0.86 ± 0.10	0.85 ± 0.09
	SVM	0.82 ± 0.11	0.78 ± 0.12	0.82 ± 0.12	0.82 ± 0.11	0.83 ± 0.11	0.83 ± 0.11
	DT	0.85 ± 0.11	0.79 ± 0.13	0.80 ± 0.11	0.85 ± 0.09	0.83 ± 0.13	0.83 ± 0.14
Heater Segment	KNN	0.86 ± 0.11	0.81 ± 0.15	0.81 ± 0.12	0.85 ± 0.12	0.85 ± 0.12	0.85 ± 0.11
	RF	0.83 ± 0.13	0.79 ± 0.16	0.81 ± 0.11	0.84 ± 0.13	0.84 ± 0.12	0.84 ± 0.12
	SVM	0.80 ± 0.14	0.76 ± 0.15	0.78 ± 0.15	0.81 ± 0.13	0.79 ± 0.15	0.80 ± 0.15
	DT	0.82 ± 0.17	0.76 ± 0.21	0.80 ± 0.14	0.82 ± 0.15	0.83 ± 0.13	0.83 ± 0.14
All Segments	KNN	0.78 ± 0.06	0.76 ± 0.12	0.78 ± 0.10	0.78 ± 0.07	0.80 ± 0.05	0.80 ± 0.06
	RF	0.72 ± 0.08	0.72 ± 0.12	0.76 ± 0.12	0.73 ± 0.09	0.78 ± 0.08	0.78 ± 0.09
	SVM	0.73 ± 0.09	0.68 ± 0.11	0.75 ± 0.09	0.72 ± 0.09	0.76 ± 0.09	0.77 ± 0.09
	DT	0.69 ± 0.12	0.66 ± 0.10	0.73 ± 0.13	0.69 ± 0.11	0.77 ± 0.10	0.76 ± 0.10

Table 3
Prediction accuracies for satisfied and dissatisfied conditions for each segment.

Segment	Algorithm	Environmental only	Wearable only	Thermal Imaging only	Wearable and Environmental	Thermal Imaging and Environmental	All Sensors
Regular Segment	KNN	0.94 ± 0.08	0.92 ± 0.08	0.92 ± 0.07	0.94 ± 0.07	0.92 ± 0.09	0.93 ± 0.08
	RF	0.93 ± 0.06	0.91 ± 0.09	0.91 ± 0.09	0.94 ± 0.06	0.92 ± 0.08	0.94 ± 0.07
	SVM	0.90 ± 0.12	0.86 ± 0.15	0.88 ± 0.14	0.91 ± 0.10	0.90 ± 0.12	0.90 ± 0.11
	DT	0.92 ± 0.10	0.89 ± 0.11	0.89 ± 0.11	0.92 ± 0.09	0.91 ± 0.11	0.93 ± 0.10
Fan Segment	KNN	0.88 ± 0.07	0.84 ± 0.12	0.88 ± 0.06	0.87 ± 0.06	0.88 ± 0.05	0.88 ± 0.06
	RF	0.85 ± 0.08	0.83 ± 0.14	0.85 ± 0.08	0.85 ± 0.07	0.86 ± 0.07	0.86 ± 0.06
	SVM	0.80 ± 0.12	0.78 ± 0.11	0.81 ± 0.11	0.81 ± 0.11	0.83 ± 0.11	0.82 ± 0.12
	DT	0.83 ± 0.09	0.79 ± 0.17	0.86 ± 0.08	0.84 ± 0.09	0.86 ± 0.10	0.86 ± 0.10
Heater Segment	KNN	0.86 ± 0.08	0.75 ± 0.11	0.81 ± 0.11	0.84 ± 0.09	0.84 ± 0.09	0.85 ± 0.08
	RF	0.82 ± 0.12	0.73 ± 0.10	0.78 ± 0.16	0.81 ± 0.11	0.81 ± 0.12	0.80 ± 0.12
	SVM	0.74 ± 0.14	0.69 ± 0.11	0.74 ± 0.14	0.75 ± 0.11	0.76 ± 0.12	0.76 ± 0.12
	DT	0.80 ± 0.15	0.69 ± 0.13	0.78 ± 0.16	0.77 ± 0.14	0.80 ± 0.14	0.78 ± 0.14
All Segments	KNN	0.81 ± 0.08	0.75 ± 0.11	0.76 ± 0.11	0.80 ± 0.08	0.81 ± 0.10	0.82 ± 0.08
	RF	0.75 ± 0.11	0.73 ± 0.17	0.72 ± 0.12	0.76 ± 0.13	0.75 ± 0.13	0.77 ± 0.12
	SVM	0.72 ± 0.12	0.70 ± 0.11	0.72 ± 0.15	0.72 ± 0.12	0.74 ± 0.13	0.75 ± 0.13
	DT	0.73 ± 0.12	0.70 ± 0.15	0.69 ± 0.13	0.74 ± 0.13	0.71 ± 0.11	0.72 ± 0.11

However, KNN generally outperformed other algorithms by a small margin. We also notice that building separate models for three segments: regular (no fan or heater), fan, and heater results in a higher accuracy compared to building a single model for all conditions. The highest accuracy achieved when a single model is built for all segments is 80%, whereas accuracies upwards of 85% are possible when separate models are built for different segments. Regardless of the algorithm used, using the data only from the environmental sensors leads to a better prediction accuracy compared to using data only from the wearable device or only from the thermal imaging. Combining data from environmental and physiological sensors results in a similar or slightly better accuracy compared to using data from environmental sensors alone.

Past studies have shown that the thermal sensation of neutral or comfortable does not necessarily correspond to thermal satisfaction [46, 47], and a significant number of occupants may be satisfied under cool or warm conditions [6]. If an occupant is dissatisfied, then a thermal sensation prediction model would still be needed to decide the appropriate control action (e.g., turn fan/heater on) based on their thermal sensation. However, if the occupant is satisfied even when they are cool or warm, then no control action would be necessary to make them satisfied. Therefore, if the objective of using personalized models is to optimize occupant satisfaction instead of optimizing for a neutral sensation, it might be useful to directly predict thermal satisfaction in addition to thermal sensation. We repeated the procedure described in section 3.2.3 for predicting thermal satisfaction directly. The average prediction accuracies and standard deviation for thermal satisfaction prediction are shown in Table 3. Similar to the thermal sensation predictions, we observe that KNN outperforms other algorithms by a small margin. Building separate models for different segments depending on whether fan or heater are in use results in more accurate models compared to building a single prediction model for all segments. Furthermore, using data from environmental sensors only outperforms using data from physiological sensors (wearable device or thermal imaging), and combining physiological sensor data with environmental sensor data improves the prediction slightly, similar to predicting thermal sensation. It is important to note that predicting thermal satisfaction is a two-class prediction problem (satisfied vs dissatisfied), which results in slightly higher accuracy overall compared to a three-class prediction problem for thermal sensation (cold, comfortable, hot).

The feature selection based on the chi-squared statistic as described in section 3.2.3 distinguishes features that are dependent on the training label and enables selecting features that are most useful for the classification problem. The feature selection process also provides insight into which sensor signals are most useful for the particular prediction problem. Since the 15 features used to train individual comfort models can differ from one participant to another, we evaluated 10 most useful features based on the frequency of those features selected for thermal sensation and satisfaction models for the 15 participants. The 10 most useful features for predicting thermal sensation and thermal satisfaction for each segment are listed in Table 4. We observe that Ambient Temperature is the most useful sensor overall for both sensation and satisfaction prediction. Furthermore, other environmental measurements, such as Dry Globe Temperature and Wet Globe Temperature are also quite useful. The variables indicating the state of the fan and heater are also important when a single model is built for all segments, instead of a single model for each segment. Physiological data from thermal imaging and the wearable device are only somewhat useful based on their feature importance seen in Table 4. This further solidifies the results from Tables 2 and 3 where using environmental measurements led to more accurate models.

The prediction accuracies when thermal sensation prediction models from the regular segment are used to predict thermal sensation in the fan and heater segments are shown in Table 5. Four different algorithms, KNN, RF, SVM, and DT used in section 3.2.3, were evaluated with and without corrective power integrated to the input features. The results

Table 4
Ten most useful features for thermal sensation and satisfaction prediction for each segment.

	Regular	Fan	Heater	All Segments
Sensation Prediction	AmbTemp_max	AmbTemp_last	AmbTemp_last	AmbTemp_last
	AmbTemp_avg	AmbTemp_min	AmbTemp_max	LCheekTemp_avg
	AmbTemp_min	AmbTemp_max	AmbTemp_min	Fan_state
	AmbTemp_last	WetGlobe_min	AmbTemp_avg	RCheekTemp_avg
	DryGlobe_min	WetGlobe_max	WetGlobe_max	NoseTemp_avg
	DryGlobe_avg	WetGlobe_avg	WetGlobe_min	Heater_state
	WetGlobe_last	AmbTemp_avg	WetGlobe_avg	AmbTemp_min
	Humidity_min	DryGlobe_min	WetGlobe_last	AmbTemp_max
	WetGlobe_min	WetGlobe_last	WristTemp_avg	AmbTemp_avg
	WetGlobe_max	DryGlobe_max	WristTemp_last	NoseTemp_max
Satisfaction Prediction	AmbTemp_max	AmbTemp_last	AmbTemp_min	Heater_state
	AmbTemp_avg	AmbTemp_min	AmbTemp_last	Fan_state
	WristTemp_max	WetGlobe_min	Humidity_avg	WristTemp_std
	AmbTemp_last	AmbTemp_max	AmbTemp_max	Humidity_min
	WristTemp_avg	AmbTemp_avg	AmbTemp_avg	Humidity_last
	AmbTemp_min	WetGlobe_avg	Humidity_min	DryGlobe_std
	Humidity_min	WetGlobe_max	Humidity_max	AmbTemp_max
	Humidity_last	WetGlobe_last	Humidity_last	Humidity_max
	WetGlobe_max	NoseTemp_last	WetGlobe_min	Humidity_avg
	WristTemp_last	DryGlobe_min	WetGlobe_max	AmbTemp_avg

Table 5
Thermal sensation prediction accuracies when using models from regular condition to predict thermal sensation when PCS devices are used, with and without corrective power.

Segment	Algorithm	Using CP	Not using CP
Regular Segment	KNN	0.90 ± 0.07	0.90 ± 0.07
	RF	0.89 ± 0.06	0.89 ± 0.06
	SVM	0.88 ± 0.11	0.88 ± 0.11
	DT	0.88 ± 0.07	0.88 ± 0.07
Fan Segment	KNN	0.41 ± 0.23	0.35 ± 0.27
	RF	0.52 ± 0.21	0.42 ± 0.27
	SVM	0.38 ± 0.29	0.33 ± 0.27
	DT	0.49 ± 0.24	0.38 ± 0.26
Heater Segment	KNN	0.55 ± 0.23	0.44 ± 0.24
	RF	0.58 ± 0.21	0.49 ± 0.20
	SVM	0.49 ± 0.36	0.37 ± 0.27
	DT	0.51 ± 0.26	0.40 ± 0.23

indicate that there is an improvement of around 5%–12% in thermal sensation prediction when corrective power is integrated into the input features, compared to not using corrective power, when models from the regular condition are used to predict thermal sensation when PCS devices are in use. However, when comparing the results from Tables 2 and 5, the overall accuracy of thermal sensation prediction when PCS devices are in use is relatively poor even when corrective power is added to the input features (about 50%), compared to when separate models are built (about 84%) when PCS devices are in use. Furthermore, the relatively large standard deviation when using regular comfort models to predict thermal sensation under PCS use as seen in Table 5 suggests that separate models are needed to predict thermal sensation when PCS devices are used.

5. Discussion

The difference in the performance of the evaluated algorithms for different combinations of sensor inputs was consistent, and using features extracted from the environmental sensors led to better performance compared to both wearable device and thermal imaging, although only by a small margin of 2%–5%. The ranking of important features based on chi-squared statistic also suggests that environmental sensors are more useful in predicting thermal sensation and satisfaction compared to the physiological sensors. Overall, the results from this study as shown in Table 2, Table 3, and Table 4 show that environmental measurements are more useful compared to the wrist skin temperature or facial temperature from thermal imaging for predicting thermal sensation and satisfaction at an individual level when PCS devices are in use. The results are consistent with our previous study where environmental sensors were found to be more useful for building personal thermal comfort models when PCS devices were not in use [6]. Due to relatively small number of participants in this study, the differences observed were not statistically significant, and future studies with a larger number of participants are needed to solidify the findings of this study.

One of the potential reasons for relatively better performance when environmental measurements are used is that physiological measurements are more prone to noise. Wearable devices, especially wrist-worn devices, can move when an occupant moves their hand while performing regular activities like working on a computer, which leads to sudden changes in sensor measurements and adds noise to the measured signals. Skin temperatures extracted from thermal imaging is also more prone to noise because when the participant moves relative to the camera, the calculated location of different ROIs can move slightly, which adds noise to the extracted temperature measurements [21]. Environmental sensors, on the other hand, do not get affected by occupant movement which leads to a more stable signal. Among the evaluated algorithms, KNN and Random Forest performed relatively better compared to SVM and Decision Trees. One of the reasons behind a better performance of KNN compared to other algorithms is because of the way KNN makes predictions. KNN predicts a label based on a majority vote among k nearest points, which in case of thermal comfort models means that the thermal sensation or satisfaction of a data point is assigned based on k closest data points. The way KNN makes predictions closely matches occupants' thermal sensation and satisfaction. For instance, if someone feels comfortable at a temperature of 22 °C and 23 °C, then they are likely to feel comfortable at a temperature of 22.5 °C as well.

Although using data from the environmental sensors resulted in overall higher prediction accuracy compared to the physiological measurements, other considerations are also important from a practical deployment perspective. Although ambient air temperature sensors are relatively cheap, anemometer needed to monitor air speed and black globe temperature sensor needed to monitor radiant heat are more expensive. In our study, the cost of ambient temperature sensor used is around \$5, an anemometer costs around \$30, and the black globe temperature sensor costs around \$40. The overall cost of all the environmental sensors is around \$75. Wearable devices to collect skin temperature costs around \$100, and the FLIR Lepton, which is one of the cheaper thermal cameras, costs around \$250. When considering the costs of different sensors, environmental sensors are less expensive than physiological sensors. Furthermore, collecting physiological data could raise privacy concerns among occupants compared to collecting environmental measurements. Overall, when considering the cost, prediction accuracy, and associated privacy concerns, environmental sensors seem to be a more suitable option for collecting data for building personalized thermal comfort models.

The primary motivation for building personalized comfort models is to control the HVAC system. Previous studies that utilized PCS devices to control the thermal environment left the control to be manually adjusted by the user. Understanding and modeling of occupant comfort under the operation of PCS devices are useful to directly control the PCS devices and to incorporate the impact of PCS operation on occupant comfort into HVAC operations. If personalized comfort models are to be used when PCS devices are operated, then our study shows that having separate models for each PCS device state leads to an overall better accuracy (85%–90%) compared to a single comfort model (around 80%). Our results show that under regular conditions when PCS devices are not in use, both thermal sensation and satisfaction can be predicted with an accuracy of around 90%. However, the prediction accuracy drops to around 84% when a fan or heater is in use even when separate models are built for those conditions. This suggests a need for better sensing and modeling methods when PCS devices are used in order to achieve prediction accuracy on par with regular conditions when PCS devices are not in use and should be considered in future studies.

When PCS devices are used in real world scenarios, they would either be controlled by the occupants or be automatically controlled by an intelligent control agent. In this study, participants did not have control over the PCS devices because the goal of this study was to compare the differences in accuracy of comfort models when PCS devices are used vs. when PCS devices are not used. Therefore, an experiment protocol to compare conditions with and without PCS devices was used in this study. From a practical deployment perspective, our results suggest the need to have separate comfort models with and without PCS, and if an intelligent agent is used to control the PCS devices, then the agent would need to consider the state of PCS devices and use a separate comfort model when making comfort predictions under PCS use. Future studies could focus on developing control agents that monitor for changes in the state of PCS devices and utilize separate comfort models to achieve higher occupant satisfaction.

In this study, thermal sensation with PCS by integrating the corrective power into the regular comfort models resulted in an accuracy of about 50%, compared to an accuracy of about 40% without integrating corrective power, as seen in Table 5. Although integrating corrective power improved the thermal sensation prediction accuracies by about 10%, the overall thermal sensation prediction accuracy when relying on models built without PCS devices is quite low. One of the potential reasons why integrating corrective power into the comfort models resulted in only a small improvement in accuracy is that the local effects of PCS devices on thermal sensation varies from one person to another, and an averaged corrective power is not sufficient to greatly improve the comfort models. The large standard deviations observed in the accuracy of comfort models in Table 5 also supports that there is a large variation in thermal sensation between participants when PCS devices are used, which is not sufficiently captured by the averaged corrective power. The results in Table 5 further support that separate comfort models are necessary to predict thermal sensation when PCS devices are used. Future studies can also focus on developing new ways to utilize regular comfort models for thermal comfort prediction when PCS devices are used in order to reduce the requirement of large amounts of training data for personal comfort models.

One of the limitations of this study is that it involved 15 participants. Although the number of participants is slightly smaller compared to the previous studies that involved around 20–25 participants, each participant in this study participated in three segments and the experiment took around 8 h per participant. The data collection protocol was designed to have variation in the collected dataset by exposing the participants to a wide range of environmental conditions so the participants would potentially report a wide range of different thermal sensation and satisfaction votes. A ML model trained on a dataset without much variation might give an artificially high accuracy due to lack of diverse training classes in the dataset. To avoid this issue, we prioritized the length of data collection and the range of conditions that the participants were exposed to, as shown in Fig. 3, over the number of participants. The overall dataset consists of 1276 sets of features and corresponding TSVs, equivalent to roughly 85 TSVs per participant, which is twice as large when compared to similar studies [6,23,24,52,53]. Even though the dataset is comparable to similar previous studies, neither this study nor prior studies are large enough to draw broadly generalizable conclusions. Furthermore, due to the small number of female participants, the potential impact of gender differences on the accuracy of comfort models could not be evaluated. However, because the comfort models are trained for each individual participant, the average accuracies of the comfort models reported in Table 2, Table 3, and Table 5 should be reflective of the accuracy that can be expected when individual comfort models are trained using a similar approach. Another limitation of this study is that the experiment was performed in a room without windows, and further studies are needed to understand the impact of solar radiation on occupant comfort when PCS devices are used. Furthermore, this study was designed as a climate-controlled study when the temperature was ramped up or down in a relatively short timeframe to understand the effectiveness of different sensing and modeling methods under a large range of thermal conditions. However, thermal conditions in actual buildings are relatively stable and do not cover a large range of temperatures as covered by this study. Future studies with a larger number of participants and long-term observations in real-world settings are necessary to solidify the findings of this study.

6. Conclusions

Centralized HVAC systems are unable to meet the comfort requirements of most building occupants due to the centralized “one size fits all” operation that does not consider real-time occupant requirements, and due to their inability to control the thermal environment at a more local level than an HVAC zone, which could be shared by multiple occupants. Personalized comfort models can improve the controls of HVAC systems by providing information about occupant requirements instead of current “one size fits all” operations. PCS devices enable more local control of the thermal environment by creating a microclimate around each occupant and providing small adjustments to improve occupant satisfaction. Although several studies have developed personalized comfort models for controlling HVAC temperature setpoints, there is a lack of studies that developed personalized comfort models for operating PCS devices. Personalized comfort models when PCS devices are in use are needed to either directly control the PCS devices or to incorporate the impact of PCS operation on occupant comfort into HVAC operations. In this study, we compared different sensing and modeling methods for predicting thermal sensation and thermal satisfaction when PCS devices are used. We also evaluated the effectiveness of integrating the idea of corrective power for thermal sensation prediction when PCS devices are in use.

Our results indicate that using a combination of environmental sensors (ambient temperature, humidity, air speed, and radiant temperature) results in higher predictive accuracy for both thermal sensation and thermal satisfaction, compared to using a wearable device that monitors skin temperature from the wrist, or thermal imaging that monitors skin temperature from different regions of the face. In general, using environmental sensors led to 2%–5% better accuracy compared to physiological sensors. Among the different algorithms evaluated, KNN outperformed other algorithms by a small margin. The observation that environmental sensors were more useful was consistent regardless of the ML algorithm used, which is also supported by the relative dependence of features evaluated using the chi-squared statistic. Furthermore, environmental sensors have a lower cost and relatively fewer privacy concerns compared to physiological sensors. Therefore, we suggest the use of environmental sensors as the preferred data source for building personalized thermal comfort models under regular conditions when PCS devices are not used, as well as when PCS devices are in use. Our results also support building separate personal comfort models when PCS devices are used and when they are not used instead of using a single personal comfort model for comfort predictions with and without PCS.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This material is based upon the work supported by the National Science Foundation under Grant No. 1763134. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation. The help of research assistant Kengo Tanaka and Yingan Cui is greatly appreciated.

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