

Personal comfort models: predicting individuals' thermal preference using occupant heating and cooling behavior and machine learning

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Abstract

A *personal comfort model* is a new approach to thermal comfort modeling that predicts individuals' thermal comfort responses, instead of the average response of a large population. However, securing consistent occupant feedback for model development is challenging as the current methods of data collection rely on individuals' survey participation. We explored the use of a new type of feedback, occupants' heating and cooling behavior with a personal comfort system (PCS) for the development of personal comfort models to predict individuals' thermal preference. The model development draws from field data including PCS control behavior, environmental conditions and mechanical system settings collected from 38 occupants in an office building, and employs six machine learning algorithms. The results showed that (1) personal comfort models based on all field data produced the median accuracy of 0.73 among all subjects and improved predictive accuracy compared to conventional models (PMV, adaptive) which produced a median accuracy of 0.51; (2) the PMV and adaptive models produced individual comfort predictions only slightly better than random guessing under the relatively mild indoor environment observed in the field study; and (3) the models based on PCS control behavior produced the best prediction accuracy when individually assessing all categories of field data acquired in the study. We conclude that personal comfort models based on occupants' heating and cooling behavior can effectively predict individuals' thermal preference and can therefore be used in everyday comfort management to improve occupant satisfaction and energy use in buildings.

Key words: Thermal comfort; personal comfort model; machine learning; occupant behavior; personal comfort system

1. Introduction

Providing an acceptable indoor environment is one of the primary functions of buildings as it affects occupant satisfaction [1,2], health [3,4], and productivity [5–8]. Thermal comfort, in particular, is of great importance because it drives the operation of HVAC (heating, ventilating, and air conditioning) systems which consume 50% of building energy use in developed countries [9]. To establish criteria for thermal comfort in building design and operation, the standards [10–12] use two main models – Predictive Mean Vote (PMV) and adaptive comfort models, and specify a set of thermal conditions that would satisfy a majority (80%) of the occupants. The PMV model [13] provides a mathematical expression of occupants' thermal sensation in terms of environmental (air temperature, radiant temperature, air speed, humidity) and personal (metabolic rate, clothing insulation) factors. Fanger derived the model from chamber experiment data based on heat balance principles, which is now the default thermal comfort model for building design and operation. The adaptive models [14,15] provide a linear regression of acceptable indoor operative temperatures, derived from field study data, as a function of outdoor temperature, and are an alternate thermal comfort model for naturally-conditioned spaces.

However, both PMV and adaptive models have inherent limitations when used to predict occupants' comfort in real buildings. First, both PMV and adaptive models show poor predictive accuracy when applied to a small group of people or individuals because they are designed to predict the average comfort of a large population [16,17]. Second, a full implementation of the PMV model requires very specific input variables (e.g., air speed, metabolic rate, clothing insulation) that are costly and difficult to obtain in the real-world settings and therefore, they are often assumed or simplified. Third, the models do not allow additions to their respective set of input variables; hence new variables that show relevance to the occupants' thermal comfort in the real-world settings cannot be incorporated in their predictions (e.g., sex, body mass index, time of day, etc.). Lastly, the model properties (e.g., function, coefficients) are fixed by the original data set (i.e., laboratory

data for the PMV model, and field data for the adaptive models), and cannot be updated to reflect the actual comfort conditions of individuals in a particular setting.

To overcome the drawbacks listed above, we propose a new modeling approach called a **personal comfort model**. A personal comfort model predicts individuals' thermal comfort responses instead of the average response of a large population. The key characteristics of personal comfort models are that they: (1) take an individual person as the unit of analysis rather than populations or groups of people; (2) use direct feedback from individuals and relevant data to train a model; (3) prioritize cost-effective and easily-obtainable data; (4) employ a data-driven approach, which allows flexible testing of different modeling methods and potential explanatory variables; and (5) has the capacity to adapt as new data is introduced to the model. Personal comfort models can be used to better understand specific comfort needs and desires of individual occupants and characterize a set of conditions that would satisfy their thermal comfort in a given space. Such information can inform the design and control decisions of a building or a system to provide optimal conditioning for improved comfort satisfaction and energy efficiency. These qualities are in line with the current trend of intelligent comfort management [18].

In recent years, an increasing number of studies [17,19–25] have attempted to develop different forms of personal comfort models in order to describe unique comfort characteristics of individual occupants based on the data collected from the actual spaces. These models predict individuals' thermal comfort by correlating environmental measurements with occupant feedback obtained via survey. They employed various machine learning algorithms such as support vector machine [21,24], neural networks [19], fuzzy rules [26], logistic regression [20], Gaussian process [25], and Bayesian network [17,23] for their model development to improve data representations and predictive performance. The results showed significantly improved predictive accuracy (17-40% gain) compared to conventional comfort models (PMV, adaptive), reinforcing the need for an individualized approach to predict thermal comfort. One study [27] showed the integration of personal comfort models in thermostat control to determine optimal temperature setpoints for select zones. The results showed a 12% reduction in average airflow rate in tested zones while maintaining or improving comfort. While these studies suggest a promising role of personal comfort models in comfort prediction and building control, many of them share a common drawback – using surveys as the sole mechanism to obtain occupant feedback about thermal comfort as an ongoing part of building operations. In practice, securing sufficient data collection through surveys for training the model is difficult due to the potential fatigue and eventual decay in participation [21]. Without sufficient comfort feedback, a personal comfort model cannot describe individual-specific comfort needs and desire. Hence, an alternative and/or supplementary feedback source that informs about individuals' thermal comfort is needed for the development of personal comfort models.

Research shows that tracking occupant behavior with thermal control devices (e.g., thermostats, fans) can be non-intrusive yet provide additional data points that can be used to infer individuals' thermal comfort [28]. Individuals interact with thermal control devices available in the space to meet their cooling and heating needs; hence, the resulting behavior can be regarded as an expression of one's thermal preference. The difference is that we can record behavior in a far less intrusive way than surveys. Personal Comfort System (PCS) such as a heated and cooled chair (hereinafter referred to as a PCS chair) provides local heating and/or cooling via embedded heating strips and fans (Figure 1) [29–31]. With personally-owned thermal control devices such as PCS, we can trace the associated behavior back to individual occupants, creating a direct link to personal comfort. In addition to thermal control behavior, tracking occupants' physiological conditions via wearable sensors offers another convenient way of collecting additional data points about human thermal comfort, and recent studies [32–34] have used skin temperatures to predict individuals' thermal comfort. However, no studies have used records of occupant behavior with personally-owned thermal control devices for individuals' comfort predictions.



Figure 1. PCS chair developed by the Center for the Built Environment at the University of California, Berkeley. The images show hardware and heating and cooling elements of the chair and the new controller with wireless connectivity.

In this paper, we present a novel approach for developing personal comfort models that use occupant behavior with PCS chairs to predict individuals' thermal preference. The predictions on individuals' thermal preference can inform who needs additional heating or cooling on top of PCS to meet their desired comfort level and can help HVAC systems to provide preventive or corrective control strategies to improve comfort satisfaction of building occupants. In addition, we offer the following contributions to the field of thermal comfort modeling: (1) evaluating new variables (i.e., behavior, time factors, system control settings) that may affect thermal comfort; (2) comparing the performance of six machine learning algorithms (i.e., Classification Tree, Gaussian Process Classification, Gradient Boosting Method, Kernel Support Vector Machine, Random Forest, Regularized Logistic Regression) for the development of personal comfort models; and (3) developing evaluation criteria that account for prediction accuracy, variability, and convergence of personal comfort models.

2. Background

2.1 Linking behavior to thermal comfort

Occupants interact with a variety of building elements (e.g., thermostats, fans, local heaters, shades, operable windows, etc.) that impact their comfort. Starting with the premise that, when experiencing discomfort, "people react in ways which tend to restore their comfort"—such reaction is described as adaptive behavior [35]. Field studies show ample evidence of adaptive behavior displayed through the use of various thermal control devices available in buildings [36–41]. Opening windows for a cool breeze and turning up the thermostat to heat the room are examples of adaptive behavior. With the lowered cost of sensors and ubiquitous wireless connectivity in buildings, tracking occupants' interaction with thermal control devices has become more affordable over the years. Once the initial infrastructure is installed, continuous data acquisition can be automated, requiring no additional work by the occupants other than their normal behavior. Hence, thermal control devices provide an excellent platform to learn about occupants' thermal preferences.

Most existing literature to date has studied thermal control behavior and thermal comfort in isolated manners without quantitatively linking the two. Behavior literature [42–46] tends to focus on predicting the state of thermal control devices to estimate their effects on the indoor environment, without analyzing the impact on comfort. Conversely, comfort literature [14,15,36] generally focuses on assessing the thermal comfort of occupants who have access to those devices without explicitly accounting for their actual control actions. Understanding the link between the two can provide insights into the underlying comfort drivers behind the control actions. A few studies [47–49] map thermal control actions to occupants' comfort to quantitatively describe the relationship between the two. However, their unit of analysis is individual devices that are typically shared in buildings (e.g., windows). As such, their findings cannot be personalized (with the exception of private offices). Despite the substantial use of personally-owned thermal control devices (e.g., desk fans, space heaters) when available, only two studies [49,50] addressed them, but their analysis is based on aggregated users instead of following individuals. Characterizing individuals' thermal control behavior is important since occupants often have different thermal preferences. This research gap represents an excellent opportunity to learn individuals' thermal preferences based on their behavior with personally-owned thermal control devices.

2.2 Connected PCS chair and continuous data

Personal comfort system (PCS) refers to heating and cooling devices that allow individuals to control their local thermal environment to meet their comfort needs or desires [51,52]. The current practice of delivering uniform thermal conditions does not account for individual differences in comfort requirements. Grivel and Candas [53] show that the standard deviation in individual differences in preferred temperature is 2.6°C, all other things being equal. But given the natural variations in people's clothing and activity levels, differences in people's preferred temperature in the same building are likely to be even greater. Hence, it is impossible to satisfy everyone sharing the same space with a single thermostat. PCS offers a complementary solution to centralized systems by creating a highly customizable microclimate zone in an occupant's workstation without affecting others in the same space. In this case, the centralized system is then responsible for maintaining ambient conditions within a range in which the PCS can correct for each individual's thermal comfort needs, instead of a much narrower range that is a compromise for all occupants in that space. The wider range of acceptable ambient temperature conditions will allow HVAC systems to operate under a wider temperature setpoints, leading to significant energy savings [54–57].

PCS comes in many different forms including personal fans (desk, tower, standing), personal heaters (convective, radiant, or conductive), and systems such as heated and/or cooled chairs. These devices target sensitive body parts that can have a significant influence on the whole-body thermal comfort. Studies have shown that local cooling and heating via PCS can improve thermal satisfaction [58–60] and lead to higher acceptance of wider temperature excursions [52]. In recent years, a

group of researchers at the Center for the Built Environment (CBE) at the University of California, Berkeley developed a new controller for PCS chairs that can record continuous streams of heating and cooling usage data, occupancy status, and environmental measurements (e.g., air temperature, relative humidity) via embedded sensors (See Figure 1) [61]. This presents a unique opportunity to learn individuals’ thermal control behavior and comfort preferences. Such knowledge can enable intelligent comfort management in both new and existing buildings to provide ‘just the right’ amount of conditioning to meet occupant needs, in contrast to over-conditioning that results from tight setpoint management.

3.Methods

3.1 Data sets

To develop personal comfort models, we used the data from a field study that examined the behavior and thermal comfort perceptions of 38 occupants who used a PCS chair, developed by CBE, in an office building located in northern California, between April and October 2016. To our knowledge, it is the largest field study ever conducted with PCS. [62] provides detailed descriptions of the field study methods.

The field study produced the following data sets: (1) PCS chair data: Each PCS chair recorded heating/cooling intensity (in a scale from 0 to 100%) and heating/cooling location (seat, back), chair occupancy, air temperature, and relative humidity at 20-s intervals. Figure 2 shows an example of PCS chair data; (2) Environmental data: HOBO data loggers (Model U12-012, Onset, USA) recorded air temperature, relative humidity, and globe temperature (only for perimeter offices) at 5-min intervals in each workstation where the subjects were located; (3) Survey data: The subjects completed an online survey three times daily to report their current thermal acceptability, thermal preference, and clothing ensembles; (4) HVAC system data: Variable Air Volume (VAV) control settings and thermostat readings in the HVAC zones where the subjects were located were downloaded at 5-min intervals from the building’s BAS; and (5) Weather data: The hourly weather data of a nearby weather station was downloaded from the National Centers for Environmental Information, National Oceanic and Atmospheric Administration (<https://www7.ncdc.noaa.gov/CDO/cdo>).

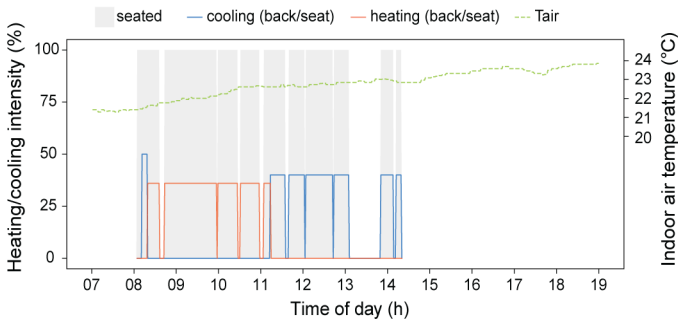


Figure 2. Example of continuous PCS chair data of a subject between 7am and 7pm. Tair refers to indoor air temperature measured via the temperature sensor embedded in the PCS chair. The location of heating and cooling shown here refers to either the back or the seat.

Table 1 summarizes the field study conditions represented in the data sets.

Table 1. Statistical summary of field conditions (indoor and outdoor) across all subjects during occupied hours excluding weekends and holidays.

	Indoor			Outdoor
	Air temperature (°C)	Globe temperature* (°C)	Relative humidity (%)	Temperature (°C)
Mean	24.3	24.0	47.4	14.4
Median	24.2	23.8	47.1	13.9
Lower and upper percentiles (5/10/90/95)	22.2 / 22.6 / 26.2 / 26.9	21.8 / 22.2 / 26.0 / 26.7	41.8 / 43.0 / 52.1 / 54.1	12.2 / 12.2 / 17.2 / 17.8

* Globe temperature only reflects the conditions in perimeter workstations.

3.2 Data preparation

We processed the data using the following steps: (1) Data cleansing: We grouped the PCS chair data into 1-min intervals. The anomalous (i.e., outside of equipment control range) and unlikely (i.e., outside of normal exposed environmental conditions) values were replaced with a value from the prior interval; (2) Feature creation: We created new features from the existing data sets to provide additional information about individuals’ behavior and environmental conditions. First, we calculated duration and frequency of heating/cooling use in the previous 1 h, 4 h, 1 d, and 1 wk to describe short- and long-term control behavior patterns. We normalized the duration of heating/cooling use by the occupied duration of each time interval. Second, we

quantified ramping conditions in air temperature (slope, °C/h) to indicate changes in ambient conditions experienced in the occupied space. Positive values indicate warming conditions while negative values indicate cooling conditions. The absolute value indicates the magnitude of changes. Lastly, we computed weighted running mean outside air temperature over the previous 30 days as per the calculation methods in ASHRAE 55, Informative Appendix I [12] to measure the impact of prevailing outdoor conditions; (3) Data merging: We merged the survey data with chair, HVAC, and weather data based on the nearest date/time for each subject. The final set consists of 4743 entries with 67 features. Table 2 shows the list of features used for model development. Note that the term “feature” is the same as “variable” in the present paper; and (4) Pre-processing: We standardized all numerical features to have zero mean and unit variance. All levels of categorical features were converted into dummy features encoded in a series of zero and one. We removed constant features (with zero variance) and missing values from the data set.

Table 2. Description of features used for personal comfort models.

Category	Feature	Unit	Type*
Survey	Thermal preference	warmer/no change/cooler	C
	Clothing insulation level	clo	N
PCS control behavior	Control location	seat/back/both/none	C
	Control intensity	%	N
	Control frequency in the past x (x = 1h, 4h, 1d, 1wk)	number of use	N
	Occupancy status	seated/unseated/unknown	C
	Occupancy frequency in the past x (x = 1h, 4h, 1d, 1wk)	number of occupancy	N
	Ratio of control duration over occupancy duration in the past x (x = 1h, 4h, 1d, 1wk)	%	N
	Hour of day	h (0-23)	N
Date/Time	Day of week	d (0-6)	N
	Air temperature	°C	N
Indoor environment	Operative temperature	°C	N
	Relative humidity	%	N
	Slope in air temperature	°C/h	N
Outdoor environment	Outdoor air temperature	°C	N
	Sky cover	clear/scattered	C
	Weighted mean monthly temperature	°C	N
	Precipitation	Yes/No	C
	Room temperature**	°C	N
HVAC system	Room airflow	ft ³ /min	N
	Room damper position	%	N
	Room heating output	%	N
	Room discharge air temperature	°C	N

* Type includes categorical (C) and numerical (N) features.

** Room temperature was measured at the thermostat on the wall.

3.3 Machine learning algorithms

In this paper, we use machine learning to solve multiclass classification problems of an occupant’s thermal preference (‘warmer’/‘no change’/‘cooler’). We used thermal preference as the dependent variable because it informs about how to improve current comfort conditions by describing the occupant’s preferred comfort state; hence, thermal preference can be used to make actionable recommendations for HVAC control to improve the occupant’s comfort satisfaction. We use survey responses of thermal preference as the ground truth to verify the predicted thermal preference of individual occupants. As such, the data size for each model is limited by the total survey responses per occupant. Although a wide variety of algorithms exist in machine learning, the given dataset precludes some algorithms (e.g., deep neural network) due to its high dimensional and small size data. Considering this, we selected six machine learning algorithms that do not require strong data assumptions, and describe each algorithm and its hyper-parameter settings below. We used an exhaustive grid search to identify the best performing parameter settings for each machine learning algorithm.

Classification Tree (CTree): CTree creates a tree-like model that predicts the value of a target variable by learning simple decision rules inferred from the data features. We adopted the non-parametric conditional inference tree algorithm implemented in the Party package (version 1.2-3), which used multiple significance tests to grow the tree. We varied the maximum tree depth from 10 to 50 by factors of ten. The splitting threshold was varied from 0.1 to 0.9 with 0.1 intervals.

Gaussian Process Classification (GPC): GPC solves a latent function for classification with a generic Gaussian process, which is then squashed through a logistic function to produce probabilistic classification. We implemented GPC with the

kernlab package (version 0.9-25), which included several approximation algorithms for acceleration. We used the radial basis kernel and varied the kernel width from 2^{-5} to 2^3 with an incremental factor of 2.

Gradient Boosting Method (GBM): GBM generates a prediction model based on an ensemble of many weak classifiers to build a stronger classification committee. We used the AdaBoost procedure [63] implemented in the gbm package (version 2.1.3) to combine basic tree classifiers for ensemble learning. We varied the maximum depth of feature interaction from 1 to 5 by a step size of one, and the number of boosting iterations from 100 to 500 by a step size of 100.

Kernel Support Vector Machine (kSVM): kSVM uses optimal separating hyperplane that maximizes the separation margin of two data groups (classes) to build a prediction model. Its dual form allows the use of kernels to efficiently operate in high dimensional spaces. We used the kernlab package (version 0.9-25) which implemented the sequential minimal optimization algorithm to train SVM classifiers with the Gaussian radial basis function kernel. We varied the kernel width from 2^{-5} to 2^3 with a factor of 2. We varied the penalty parameter from 0.1 to 5 by 0.5.

Random Forest (RF): RF is an ensemble classifier that produces mean predictions of many decision trees constructed from random subsets of the dataset. We implemented RF using the randomForest package (version 4.6-12). We grew 500 trees and fixed the size of the feature set considered at each split to 15.

Regularized Logistic Regression (regLR): LR models a posterior distribution for classification as a sigmoidal function of linear combinations of features. We combine LR with elastic net regularization to penalize inefficient logistic regression coefficients [64]. We use the glmnet package (version 2.0-10) to train LR models with elastic net regularization. We varied the penalty parameter from 10^0 to 10^1 by 0.02. The mixing parameter was varied from 0 (Ridge) to 1 (Lasso) by a step size of 0.2.

We used k-fold cross validation to randomly split the data into training and test sets to estimate the predictive performance of a model. The cross validation was split in two folds to avoid small sample size in each class and repeated 150 times to reduce bias that may be introduced by certain data splits. We applied the same data splits across all tested algorithms to allow direct comparison of their performance. Note that the current data set exhibits unequal distribution in thermal preference classes. To address this imbalance, we randomly resampled the training data to match the size of minority classes to that of the majority class (i.e., over-sampling) [65]. The final model was tuned based on the parameters that produced the best predictive performance on the cross validation set. We used R (version 3.4) and RStudio (version 1.0.143) to run all of our models described in this paper. We used the caret package (version 6.0-76) as a wrapper to interface different machine learning algorithms and conduct pre-processing, resampling, and cross validation.

3.4 Performance evaluation

To evaluate the performance of personal comfort models, we used the following criteria:

- **Prediction accuracy:** does the model correctly predict?
- **Prediction variability:** how consistent is the model prediction?
- **Model convergence:** has the model converged its learning?

These criteria help to assess how good a model is in predicting individuals' thermal preference, identify aspects of a model in need of improvement, and provide the basis for comparing different modeling methods.

We use the Area Under the Receiver Operating Characteristic (ROC) Curve as the base metric to quantitatively assess the above criteria. ROC curves provide a standard way of describing the predictive behavior of a binary classifier [66,67]. The curve plots the probability of true positive rate (i.e., the probability of correctly classifying samples as positive) over false positive rate (i.e., the probability of falsely classifying samples as positive) across all possible discrimination thresholds (Figure 3). Hence, it is ideal when the optimal threshold is unknown. The Area Under the Curve (AUC) reduces the information of the ROC curve into a single index to estimate the predictive accuracy of a classification model. AUC can vary between 0 and 1; AUC = 0.5 denotes random guessing while 1.0 indicates perfect accuracy. We use the "one versus the rest" method [68] to extend binary ROC into the three-class classification problem of thermal preference. The overall performance of a thermal preference classifier is computed by averaging AUC of the ROC curves for all three classes.

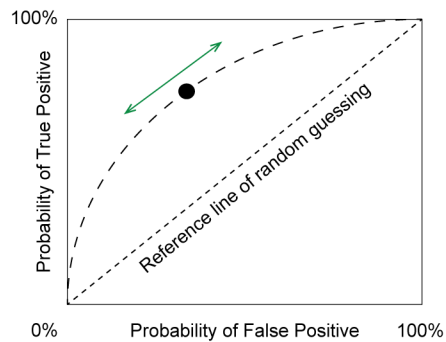


Figure 3. Graphical definition of receiving operating characteristic curve.

Using AUC, we quantify each performance criterion listed above. Table 3 lists the performance criteria and corresponding measures used for model evaluation in this paper where: prediction accuracy is the average AUC of all cross validation sets, prediction variability is the standard deviation of AUC within the cross validation sets, and model convergence is the rate of change in AUC over training data size.

Table 3. Performance criteria and measures used for model evaluation

Criteria	Description	Measure
Predictive accuracy	Accuracy of model predictions	Mean AUC of cross validation sets
Prediction variability	Dispersion of model predictions	Standard deviation of AUC of cross validation sets
Model convergence	Convergence of learning rate	Derivative of AUC over training data size

4. Results and discussion

4.1 Prediction accuracy and variability

Table 4 summarizes the prediction accuracy and variability of the six algorithms (CTree, GPC, GBM, kSVM, RF, and regLR) used to develop personal comfort models for 34 out of the 38 subjects who participated in the field study. There were 4 subjects who only voted for ‘no change’ as a result of mild indoor temperatures during the study period. Table 4 does not include these subjects since models cannot be trained on a single class. We report the results in mean and standard deviation of cross-validated AUC. The last row in the table shows the average performance of each algorithm across all subjects. The last column shows the average and the highest AUC of the six algorithms used for personal comfort models for each subject. We also provide the prediction results of the PMV and adaptive models to compare the personal and conventional comfort models. We used the *comf* package (version 0.1.4) to compute the PMV and adaptive models as per the calculation methods in ISO 7730 [10] and ASHRAE 55 [12], respectively. We used the field data (i.e., air temperature, operative temperature, humidity) and the static values (i.e., air velocity = 0.1 m/s, metabolic rate = 1.2 met, clothing insulation = 0.6) for the PMV calculation. To compare the results on the same scale, we convert PMV into thermal preference classes based on the following assumptions: $|\text{PMV}| \leq 0.5$ is ‘no change’; $\text{PMV} > 0.5$ is ‘want cooler’; and $\text{PMV} < -0.5$ is ‘want warmer’, as used in [23]. These assumptions reflect 80% thermal satisfaction with 10% dissatisfaction from whole-body discomfort and 10% dissatisfaction from local discomfort. To convert the output of the adaptive model into thermal preference classes, we assume acceptable operative temperature within 80% acceptability limits to be ‘no change’; and greater/less than the upper/lower 80% acceptability limits to be ‘want cooler/warmer’, respectively.

Table 4. Predictive performance of personal comfort models and conventional comfort models across all subjects. Prediction accuracy and variability are expressed as the mean and standard deviation (shown in brackets) of all cross-validated AUC respectively.

User ID	Data size	Conventional comfort models		Personal comfort models*							Median / Best
		PMV	Adaptive	CTree	GBM	GPC	kSVM	RF	regLR		
1	172	0.55 (0.04)	0.50 (0.00)	0.76 (0.05)	0.80 (0.06)	0.84 (0.04)	0.83 (0.03)	0.86 (0.05)	0.83 (0.05)	0.83 / 0.86	
2	132	0.52 (0.04)	0.52 (0.04)	0.52 (0.06)	0.53 (0.06)	0.48 (0.07)	0.48 (0.08)	0.58 (0.06)	0.53 (0.05)	0.52 / 0.58	
3	167	0.52 (0.04)	0.50 (0.00)	0.61 (0.06)	0.64 (0.06)	0.75 (0.04)	0.73 (0.05)	0.73 (0.05)	0.69 (0.06)	0.71 / 0.75	
4	138	0.60 (0.02)	0.54 (0.03)	0.76 (0.07)	0.85 (0.05)	0.81 (0.06)	0.82 (0.05)	0.87 (0.04)	0.86 (0.05)	0.83 / 0.87	
5	147	0.50 (0.00)	0.50 (0.00)	0.60 (0.13)	0.62 (0.13)	0.73 (0.07)	0.70 (0.09)	0.65 (0.11)	0.61 (0.13)	0.64 / 0.73	
6	135	0.50 (0.00)	0.50 (0.00)	0.60 (0.11)	0.67 (0.11)	0.62 (0.14)	0.63 (0.12)	0.66 (0.11)	0.65 (0.13)	0.64 / 0.67	
7	82	0.53 (0.04)	0.50 (0.00)	0.51 (0.06)	0.59 (0.08)	0.58 (0.07)	0.57 (0.08)	0.61 (0.08)	0.63 (0.08)	0.58 / 0.63	
8	132	0.72 (0.03)	0.50 (0.00)	0.54 (0.08)	0.61 (0.10)	0.58 (0.07)	0.59 (0.08)	0.64 (0.10)	0.60 (0.10)	0.59 / 0.64	

9	110	0.67 (0.13)	0.50 (0.00)	0.50 (0.10)	0.51 (0.20)	0.74 (0.08)	0.74 (0.09)	0.56 (0.17)	0.48 (0.13)	0.53 / 0.74
10	118	0.50 (0.00)	0.50 (0.00)	0.49 (0.09)	0.55 (0.14)	0.68 (0.09)	0.68 (0.09)	0.59 (0.11)	0.52 (0.13)	0.57 / 0.68
11	110	0.47 (0.01)	0.50 (0.00)	0.52 (0.11)	0.58 (0.11)	0.54 (0.07)	0.53 (0.09)	0.55 (0.12)	0.59 (0.11)	0.55 / 0.59
12	124	0.40 (0.12)	0.50 (0.00)	0.51 (0.11)	0.68 (0.15)	0.67 (0.17)	0.71 (0.15)	0.81 (0.10)	0.75 (0.13)	0.70 / 0.81
13	147	0.50 (0.00)	0.50 (0.00)	0.64 (0.06)	0.70 (0.05)	0.67 (0.05)	0.66 (0.05)	0.71 (0.05)	0.71 (0.05)	0.69 / 0.71
14	33	0.46 (0.08)	0.50 (0.00)	0.67 (0.20)	0.60 (0.11)	0.51 (0.07)	0.59 (0.12)	0.73 (0.16)	0.68 (0.11)	0.63 / 0.73
15	110	0.54 (0.04)	0.50 (0.00)	0.62 (0.09)	0.73 (0.07)	0.72 (0.07)	0.71 (0.07)	0.74 (0.06)	0.70 (0.07)	0.72 / 0.74
16	141	0.50 (0.00)	0.50 (0.00)	0.60 (0.08)	0.66 (0.07)	0.68 (0.07)	0.66 (0.06)	0.68 (0.07)	0.66 (0.07)	0.66 / 0.68
17	103	0.57 (0.10)	0.50 (0.00)	0.57 (0.12)	0.69 (0.17)	0.66 (0.18)	0.70 (0.20)	0.69 (0.17)	0.64 (0.25)	0.67 / 0.70
18	140	0.50 (0.00)	0.50 (0.00)	0.77 (0.06)	0.83 (0.04)	0.79 (0.06)	0.82 (0.05)	0.85 (0.04)	0.83 (0.04)	0.82 / 0.85
19	148	0.53 (0.02)	0.50 (0.00)	0.57 (0.06)	0.62 (0.06)	0.60 (0.05)	0.60 (0.05)	0.65 (0.06)	0.63 (0.06)	0.61 / 0.65
20	132	0.50 (0.00)	0.50 (0.00)	0.74 (0.07)	0.85 (0.05)	0.82 (0.03)	0.81 (0.04)	0.85 (0.04)	0.83 (0.06)	0.83 / 0.85
21	65	0.50 (0.00)	0.50 (0.00)	0.55 (0.07)	0.58 (0.09)	0.68 (0.08)	0.66 (0.12)	0.66 (0.08)	0.59 (0.09)	0.62 / 0.68
22	121	0.50 (0.00)	0.50 (0.00)	0.66 (0.09)	0.70 (0.06)	0.77 (0.06)	0.76 (0.06)	0.72 (0.06)	0.72 (0.06)	0.72 / 0.77
23	134	0.54 (0.04)	0.50 (0.00)	0.67 (0.08)	0.76 (0.07)	0.77 (0.05)	0.76 (0.05)	0.80 (0.05)	0.77 (0.05)	0.76 / 0.80
24	116	0.62 (0.03)	0.60 (0.03)	0.75 (0.05)	0.83 (0.03)	0.84 (0.03)	0.83 (0.03)	0.87 (0.03)	0.87 (0.03)	0.84 / 0.87
25	109	0.50 (0.00)	0.50 (0.00)	0.85 (0.08)	0.94 (0.04)	0.94 (0.03)	0.94 (0.02)	0.96 (0.02)	0.93 (0.05)	0.94 / 0.96
26	49	0.72 (0.12)	0.50 (0.00)	0.53 (0.13)	0.58 (0.14)	0.52 (0.14)	0.61 (0.16)	0.62 (0.13)	0.71 (0.13)	0.59 / 0.71
27	138	0.54 (0.03)	0.50 (0.00)	0.61 (0.06)	0.62 (0.06)	0.65 (0.05)	0.64 (0.06)	0.67 (0.05)	0.61 (0.06)	0.63 / 0.67
28	218	0.52 (0.02)	0.50 (0.00)	0.86 (0.04)	0.92 (0.02)	0.90 (0.02)	0.90 (0.02)	0.93 (0.02)	0.90 (0.02)	0.90 / 0.93
29	185	0.50 (0.00)	0.50 (0.00)	0.77 (0.22)	0.95 (0.04)	0.78 (0.20)	0.87 (0.11)	0.93 (0.07)	0.94 (0.07)	0.90 / 0.95
30	86	0.52 (0.02)	0.50 (0.00)	0.59 (0.07)	0.60 (0.06)	0.62 (0.05)	0.64 (0.05)	0.62 (0.05)	0.65 (0.05)	0.62 / 0.65
31	133	0.49 (0.01)	0.50 (0.00)	0.55 (0.07)	0.52 (0.07)	0.58 (0.07)	0.57 (0.08)	0.54 (0.07)	0.54 (0.07)	0.54 / 0.58
32	44	0.58 (0.08)	0.50 (0.00)	0.64 (0.11)	0.74 (0.10)	0.83 (0.08)	0.83 (0.09)	0.81 (0.08)	0.76 (0.12)	0.79 / 0.83
33	133	0.56 (0.04)	0.54 (0.03)	0.83 (0.05)	0.88 (0.03)	0.89 (0.03)	0.89 (0.03)	0.91 (0.03)	0.89 (0.03)	0.89 / 0.91
34	136	0.53 (0.05)	0.50 (0.00)	0.84 (0.05)	0.90 (0.03)	0.90 (0.03)	0.89 (0.03)	0.91 (0.03)	0.92 (0.03)	0.90 / 0.92
Median	123	0.52 (0.03)	0.50 (0.00)	0.61 (0.08)	0.68 (0.07)	0.70 (0.07)	0.71 (0.07)	0.71 (0.06)	0.70 (0.06)	0.68 / 0.73

* The best and worst performing algorithm among the six personal comfort models are marked in green and purple colors respectively for each subject.

For these subjects with PCS chairs, the median accuracy of personal comfort models was 68%. When we only consider the best performing algorithm from each subject, this value became 73%. On average, personal comfort models based on the best performing algorithms improved predictions by 43% from that of conventional comfort models. The PMV and adaptive models predicted individual thermal preference only slightly better than random guessing (50%). This is because conventional comfort models are designed to predict the comfort of a large population instead of specific individuals, and their predictions are biased towards ‘no change’ due to the relatively mild indoor environmental conditions observed in the field study. There was a large variation in prediction accuracy between individual’s models. Some models produced over 90% prediction accuracy while others predicted worse than random guessing. This could be due to the fact that individual’s decision-making process for thermal preference differed a lot in their complexity and/or that some people were more predictable than others based on the predictor variables and machine learning algorithms used in this study. The variability in prediction accuracy among the repeated cross validations sets (300 sets) for individuals’ personal comfort models was fairly small, mostly within 0.10 standard deviation, indicating stable prediction behavior in the trained models. However, this value increased to 0.25 depending on the subjects and modeling methods.

To compare the prediction accuracy of different modeling methods, we plot a bar chart by grouping the results by modeling methods (Figure 4). The boxplots are ordered by their mean value. Among the tested algorithms, RF displayed the highest performance (median AUC=0.71), followed by kSVM and regLR. The difference between the top three algorithms was small (within 1% of each other). The middle tier included GPC and GBM with the median AUC of 0.70 and 0.68 respectively. The worst performing model was CTree. On average, CTree performed 10% worse than RF and 7% worse than the average of all other algorithms. This is not surprising as CTree draws its decision rules by recursive splitting of a dataset which can lead to myopic rule selection and overfitting. However, CTree generates a highly interpretable model (easy to understand how the model generates rules/fits) and runs fast with large datasets. More complex models such as RF, kSVM, and regLR tend to produce better predictive accuracy because they are effective at handling high dimensions (i.e., a large number of features) and controlling noise in the data. But, they are often difficult to interpret and computationally expensive (e.g., kSVM required three more CPU times on average to complete the same task as CTree for this dataset).

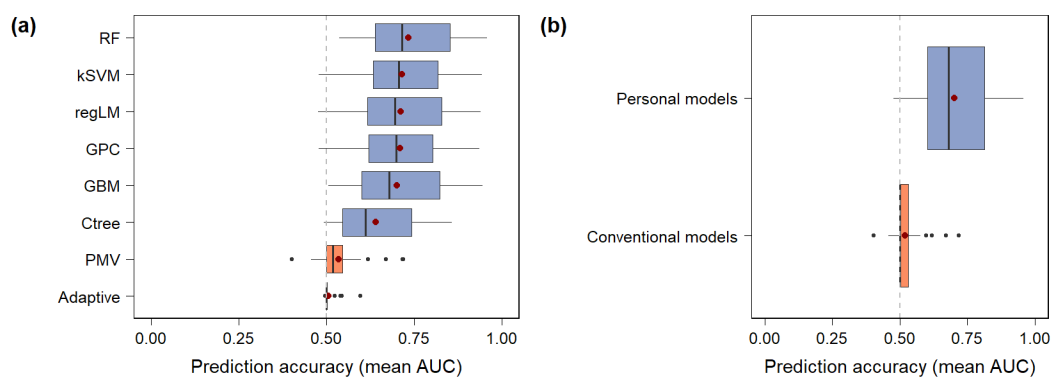


Figure 4 (a) Distribution of prediction accuracy across all subjects for each modeling method. The top boxplots six represent personal comfort models. The bottom two represents conventional comfort models. The boxplots are ordered by the decreasing order of mean AUC, marked as a red circle. The dashed line indicates a reference line for random guessing. (b) Distribution of prediction accuracy across all subjects grouped into personal comfort models and conventional comfort models (labeled as “Personal models” and “Conventional models” respectively).

While we focus on predictive accuracy to compare different modeling methods here, note that there are other factors such as computational speed, interpretability, robustness, scalability, etc. that impact the quality of a model. Depending on the application of the model (e.g., real-time HVAC control), some of these factors may have a greater influence on model selection than others.

4.2 Model convergence

Model convergence indicates whether the current model has converged its learning to produce stable predictions or not. Figure 5 shows the learning curve of the individuals’ personal comfort models as a function of prediction accuracy over training data size. To plot this curve, we repeatedly ran each subject’s model by adding five data points at a time in the sequential order of data collection until the model exhausts the full data set. The x-axis represents the number of data points increased from left to right. The y-axis represents the mean AUC of cross validation sets (two folds repeated 150 times). We applied the same tuning parameters across all subset models in this figure. To determine whether a model has converged or not, we calculated the rate of learning by taking the derivative of the curve with respect to data size. We considered a model to have converged when the derivative plateaus (within ± 0.001) for two successive runs. Based on this rule, we determined the training data size at which the individuals’ model first converged and showed this as a boxplot in this figure as well. Note that the boxplot does not include the data from the four individuals (User 10, 14, 26, and 32) whose model did not converge within the given data set. The Appendix includes separate plots of the individuals’ learning curve to show their unique convergence pattern more clearly. We also show the overall learning trend across all subjects in this figure by fitting a local polynomial regression line to the aggregated prediction accuracy of everyone’s personal comfort models.

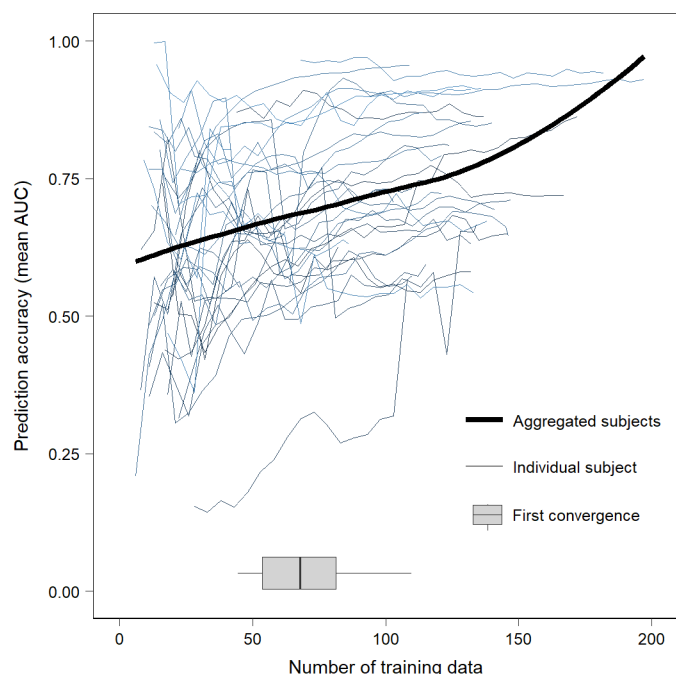


Figure 5. Learning curve of individual subjects' personal comfort models expressed as the derivative of mean AUC with respect training data size (shown in dashed lines). The solid line is the local polynomial regression (LOESS) fit to aggregated mean AUC of all subjects' models over training data size. The boxplot shows the distribution of the training data size at which the individuals' model first converged.

The aggregated trend shows that prediction accuracy generally improves as the number of samples increases. However, the individual subjects display different learning trends from one another. For some, the learning converged quickly while for others it is still ongoing (as shown in Appendix Fig.A.1). This indicates that the amount of data needed to achieve a stable prediction behavior varies between individuals. We observe that convergence occurs when sample size reaches 64 on average. This means that individual subjects need to supply over 60 survey responses in order to produce a model with stable predictions. However, depending on the occupants' survey participation, obtaining sufficient training data can be challenging if the survey participation rate is low (e.g., User 14, 26, and 32 submitted less than 50 survey responses over the three-month period). Note that some models go through more than one convergence (See Appendix Fig.A.1). This is because the model has to relearn new patterns in the data with the addition of new data points. And, each time the model relearns, it needs enough sample size to reach stable predictions. For future studies, we suggest the use of online machine learning to automatically update models as new samples of data arrive. Convergence does not guarantee good predictive performance. Converged models can suffer from poor accuracy and large variability in predictions. Hence, the evaluation of a personal comfort model should consider all three criteria – prediction accuracy, variability, and convergence.

4.3 Variable importance

Understanding which variables contribute the most to the predictive power of a model can help to eliminate ineffective variables and reduce the cost of data collection. However, testing significance of all variables and their possible combinations in a high dimensional dataset is computationally impossible ($>10^{10}$ years). We simplified this process by grouping variables that come from a single data source and measuring their predictive performance to understand how little data one might need to collect to have a model with strong predictive power. We took a stepwise approach to run models for all subjects by adding the variables from each variable group until the model included all variable groups. The intent was to quantify the additional improvement that each variable group contributed to the prediction accuracy. We fixed the modeling method to RF and applied two-fold cross validation repeated 150 times. The order of the variable groups is determined based on the effort involved in data collection during the field study so that most easily obtainable data is introduced to the model first. The order was: 1) PCS control behavior, because the data was automatically reported via PCS chairs; 2) date/time, because they were extracted from the time stamp of the PCS chair data; 3) HVAC system and 4) outdoor environment, because they required interfacing with a third-party online software to access the data; 5) indoor environment, because the data collection required additional sensor installation for globe temperature measurements; 6) clothing insulation, because it required occupant's survey participation to collect the data. Note that this order is applicable to this particular field study and it may

change in different settings. Since the variables in each group come from a single data source, there is no difference in the cost of data collection within each variable group.

Figure 6 (a) summarizes the results from the model runs. The results show that PCS control behavior alone (Comb. 1) could produce 69% prediction accuracy on average, which is a notable increase over the prediction accuracy of conventional comfort models (PMV and adaptive) for this dataset (0.52 and 0.50 respectively). Adding other variable groups only improved the mean prediction accuracy by 4% compared to the model with PCS control behavior alone. This means that, on average, the models based on PCS control behavior alone could attain the majority of prediction accuracy produced by the models that include all field data (0.73). To give a sense of how different variable groups independently perform from one another, we plot the prediction results of individual variable groups in Figure 6 (b). The main takeaway from this analysis is that the variable group with PCS control behavior (69%) still produced the best results among all. The prediction accuracy of all other variable groups ranged between 60–63%. As an interesting side note, even the lowest group (outdoor environment), with a prediction accuracy of 0.60, achieves a significant improvement over conventional comfort models. Thus, in general, it is clear that machine learning helps to improve prediction accuracy. However, unlike conventional models, applying these machine learning methods to predict individual's thermal comfort requires training data (i.e. approximately 60 surveys per occupant in this case), which the conventional comfort models do not. Note also that these results are based on the comfort conditions that the subjects were exposed to during the field study – a relatively narrow range of indoor environmental conditions that are typical in mechanically-conditioned office buildings. Outside these narrow conditions, the indoor environment will become a more important factor to individuals' thermal preference.

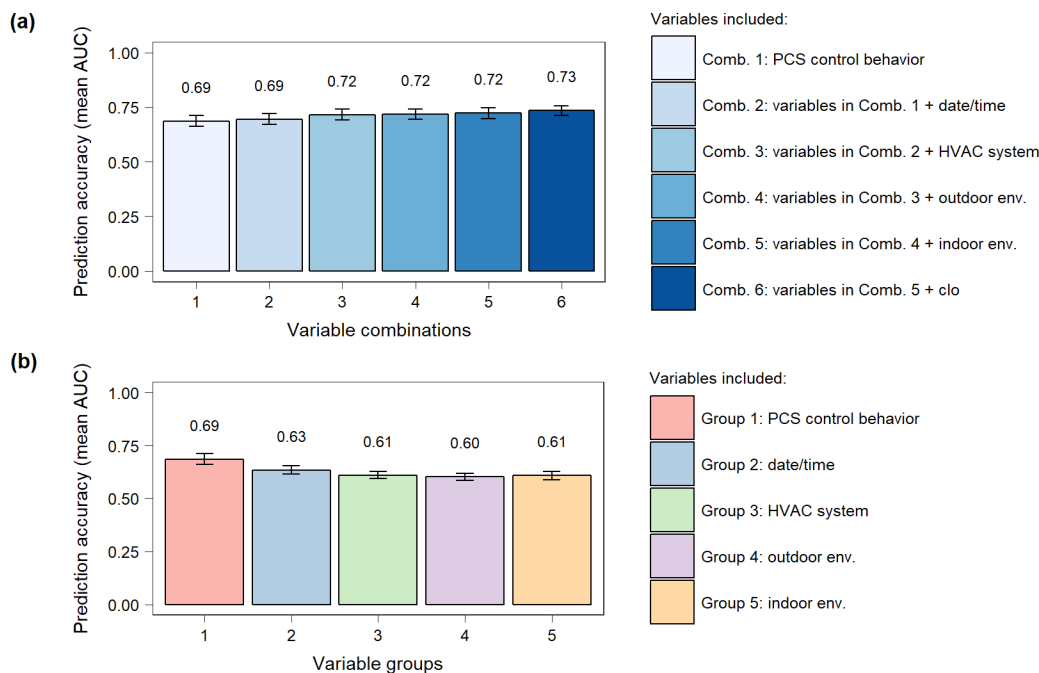


Figure 6 (a) Prediction accuracy of model runs with different variable combinations. The variable combinations are constructed by accumulatively adding features from each variable groups until all features in the database are included in the model. (b) Prediction accuracy of separately evaluated variable groups (PCS control behavior, date/time, HVAC system, outdoor environment, and indoor environment). Clothing insulation is not included since a fixed value (0.6) was used in all model runs. Bar plots and error bars indicate the average and standard deviation of AUC across all subjects respectively.

Practically speaking, the choice of model parameters is not always based on accuracy but rather on the cost of collecting the data. For this study, PCS chairs provided a convenient platform to collect continuous data that can be individually identifiable. The strong predictive power of PCS control behavior signals that it can potentially replace survey feedback as the “ground truth” when you have these kinds of systems. This means that one can use the continuous PCS data to directly model individuals' thermal preference and dynamically control thermostat setpoints to match their preferences. Such is the case for many commercial “smart” thermostats (e.g., Nest) that learn occupants' thermal preference based on their thermostat control behavior and automatically create a temperature schedule according to their desired settings. However, the learning based on thermostats may represent more than one person since they are typically shared in many spaces; hence, it can be biased toward a few individuals who drive the thermostat settings. The PCS chairs are usually individually owned and

operated; therefore, the temperature schedule can be determined based on the learning of individuals' thermal control behavior rather than group behavior.

5. Limitations

There are several limitations in our current modeling approach. First, the size of the dataset, which is determined by the number of survey responses received from each person, limits the performance of the model. This limitation also applies to all previous thermal comfort studies that rely on survey feedback. One way to overcome this limitation is to use continuous PCS control behavior to directly model individuals' comfort requirements. Another solution is to increase the data size by pooling relevant survey responses from other occupants [69]. Second, we based our models on one-time batch learning. However, batch learning can be computationally challenging over time as the data size grows. Hence, we suggest online machine learning to dynamically adapt new patterns in the data and automatically update the model as needed. Third, we treat misclassification costs among different thermal comfort classes the same in the present analysis. We acknowledge that the cost of misclassifying certain classes (e.g., 'cooler', 'warmer') can differ from others (e.g., 'no change'). However, current literature at the time of this work did not offer information that could help to specify the exact consequences/cost of misclassifying thermal preference. This void represents an area for future research.

6. Conclusions

Thermal comfort is a subjective phenomenon which can display large differences among individual occupants. Therefore, providing a satisfactory thermal environment requires an understanding of the unique comfort requirements of individuals. In this paper, we present a new modeling approach, *personal comfort models* to predict individuals' thermal preference based on learning from a novel type of occupant feedback – thermal control behavior with PCS chairs and six different machine learning algorithms to improve consistent data collection and prediction accuracy. From our results, we draw the following conclusions.

- Personal comfort models produced the median accuracy of 0.73 based on the best performing algorithm, improving the predictions of conventional comfort models (PMV and adaptive) which produced a median accuracy of 0.51. The PMV and adaptive models predicted individual thermal preference only slightly better than random guessing for the relatively mild indoor environmental conditions observed in the field study. Such outcome confirms that an individual approach can significantly improve comfort predictions of the actual occupants in building space.
- Among the six machine learning algorithms used for model development, the algorithms with capabilities to control high dimensions and noise in the data (e.g., RF, kSVM, regLR) produced higher accuracy than the algorithms without them, but they were more computationally expensive. Hence, depending on the application of the model, one may need to assess the value of accuracy against the computational cost when selecting algorithms.
- The personal comfort models generally converged when the data size reached 64 survey inputs. This means that occupants need to supply over 60 survey responses to produce a stable prediction of their thermal preference. This is a limiting factor for models that require survey feedback for training purposes.
- Personal comfort models based on PCS control behavior produced the best prediction accuracy when individually assessing all categories of field data acquired in the the study (i.e., date/time, HVAC system, outdoor environment, indoor environment, and clothing insulation). This shows that individuals' heating and cooling behavior with PCS is a strong comfort predictor and can potentially replace survey feedback as the ground truth for personal comfort models.

Personal comfort models can provide more accurate representations of occupants' comfort needs and desires. Moreover, they can produce continuous predictions that can inform temperature settings in day-to-day building operations. The next logical step is to demonstrate the integration of personal comfort models into thermostat control to close the feedback loop between occupants and HVAC systems – this is a topic well worth pursuing to make a tangible impact on occupant satisfaction and energy use in buildings.

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Appendix

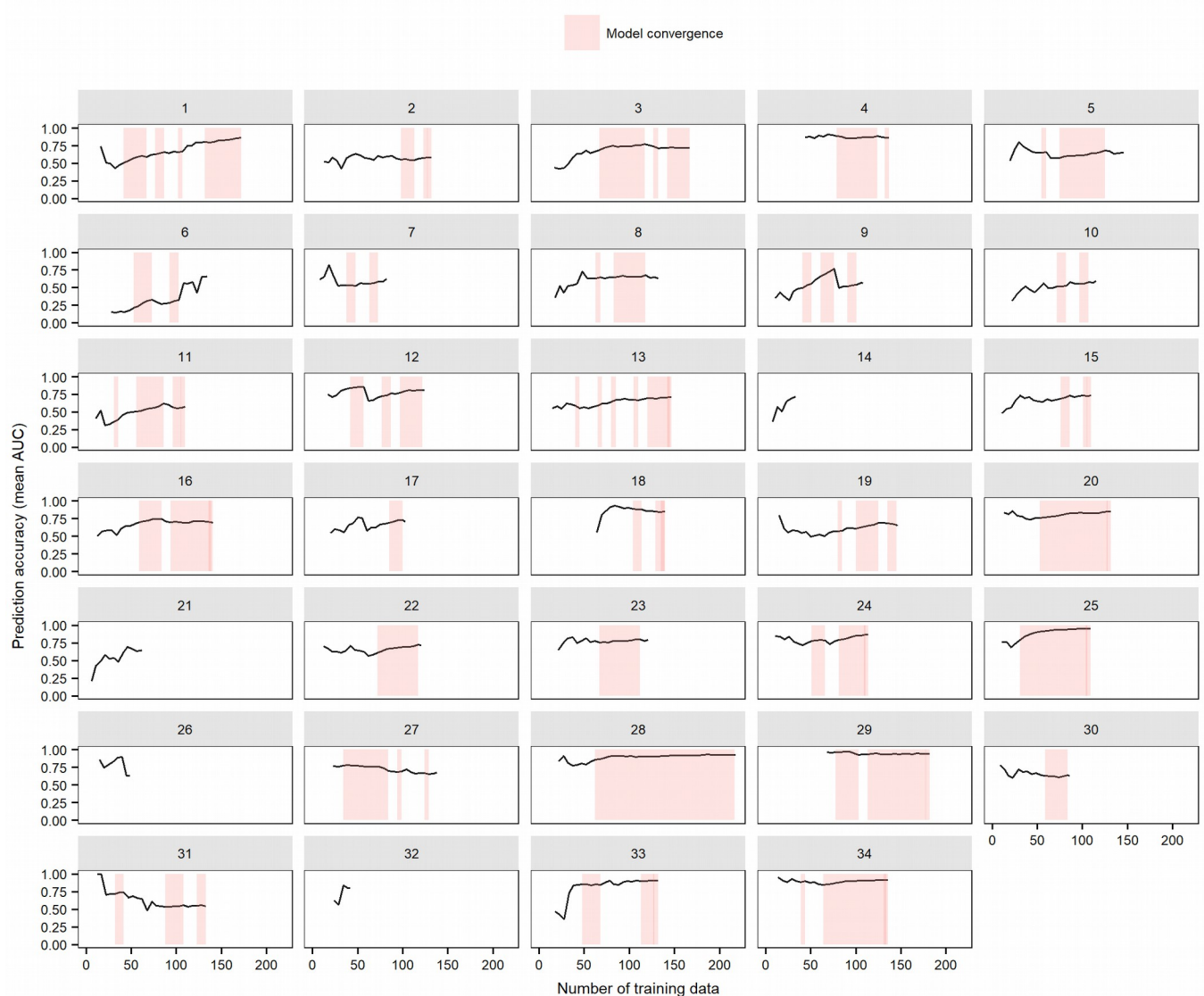


Fig.A.1. Learning curve of each subject's personal comfort model expressed as a function of mean prediction accuracy over training data size. The shadow indicates the confidence interval of cross-validated AUC.

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