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1. ABSTRACT

We analyzed the ASHRAE Global Thermal Comfort Database II to answer a fundamental but overlooked question in thermal comfort studies: how many and which subjective metrics should be used for the assessment of the occupants' thermal experience. We found that the thermal sensation is the most frequently used metrics in Thermal Comfort Database II, followed by thermal preference, comfort and acceptability. The thermal sensation/thermal preference, thermal comfort/air movement acceptability and thermal comfort/thermal preference are the top three most dependent metrics pairs. A principal component analysis confirmed that the personal experience of thermal conditions in built environment is not a one-dimensional problem, but at least a two-dimensional problem, and suggested thermal sensation and thermal comfort should be asked in right-now surveys as the first two Principal Component are majorly constructed by thermal sensation and thermal comfort. To further confirm the predictive power of thermal sensation and comfort, we used logistic regression and support vector machine to predict thermal acceptability and thermal preference with thermal sensation and comfort. The prediction accuracy is 87% for thermal acceptability and 64% for thermal preference. The prediction error might be due to occupants' individual difference and people errors in answering survey. These findings could help the design of chamber experiments, field studies, and human-building interaction interfaces by shedding light on the choice of subjective thermal metrics to effectively and accurately collect information on occupants' thermal experience.

Key words:
Thermal comfort, Subjective thermal metrics, ASHRAE Global Thermal Comfort Database II, Machine learning, Occupancy responsive control, Principal Component Analysis

Nomenclature

Abbreviations

ASHRAE	The American Society of Heating, Refrigerating and Air-Conditioning Engineers
DC	Distance Correlation
HVAC	Heating, Ventilation, and Air Conditioning

LR	Logistic Regression
PC	Pearson Correlation
PC	Principal Component
PCA	Principal Component Analysis
PMV	Predicted Mean Vote
POE	Post Occupancy Evaluation
RF	Random Forest
SET	Standard Effective Temperature
SVM	Support Vector Machine
TA	Thermal acceptability
TC	Thermal comfort
TP	Thermal preference
TS	Thermal sensation

2. Introduction

The building sector is a significant energy consumer and carbon emitter, consuming 40% of the total energy usage in the US and UK [1], [2], and is responsible for around one third of greenhouse gas emissions globally [3]. In buildings, a substantial proportion of energy is consumed to maintain comfortable and desirable indoor thermal environment. For instance, in commercial buildings, around 40% of energy is consumed by HVAC systems [4].

Despite the huge amount of energy consumed by building [1-4], high thermal discomfort is present. A recent field study on 3892 respondents from 60 office buildings in the US found that: around 40% of respondents were dissatisfied with the thermal environment [5], way above the 20% target satisfaction rate specified in ASHRAE standard 55 [6]. As for the causes of the low satisfaction rate, the frequently identified overcooling or overheating problems in variant building types (airport terminals [7], [8], hospitals [9], and office buildings [10]) indicate actually we consume more energy than we need but still did not achieve our comfort target.

Shifting our control goal from physical parameters to subjective responses might be a solution to improve thermal comfort without necessarily increasing energy consumption. For example, the occupancy responsive control that takes occupants' subjective response into the control loop has attracted the interests of researchers, device manufactories, and building operators. Compared with the conventional way to maintain the indoor temperature and humidity within a fixed pre-set range regulated or suggested by building standards, the occupancy responsive control collect occupants' real-time responses on the thermal environment and then adjust the control target settings accordingly. Integrating occupants' thermal responses, such as hot/cold complaints [11], online thermal votes [12] and etc., has demonstrated the potential to enhance thermal comfort while save energy as much as 20% - 40% in office settings [13], [14].

2.1 Thermal comfort metrics

The first question to use occupant feedback to control the building is which metric should be used to quantify the subjective responses, because it is impossible to manage something that you cannot measure. To be more specific, how many and which thermal comfort metrics should be used to collect occupants' evaluations on the thermal environment. Thermal sensation, thermal comfort, thermal acceptability, thermal preference, thermal satisfaction are commonly used to assess different perspectives of the personal experience of thermal conditions in built environments [15].

- **Thermal sensation** metrics has been widely used in subjective thermal comfort studies [16]. Thermal sensation is considered to be "objective" compared with other metrics, due to its direct association with physical measurements (Temperature) and PMV models. The thermal neutrality is assumed to be the goal for built environment engineering.
- **Thermal comfort** and **thermal acceptability** are frequently used both in chamber experiments and field studies. These two

metrics are more "subjective" than thermal sensation. You might feel the thermal environment is comfortable or acceptable even if it is not neutral. Previous study confirmed that the thermal acceptability has a lower threshold than thermal comfort since you might not feel comfortable but can still accept the environment [17],[18].

- **Thermal satisfaction** is often used in Post Occupancy Evaluation (POE). Unlike other metrics more focus on the thermal experience of an individual, the thermal satisfaction (rate) is more frequently used to evaluate the overall thermal environment of a building.
- **Thermal preference** directly measures how would you prefer to adjust the thermal environment if you had the control. Therefore, thermal preference has a wide application in personalized human-in-the-loop HVAC control systems [19].

Broadly speaking, the five metrics could be classified into two categories. Thermal sensation and thermal preference are symmetrical index which could distinguish between cold and hot. However, thermal comfort, thermal satisfaction and thermal acceptability are asymmetrical and not able to provide any information to the HVAC system regarding the action that it should take (heating or cooling).

Though the five metrics mentioned above are proposed for different research purposes, there is no doubt that the five subjective thermal comfort metrics mentioned above are correlated with each other. It might be unnecessary to ask all those five questions in either chamber experiments or field studies, because we do not want to collect redundant information at the risk of fatiguing subjects, especially in some cases that occupants are repeatedly and frequently asked to answer the survey. Therefore, a key research question is which metrics should be used to measure the personal thermal experience in built environments so that we could collect adequate information to assess the occupants' thermal experience while not disturbing the occupants too much. Actually, this is a fundamental question in thermal comfort experiments, field tests and building thermal environment management, which has not been clearly answered.

2.2 Methods for thermal comfort studies

A major goal of thermal comfort studies is to find out how the ambient thermal environment would influence occupants' thermal perception. To achieve this goal, different research methodologies have been utilized. The Predicted Mean Vote (PMV) and Standard Effective Temperature (SET) are built on the physics-based heat balance and transfer model. Additionally, regression techniques are also used to map the subjective thermal comfort metrics to the measured physical conditions at the same time. Linear/polynomial univariate/multivariate regression and logistics regression are the mathematical tools we commonly used to identify the relationship between physical environments and subjective perceptions. For instance, the Thermal Adaptive Model was built upon regression techniques.

In addition to the above two conventional methods, more complicated machine learning approaches could also be used to map subjective responses to physical environment and to identify hidden trends. The machine learning techniques are actually more powerful than regression tools in capturing non-standard non-linear relations between independent and dependent variables. Random Forest [20], Support Vector Machine [21], Neural Network [22], Bayesian network [23], [24], [25], [26], Gaussian Process Classification [27], have been utilized in thermal comfort studies to predict thermal sensation [21], [23], thermal comfort [25], [22], thermal acceptability [27], and thermal preference [20], [24].

A key challenge hinders the application of machine learning approach is there are so many different algorithms and it is hard to decide which one should be chosen for a specific problem. Kim et al. [15] compared 6 widely used algorithm including Classification Tree, Gaussian Process Classification, Gradient Boosting Method, Support Vector Machine, Random Forest and Regularized Logistic Regression in the prediction of thermal preference. The prediction accuracy difference of the best (RF) and the worst (CTree) algorithm is only 10%. And the prediction accuracy difference of top three algorithms (RF, SVM, regLR) is within 1%. Actually, a pioneer research [28] in the field of machine learning has pointed out that different machine learning algorithms have marginal performance differences in terms of prediction accuracy once the algorithms are properly applied (choose the right algorithm for a specific problem, and properly tune the hyperparameters). What really matters is the sample size of the training set, especially in thermal comfort studies, the typical sample size of which is only on the scale between 100 and 1000, less than enough for the training and testing of machine learning algorithms.

2.3 ASHRAE Global Thermal Comfort Database II

The ASHRAE Global Thermal Comfort Database II, as an international collaboration led by University of California at Berkeley and University of Sydney, aims to advance thermal comfort studies by integrating and harmonizing the abundant data from worldwide thermal comfort studies [29]. As a successor work of the ASHRAE Thermal Comfort Database I [30], Thermal Comfort Database II collected data from research published in the past two decades since the releasing of Database I in late 1990s.

Several criteria on the data selection have been used for the development of the database [29], including: 1) data should come from field tests rather than chamber experiments; 2) both physical indoor climatic observations and 'right-now-right-here' subjective evaluations should be measured; 3) raw data rather than processed should be provided.

Currently, 81846 data points from 52 field studies conducted in 160 buildings are included and open-sourced in Comfort Database. ASHRAE Global Thermal Comfort Database recorded 68 attributes, covering subjective thermal comfort vote, objective physical measurement, building characteristics, demographic information of subjects, and local climate/weather condition [29]. Those field studies were conducted in 28 countries globally, both developing and developed countries were included. This combined dataset, with the largest sample size in this field, provides a unique opportunity to leverage the emerging technique of machine learning to address some fundamental questions in the field of thermal comfort. As the dataset is fully open-sourced, the results could be reproduced by other researchers.

2.4 Objectives

This paper aims to explore a fundamental but overlooked question in thermal comfort studies: the dimensions of subjective thermal metrics, to be more specific, how could we measure the subjective thermal experience with as few questions as possible? An affirmative answer would indicate a chance to collect adequate information to assess the occupants' thermal experience without asking all of the thermal sensation, comfort, acceptability and preference questions. This would be beneficial since we could ask fewer questions in the survey and avoid the risk of fatiguing the subjects. To achieve this research objective, the following three research questions are proposed:

- What is the minimum number of questions should be asked to collect adequate information for the assessment of the occupants' thermal experience?
- Which subjective thermal comfort metrics need to be asked in thermal comfort surveys?
- Could we use the collected thermal comfort metrics to predict the unasked/unknown ones? What is the accuracy of this prediction?

To answer the above questions, a three-step work flow has been proposed, as shown in Figure 1. We first examined all the 52 studies listed in ASHRAE Global Thermal Comfort Database to see which comfort metrics are most widely used and how this popularity varies in different times and in different building type setting (Section 2.1). Then we used the tools of correlation matrix (Section 2.2) and principal component analysis (PCA) (Section 2.3) to quantify the dimensions and to select the metrics. The idea is we want to keep those metrics that are not correlated and could explain the largest possible variance of observed thermal experiences. The final step is we want to validate the selected metrics by checking if we could use them to predict the unknown thermal metrics (Section 3). We tried two widely used machine learning algorithms - logistic regression and support vector machine (SVM) to do this validation. Then we would discuss the influence of anomalies (Section 4.1) and compare the logistic regression with SVM approach (Section 4.2) in Section 4. This paper will be concluded in Section 5.

Findings of this paper could help the design of chamber experiments, field studies, and human-building interaction interfaces by shedding light on which thermal comfort metrics should be used in subjective thermal comfort surveys.

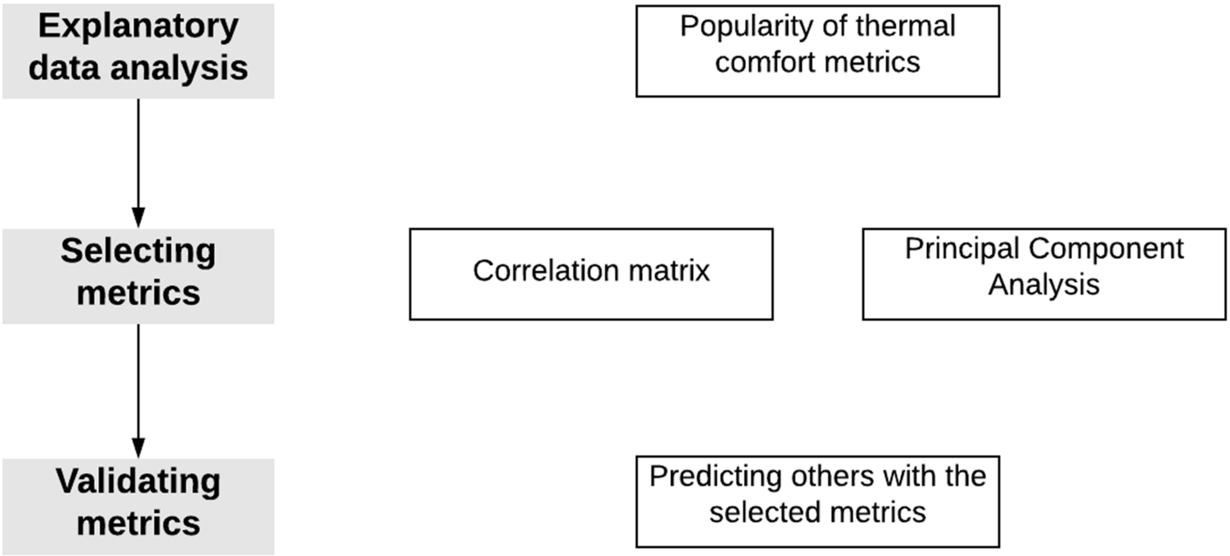
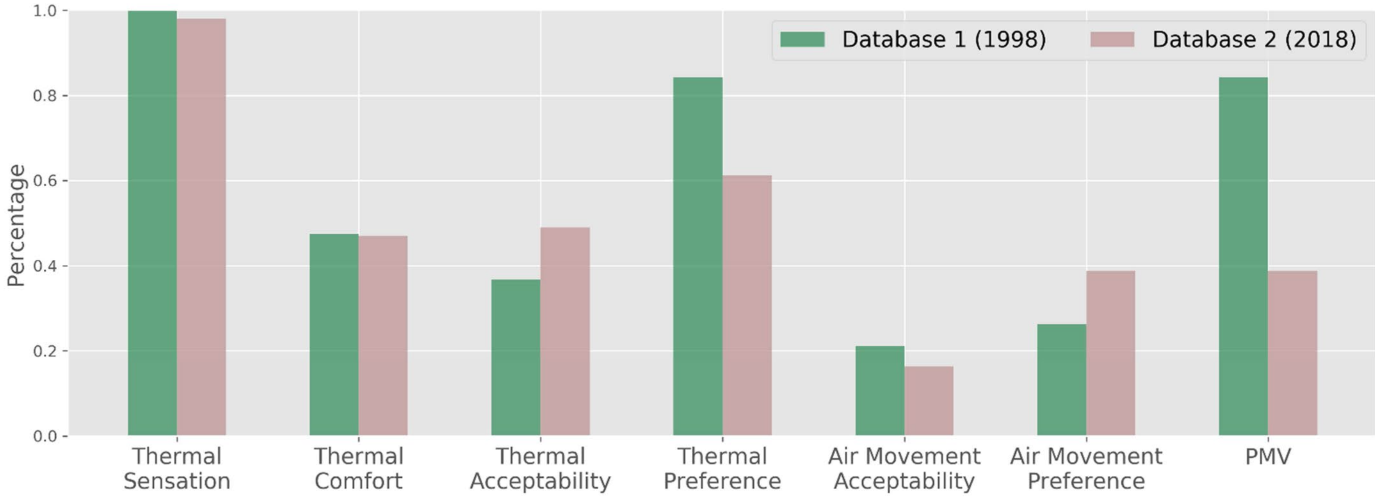


Figure 1 Work flow of this study

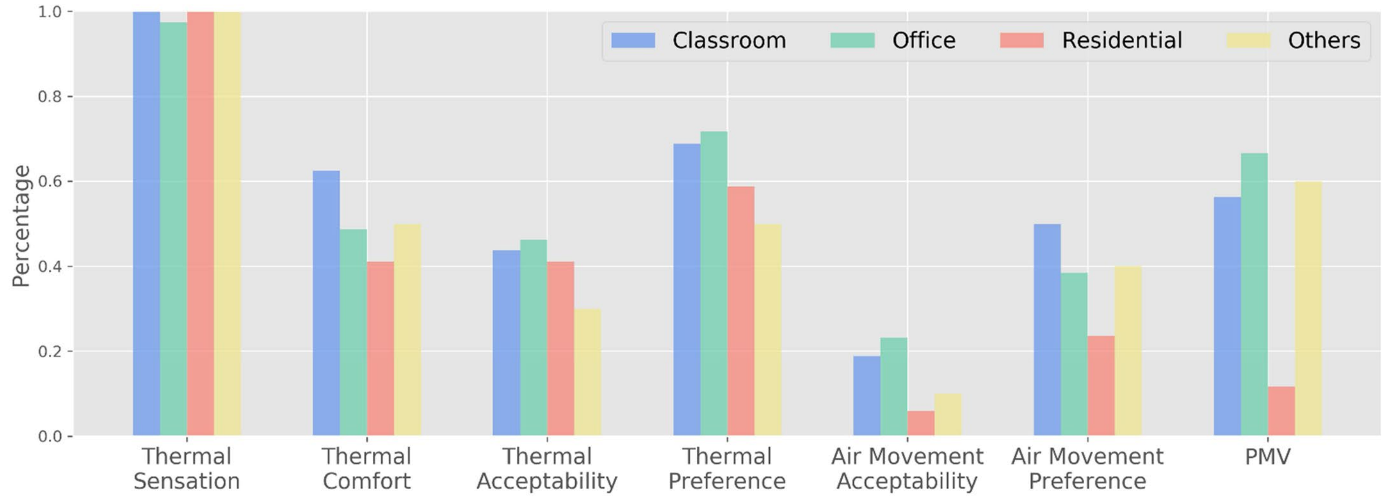
2. Metrics Selection

2.1 Metrics used in thermal comfort studies

Before deciding which subjective thermal metrics should be used, it is helpful to review which metrics are being used in current field studies. As shown in Figure1, six subjective thermal metrics, thermal sensation, thermal comfort, thermal acceptability, thermal preference, air movement acceptability, air movement preference are recorded in Thermal Comfort Database I and Thermal Comfort Database II. Another commonly used metrics, thermal satisfaction has not been included. Though PMV does not belong to the subjective metrics, it is presented in Figure 2 as a comparison.



(a) Usage of subjective thermal metrics in DBI and DBII



(b) Usage of subjective thermal metrics in different building types[1]

Figure 2 Usage percentage of thermal comfort metrics

Since Thermal Comfort Database I was released in 1998 while Thermal Comfort Database II was released very recently in 2018, exploring and comparing the popularity of subjective thermal metrics in Database I and Database II could give us a hint about the evolution of thermal comfort studies by comparing what thermal comfort researchers focusing on adaptive comfort research care about most now and two decades ago. It is obvious from Figure 2 that thermal sensation is the most widely used subjective thermal metrics, almost all thermal comfort field studies retrieved by Thermal Comfort Database I and Database II collected occupants' thermal sensation. Thermal preference is the second most popular metrics; however, within this database becomes less popular now compared with 20 years ago. Around half of studies asked thermal comfort and thermal preference in their surveys. Thermal acceptability becomes 10% more popular compared with two decades ago. The two air movement metrics are less frequently used in field studies.

It is interesting to find that the most marked change between Database II and Database I is the popularity of PMV. More than 80% of studies in Database I measured PMV. 20 years later, less than 40% studies in Database II collected PMV. 20 years ago, Fanger's heat balance-based PMV-PPD model dominated thermal comfort studies. As a result, almost all thermal comfort field studies measured PMV [31]. However, Richard de Dear and Gail Brager proposed thermal adaptive model by analyzing the data of Database I, starting to shift the paradigm in thermal comfort studies [32], [33]. This paradigm shift was clearly reflected in the popularity of PMV in thermal comfort studies.

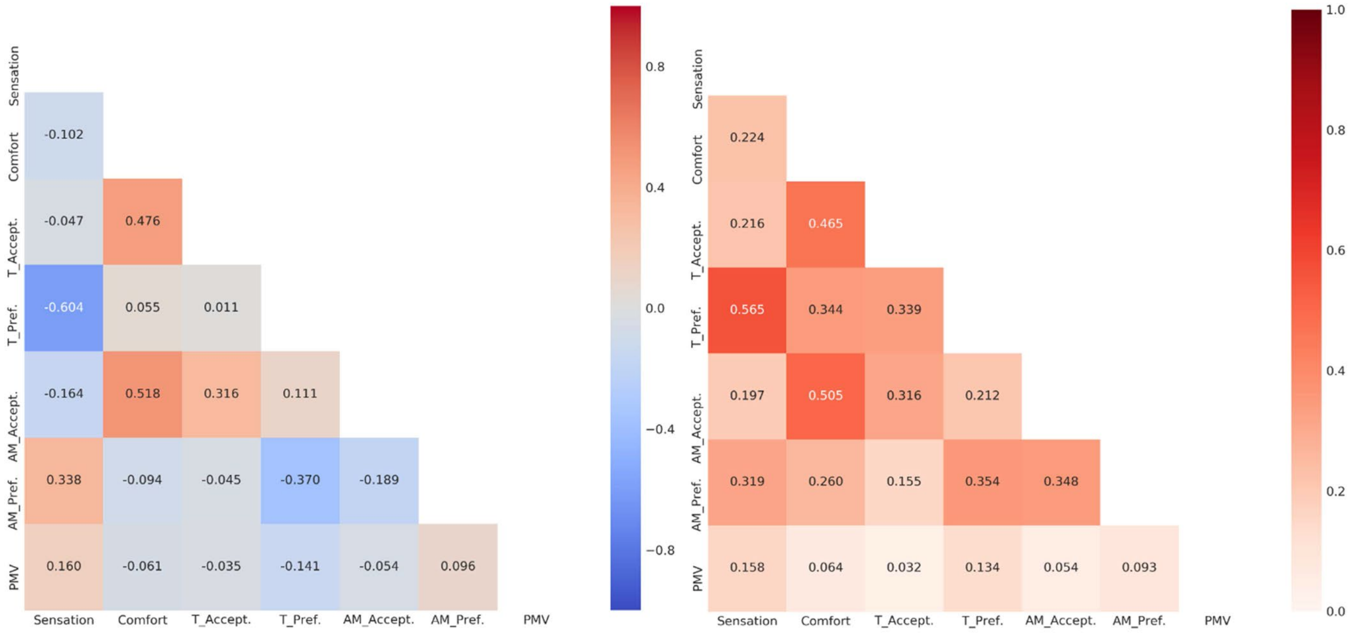
Figure 2(b) compared the usage percentage of subjective thermal metrics in different building types. We found that more subjective thermal responses were collected in classrooms and office buildings than in residential, confirming the challenge of collecting data in residential buildings since residential are considered as private spaces and subjects are not as cooperative to answer the survey as when they are in office buildings. One strategy to collect more data from residential buildings is to reduce the number of questions and make the survey as short as possible, which is exactly the research purpose of this paper.

2.2 Correlation Matrix

The second step to choose which subjective comfort metrics should be included in the survey is to investigate the correlation between different metrics. If two metrics are linearly correlated, then one of them could be removed to simplify the survey. For the feature selection purpose, two index were used to quantify the correlation between metrics, the Pearson Correlation Coefficients and the Distance Correlation Coefficients, as shown in Figure 3(a) and Figure 3(b) respectively. The Pearson Correlation (PC) Coefficients vary from -1 to +1, with 0 meaning not correlated. The Distance Correlation (DC) Coefficients vary from 0 to 1, with 0 indicating the two variables are independent. It should be noted that the Pearson Correlation Coefficients only measures the

[1] There are five building types included in ASHRAE Database I and Database II, Classroom, office, Residential, Senior Center, and others. Since there are only 2 studies investigated Senior Center, the Senior Center was reclassified into others in Figure 2(b).

linear relationship between two variables. Therefore, a meaningful relationship can exist even if the Pearson Correlation Coefficients are close to zero, for instance, thermal sensation and thermal comfort in Figure 3(a). However, a non-zero (especially above 0.5 or below -0.5) Pearson Correlation Coefficients demonstrate a strong linear relation between two variables, indicating that we could only use one of these variables as predictor. In this regard, the air movement acceptability and preference would be excluded from further analysis for two reasons. First, air movement acceptability is highly linearly correlated with thermal comfort (0.518) and air movement preference is highly correlated with thermal sensation (0.338) and thermal preference (-0.370). Second, the missing rates of air movement acceptability and preference are high in the Comfort Database. Only a few researches collected these two metrics.



(a) Pearson Correlation Coefficients (b)Distance Correlation Coefficients

Figure 3 Usage percentage of thermal comfort metrics

Both the Pearson and Distance Correlation Matrix indicates highest correlations between pairs of thermal sensation/thermal preference (PC: -0.64, DC: 0.57), thermal comfort/air movement acceptability (PC: 0.52, DC: 0.51), thermal comfort/thermal preference (PC: 0.48, DC: 0.47). The correlation coefficients between PMV and all the six subjective thermal metrics are surprisingly low (less than 0.2), confirming the importance of using the subjective thermal metrics, rather than the physical parameters alone, in the HVAC control. Since the physical parameters, such as PMV[2], might not be able to reflect occupants' experience of thermal conditions.

2.3 Principal Component Analysis

Principal Component Analysis (PCA) is a well-developed dimension reduction technique, which has extensive applications in fields such as video compression, feature selection etc. The key idea of PCA is to map high-dimensional observations/samples into another space with fewer dimensions but still could explain the largest possible variances of the observations.

For the purpose of metrics selection, only four subjective thermal metrics (thermal sensation, comfort, acceptability and preference) were included in the PCA and the prediction task presented in the next Section. We removed he air movement preference and acceptability from the PCA for two reasons. First, Figure 3 has shown that the air movement preference has a high dependence with thermal sensation (PC: 0.34; DC: 0.32) and thermal preference (PC: -0.37; DC:0.35), while the air movement acceptability has a high dependence with thermal comfort (PC: 0.52; DC:0.51), and thermal acceptability (PC: 0.32; DC: 0.32). The high dependence means the information reflected by air movement preference and acceptability could be explained and

[2] PMV is calculated from six measured or estimated physical parameters - air temperature, radiation temperature, humidity, air speed, metabolic rate, and clothing. PMV might also be influenced by psychophysiology factors because psychophysiology factors, such as adaptive behaviors, might influence metabolic rate and clothing [34].

predicted by the other four metrics. The second reason is as shown in Figure 2, air movement acceptability and preference were not widely used in the current thermal comfort studies; and had a high missing rate in the current thermal comfort database. If air movement acceptability and preference were included in the PCA and prediction tasks, the sample size would be reduced by 40%. As we've discussed, a large sample size is critical for the application of machine learning approach.

Table 1 presented the result of PCA. The first and second Principal components could explain 49.3% and 36.3% of the total variance respectively, indicating that it is possible to explain occupants' experience of thermal conditions with two variables without worrying too much about the loss of useful information, since the first and second Principal Components alone could retain 85% of variance. Table 1 recorded how each Principal components is constituted from the original four attributes. We found that the first and second Principal Components are majorly spanned by the thermal sensation and thermal comfort, while PC3 and PC4 are majorly constructed from thermal preference and thermal acceptability respectively.

Table 1 PCA results

	Explained Variance	Thermal sensation	Thermal comfort	Thermal acceptability	Thermal preference
PC1[3]	49.3%	0.63	-0.75	-0.12	-0.17
PC2	36.3%	-0.74	-0.65	-0.04	0.15
PC3	10.6%	0.23	-0.02	-0.10	0.97
PC4	4.8%	-0.07	0.11	-0.99	-0.09

As a brief summary of this Section, two conclusions could be drawn from the Principal Component Analysis, which answered the first two research questions proposed in Section 1.4.

- At least 2 questions should be asked to collect adequate information for the assessment of the occupants' thermal experience. If only one question is asked, then 50% of information would be missing. If two questions are asked, 85% of information could be retained. Our PCA confirmed Schweiker et al. (2016)'s finding that the personal experience of thermal conditions in built environment is not a one-dimensional problem [16], but at least a two-dimensional problem, one quantifies the physiological factor, and the other quantifies the psychological factor.
- Thermal sensation and thermal comfort should be asked in order to collect as much information as possible if only two questions were asked, since the first and second Principal components are majorly constructed by the thermal sensation and thermal comfort, rather than thermal acceptability and thermal preference. We acknowledge that different thermal metrics have different uses, for instance the thermal preference might be very useful in occupant responsive control. The choice of metrics highly depends on the research purpose. But in general, the metrics of thermal sensation and thermal comfort are more recommended since these two metrics could provide more information than other metrics.

As we've discussed in Section 1.1, subjective thermal metrics could be divided into two categories, symmetrical and asymmetrical. The symmetrical metrics could distinguish between cold and hot. While the asymmetrical metrics are not able to provide any information on whether the occupants' thermal experience could be improved by increasing or decreasing the indoor temperature. The two metrics we chose - thermal sensation and thermal comfort - belongs to the symmetrical and asymmetrical metrics respectively. By collecting thermal sensation and thermal comfort together, we could know both the direction and the scale of the change they desire.

3. Prediction with thermal sensation and comfort

To further prove that it is adequate to ask only thermal sensation and thermal comfort in surveys, we need to be able to use thermal sensation and comfort to accurately predict other subjective thermal metrics that have not been collected. In this section, we will apply a conventional logistic regression method and a widely used machine learning technique, i.e. Support Vector Machine, to predict thermal acceptability and preference.

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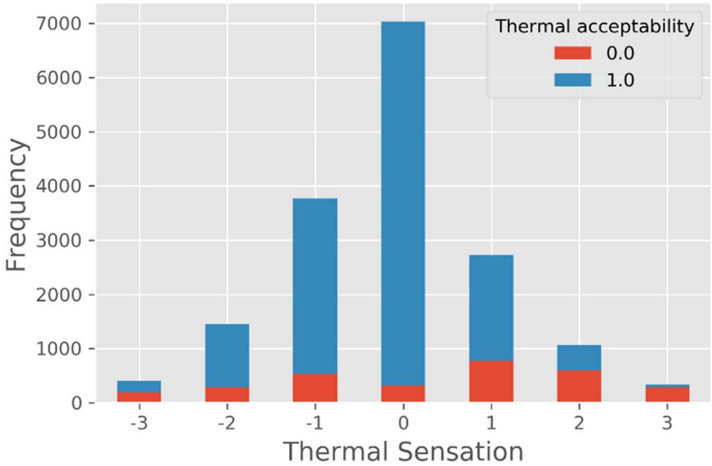
[3] Principal components are linear combination of the original metrics; the coefficients are listed in the Table. For instance, *PC1 = 0.63*TS – 0.75*TC – 0.12*TA – 0.17*TP*

10-fold cross validation has been utilized to evaluate the two methods. We would randomly divide the whole dataset into 10 subsets. Each time, 9 sets will be used as the training set and 1 set will be used as the test set. We repeat this process for 10 times until each set has been used as the test set for once, and report the average accuracy as an evaluation of the model's predictive power.

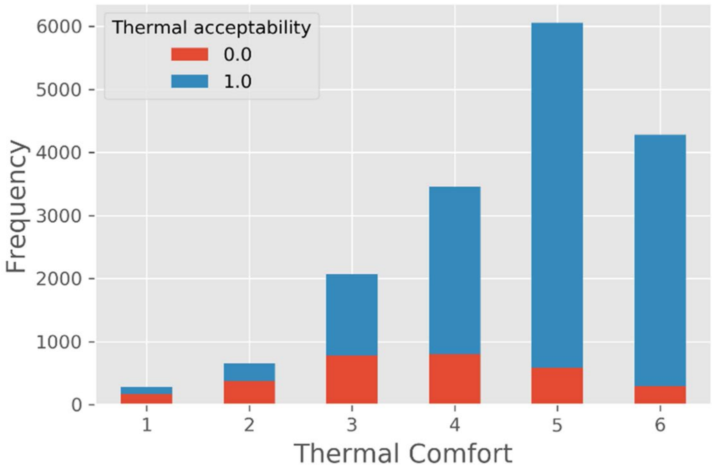
To predict thermal acceptability and preference with thermal sensation and comfort, it is required that all the four subjective thermal metrics have been collected. In Thermal Comfort Database I and Database II, there are 107583 records in total, 25616 from Database I and 81967 from Database II. Among the more than 107 thousand records, there are 16795 data points having collected all the four thermal metrics. We use those 16795 data points in the analysis of this Section.

3.1 Predicting thermal acceptability

It is a common practice to conduct exploratory data analysis before applying more complicated algorithms as shown in Figure 4, which presents a reasonable trend that the acceptability rate will increase with the thermal sensation approaching neutrality and the thermal comfort level raising.



(a) by thermal sensation



(b) by thermal comfort

Figure 4 Histogram of thermal acceptability: blue (1.0) for acceptable, red (0.0) for unacceptable

In logistic regression, we need to manually select the features to be input into the classifier. We tried different combinations of features due to the curiosity in two aspects: first, could we improve the model accuracy by introducing non-linear term, for instance TS squared or TC squared; second, could we improve the model accuracy by adding the feature of PMV or using PMV to replace TC or TS.

As shown in Table 2 that adding TS^2 is more helpful to improve accuracy than adding TC^2, indicating that with thermal sensation departing from the neutrality, approaching either cold or hot, subjects would feel the thermal environment unacceptable at an accelerating rate. As a contrary, the relation between thermal acceptability and comfort is more linear.

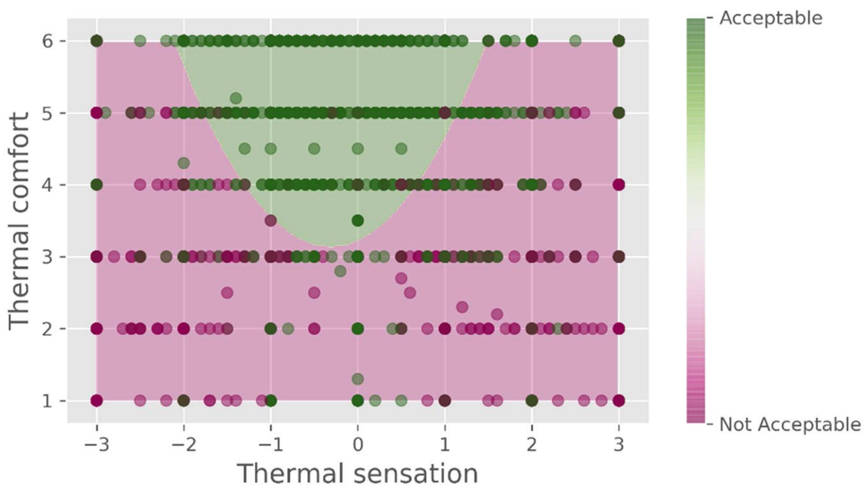
Additionally, adding PMV is not effective to enhance model's predictability. For the purpose of predicting thermal acceptability, it is not necessary to collect PMV in addition to collecting thermal sensation and thermal comfort, especially considering how complicated the work is to collect PMV, which requires measuring or estimating clothing, metabolic rate and etc.

In SVM, the kernel term would automatically depict the non-linear behavior. Therefore, we do not need to manually select the non-linear combinations of features when implementing SVM, and this is considered as one of the merits of SVM. As for the predicting power, logistic regression and SVM have similar accuracy (85.7% for logistic regression vs. 87.4% for SVM).

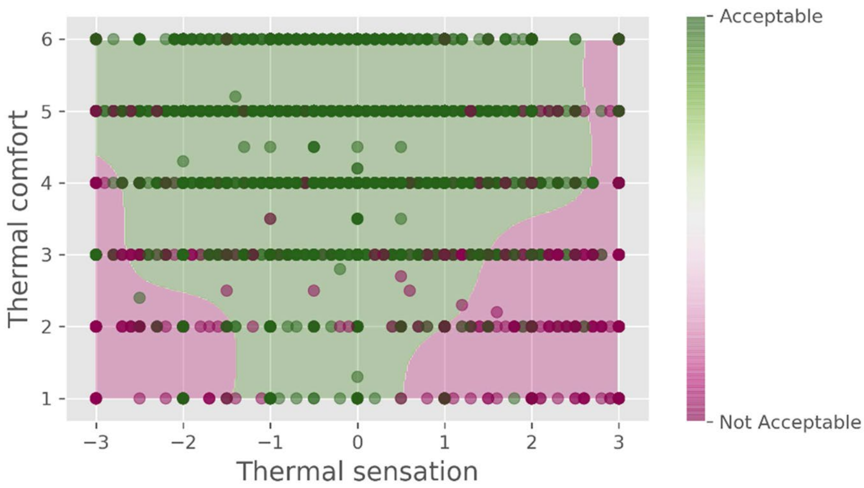
Table 2 Prediction performance with different input features

Input features	Performance metrics			
	Accuracy	Precision	Recall	F1-score
TS, TC	83%	81%	77%	78%
TS, TC, TS^2	86%	84%	81%	82%
TS, TC, TC^2	85%	84%	74%	77%
TS, TC, TS^2, TC^2	86%	84%	81%	82%
TS, PMV	84%	77%	69%	72%
TC, PMV	84%	83%	77%	79%
TS, TC, PMV	84%	82%	77%	79%

Figure 5 outlined the decision boundary predicted by logistic regression and SVM. The two classifiers give the same prediction when subjects are neutral-comfortable (middle top region) and nonneutral-uncomfortable (peripheral bottom region), while give opposite predictions when subjects feel neutral-uncomfortable (middle bottom region) or nonneutral-comfortable (peripheral top region). Actually, individual difference in thermal comfort was observed in the conflicting area (middle bottom region and peripheral top region). In this region, subjects with similar thermal sensation and comfort vote, vote differently in thermal acceptability. This inter-individual variability could not be explained by thermal sensation and comfort. Some meaningful information, which might be relevant to subjects' individual preference, is missed. We could not predict the thermal acceptability by asking thermal sensation and comfort only in the survey. PCA actually quantifies the proportion of this variety, which is around 15% of the total variance.



(a) Logistic regression (prediction accuracy: 85.7%)



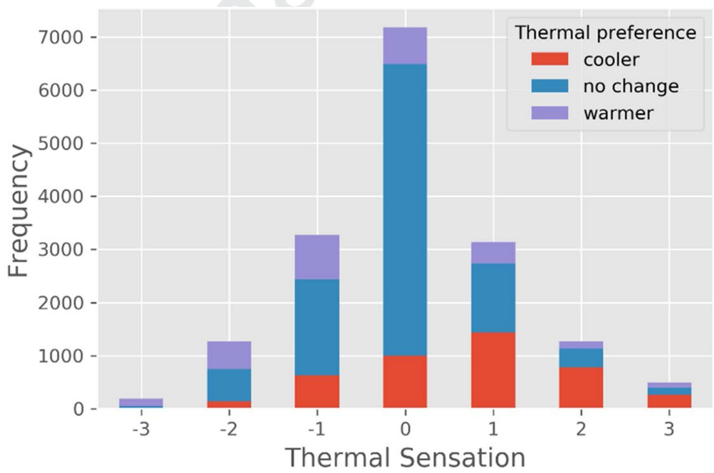
(b) Support Vector Machine (prediction accuracy: 87.4%)

Figure 5 Prediction boundary of thermal acceptability

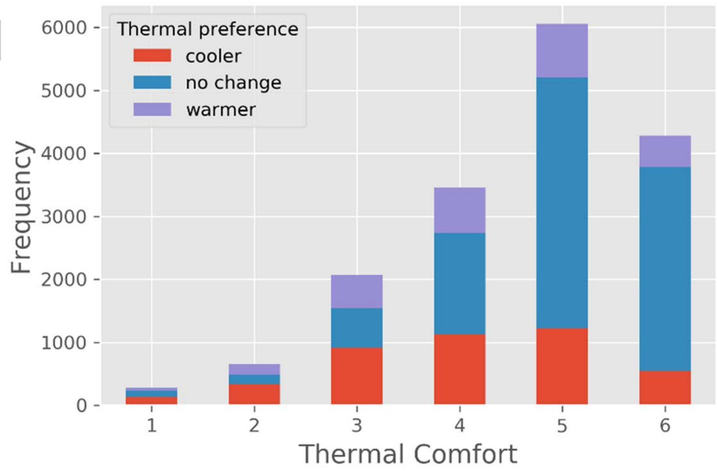
The last thing worthy to be pointed out is the shape of decision boundary. The logistic regression presents a decision boundary with a more regular shape, which is because the equation form in the logistic regression is a binomial which is pre-defined and regularly-shaped. While the decision boundary given by SVM is much more irregular and difficult to interpret. From the perspective of model interpretation, logistic regression outperforms SVM.

3.2 Predicting thermal preference

Again, we start with exploratory analysis by drawing the histogram. Figure 6 identifies a clear trend of higher percentage of subjects preferring "no change" when the thermal sensation is close to neutral and the thermal comfort level is high.



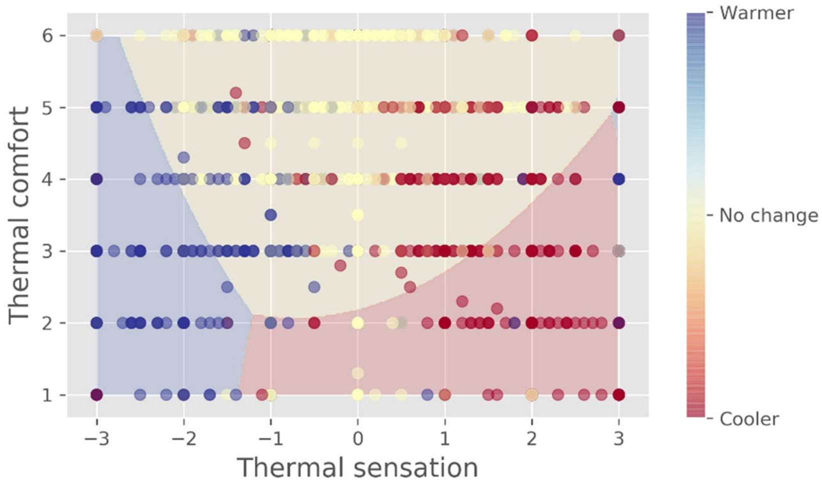
(a) by thermal sensation



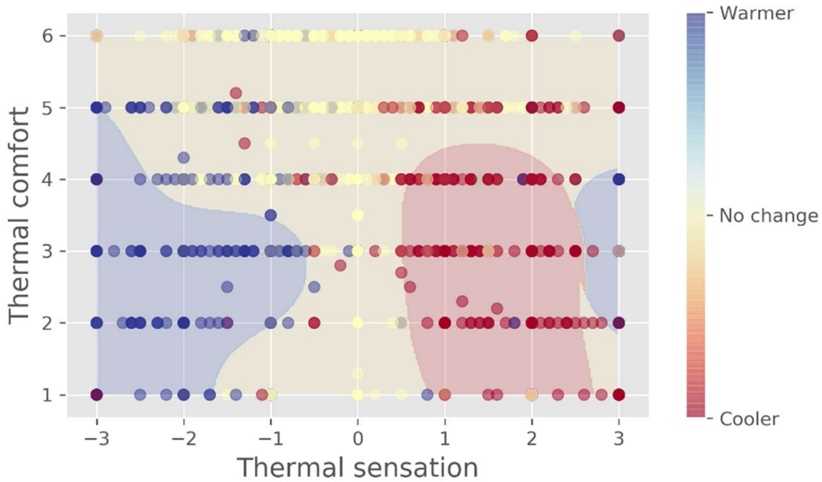
(b) by thermal comfort

Figure 6 Histogram of thermal preference

Similar to the case of predicting thermal acceptability, we included *TS*, *TC*, and TS^2 in the logistic regression to depict the non-linear influence of thermal sensation, which is not need in the implementation of SVM. The average accuracy of 10-fold cross validation of logistic regression is 63.4%, which is very similar to that of SVM (63.9%). It is not a surprise that the accuracy to predict thermal preference would be lower than the accuracy to predict thermal acceptability. Since there are three outcomes (prefer cooler, no change, and prefer warmer) in thermal preference prediction, rather than only two in thermal acceptability prediction.



(a) Logistic regression (prediction accuracy: 63.4%)



(b) Support Vector Machine (prediction accuracy: 63.9%)

Figure 7 Prediction boundary of thermal preference

Two types of prediction errors could be observed from Figure 7. The first type is due to the individual difference [35]. For instance, in the middle of figure, when the thermal sensation is close to neutral and the thermal comfort is 3 (slightly uncomfortable), some people might prefer warmer, some prefer no change while some prefer cooler. In this case, it is difficult if not impossible for human, as a real intelligence, to predict which direction the subjects would choose only given the information of thermal sensation and comfort, not to mention to require the classifier, as an artificial intelligence, to accurately predict. The second type of the prediction error is due to the irregular behaviors. For instance, in the left area of Figure 7, some subjects voted hot as thermal sensation but still prefer warmer. The irregular behaviors, which would be discussed in more details in Section 4.1, might lead to a wrong classification of themselves, as in Figure 7(a), or even worse, lead to a wrong decision boundary, as in Figure 7(b).

Similar to the acceptability prediction, the prediction boundary given by SVM is more irregular and more difficult to interpret. Furthermore, Figure 7 indicates that SVM is more sensitive to outliers. There is a half-oval region on the right counter-intuitively predicted as “prefer warmer”, due to some subjects with irregular behaviors (“hot” thermal sensations while still want to be warmer). However, this area is correctly predicted as “prefer cooler” by the logistic regression.

4. Discussion

4.1 Illogical votes and anomaly detection

We could clearly observe illogical votes in Figure 4 and Figure 5 where the thermal comfort vote is comfortable or very comfortable, but still fell the thermal environment is not acceptable; or from Figure 6 or Figure 7 when the thermal sensation is hot but prefer warmer or when the thermal sensation is already cold but still prefer cooler. Illogical votes are unavoidable in subjective thermal comfort survey, which might be due to several reasons, such as subjects misunderstood the survey questions, subjects were distracted by other issues, or sometimes the experimenter mis-recorded the result and etc.

Illogical votes are like random noise and would bring in variance that could not be captured by the two Principal components and constitutes a part of 15% unexplained variance in the PCA. It is reasonable to believe the explanation power of the first two Principal components would increase above 85% if those illogical votes are removed.

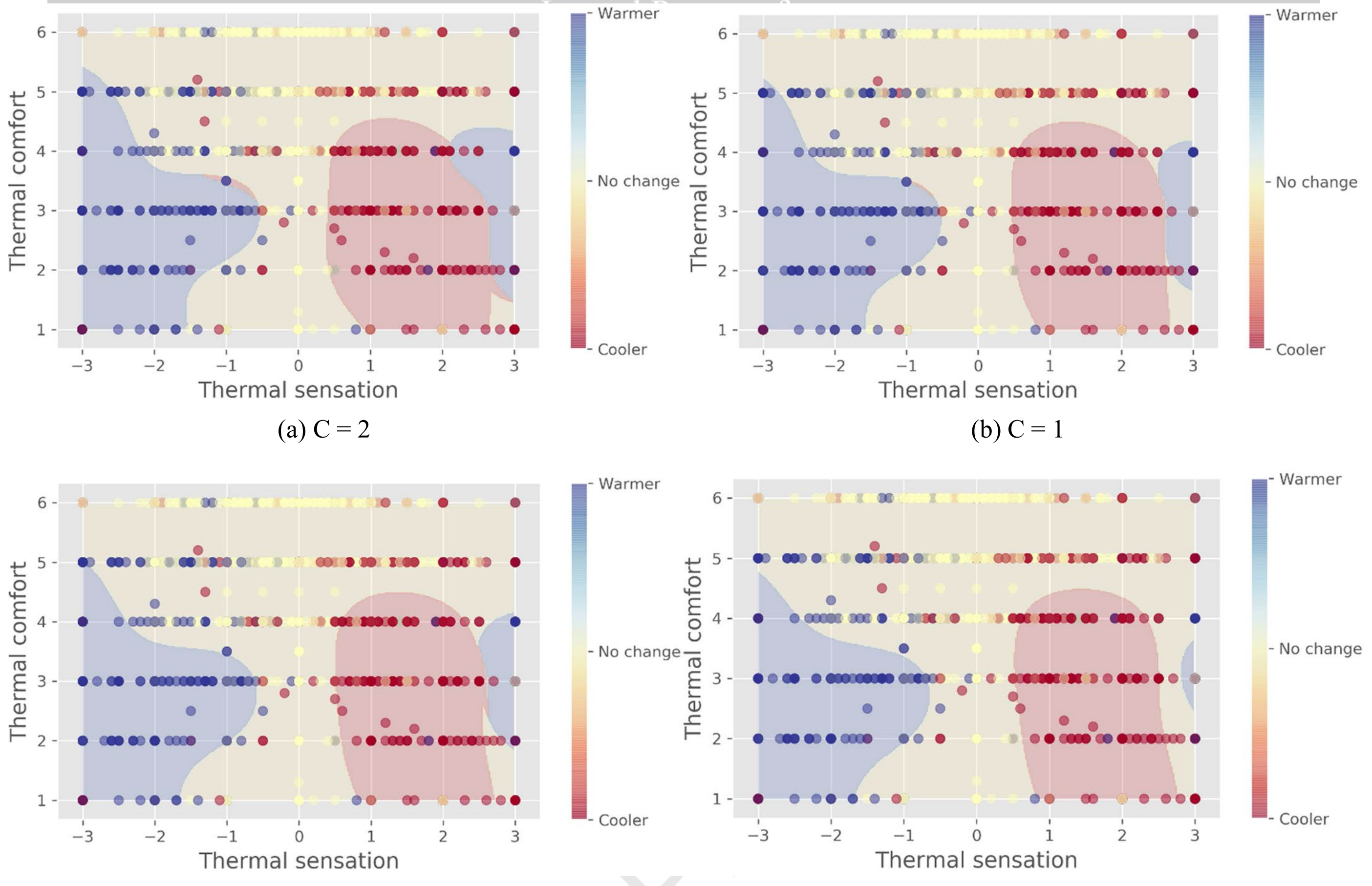
Given the fact that the existence of anomalies would significantly bias the model we built, even in a study with more than 18,000 observations, it could imagine how the anomalies would bias the conclusion in a chamber experiment or on-site study with a sample size on the scale of 100 or 1000. Therefore, recognizing the existence of anomalies and proposing a method to automatically detect them would be very helpful in thermal comfort studies. To further explore this topic, a stochastic-based two-step framework to detect outliers in thermal comfort votes has been proposed in [36].

4.2 Logistic regression vs. SVM

We applied a conventional logistic regression method and a machine learning technique (SVM) in this study to predict thermal acceptability and thermal preference. These two algorithms predict markedly different prediction boundary but surprisingly with similar prediction accuracy. Some advantages and disadvantages of these two approaches could be observed from this study:

- More manual work is required by logistic regression because the features and regression equation forms need to be specified manually to depict the non-linear behavior. However, the prediction boundary of logistic regression is easier to interpret and more robust to outliers.
- SVM is easier to run since practitioners do not need to manually specify a non-linear regression form. However, the prediction boundary of SVM is more irregular and difficult to interpret. Additionally, SVM is more sensitive to anomalies.

The characteristic of being easily influenced by anomalies is partly due to the issue of overfitting, which refers to the fact that the classifier is strongly affected by the observed data and failed to be generalized to unobserved data. SVM provides the chance to address the overfitting issue by tuning the hyperparameters C. As illustrated by Figure 8, by decreasing the value of hyper-parameter C, we could relieve the overfitting problem.



(a) C = 2 (b) C = 1

(c) C = 0.5 (d) C = 0.25

Figure 8: Ways to reduce overfitting of SVM

In terms of the selection of prediction algorithm, we tend to prefer logistic regression, as it has smoother and easier-to-interpret boundary, while its accuracy is as high as SVM. Recent studies shown that ensemble learning (such as random forest [15] or XGBoost [37]) could provide more accurate and robust prediction, which is worthy further investigation as well. However, the selection of machine learning algorithm is beyond the scope of this paper as the focus of this study is thermal comfort metrics.

4.3 Contribution and limitation

Creating a thermally comfortable indoor environment is an important topic in building engineering. As it is energy intensive and markedly influence occupants' overall satisfaction [8]. As the prominent management thinker Peter Drucker [38] once said you cannot manage what you cannot measure, the first step to maintain a good thermal environment is to accurately measure it. This study discussed how many and which subjective metrics should be used to assess the thermal environment. The findings of this paper could help the design of chamber experiments, field studies, and human-building interaction interfaces by shedding light on the choice of subjective thermal metrics to effectively and accurately collect information on occupants' thermal experience with as few questions as possible.

The first limitation of this study is we only analyze the data from ASHRAE Global Thermal Comfort Database. Though it is the largest database so far in the field of thermal comfort, it is unavoidable that lots of field studies are not included in this database. Therefore, some conclusions (such as PMV become less popular in the past two decades) might not necessarily be true in the whole thermal comfort research community. Additionally, to accurately assess the thermal environment, we need not only select the most relevant metrics, but also collect enough samples. Another limitation of this study is we only discussed the selection of metrics, but overlooked the influence of sample size. How the sample size would impact the uncertainty of thermal comfort measurement has been discussed in [39]. The third limitation of this study is we only used two machine learning algorithm – Logistic Regression and SVM – to validate the effectiveness of thermal comfort metrics we selected. Some cutting-edge algorithms such as XGBoost have been overlooked.

5. Conclusion

This paper applies machine learning techniques on the data collected in the recently released ASHRAE Global Thermal Comfort Database II, to answer a fundamental but overlooked question in thermal comfort studies: which subjective metrics should be used for the assessment of the occupants' thermal experience.

We found that the thermal sensation is the most frequently used metrics in Thermal Comfort Database II, which was asked almost in every thermal comfort study, followed by thermal preference, comfort and acceptability. PMV, as another important thermal metrics, was only as half-popular as 20 years ago.

The Pearson Correlation Coefficients and Distance Correlation Coefficients were used to quantify the dependence between thermal metrics. The pair of thermal sensation/thermal preference, thermal comfort/air movement acceptability and thermal comfort/thermal preference are the top three most dependent pairs. The correlation coefficients between PMV and all the six subjective thermal metrics are less than 0.2.

The Principal Component Analysis was used to study the dimensions of subjective thermal metrics. We found the first and second Principal Components could explain 49.3% and 36.3% of the total variance respectively. Therefore, the personal experience of thermal conditions in built environment is not a one-dimensional problem, but at least a two-dimensional problem, one quantifies the physiological factor, and the other quantifies the psychological factor. Additionally, the first and second Principal Components are majorly constructed by the thermal sensation and thermal comfort, therefore, thermal sensation and thermal comfort should be asked in order to collect as much information as possible if only two questions were asked.

To further confirm that thermal sensation and comfort have strong predictive power, we used Logistic Regression and Support Vector Machine to predict thermal acceptability and thermal preference. The prediction accuracy is 87.4% for thermal acceptability and 63.9% for thermal acceptability. The prediction error might be due to occupants' individual difference in thermal comfort and illogical subjects' behaviors.

The findings of this paper could help the design of chamber experiments, field studies, and human-building interaction interfaces by shedding light on the choice of subjective thermal metrics to effectively and accurately collect information on occupants' thermal experience with as few questions as possible.

Declaration of competing interest

All co-authors declare there is no conflict of interest in the reported work.

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