Personal comfort models – a new paradigm in thermal comfort for occupant-centric environmental control

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Abstract

A *personal comfort model* is a new approach to thermal comfort modeling that predicts an individual's thermal comfort response, instead of the average response of a large population. It leverages the Internet of Things and machine learning to learn individuals' comfort requirements directly from the data collected in their everyday environment. Its results could be aggregated to predict comfort of a population. To provide guidance on future efforts in this emerging research area, this paper presents a unified framework for personal comfort models. We first define the problem by providing a brief discussion of existing thermal comfort models and their limitations for real-world applications, and then review the current state of research on personal comfort models including a summary of key advances and gaps. We then describe a modeling framework to establish fundamental concepts and methodologies for developing and evaluating personal comfort models, followed by a discussion of how such models can be integrated into indoor environmental controls. Lastly, we discuss the challenges and opportunities for applications of personal comfort models for building design, control, standards, and future research.

Keywords: personal thermal comfort, data-driven modeling, machine learning, Internet of Things, occupant-centric environmental control, smart buildings

1. Introduction

An increasing number of researchers are investigating the possibility of learning about individuals' thermal comfort requirements, and predicting their comfort needs, directly from data collected in their everyday environment. We term the output of these efforts as personal comfort models (defined in more detail below). This new modeling approach can fundamentally change today's generic, 'one-size-fits-all' comfort management by making individual-specific and context-relevant comfort predictions available for occupant-centric environmental control. The opportunities associated with personal comfort models have generated significant interest within the research and industry communities. Academics are exploring new data types and modeling techniques to better predict individuals' thermal comfort in buildings or other systems (e.g., vehicles). The industry is leveraging advanced analytics and cloud-based control to deliver customized heating and cooling in the occupied spaces (e.g., Nest, Comfy). However, the efforts to date have been quite fragmented across a wide range of disciplines and display significant variations in their approach from each other, as well as from traditional thermal comfort research. To address these issues, we developed a unified framework for personal comfort models to understand the variety of activities on this topic, and provide guidance on future efforts in this emerging research area.

2. Problem definition

Thermal comfort is an important goal for the built environment as it affects occupant satisfaction [1,2], health [3,4], and productivity [5–8]. To understand what makes an environment thermally comfortable to the occupants, researchers have focused on developing empirical models that can represent human perception of thermal comfort in terms of the given conditions or factors (e.g., personal, environmental, etc.). There are two main models that underpin the current practice of comfort management in buildings: predicted mean vote (PMV) and adaptive models. The PMV model treats thermal comfort as a physical-physiological phenomenon and expresses human thermal sensation as an outcome of the heat transfer between a human body and its surrounding environment. It is the most widely accepted model, developed through extensive laboratory experiments by Fanger [9], which became the basis of the standards ISO 7730 [10] and ASHRAE 55 [11]. In contrast, adaptive models account for people's inherent ability to adapt to variable environment conditions in naturally-conditioned buildings by drawing a linear relationship between comfortable indoor temperature and prevailing outdoor temperature based on global field study data. Currently, there are mainly two adaptive models standards: the ASHRAE 55 adaptive model by de Dear and Brager [12] and the EN 15251 adaptive model by Nicol and Humphreys [13]. Despite their successful adoption into international standards, both types of models (PMV and adaptive) have several inherent limitations when applied to comfort management in buildings.

First, a full implementation of the PMV model requires very specific input variables that are costly and difficult to obtain in buildings. Two of the environmental variables – mean radiant temperature and air velocity – are not typically monitored in existing buildings and require expensive instruments to accurately measure (in particular, air velocity). Two personal variables – clothing insulation and metabolic rates – are impossible to collect in an automated fashion, and their values are often assumed or simplified, which undermines the predictive accuracy of the model [14].

Second, even if all of the input variables are accurately obtained, both existing models show poor predictive performance when applied to individuals [15,16]. This is because the models are aggregate models, designed to predict the average comfort of large populations; hence, their accuracy decreases when predicting individuals' thermal comfort responses due to large variations in thermal comfort between people. The irony is that this is exactly the situation in practice where the models are used – groups of occupants in a building with varying degrees of comfort perception sharing the same thermal zone.

Third, both models do not adapt or re-learn. They are based on a fixed set of data collected from either laboratory (PMV) or the field (adaptive) measurements. Hence, model properties and coefficients may not accurately describe the comfort characteristics of individual occupants in a particular field setting. Unfortunately, there is no provision that allows for the update of either of these existing models based on occupant feedback and field-collected data in new circumstances. Therefore, they cannot be calibrated to better match the relationships in a particular setting.

Lastly, these models do not allow modifications to their respective set of input variables. Only pre-defined variables are entered into the models regardless of the existence of other factors that may affect the actual outcome. New variables (e.g., sex, body mass index, time of day, age, health status, etc.) that may potentially be relevant to the occupants' thermal comfort in a particular setting cannot be incorporated into the model, thus reducing the potential to improve predictive accuracy and enhance our understanding of contextual impacts on human thermal comfort.

To overcome the drawbacks listed above, both academia and industry have been looking for ways to improve the practical relevance of thermal comfort models for building operations. With the emergence of the Internet of Things allowing us to generate highly granular and personal data, efforts have begun to analyze such data for the prediction of individuals' thermal comfort. This paper provides a synthesis of this new research area called *personal comfort models*.

3. Personal comfort models

3.1 Definition

A ***personal comfort model*** predicts an individual's thermal comfort response, 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 (e.g., thermal sensation, preference, acceptability, pleasure) and additional relevant data (e.g., personal, environmental, technological), 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) have 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 other systems (e.g., vehicle, aircraft, personal comfort systems) to provide optimal conditioning for improved comfort satisfaction and energy efficiency. These qualities are in line with the current trend of intelligent comfort management [17].

3.2 Review of current state of research

In recent years, there have been an increasing number of publications on the topic of personal comfort models. Interestingly, many of these efforts did not originate from the traditional thermal comfort research, but rather consist of independent work across various academic disciplines as well as industry organizations. As such, this research often shows a significant departure from the conventional approach to thermal comfort modeling, and therefore represents a unique perspective and contribution to our field.

To better understand the current state of research and development on personal comfort models, we provide a review of relevant literature published in the past ten years. To address the first two characteristics of personal comfort models noted above, the review only includes studies that focus on individual occupants as a unit of analysis, and use human feedback in the model development. This effectively excludes 1) studies that adopt a data-driven approach to modeling, but predict thermal comfort of general populations rather than individual occupants [18–23], and 2) studies that use synthetic data instead of real-world data to model individuals' thermal comfort [24–26]. Table 1 summarizes the findings from this literature review. It is organized by data sources, input and output variables, modeling methods, model evaluation, and continuous learning methods, and ordered by the year of publication.

Table 1. Summary of major studies of personal comfort models

Source	Data	Input variables*		Output variables	Modeling methods	Model evaluation		Continuous learning methods
		Occupant feedback	Physical measurement			Accuracy	Convergence	
[27]	Field data from 7 subjects	3-point thermal preference (warmer / no change / cooler), clo, heart rate, skin temperature, activity	Ta, RH, CO_2, window state (open/close), Tout, outdoor humidity	3-point thermal preference (warmer / no change / cooler)	Random Forest	Overall accuracy = 80%	80% classification accuracy achieved after 50 samples (60% of the total data)	N/A
[28]	Field data from 15 subjects	Continuous thermal acceptability scale with 4 labels (clearly acceptable / just acceptable / just unacceptable / clearly unacceptable), activity, air-conditioning status, location	Ta, RH, CO_2	Continuous thermal acceptability scale with 4 labels (clearly acceptable / just acceptable / just unacceptable / clearly unacceptable)	Gaussian Process	R^2 between predicted and actual votes = 0.18 and 0.26 for 2 subjects respectively	N/A	N/A
[29]	Field data from ASHRAE RP-884 database	3-point thermal preference (warmer / no change / cooler), clo, MET	Ta, MRT, RH, Va	3-point thermal preference (warmer / no change / cooler)	Bayesian inference, clustering	Logloss maximized with optimal number of clusters	N/A	N/A
[30]	Lab data from 20 subjects	ASHRAE 7-point thermal sensation scale, clo, MET	Ta, MRT, RH, Va	ASHRAE 7-point sensation scale	C-Support Vector, Classification	Mean accuracy: proposed model = 89.8% PMV model = 49.7%	N/A	N/A
[16]	Field data from ASHRAE RP-884 database	ASHRAE 7-point thermal sensation scale, clo, MET	Top, RH, Tout, seasons	ASHRAE 7-point sensation scale	Bayesian network	17.5 – 23.5% accuracy gains compared to PMV and ASHRAE-55 adaptive models	Root mean square error converged after 10 votes	Full relearning with new votes
[31]	Field data from 33 subjects	11-point thermal preference scale with 3 labels (cooler /no change / warmer)	Ta	3 comfort conditions (uncomfortably warm / comfortable / uncomfortably cool)	Bayesian network, online learning	Mean accuracy: proposed model = 70.1% PMV model = 56.1%	N/A	Kolmogorov-Smirnov test to remove statistically irrelevant data points as new votes are added
[32]	Field data from 4 subjects	Continuous thermal preference scale with 2 labels (cooler / warmer) at both ends	Ta	5-level thermal sensation index (very cold / cold / neutral / warm / very warm), associated	Fuzzy rules	Mean error in predicted associated air temperatures = 1.17 °C	N/A	N/A
[33]	Field data from 9 subjects	Continuous thermal sensation scale with 5 labels (hot / warm / neutral / cold / extremely freezing)	Ta, MRT, RH, Va	ASHRAE 7-point thermal sensation scale	Least square estimation	Mean square error: proposed model = 0.53 PMV model = 1.16	N/A	Weighted forgetting factor to place more emphasis on recent data and gradually remove historical data
[34]	Lab data from 11 subjects	2 complaint conditions (too hot / too cold)	Ta, RH	2 complaint conditions (hot / cold)	Classification	False positive rate ≤ 0.3	N/A	N/A
[35]	Field data from 1 subject	ASHRAE 7-point thermal sensation scale	Ta, RH, Va, infrared intensity of clothing	ASHRAE 7-point thermal sensation scale	Least square linear regression	Root mean square error = 0.54, Pearson correlation coefficient = 0.89 between predicted and actual votes	N/A	N/A
[36]	Field data from 6 subjects	ASHRAE 7-point thermal sensation scale	Ta, RH	ASHRAE 7-point thermal sensation scale	Support vector machine, humidex	Overall accuracy = 80%	N/A	N/A
[37]	Field data from 6 subjects	ASHRAE 7-point thermal sensation scale	Ta	Probability of 3 comfort conditions (too hot / comfortable / too cold)	Logistic regression	N/A	Model congruency increased from 0.66 to 0.87 after 90 votes based on one subject	Removal of votes older than 30 days in the vicinity of Ta ± 0.25 °C with new data entry
[38]	Field data from 10 subjects	3 comfort states (hot / cold / neutral)	Ta, RH	comfort distance from the decision boundary between 'hot' and 'cold' data points	Linear discriminant	Except for a few points, the predicted comfort states match with the reported comfort state during the study period	N/A	Recalculation of the comfort distance with new data entry
[39]	Field data from 113 subjects	ASHRAE 7-point thermal sensation scale	Ta, MRT, RH, Va	3 comfort conditions (cool / warm / comfort)	Neural network	80% accuracy achieved with 20 samples based on 2 subjects	Neural network converged after 3000 iterations	N/A

*Note: Ta = indoor air temperature, Top = operative temperature, MRT = mean radiant temperature, RH = relative humidity, Va = air velocity, clo = clothing insulation, MET = metabolic rate, CO_2 = carbon dioxide level, Tout = outdoor air temperature

Key advances made in this collective research about personal comfort models include (1) improved predictive power with 20-40% accuracy gains compared to conventional comfort models by employing machine learning algorithms, and (2) diversities in types of data and occupant feedback obtained from various sensors and connected devices, well beyond the traditional thermal comfort variables.

Current research gaps include:

- Lack of a unified modeling framework. Research primarily focuses on predictive accuracy of the model rather than developing a systematic approach to build and evaluate the model for general benefits.
- Lack of connection to thermal comfort fundamentals. Previous researchers often apply their own interpretations or assumptions in their proposed models that are not necessarily grounded in existing thermal comfort research.
- Lack of vision for real-world integration. Past research is typically missing efforts to describe how the proposed models can be integrated into real-world systems to enable intelligent comfort management.
- Lack of industry standards. There have been no standardization efforts to guide the development and evaluation of personal comfort models and ensure their performance in building design and control.

4. A modeling framework

Developing a personal comfort model involves the following processes (see Figure 1), including:

- **Data collection** – determine what data will be the basis for the learning algorithms and how to collect it
- **Data preparation** – process and prepare raw data into the format ready for modeling
- **Model selection** – select learning algorithms appropriate for the given data and application goals
- **Model evaluation** – validate predictive performance of the model and readiness for its use in applications
- **Continuous learning** – update the model based on new data to ensure accuracy and relevance over time

Figure 1. Modeling process of personal comfort models

4.1 Data collection

To model an individual's thermal comfort, we need data that: 1) expresses his/her perception of thermal comfort, and 2) describes the given conditions or factors (e.g., personal, environmental, etc.) influencing that perception. Table 2 lists the type of data and possible collection methods that can be used for the development of personal comfort models.

Table 2. Examples of data types and collection methods* for personal comfort models

Category	Data types
Thermal comfort perception[1]	Sensation, preference, acceptability, pleasure
Personal factors	
Physiological	Skin temperature[2], heart rate[2], metabolic rate
	Clothing insulation
	Sex, age, body mass index, health status (e.g., dementia)
Behavioral	Turning on/off fans or heater, thermostat adjustments, opening/closing windows
Environmental factors	
Indoor[3]	Air temperature, mean radiant temperature, operative temperature, relative humidity, air velocity
Outdoor[4]	Air temperature, running mean temperature, humidity, precipitation
	Climate, season
Other factors	Time, location, context (e.g., home, office, car, outdoor), occupancy type (e.g., private, shared)
	Thermal history, cultural expectations (e.g., dress code)
	Mechanical system settings[5] (e.g., thermostat setpoints), availability of occupant controls

*Frequently used data collection methods include [1]survey, [2]wearable sensors, [3]environmental sensors, [4]weather stations, [5]building automation systems, etc.

Data collection is more straightforward for some of these variables than others, and here are some of the key considerations for some of them. The Appendix includes additional criteria to consider.

- **Thermal comfort metrics:** Thermal comfort can be assessed using survey questionnaires that ask about thermal sensation, acceptability, preference, satisfaction, or a combination [40]. The perceptions are then mapped to the measured physical conditions at the time. Thermal sensation is by far the most frequently used metric in personal comfort models due to its association with the PMV model, and an assumption is then made associating comfort with neutral sensation. Thermal acceptability can also be used with the assumption that "acceptability" is equated with "comfort". It is possible that even when people are not in their ideal state of comfort, they may still find it "acceptable", meaning that it is tolerable or not bad enough to complain. Thermal preference is a closer measure of what ideal conditions would be, and can be effective if the objective is to use it for the control of HVAC (Heating, Ventilation, and Air Conditioning) systems because it suggests a direction of change. Thermal satisfaction is often used in the assessment of buildings during post occupancy evaluations. It is important to understand that different metrics can lead to different assessment of comfort requirements, which can have different energy consequences [41,42]. Hence, one can consider the impact of different metrics on both comfort and energy outcome when selecting specific metrics to model individuals' thermal comfort.
- **Variations in scale construction:** The standards suggest the use of a 7-point ordered or continuous scale for thermal sensation ('hot' to 'cold'), a 3-point categorical scale for thermal preference ('warmer'/'no change'/'colder'), and a continuous or 7-point categorical scale for thermal acceptability ('acceptable' to 'unacceptable') (see Figure 2). Although it would be ideal if researchers used standardized scales for consistency and easy comparisons between different models, that is not always the case. Some modelers [31,33] have opted to modify or create new scales to satisfy their own modeling purposes (e.g., 11-point thermal preference scale, 5-point thermal sensation scale). The effects of varying scale points are not yet well understood in thermal comfort research and the existing ones have been challenged [40]. A classic psychology experiment [43] recommends limiting the response options to 5-7 because our ability to make judgments significantly decreases when we are presented with more than 7 alternatives simultaneously.
- **Determining survey frequency:** Surveying too often can burden occupants, while not surveying enough can lead to insufficient data collection. The reviewed studies applied different survey frequencies. Jiang and Yao [30] surveyed subjects every 10 min during the chamber experiments; however, such frequency is not realistic in practice as it can significantly interfere with occupants' daily tasks. Most field studies limit survey requests to a few times a day [36], or to every hour [33], or allow occupants to freely submit surveys with certain rules in place (e.g., minimum intervals between consecutive surveys) [31]. Determining the right level of survey frequency can, in part, be best informed by the number of data points required to produce reliable predictions – this is further discussed in 4.4 Model Evaluation.
- **Measuring clothing insulation:** Most personal comfort models do not include clothing insulation as their input variable. This may be a deliberate choice to reduce the burden of monitoring variables that are difficult to track in real-world settings. The only exception is the study by Gao and Keshav [35], in which the occupant's clothing insulation was estimated based on the infrared intensity of clothing measured by an infrared camera installed in the room. However, tracking occupants' clothing insulation via an infrared camera is not only expensive but can also be perceived as invading one's privacy. An alternative method is to use the ASHRAE-55 dynamic predictive clothing model [44] to approximate daily clothing pattern based on the early morning outdoor temperature. Although this model would only predict the average clothing of a group of people and does not distinguish between individual differences in clothing choice, it can at least provide an estimated input that follows climate variations.
- **Physiological and behavioral data:** Personal data about either comfort-related physiological states of the body or behavioral coping strategies are most commonly obtained via surveys. As such, the data collection is often stochastic and the data accuracy is difficult to validate due to the self-reported and self-measured nature of survey responses. Hence, one might supplement surveys with objective methods of collecting

individual-specific data to ensure consistency and quality of the data that can be integrated into personal comfort models. As examples, research shows that wearable sensors or connected devices can provide continuous data tracking of occupants' physiological conditions (e.g., skin temperature, heart rate) [45,18,46,21,47,23,27] or behavioral actions (e.g., personal fan use, thermostat adjustments) [25,27].

- **Challenging environmental measurement:** Radiant temperature and air velocity are often omitted or simplified in the development of personal comfort models, largely because modelers intentionally target easily obtainable data and the instrumentation to collect these variables is costly. However, several studies [14] have shown that these variables significantly affect thermal comfort predictions. Efforts are underway to reduce the cost and increase the capabilities (e.g., wireless data transfer, longer battery life, reduced equipment size) of these instruments for scalable and automated data collection in practice (e.g., Hamilton wireless sensor [48]).
- **Other influencing factors:** Other factors that may influence individuals' thermal comfort include, but are not limited to, time factors (e.g., hour, day, season) [16,49]; thermal conditioning systems and settings (e.g., active or passive systems, heating/cooling setpoints, availability of occupant control) [12,50]; building types (e.g., home vs. office) [51,52]; culture (e.g., socio-economic status, dress code) [53–55]; health, mood, demographic attributes (e.g., sex, age) [56–58]; and thermal history (e.g., living/working in air-conditioned vs. naturally ventilated buildings, temperature cycles and ramps, short and long term thermal exposure) [53,49,59,60]. Many of these factors can be easily obtained without instrumentation to record. Hence, efforts are needed to evaluate their importance in predicting individuals' thermal comfort.
- **Prioritizing data collection:** In practice, it may not be possible to capture all the relevant information one needs to develop a personal comfort model. The degree to which a certain data type is relevant for a particular individual or physical setting may not be apparent. We recommend an iterative approach by first targeting the most relevant data for human thermal comfort, and the most easily obtainable data for a particular setting, to build the initial model; subsequent steps could then expand the datasets as needed to improve the model. Note that certain variables may not contribute much to the predictive power of the model initially or continuously; however, their relative contributions can change over time. For example, humidity may have more of an effect in warmer seasons than others, or mean radiant temperature may have an effect only during times when there is direct solar gain into the space. Hence, it is useful to create a repository of relevant data and periodically update the model to reflect changing relationships in the data.

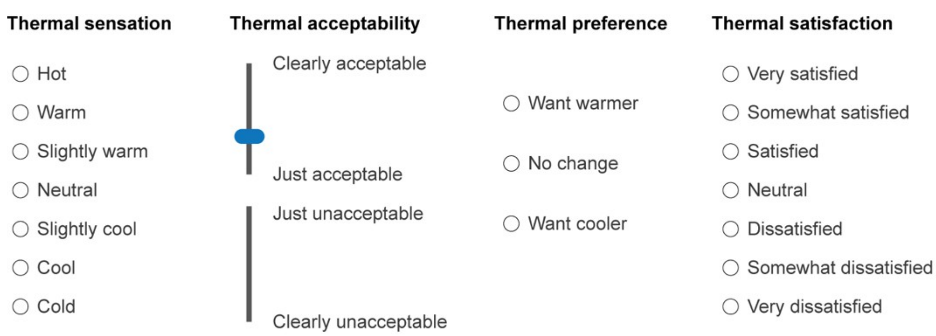

Figure 2. Examples of thermal comfort scales (Adopted from ISO 10551 [61])

4.2 Data preparation

Personal comfort models integrate highly heterogeneous data sets that are often presented in different structures, granularity, and volume. Therefore, it is important to prepare the raw data into a format ready for modeling. This involves (1) *cleaning* missing values, outliers, and measurement errors that can misrepresent the general trends in observed data; (2) *feature scaling* to normalize numerical data into a consistent range and mean when different scales can skew the model outcome (e.g., distance-based clustering) or affect computational speed (e.g., gradient descent); (3) *aggregating* to reduce the volume and granularity of the data by summarizing raw values into statistically representative values (e.g., mean) or grouping into discrete categories (e.g., Yes/No); (4) *feature creation* to explore new variables (e.g., rate of temperature change) drawn from the raw data that may influence individuals' thermal comfort; (5) *merging* to combine time-series data from heterogeneous sources with different logging intervals and frequencies; and (6) *partitioning* to split the data set into training and test sets in order to evaluate and fine-tune the trained model based on new data.

4.3 Model selection

Personal comfort models often explore non-traditional data types and relationships in order to better predict individuals' thermal comfort. Because of this, there is a strong interest in adopting machine learning to make predictions directly from the patterns learned from the data. This is a significant departure from the traditional modeling approach which was predominantly based on statistical modeling (e.g., linear regression) to discover generalizable findings. There are many algorithms available in machine learning, and so it is easy to get overwhelmed when trying to select one for personal comfort models.

One way to help navigate the different algorithms is to identify the type of predictions expected from the model. The predictions of personal comfort models can be *numerical* (e.g., comfortable temperatures), or *categorical* (e.g., thermal preference classification – 'warmer'/ 'no change'/ 'cooler'). Moreover, one can evaluate whether the underlying assumptions and rules adopted by these algorithms are appropriate for the given dataset (e.g., data size, quality) and application goals (e.g., real-time thermostat control). To guide the selection of appropriate algorithms for personal comfort models in particular, we first briefly describe the functional distinctions of popular machine learning algorithms in a general way [62].

- **Regression algorithms** predict response variables by establishing mathematical relationships between different variables. Examples include ordinary least squares, linear, and logistic regressions. Since regression algorithms require specific mathematical equations to express the relationships between variables, their predictive performance depends on how accurately these equations represent the true relationships in the real-world. The predicted outcomes are usually numerical as the regression is drawn from continuous data. However, one can use logistic regression to transform linear predictions into probability outcomes between 0 and 1 in order to generate categorical predictions.
- **Decision tree algorithms** construct a tree-like model that predicts the target response by learning decision rules inferred from the data. Examples include Classification and Regression Tree (CART) and conditional decision trees. They can be used for both numerical and categorical predictions. Although these algorithms perform fast with large datasets, they are prone to overfitting. One can use more advanced tree algorithms such as Random Forests or Gradient Boosted Trees to reduce the risk of overfitting by aggregating predictions of many decision trees.
- **Bayesian algorithms** apply Bayes' Theorem to make predictions based on the probability of prior events. Examples include Naïve Bayes and Bayesian Network. Bayes' Theorem assumes all input features are independent from one another despite the fact that such independence rarely occurs in reality. However, Bayesian algorithms tend to perform fairly accurately and can efficiently handle large datasets [63]. They can be used for both numerical and categorical predictions.
- **Kernel algorithms** map input data into a higher dimensional vector space to model non-linear relationships or patterns. Examples include Support Vector Machines, Radial Basis Function, Gaussian Process, and Linear Discriminant Analysis. They can be effective at modeling complex problems such as human thermal comfort and are fairly robust against overfitting [64]. However, kernel algorithms can become computationally expensive with high dimensional datasets. They can be used for both numerical and categorical predictions.

4.4 Model evaluation

The goal of model evaluation is to assess how good the model is in predicting individuals' thermal comfort, identify aspects of the model in need of improvement, and provide the basis for comparing different models. We list the following criteria that can help the evaluation process.

- **Prediction accuracy** assesses how correctly the model predicts. This is typically measured based on the differences between the predicted outcome and true outcome. For numerical predictions (e.g., acceptable temperature), frequently used metrics include the square of the Pearson correlation coefficient (R^2) and root mean square error (RMSE). For classifications (e.g., thermal preference), common metrics include classification accuracy (i.e., the fraction of all instances that are correctly classified) and Receiving Operating Characteristics (ROC) [65]. Note that when the model produces probability estimates, calculating prediction accuracy requires a threshold to separate one class from another. Also, evaluating the model accuracy of different classes require an understanding of their respective misclassification costs as predicting a particular class wrong may have bigger consequences than others. See the Appendix for a further discussion of the optimal thresholds and misclassification costs.
- **Prediction consistency** assesses how much the model predictions vary from one sample to another. This helps to evaluate the generalizability of a model outside of the training samples. We can measure prediction consistency as the degree of spread in predicted values within or across different test sets for numerical estimations, and as the degree of spread in prediction accuracy across different test sets for classifications. Prediction consistency can be expressed using metrics such as variance, standard deviation, or confidence interval.
- **Model convergence** assesses whether the model has converged its learning to produce a stable prediction behavior. This helps to determine a quantifiable target for data collection and model performance. For personal comfort models, model convergence can be evaluated based on: 1) number of data points to reach steady-state prediction errors (see Figure 3) [16]; 2) number of iterations to reach target performance level [39]; or 3) congruency represented as the area of overlap between trained and idealized models [37].

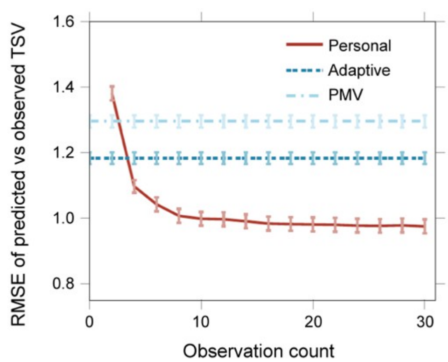

Figure 3. Example of model convergence. RMSE refers to the root mean square error of predicted vs. observed thermal sensation votes. In the legend box, 'Personal' refers to the proposed personal comfort models in [16]; 'Adaptive' refers to the ASHRAE-55 adaptive model; and 'PMV' refers to the Predicted Mean Vote model.

4.5 Continuous learning

Both human perception and physical conditions of thermal comfort can change over time. For example, seasons [66] and prevailing outside weather [67] can influence people's preference for cooling and heating. Therefore, personal comfort models should adapt to changes observed in the new data, when available, in order to stay relevant and accurate over time. Previous studies suggest the following methods to continuously update personal comfort models: (1) remove statistically irrelevant points from the data set as new data is entered [31]; (2) apply forgetting factors to give more weight to recent data and less weight to historical data [33]; (3) remove samples older than one month within similar temperature ranges when new data is entered [37]; and (4) perform full relearning upon every new data entry [16]. While these proposed methods show how personal comfort models can adapt to changes over time, only Ghahramani et al. [31] tested their proposed method against an actual dataset. Hence, more efforts are needed to evaluate these methods as well as other promising methods against real data. Lastly, techniques for continuous learning should be performed efficiently in a scalable fashion to handle the growing volume of data collected from various connected sensors and devices.

5. Integration into thermal controls

Integrating personal comfort models into indoor environmental control of buildings or other systems (e.g., vehicle) offers an opportunity to respond to individuals' comfort needs and desires in everyday comfort management. Such integration requires the following major technological components, as shown in Figure 4.

Connected sensors and devices enable collection of input data for the development of personal comfort models (e.g., thermal comfort perception, personal and environmental measurements). For occupants' thermal comfort, personal computers or mobile devices are an effective way to collect survey feedback on current thermal perception. For physiological data, wearable devices or infrared cameras with communication capabilities can help to monitor occupants' heart rate, skin temperature, metabolic activity, etc. For behavioral data, one can leverage various connected devices or mobile applications available in the market (e.g., occupancy sensor, pedometer, GPS tracker, smart thermostat) to track individuals' occupancy status, location, movements, and heating and cooling behavior. HVAC systems typically monitor air temperature and sometimes carbon dioxide levels via environmental sensors installed in thermal zones. They also track control settings (e.g., heating and cooling setpoints, airflow rate) that drive the thermal condition in each zone. Additional environmental sensors with wireless connections can be installed to monitor individuals' local environmental conditions and provide additional coverages in the building's environmental sensor network. For outdoor environmental conditions, one can set up a local weather station or access a public record of weather information available online.

Network and connectivity enables data transfer from various sensors and devices to a central server. The sensors or devices can transmit data directly to the server or through a local network hub or gateway via various wireless and wired communication channels (e.g., Wi-Fi, RFID, Bluetooth, Cellular, Ethernet). The HVAC sensors and control settings can be obtained from the building's BAS (Building Automation System) trend logs. Sending the BAS data to the server may require a communication driver to interface the BAS software. The frequency of data reporting can range from several minutes to a few seconds depending on the time resolution required by the controller to make control decisions.

A central server hosts the function of data warehousing, analytics, optimization, and actuation commands. 1) *Data warehousing* refers to the electronic storage of historic data collected from different sources. It supports archives and queries of historic thermal comfort data. 2) *Analytics* includes the function of developing and updating personal comfort models as well as synthesis of real-time information and model predictions to determine which control actions needed to improve thermal satisfaction in the occupied spaces. 3) *Optimization* processes recommendations from the analytics and determines the best course of actions that would support the organization's comfort goals and other interacting or competing goals (e.g., energy efficiency, cost savings). Dounis and Caraiscos [68] provide a comprehensive review of advanced control algorithms for optimization that can be used to manage occupants' thermal and illuminance comfort, indoor air quality and energy conservation. 4) *Actuation commands* involves sending specific instructions to controllers including the type of systems (e.g., HVAC systems, ceiling fans), control settings (e.g., thermostat setpoints, terminal air flow rate), spatial scales (e.g., whole building, single thermal zone), time factors (e.g., duration, schedules), etc.

The controllers receive actuation commands from the server to drive the operation of thermal conditioning systems. In commercial buildings, the controller is typically a BAS which controls the building's HVAC systems. But, it can also be other systems that provide thermal conditioning with the capability to electronically receive actuation commands (e.g., Nest, ecobee). The server can use the system's communication protocols (e.g., BACnet) or

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Application Programming Interface (API), if available, to send actuation commands to the controller. The challenge of working with these communication protocols or APIs includes the lack of public access and standardization – without these it is difficult to develop new applications that leverage existing systems and scale them across different systems. sMAP (Simple Measuring and Actuation Profile) is an open source information exchange and actuation platform that can greatly simplify the interaction between the server and different control systems due to its vendor-agnostic approach that unifies control access points [69].

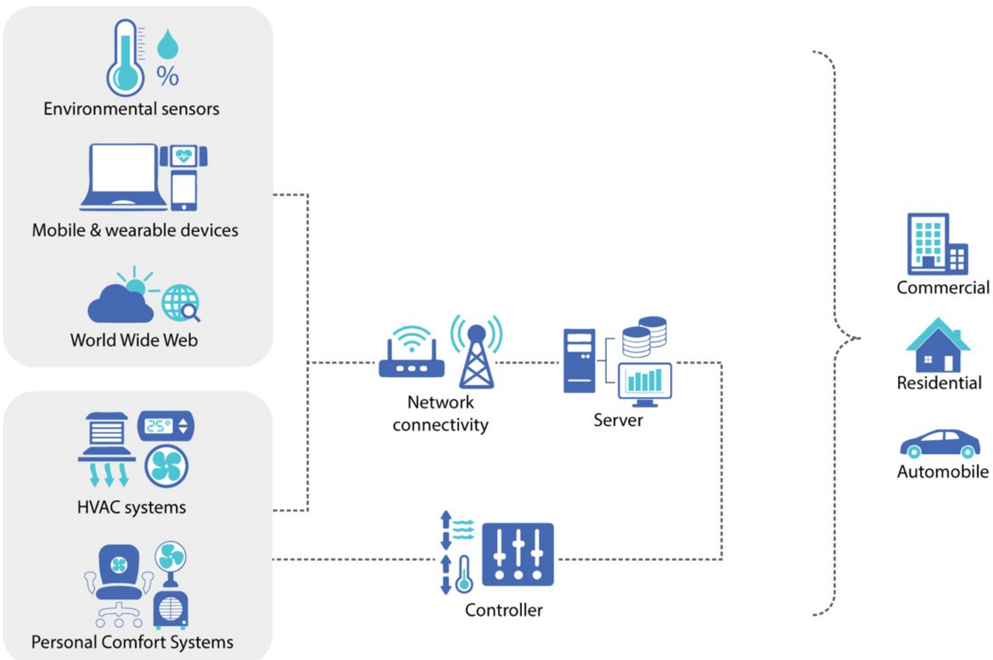

Figure 4. System architecture for occupant-responsive environmental control

6. Discussion

We discuss some of the challenges and opportunities for applications of personal comfort models by answering the following critical questions.

1. How can we ensure sufficient collection of occupant feedback on thermal comfort?

Collecting sufficient data that expresses individuals' perception of thermal comfort is critical. Currently, this data is captured through surveys. However, securing consistent feedback is difficult [36]. Some strategies may help, such as using survey reminders via email or pop-up notifications. Another option is to pool relevant survey responses from other occupants in order to increase the data size when there are insufficient data points to develop a personal comfort model [70]. The relevance can be determined based the degree of similarity in environmental conditions (e.g., temperature ranges), building types (e.g., naturally-ventilated vs. mechanically-conditioned), or personal attributes (e.g., age, sex). Proxy variables that supplement or replace direct survey responses on thermal comfort after training are also a valid path. Research has shown correlations between individuals' thermal comfort survey responses and thermal control behavior (e.g., thermostat adjustments) [25] and physiological conditions (e.g., heart rate, skin temperature) [45,21,23,22,71], both of which can be measured continuously via non-intrusive monitoring technologies (e.g., smart thermostats, wearable sensors). Hence, they could potentially be used in personal comfort models as proxy variables to infer individuals' thermal comfort.

2. How can personal comfort models be generalizable to a larger population?

Personal comfort models are designed to predict thermal comfort for a single person; hence, they are not necessarily directly applicable to other occupants. However, as the size and diversity of data increases, repeatable patterns may surface that can be generalized to a larger population. For example, grouping of models may form to provide general descriptions about thermal comfort that can be attributed to certain population segments (e.g., gender, age) or space types (e.g., office, home, car). These repeatable patterns can serve as the foundation for creating generalizable thermal comfort profiles. The profiles can provide several benefits to the building industry at large, including serving as: 1) reasonable baseline models that can be readily applied to a new person who does not yet have a personal comfort model or whose personal comfort model is still under development; 2) a set of thermal comfort profiles that can be used for building/system design and operation to better characterize specific thermal comfort requirements across different segmentations of the building population; and 3) a more realistic building energy estimation that reflects the differences in individuals' thermal comfort requirements in HVAC control settings.

3. *How can we resolve the differences in thermal preferences among the occupants in shared spaces?*

This is not a new problem. It exists whether personal comfort models are available or not. With personal comfort models, such differences are revealed and quantified so that they can be addressed. The existing studies have explored two approaches regarding this issue: 1) consensus-based solutions, and 2) technological solutions (for either individuals or groups), often with overlaps between them.

For consensus-based solutions, Jazizadeh et al. [32] selected a temperature setpoint that minimized the error between everyone's preferred and actual room temperatures. In the case that acceptable comfort levels could not be achieved for all occupants in a zone, Ghahramani et al. [72] incrementally increased the acceptable temperature range of individuals within a pre-defined discomfort threshold. Murakami et al. [73] determined the temperature setpoint by a majority vote. Lee et al. [74] assigned varying priorities to different occupant groups (e.g., more emphasis on employees over visitors) in order to determine optimal temperature in public zones. Although these strategies needed a system to ultimately adjust the setpoint, the underlying decision making was consensus-based.

For technological solutions, Erickson and Cerpa [75] enabled real-time thermostat setpoint adjustments based on occupants' requests to address the comfort issues in shared spaces as they occur. However, this scheme can introduce potential gaming of the system and biases toward more vocal occupants. To reduce these effects, they limited the vote per person to one in every 10 min and averaged the votes to determine the new temperature setpoint at the end of the voting period. Another example of a technological solution used personal comfort systems (PCS) to provide local heating and cooling without affecting others in the same space [76]. With PCS, individuals can address their own comfort needs or desires in shared spaces, and therefore be less vulnerable to the thermal conditions set by the centralized systems. In shared spaces, increasing the granularity of the control (e.g., lowered number of occupants per variable air volume box) is also a technological solution that could help.

4. *What is the impact on energy when using personal comfort models to make control decisions?*

The ultimate goal for improved building operation is to simultaneously improve both energy and comfort performance, but many people still view this as a tradeoff where you can only improve one at the expense of the other. Conceptually, personal comfort models can help improve performance in both comfort and energy by providing information about individuals' thermal comfort requirements, such as acceptable temperature limits for a given space. If the acceptable temperature limits are greater than the default temperature setpoint ranges, one can expect HVAC energy savings (i.e., fans, reheat) by widening the temperature setpoints [77–80]. Examples of demonstrated energy savings include: 10% energy savings by implementing real-time setpoint control using individuals' online requests [75]; more than 20% savings using the consensus-based temperature control strategy [73]; up to 24% by adjusting temperature setpoints based on hot or cold complaints by the occupants [38]; 39% reduction in daily average airflow by resetting temperature setpoints according to occupants' preferred temperatures [32]; and 51% reduction in daily average air flow by allowing occupants' comfort level to slightly deviate from their preferred temperatures [72]. These savings are based on the volume of energy consumption (i.e., kWh). The buildings can also save on the utility cost (i.e., $) under variable rates and demand charges by dynamically adjusting HVAC loads during peak hours.

Whether such savings are transferable to another zone or another building depends on the thermal comfort requirements of individuals in a given space. It also depends on how acceptable temperature limits are defined, such as which thermal comfort metric (i.e., thermal sensation, acceptability, preference) is used to determine comfort conditions in the personal comfort model. For example, anchoring the model on thermal acceptability can lead to wide temperature ranges that are tolerable but not ideal. On the other hand, thermal preference, which can be considered the most idealistic metric, can lead to very narrow temperature ranges that are energy-intensive to maintain. Instead of relying on a single metric, we can develop an integrated model that takes into account multiple metrics. This can lead to a more holistic representation of individuals' thermal comfort [81] and allow greater flexibility to make control decisions to support various organizational goals (e.g., comfort, energy, cost).

5. What is the role of standards with respect to personalized thermal comfort models?

Existing standards take prescriptive approaches to thermal comfort provision by specifying detailed criteria of an acceptable thermal environment that would satisfy the majority of occupants (i.e., 80%). However, a very small percentage of buildings fulfil this objective. Data-driven occupant-centric comfort management is gaining attention among progressive and forward-thinking building professionals [17]. Personal comfort models can play an essential role in this new paradigm by generating accurate predictions of individuals' comfort requirements and closing the loop between occupants and HVAC systems. However, the existing personal comfort models have been independently developed by both academics and corporations and are not always in agreement with the standards' approach to thermal comfort assessment. Hence, these research efforts need to be guided in order to assure accurate and reliable performance of the model, and to create a more standard protocol for different applications.

Standards can play an important role by allowing a performance-based approach to thermal comfort provision, thus allowing more flexibility in buildings to accommodate context- and occupant-specific comfort requirements that cannot currently be satisfied by the traditional prescriptive approach. Towards this end, standards should provide guidelines for this performance-based approach, addressing data collection, privacy and security requirements for data storage and access, and the development, testing, validation, and implementation of the custom models in buildings.

Conclusions

A personal comfort model is a new approach to thermal comfort modeling that predicts individual's thermal comfort responses, instead of the average response of a large population. In particular, it leverages Internet of Things and machine learning to learn individuals' comfort requirements directly from the real-world data. Our review of the existing personal comfort models shows improved predictive power compared to conventional comfort models (PMV, Adaptive). However, they lack in the following areas: systematic modeling processes, thermal comfort fundamentals, vision for real-world integration, and standardization efforts. To address these gaps, we developed a definition of personal comfort models and proposed a unified modeling framework by establishing important concepts and methodologies based on prior thermal comfort research and machine learning best practice. The modeling framework focused on data collection and preparation, model selection and evaluation, and continuous learning. We provided system architecture for the integration of personal comfort models in thermal controls, and described the potential role of standards in providing guidance to assure accurate and reliable performance of personal comfort models in real-world applications.

Personal comfort models can benefit the building industry by providing necessary data to improve the level of thermal comfort among occupants and optimize energy use in buildings. With advances in comfort technologies penetrating the built environment, the demand for personalized thermal experience will increase. To meet this demand, more research is needed to turn the insights generated from personal comfort models into actionable control strategies in order to yield a tangible impact on people's comfort satisfaction in buildings. We hope that our paper has provided a foundation for that to occur.

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Appendix

Below we provide additional considerations for data collection – in particular, thermal comfort perception, when developing personal comfort models.

Variations in mapping survey scales votes to model inputs/outputs: The model input/output of most personal comfort models is thermal sensation or preference. Feedback from occupant surveys is typically used to train the model. However, in some studies the scales used in the occupant surveys for thermal sensation or preference are different than the model input/output. When this occurs, the modelers use their own interpretations to map the occupants' survey votes to the model input/output. These interpretations are not always consistent with the assumptions used in conventional comfort models. For example, Ghahramani et al. [31], Daum et al. [37], and Liu et al. [39] mapped their thermal preference/sensation scale to three comfort conditions by grouping the data into three categories. Jazizadeh et al. [32] used a continuous preference scale as the model input but transformed it into a 5-point sensation scale in the model output. Zhao et al. [33] collected survey responses on a 5-point sensation scale but mapped the responses onto a 7-point sensation scale for the model input. Since these interpretations have not been validated, further research is required to investigate their effects on model outcome.

Categorical representation of thermal sensation: Some personal comfort models have departed from the traditional approach PMV uses, representing thermal sensation as a continuous linear scale. Zhao et al. [33], Gao and Keshav [35], and Rana et al. [36] adhered to this model representation. However, Jiang and Yao [30] and Feldmeier and Paradiso [38] treated thermal sensation as a classification problem and developed a model that produces an output from one of the discrete choices in the thermal sensation question. This is a reasonable approach considering that most thermal comfort questions are taken in the form of a Likert scale with discrete choices. Also, this better represents the way human processes information – in 5 to 7 chunks as explained by psychologists [43].

Below we provide additional considerations for the evaluation of personal comfort models.

Optimal threshold in probabilistic classifications: If the model output is a probability in classifications (i.e., the likelihood expressed as a percent), then calculating accuracy requires a threshold to separate one class from another. For example, a personal comfort model that predicts thermal acceptability with two possible classes – "thermally acceptable" and "thermally unacceptable" – will need a threshold that can map the predicted probability into one of these two classes. If the model outputs a probability value of 40% "thermally unacceptable" and 60% "thermally acceptable", the prediction will be classified as "thermally acceptable" with a threshold of 50%. However, the 50% threshold may not be optimal if it causes the model to misclassify "thermally unacceptable" more frequently than "thermally acceptable", or if misclassifying "thermally unacceptable" has more serious consequences than misclassifying "thermally acceptable" (e.g., the model prediction prevents control systems from responding to one's thermal discomfort). However, determining the threshold for thermal comfort classifications can be tricky as there is no prior research that can inform what the optimal threshold value should be. Moreover, the optimal threshold may differ from person to person as the relative weight of misclassifying different classes can be perceived differently. The ROC curve avoids this issue by considering the full range of thresholds (i.e., 0 to 100%), rather than a single threshold, when evaluating true positive rate of the trained model against false positive rate. When dealing with imbalanced data (e.g., 90% of the survey results are 'thermally acceptable' and only 10% is 'thermally unacceptable'), both accuracy and ROC can produce overly optimistic results as the score is heavily influenced by the presence of the majority class in the test set. If the real hit rate of the minority class has meaningful consequences (e.g., 'thermally unacceptable' predictions initiate heating or cooling actions to improve one's thermal comfort), it is advisable to use metrics such as precision and recall, or F1-score (i.e., the harmonic mean of precision and recall) to account for the rate of true positive in all positively predicted values. Alternatively, the Precision-Recall curve, which considers the full range of thresholds, can be used as well if one wants to avoid the need to set a threshold.

Cost of misclassification: The predictive performance of a classification problem is typically summarized as the average of all classes. However, predicting a particular class wrong may have bigger consequences or financial cost than others. For example, in thermal comfort applications where control decisions are made based on the predictions of personal comfort models, misclassifying 'cooler' as 'warmer' may have greater impact on thermal comfort than misclassifying 'cooler' as 'no change'. Such mistakes may have negative consequences. Misclassification can be weighted differently across different classes depending on the severity of the application consequences. However, since there is currently no prior research in the field of thermal comfort on quantifying these effects, it remains unknown how to determine appropriate weights in thermal comfort classifications.