Topical Issue on Thermal Environment for Special Space and/or Special Population

Individual thermal comfort prediction using classification tree model based on physiological parameters and thermal history in winter

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ABSTRACT

Individual thermal comfort models based on physiological parameters could improve the efficiency of the personal thermal comfort control system. However, the effect of thermal history has not been fully addressed in these models. In this study, climate chamber experiments were conducted in winter using 32 subjects who have different indoor and outdoor thermal histories. Two kinds of thermal conditions were investigated: the temperature dropping (24-16°C) and severe cold (12°C) conditions. A simplified method using historical air temperature to quantify the thermal history was proposed and used to predict thermal comfort and thermal demand from physical or physiological parameters. Results show the accuracies of individual thermal sensation prediction was low to about 30% by using the PMV index in cold environments of this study. Base on the sensitivity and reliability of physiological responses, five local skin temperatures (at hand, calf, head, arm and thigh) and the heart rate are optimal input parameters for the individual thermal comfort model. With the proposed historical air temperature as an additional input, the general accuracies using classification tree model C5.0 were increased up to 15.5% for thermal comfort prediction and up to 29.8% for thermal demand prediction. Thus, when predicting thermal demands in winter, the factor of thermal history should be considered.

Keywords: Thermal comfort; cold adaptation; thermal sensation; skin temperature; heart rate.

Abbreviations and Symbols

BP_{min}	minimum blood pressure, i.e. diastolic blood pressure (mmHg)
$BP_{max.}$	maximum blood pressure, i.e. systolic blood pressure (mmHg)
HR	heart rate (bpm)
HSCW	hot summer and cold winter
I_{cl}	clothing insulation (clo)
TSV	thermal sensation vote
TPV	thermal pleasure vote
TC	thermal comfort
TD	thermal demand
RH	relative humidity (%)
SET	standard effective temperature (°C)
T_{H}	historical air temperature (°C)
T_{a}	air temperature (°C)
T_{head}	local skin temperature at head (°C)
T_{chest}	local skin temperature at chest (°C)

T_{arm}	local skin temperature at arm (°C)
T_{hand}	local skin temperature at hand (°C)
T_{thigh}	local skin temperature at thigh (°C)
T_{calf}	local skin temperature at calf (°C)
d	effect size
R^2	determination coefficient
RA	relative accuracy
P	significant level
r_s	coefficient of Spearman's rank

1 Introduction

Due to the vast territory, many areas in China have significantly different indoor and outdoor climates (Li et al., 2018a). According to the basic theory of adaptive thermal comfort, people living in one area should have already adapted to the local thermal environment (Yao et al., 2009), and their thermal history may result in different thermal comfort requirements (Kong et al., 2019; Yan et al., 2019). With the fast expansion of immigration both nationally and internationally, better consideration of people's thermal history on their thermal comfort requirements will help to give a more accurate comfort modeling to help design and operate building thermal systems (Li and Yao, 2012; Yuan et al., 2020).

It is noticed that the conventional methods, such as the PMV model (Fanger, 1970), the extension of PMV (ePMV) model (Fanger and Toftum, 2002), and the adaptive model (Yau and Chew, 2014) which are originally developed for predicting the average thermal requirements of a group of people in the building, were not applicable for individual thermal comfort predictions. With the fast development of wearable and non-invasive technologies in recent years (Revel et al., 2012), many studies have tried to predict occupants' thermal comfort based on their physiological responses, such as heart rate (Choi et al., 2012), blood pressure (Gilani et al., 2016) and skin temperature (Choi and Loftness, 2012). These new prediction methods target to occupants' personal thermal requirement and provide an opportunity of improving personal thermal satisfaction and reducing energy consumption simultaneously (Aguilera et al., 2019; Antoniadou and Papadopoulos, 2017; Kim et al., 2018; Yang et al., 2020). Using these new methods, the average prediction accuracies in personal thermal comfort predictions are between 70% and 90%.

A study (Liu et al., 2019) has developed personal thermal comfort models using lab-grade wearable devices and proposed that ankle skin temperature had a better prediction performance than wrist skin temperature. Another study (Li et al., 2018b) has used wrist skin temperature and heart rate to predict people's thermal sensation at different activity levels. Chaudhuri et al. (Chaudhuri et al., 2018a) have used wearable devices to explore the gender difference in people's physiological responses to the surrounding thermal environment. Using hand skin temperature, pulse rate, and air temperature, they (Chaudhuri et al., 2020) also proposed an improved thermal comfort prediction method than the method using skin temperature alone as the physiological parameter (Chaudhuri et al., 2018b). Some scholars have developed models to predict people's overall thermal sensation based on the skin temperatures of localized body parts., and argued that to control the complexity of the prediction model the measured skin locations should not be more than three (Dai et al., 2017). Salehi et.al. (Salehi et al., 2020) have suggested that the forehead, cheek, nose, and hand were more closely related to people's instant thermal sensation, than other parts of our body. A study (Choi and Yeom, 2017) has revealed that to predict personal thermal sensation the skin temperatures at the arm, back and wrist were the best predictors. Between the skin temperature at the ankle and at the wrist, a study (Liu et al., 2019) has suggested the former one be more predictive. In these studies, however, the factor of thermal history has not been included in these thermal comfort models.

Although thermal history has not been considered in prediction models of thermal comfort, its impact on people's thermal sensation and physiology responses has been justified in many existing studies. Studies showed that the differences of long-term indoor thermal histories significantly affected the physiological adaptation (Luo et al., 2016b) and thermal expectations of occupants in cold environments (Luo et al., 2016a; Luo et al., 2018). Ning et al. revealed that the cold adaptability of occupants who had a long-term thermal history in warm indoor climate was undermined (Ning et al., 2016b) and their neutral temperature was about 2°C higher than the occupants with long-term thermal history in cooler conditions (Ning et al., 2016a), which was also proved in another study (Jowkar et al., 2020). Although tracked field studies (Liu et al., 2020; Liu et al., 2017b) showed the difference in thermal sensation between migrations and locals was decreased with time, Luo et al. (Luo et al., 2019) found the effect of long-term thermal history could last for 3 years. Studies also showed that thermal comfort was affected by the short-time (Ji et al., 2017) and immediate (Ji et al., 2019) thermal experience, but another study argued that short-time exposure was negligible (Buonocore et al., 2019). Generally, occupants' long-term thermal histories in a non-neutral warm/cold climate can make the climate more acceptable (Yasmeen et al., 2020). In our preliminary study in winter conditions (Wu et al., 2020; Wu et al., 2019b), significant differences in thermal sensation and local skin temperatures were found in two groups with different thermal histories. However, all these studies focused on the difference between two groups of occupants from different climate areas or with different levels of thermal histories. There is no effort available to quantify the impact of thermal history on thermal comfort prediction.

Many factors would affect the thermal history of occupants, including air temperature, metabolic rate (Zhang et al., 2020), mean radiation temperature, humidity (Cai et al., 2020), wind speed/draught (Wu et al., 2021b), and clothing insulation (Liu et al., 2018). For the comprehensive indoor environments, the standard effective temperature (SET) (DA., 1980), which was calculated from the Gagge two-node model (Gagge, 1986), was used to consider these factors with a standardized index. The SET is the value of air temperature when assuming that the mean radiation temperature equal to the air temperature, no wind, relative humidity is 50 % and occupants seated quietly (1.0 met) with standardizing clothing insulation (0.6 clo), in which the human body has the same heat loss/stress in actual thermal environment. In practice, a previous study in Hot summer and cold winter climate zone of China (Liu et al., 2017a) showed that the air temperature was the dominating factor that affected the thermal history and behaviors of occupants indoors. Because the metabolic rate and clothing insulation of most occupants were stable in most indoor time in winter, and the measured indoor air velocity was very small in winter. Thus, the air temperature and standard effective temperature (SET) were used as the potential parameters to represent thermal history in this study.

In existing studies, although the effect of thermal history on people's thermal sensation and physiological responses has been widely revealed, it has not yet been included in existing prediction models. To fill this gap, this study has proposed a method to quantify people's individual thermal history and applied it in the prediction of their thermal comfort requirements, based on both physical and physiological parameters. Thirty-two subjects with different indoor and outdoor thermal histories were involved in the survey, which was carried out in a climate chamber with a controllable indoor thermal environment. During the survey, participants' thermal sensation vote (TSV), as well as their local skin temperatures, blood pressure, and heart rate, were recorded for the model development.

2 Methodology

2.1 Testing subjects and thermal history

The sample size of this study was selected according to the idea of power analysis that was introduced by Lan and Lian (Lan and Lian, 2010). In this method, the minimum sample size was calculated by the priori power analysis using G*Power 3.1 (Faul et al., 2009; Faul et al., 2007) based on three indices: 1) the requested significance level P (i.e. possibility of α error); 2) the power level (1-β error) and 3) the effect size (d). In this study α and (1-β) were set at 0.05 and 0.8, respectively, as suggested in (Cohen, 1988). For a T-test, the minimum total sample sizes were 27 for a medium defect size (d = 0.5) of the studied parameters (Lan and Lian, 2010). To make sure the analysis powerful, a sample size of 32 healthy adults, who meet the requirements of experimental criteria, has been adopted to meet the minimum sample size.

The experiment was conducted in late February 2019, during the wintertime of Chongqing, China, with a mean outdoor air temperature of around 11.9°C (China Meteorological Administration, 2019).

Basic information about potential subjects was collected before the experiment, such as their name, gender, birthplace, place stayed last month, living history in naturally ventilated (non-heated) or heated buildings, and the average time spent per day indoors and outdoors. To study subjects with a variety of thermal histories, the subjects from different climate zones were needed. Thus, the recruitment ended until the required number for gender balance subjects from the different areas were fulfill, i.e. eight females and eight males from Northern China; eight females and eight males from Southern China, with the final 32 participants. The subjects from different climate areas just arrived in Chongqing for less than a week before the experiment.

In this study, the thermal history of subjects was quantified using historical air temperature (T_H), calculated based on the time-weighted air temperature and corresponding exposure time in previous days, using Equation,

$$\mathrm{T}_H = \frac{h_{AC}}{24} \times \mathrm{T}_{a,AC} + \frac{h_{NV}}{24} \times \mathrm{T}_{rm,NV} + \frac{h_{out}}{24} \times \mathrm{T}_{rm,out} \quad [1]$$

where, T_H is the value of HAT (ºC); h_{AC} is the average time per day staying in air conditioning (AC) space in the previous 30 days (h/d); h_{NV} is the average time per day staying in naturally ventilated (NV) space in the previous 30 days (h/d); h_{out} is the average time per day staying outdoors in the previous 30 days (h/d); $T_{a,AC}$ is the average indoor air temperature in space with heating (21°C for the investigated city according to existing data (Li et al., 2018a)); $T_{rm,NV}$ is running mean indoor air temperature in space without heating (ºC); $T_{rm,out}$ is the running mean outdoor air temperature (ºC).

The values of h_{AC}, h_{NV} and h_{out} were self-stated by the participants in the survey. Considering the different weighting factors of outside air temperature in previous days to people's thermal history, the running mean outdoor air temperature (Nicol and Humphreys, 2010) was decided by Equation 9,

$$T_{rm,out} = \lim_{n\to\infty} \frac{\sum_{i=1}^{n}(\alpha^{i-1} * T_{od-i})}{\sum_{i=1}^{n}\alpha^{i-1}} \quad [2]$$

where, α is a constant value (<1, set to be 0.8 in this study, which is recommended by the standard);

T_{od-i} is the daily mean outdoor temperature for the previous days (ºC).

Similarly, the historical standard effective temperature (SET_H) could be expressed as:

$$\mathrm{SET}_H = \frac{h_{AC}}{24} \times \mathrm{SET}_{a,AC} + \frac{h_{NV}}{24} \times \mathrm{SET}_{rm,NV} + \frac{h_{out}}{24} \times \mathrm{SET}_{rm,out} \quad [3]$$

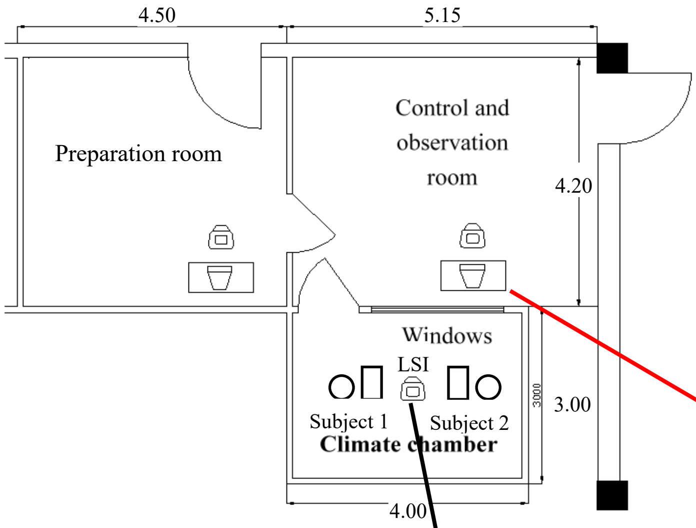
The indoor metabolic for seated occupants is about 1.2 met, the outdoor metabolic for walking is about 2.0 met (ISO, 2005). The clothing insulation for heated and NV space was about 1.0 clo and 1.3 clo, respectively (Liu et al., 2017a). The mean radiation temperatures were also close to the air temperatures when there is no obvious heating or cooling source indoors. There was no wind indoors in winter. In this study, the previous daily mean outdoor temperatures and relative humidity in 30 days (i.e. n=30) from the climate station of China Meteorological Administration (China Meteorological Administration, 2019) are used to calculate the running mean outside air temperature and relative humidity. The running mean indoor air temperature in NV space was calculated based on the relationships between indoor and outside air temperature defined from one previous study (Li et al., 2018a), as shown in Table 1. The indoor relative humidity was equal to the outdoor value for the NV buildings.

Table 1: The relationships between indoor and outside air temperature in NV space (Li et al., 2018a)

Climate zones	Regression	R^2
Cold winter climate zone	$T_{rm,nv} = 0.75\ T_{rm,out} + 5.8$	0.98
Warm winter climate zone	$T_{rm,nv} = 0.74\ T_{rm,out} + 6.3$	0.98
Temperate climate zone	$T_{rm,nv} = 0.62\ T_{rm,out} + 8.5$	0.94

2.2 Experimental setup

The experiment was conducted in a climate chamber, with a room dimension of 4.0m (L) × 3.0m (W) × 2.7m (H), as shown in Figure 1. The chamber was well insulated by a 100mm thick, double color steel plate and polyurethane filling, to minimize the effect from the ambient environment. Perforated ceiling panels and sidewall panels were used to supply and exhaust air, respectively. The air-conditioning system could adjust indoor air temperature (T_a) within the range of –5°C and 40°C, with an accuracy of ±0.30°C, and relative humidity within the range of 10% and 90%, with an accuracy of ±5%. Before the experiments, the subjects stayed in the preparation room as Figure 1 shows, which is air-conditioned using a split air conditioning unit. The control and observation room was used by the test personnel to monitor the conditions of the thermal environment and subjects in the climate chamber.



(a) Plan view of experiment rooms

(b) Control and observation platform

(c) Experimental subjects

Figure 1: Experimental conditions of the chamber

During the study, a Thermal Comfort Monitoring Station made by the LSI in Italy has been used to measure environmental parameters, including air temperature, relative humidity, air velocity and black-bulb temperature. Thus, the mean radiant temperature (T_r) was calculated based on air temperature (T_a), air velocity (V_a) and black-bulb temperature (T_g) as follows:

$$T_r = [(T_g + 273)^4 + 0.4 \times 10^8 (T_g - T_a)^{\frac{5}{4}}]^{1/4} - 273 \qquad \text{for } V_a < 0.2 \text{ m/s} \qquad [4]$$

The station was placed in the middle of the two subjects involved in each test, with a height of 0.6m (ASHRAE, 2017). The CO_2 level indoors was measured using a portable GE Telaire-7001 device. Before the experiment, the subjects' height, weight and body fat rate were also measured using a height and SUHONG weight scale and a TANITA BC-601 body fat meter.

To measure the skin temperature of subjects, thermocouples were used and connected to a four-channel HOBO UX120-006M data logger (Onset, 2019), with an accuracy of ±0.15°C. Subjects' local skin temperatures covering four clothed body parts which mostly representing mean skin temperature (Liu et al., 2011) and two unclothed surfaces were measured, namely, chest, upper arm, thigh, calf, head and hand, as Figure 2 shows. To measure their blood pressure, a HEM-6021 electronic sphygmomanometer was used. Because the blood pressure cannot be measured continuously, the readings from the instrument were recorded three times, namely, right before, during and right after each questionnaire survey (see Section 2.4). The average value of these three readings was finally used in the data analysis. When doing the measurement, the sphygmomanometer was tied to the forearm (which close to the wrist, as Figure 2 shows) and lifted to the same height as the heart. The heart rate was measured continuously for the whole experiment and it was recorded every 15s using a Polar RS400 heart rate telemeter. Before the study, all instruments were calibrated to meet the specifications shown in Table 2.

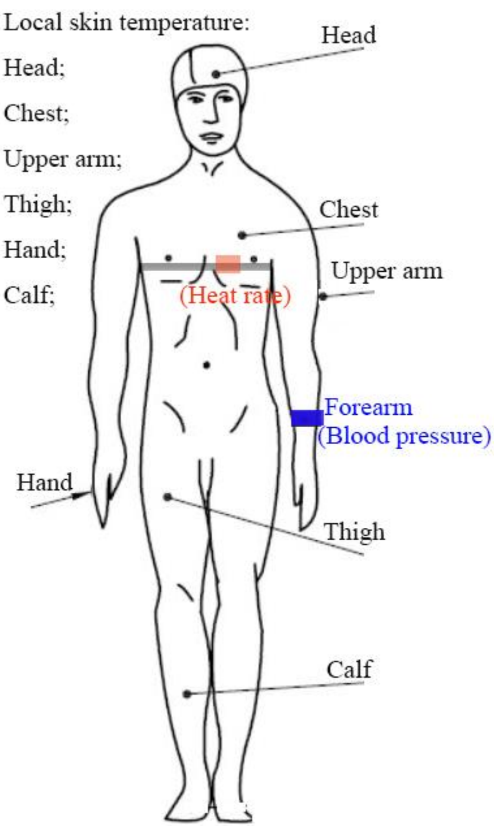


Figure 2: Measurement points of the physiological parameters on the subject

Table 2: Ranges and precision of instruments in the climate chamber study

Brand/model	Equipment	Variables	Range	Accuracy
GE Telaire-7001	CO_2 detector	CO_2 concentration	0–10000 ppm	± 50 ppm
LSI	Thermal Comfort Monitoring Station	Air temperature	−25 to 150°C	±0.1˚C
		Relative humidity	0–100% RH	±2% (15–40%) RH ±1% (40–70%) RH ±0.5% (70–98%) RH
		Air velocity	0.01–20 m/s	±0.05 m/s（0–0.5 m/s）

				±0.1 m/s（0.5–1.5 m/s）
				4% (> 1.5 m/s)
		Black-bulb temperature	−10 to 100°C	±0.15°C
TMC6-HD	Thermocouple	Skin temperature	−40 to 100°C	±0.15°C
HEM-6021	Electronic sphygmomanometer	Blood pressure	0–299 mmHg	±3 mmHg
Polar RS400	Heart rate telemeter	Heart rate	15–240 bpm	1 time/min

2.3 Experimental conditions and procedures

Using the climate chamber, the experiment mimicked two typical types of winter indoor conditions in the hot summer and cold winter (HSCW) climate region: 1) a temperature dropping condition (24 - 16°C) for buildings with heating or with partial heating (MOHURD, 2016); and 2) a constant temperature of 12°C (severe cold condition), which has been found in an existing study to be the mean indoor temperature for buildings with no heating (this type of building is still quite common the HSCW climate zone of China (Liu et al., 2017a). The relative humidity was set as 55% ± 5%, with air velocity lower than 0.15m/s.

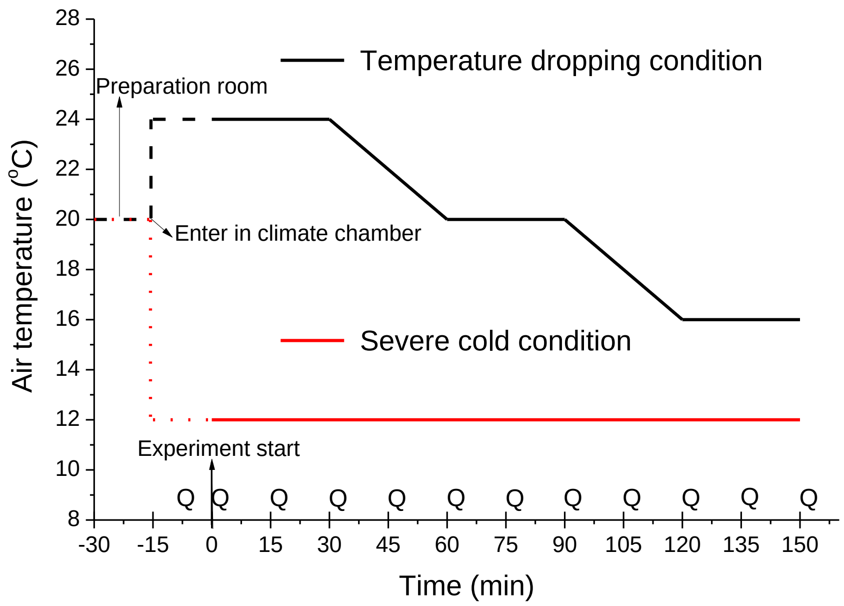


Figure 3: Experimental conditions and procedures (Q – Questionnaire)

During the experiment, all testing subjects wore winter clothing that was typical for the region, generally including underwear with long sleeves and legs, trousers, sweater, jacket, socks and shoes, with an overall level of insulation approximately to 1.0clo. The subjects were allowed to adjust their clothes before the test (i.e. 0 min) but not during the test, with their final clothing insulation in the test recorded using the checklist available in ASHRAE 55 (ASHRAE, 2017).

As Figure 3 shows, before the test, all subjects arrived at the preparation room and rested for approximately 15 minutes, with an ambient temperature of 20°C. They then entered the climate chamber for the following 15 minutes to wait for all parameters to become stable. During the preparation time, they adjusted their clothing insulation and provided their personal information. Additionally, they were also instructed about how to use all physiological monitors and the procedures of the experiment, with the consent of data usage. After the required time for the stabilization of measurement devices, the experiment started and the physiological data recorded from this time were used for analysis.

Each subject participated in the experiment for one time in each condition. All 32 participants of this study involved in the experiments of both temperature dropping and severe cold conditions, on two different days, with at least one-week interval to ensure that the earlier test did not affect the latter one. Every individual session was lasting for about 3 hours including the preparation time. Each session had two subjects, as shown in Figure 1. Once the test began, both participants were asked to fill out a questionnaire every 15 minutes. The work carried out complied with the Code of Ethics of the World Medical Association (Declaration of Helsinki) (WMA, 2013) for experiments involving human subjects. The university's ethics committee has approved all experiment protocols.

2.4 Questionnaire and data processing

During the experiment, all subjects evaluated their surrounding thermal environment using some scales representing their instant thermal perceptions and preferences, including Thermal Sensation Vote (TSV), Thermal Pleasure Vote (TPV), and thermal preference. According to ASHRAE standard 55 (ASHRAE, 2017), seven-point scales were used to assess TSV. Participants' thermal comfort (TC) was evaluated using the TSV vote by classifying into Cool-Discomfort (TC = -1 with TSV = -3 or -2), Comfort (TC = 0 with TSV =-1, 0 or +1), and Warm-Discomfort (TC =1 with TSV = +2 or +3), as that defined in the previous studies (Chaudhuri et al., 2020; Chaudhuri et al., 2018b).

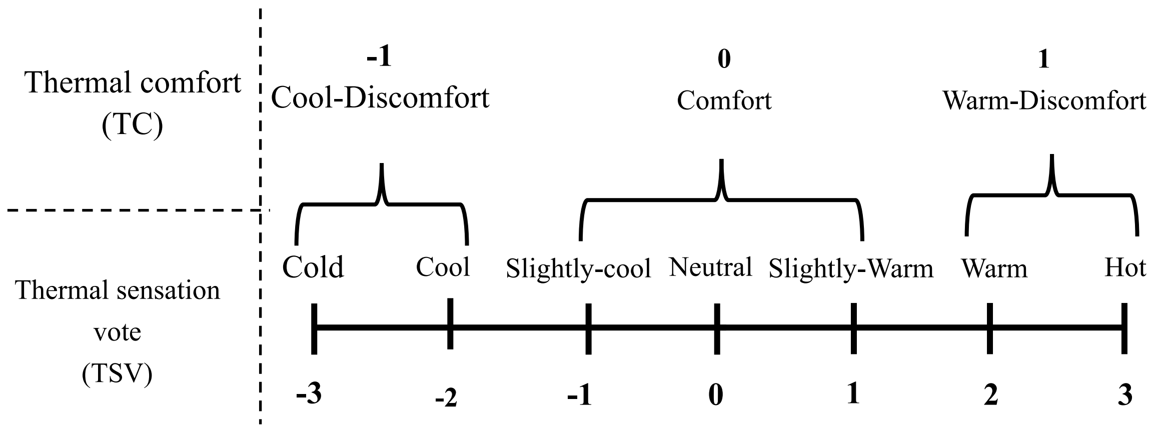


Figure 4: ASHRAE 7-point thermal sensation scale and corresponding Thermal Comfort Index.

The Thermal Pleasure Vote (TPV) was proposed by Parkinson and Richard de Dear (Parkinson et al., 2016) to explore the hedonic tones attached to thermal transients and stimuli The difference between thermal comfort and thermal pleasure is that the thermal pleasure was mainly used to express the thermal alliesthesia, which was also explained to the test subjects before the experiments. Thermal preference was assessed by a three-point scale, namely, cooler (-1), no change (0), warmer (+1), available in ISO standard 10551 (ISO, 2002). The thermal demand (TD) was proposed and defined in this study as follows: when TPV ≥ 0, TD = 0; and when TPV < 0, TD equaled to thermal preference vote, as Figure 5 shows. That means the thermal demand defined in this study only existed when subjects felt slightly unpleasant, unpleasant, or very unpleasant.

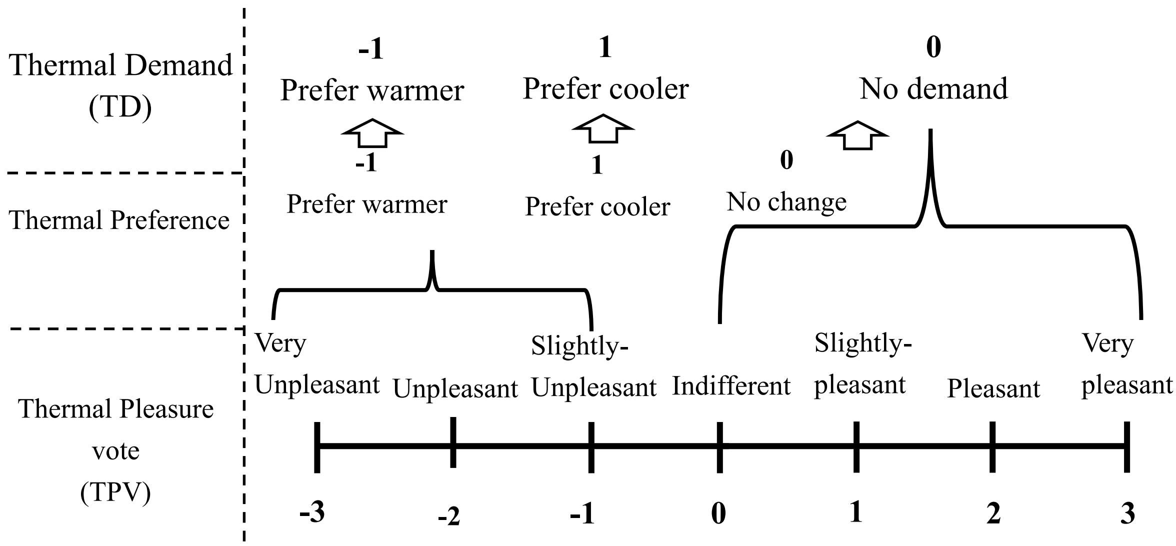


Figure 5: The thermal pleasure and preference scale and corresponding Thermal Demand Index.

Physiological responses measured by different devices were used to predict the thermal state of each subject. To obtain good prediction performance, it should consider not only the difference in physiological responses at various thermal states but also the inherent characteristics of physiological responses. Therefore, some indicators were developed to evaluate the physiological parameters.

(1) Sensitivity (whether a physiological response can sensitively reflect the change of thermal state): two methods were used to evaluate the sensitivity, 1) the spearman's rank correlations and 2) the significance test. The spearman test was applied to see if there was a relationship between physiological responses and thermal states, and the significant test was used to see if there was a significant difference between different sample groups for one physiological response under different thermal conditions.

(2) Reliability (the relative accuracy and stability of physiological response at different thermal states): two indexes were used to evaluate the reliability, 1) the Relative Accuracy (RA – Equation 3) and 2) the effect size (d – Equation 4),

$$\mathrm{RA} = \frac{\overline{x_1} - \overline{x_2}}{a} \quad [5]$$

where, a is the accuracy of the device for a physiological parameter, and x_i is the mean value of the physiological parameter at thermal state i,

$$\mathrm{d} = \frac{\overline{x_1} - \overline{x_2}}{S} \quad [6]$$

$$\mathrm{S} = \sqrt{\frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_1}} \quad [7]$$

where d is the effect size; S is the standard deviation; n is the number of samples, and subscripts 1 and 2 refer to the two groups with different thermal states.

2.5 Classification model

Data mining is a powerful method of revealing existing relationships behind large datasets (Yu et al., 2015). To evaluate the prediction performance of thermal states from different feature sets, a data mining tool named as SPSS Modeler 20.0 was used. It is a popular computational tool offering a variety of classification and regression models based on machine learning techniques. Among these models, the C5.0 model has been proven as being suitable for predicting people's thermal comfort (Du et al., 2019), with high accuracy and low memory usage (Pandya and Pandya, 2015). Therefore, it has been adopted in this study.

The C5.0 model is an improved decision tree algorithm based on information theory. It was developed by Quinlan from the C4.5 model. The C5.0 works by splitting the samples into subsets using the value of a single feature providing maximum information gain. This process is repeated on each new subsample and continues until the subsample cannot be separated. The information gain based on entropy is used to evaluate how well one attribute splits the training data according to the target model (Sharma and Mukherjee, 2012). The information gain ratio is defined by Equation (Pang and Gong, 2009; Patil et al., 2012),

$$Gain\ Ratio\ (A) = \frac{Gain(A)}{Split(A)} \qquad [8]$$

where A is an attribute; *Gain*(A) is the information gain of attribute A; *Split*(A) is the test with at least average gain.

To avoid abnormal data which may be due to measurement errors or experimental influences, all data were preprocessed using Tukey‘s test (Abdi and Williams, 2010) before the analysis, with anomalous (i.e. far outside of the normal range of instruments measurement or experimental conditions) values deleted. After that, the SPSS Modeler 20.0 also has a functional interface to demonstrate each step in the training and analyzing process, as shown in Figure 6. The types of features are defined in the step of "Variable Setting", such as nominal, ordinal, and continuous variables. The algorithm C5.0 was selected from "Model selection". After selecting the set of input features, the types and the target variables, the dataset was randomly split into the training group (80%) and testing groups (20%) in the SPSS Modeler 20.0. The prediction performance would be calculated using the testing group.

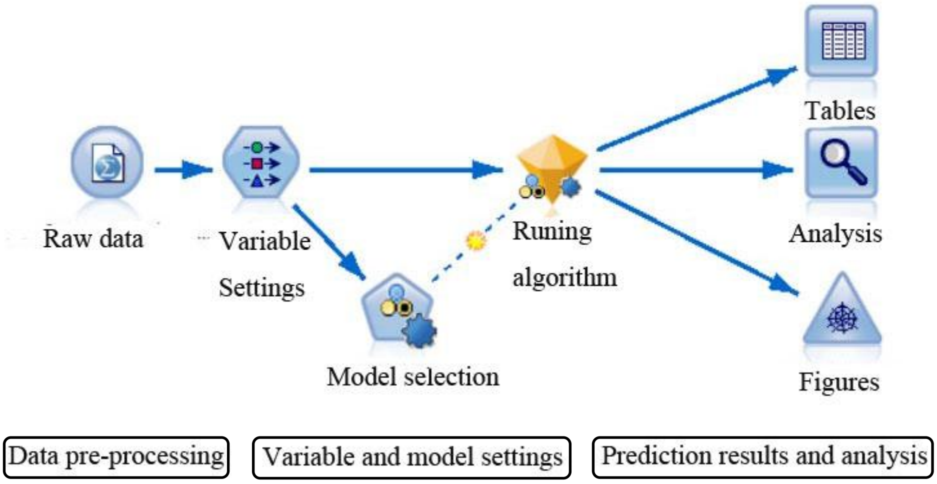


Figure 6: Analysis process in SPSS Modeler using experimental data

The results of different feature physiological responses were compared based on their accuracy of predicting personal thermal comfort. Besides that, the overlap between the target variables, i.e. thermal comfort and thermal demand, was also analyzed using precision and recall metrics. The three metrics were defined in Equations 7-9,

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad [9]$$

$$Precision = \frac{TP}{TP+FP} \quad [10]$$

$$Recall = \frac{TP}{TP+FN} \quad [11]$$

where *TP* means the true positive (i.e. the number of correctly classified positive samples); *FP* is the false positive; *TN* is the true negative, and *FN* is the false negative.

3 Results

3.1 Measured environmental data

During the tests, the mean radiant temperature was close to room air temperature, for there is no heating source in the climate chamber. The relative humidity was 57% ± 2%, and the air velocity was less than 0.15 m/s during the experiment. The measured CO_2 concentration was about 570 ± 80 ppm. The actual air temperatures were deviated to the designed values within 0.5°C in temperature dropping condition and slightly higher (about 12.76 ± 0.07°C) in the severe cold condition. The actual thermal environments could be considered to have met the requirement of experiment designs.

3.2 Performance of PMV index for individual prediction

The PMV values were calculated based on environmental parameters recorded during the experiment, and only the integer of PMV was kept to compared with the individual thermal sensation vote, as Figure 7 shows. The proportion of individual thermal sensations correctly predicted by PMV model could also be found in Figure 7. The accuracy of TSV predicted by using the PMV index is relatively low. The overall accuracies in temperature dropping and cold conditions are 30.8% and 28.9% respectively. That is because the PMV index is based and only suitable for a group of average persons. Another reason for the poor performance of the PMV index was these unstable and extreme thermal conditions.

PMV (Predicted Value)

TSV (Actual value)	-3	-2	-1	0	1	2	3
-3	0	0.03	0.05	0	0	0	0
-2	0	0.09	0.14	0.01	0	0	0
-1	0	0.33	0.19	0.08	0	0	0
0	0	0.36	0.34	0.44	0.39	0	0
1	0	0.09	0.15	0.23	0.48	0	0
2	0	0.09	0.12	0.19	0.10	0	0
3	0	0	0	0.02	0.02	0	0

(a) Temperature dropping condition

PMV (Predicted Value)

TSV (Actual value)	-3	-2	-1	0	1	2	3
-3	0.30	0.09	0.22	0	0	0	0
-2	0.25	0.24	0.24	0	0	0	0
-1	0.24	0.44	0.44	0	0	0	0
0	0.17	0.18	0.18	0	0	0	0
1	0	0.03	0.03	0	0	0	0
2	0.01	0.01	0.01	0	0	0	0
3	0	0.01	0.01	0	0	0	0

(b) Cold condition

Figure 7: Proportions of the actual individual thermal sensation vote in the predicted value of PMV

3.3 Analysis of the historical temperatures

Table 3 shows the information about the test subjects, including anthropometric data and historical air temperature (T_H). The values of T_H ranged from 8.0 to 20.2°C in this study, with an average value of 15.7±2.8°C. To reveal the variations of thermal histories of the subjects in this study, the T_H could be divided into three levels with similar sample size: high T_H group (T_H = 18.3±1.2°C), medium T_H group (T_H = 15.6±0.9°C), and low T_H group (T_H = 12.0±2.3°C), as shown in Figure 8.

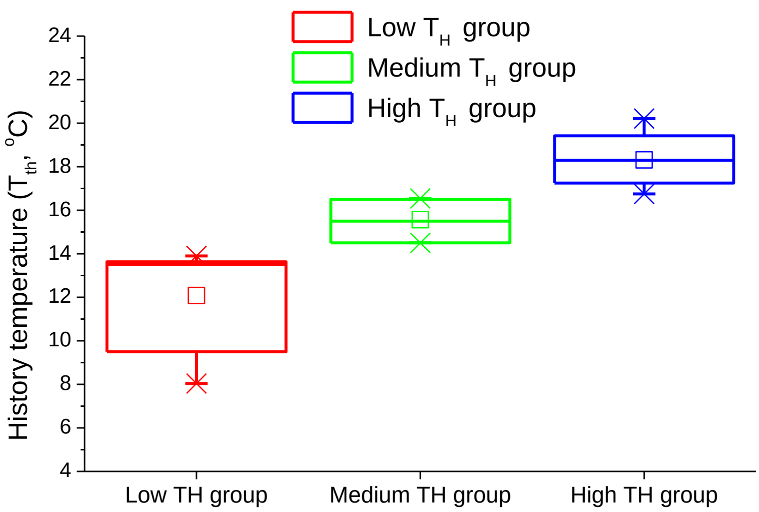


Figure 8: Variations of the historical air temperatures of the subjects

Table 3: Information of test subjects

	T_H (°C)	Age (year)	Weight (kg)	Height (cm)	BMI (kg/m^2)	Body fat (%)
Mean	15.7	22.9	60.0	169.2	20.8	20.8
SD	2.8	0.9	10.7	7.4	2.3	6.0
Min	8.0	21	43.5	158	17.4	5.0
Max	20.2	24	93	183	28.4	30.2

Note: SD-standard deviation; BMI – body mass index

As Table 3 lists, the test subjects were all young college students with a mean age of 22.9±0.9 years. Their body mass index was about 22.8±2.3 kg/m^2, which was within the normal range. Their body fat was about 20.8±6.0%. The Spearman test was used to see if there was a strong relationship between anthropometric data of test subjects and historical air temperature (T_H). Generally, there is a strong relationship between two variables when the coefficient of the Spearman's rank r_s>0.3 or r_s<-0.3. Figure 9 showed the results of the Spearman test, which revealed that none of the anthropometric data was significantly related to the values of T_H. The height, weight and BMI had weak relationships with T_H, which might due to the fact that subjects from Northern were slightly taller than that from Southern China.

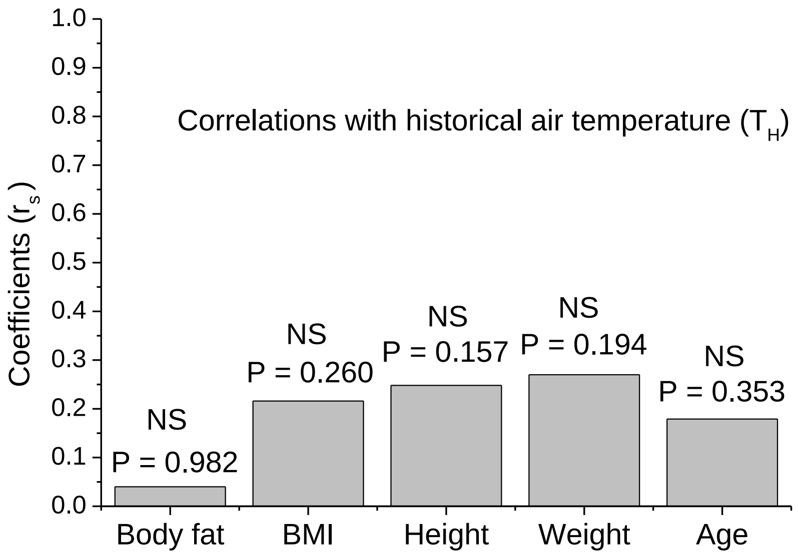


Figure 9: Relationships between anthropometric data and historical air temperature (NS- no significant correlation).

3.4 Physiological parameters

3.4.1 Brief summary

All physiological parameters of subjects measured from the experiment have been summarized in Table 4. The systolic and diastolic blood pressures were 109±14 mmHg and 71±11 mmHg, respectively. The mean heart rate was 76 bpm with a Standard Variation (SD) of 11bpm. The local skin temperatures from highest to lowest were chest (32.9±1.8°C), arm (32.5±2.0°C), thigh (31.4±2.0°C), head (30.3±2.3°C), calf (28.0±2.7°C) and hand (25.5±4.8°C). The SD was increasing with the decrease of the mean value, and it was highest at hand and lowest at chest.

Table 4: Summary of physiological parameters

Parameter	Mean	S.D.	Min.	Max.
BP_{max} (mmHg)	109	14	81	144
BP_{min} (mmHg)	71	11	46	121
HR (bpm)	76	11	48	117
T_{head} (°C)	30.3	2.3	25.3	34.5

$T_{\mathbf{chest}}$ (°C)	32.9	1.8	28.3	36.0
$T_{\mathbf{arm}}$ (°C)	32.5	2.0	27.1	36.1
$T_{\mathbf{hand}}$ (°C)	25.5	4.8	15.1	34.7
$T_{\mathbf{thigh}}$ (°C)	31.4	2.0	25.6	35.5
$T_{\mathbf{calf}}$ (°C)	28.0	2.7	19.6	33.5

3.4.2 Relationships between physiological parameters

The coefficients of spearman's rank correlation between different physiological parameters are shown in Figure 10, reflecting weak correlations between air temperature and other parameters including maximum blood pressure (BP_{max}), minimum blood pressure (BP_{min}), and heart rate (HR). However, it showed a strong correlation with local skin temperatures (LSTs). The $BP_{max.}$ was strongly correlated with BP_{min}, and there was no correlation between blood pressure and heart rate. The heart rate was slightly correlated to LST at limbs, e.g. hand and calf, because the skin temperature of these parts was corelated to blood flowrate or aerobic thermogenesis. The blood pressure was only correlated negatively to LST at the thigh, because the skin temperature at thigh was highly affected by vasoconstriction. The LSTs had strong correlations with each other, which the reduced number of skin temperature locations for thermal comfort prediction. The LST of the head had the strongest and the thigh had the weakest correlations with other LSTs.

	Ta	$BP_{max.}$	$BP_{min.}$	HR	T_{head}	T_{chest}	T_{arm}	T_{hand}	T_{thigh}	T_{calf}
Ta	1									
$BP_{max.}$	-0.200	1								
BP_{min}	-0.316	0.833	1							
HR	0.264	0.018	0.045	1						
T_{head}	0.629	-0.117	-0.253	0.154	1					
T_{chest}	0.474	-0.174	-0.222	0.004	0.540	1				
T_{arm}	0.490	0.036	-0.108	0.003	0.518	0.537	1			
T_{hand}	0.786	-0.129	-0.261	0.291	0.648	0.447	0.467	1		
T_{thigh}	0.365	-0.407	-0.472	0.082	0.248	0.294	0.285	0.294	1	
T_{calf}	0.649	-0.057	-0.176	0.296	0.512	0.354	0.292	0.685	0.253	1

Figure 10: Coefficient of Spearman's rank correlation between different physiological parameters

3.4.3 Feature selection of physiological responses

The sensitivity and reliability tests of physiological parameters in different states of thermal comfort (TC = -1 or 0) and thermal demand (TD = -1 and 0) are listed in Table 5. According to (Lan and Lian, 2010), a large effect size (d > 0.4) could be used for thermal comfort studies. Based on the significant level (P), coefficient of spearman's rank (r_s) and effect size (d), the optimal localized skin temperatures for predicting thermal comfort were decided to be at hand (T_{hand}), calf (T_{calf}), head (T_{head}) arm (T_{arm}) and thigh (T_{thigh}). The coefficient of spearman's rank (r_s) is lower at the chest, which are also more inconvenient to be measured than most of the other body parts because of the covering of clothes. The coefficient of spearman's rank (r_s) between minimum blood pressure (BP_{min}) and thermal demand is significant. However, the relative accuracy (RA) of blood pressure is much lower than other physiological parameters, and it is difficult to measure blood pressure continuously in practice. As a parameter to predict TC or TD, the heart rate (*HR*) is better than blood pressure in terms of coefficient of spearman's rank (r_s), effect size (d), and relative accuracy (RA). Therefore, it was chosen as the potential physiological parameter to be further analyzed.

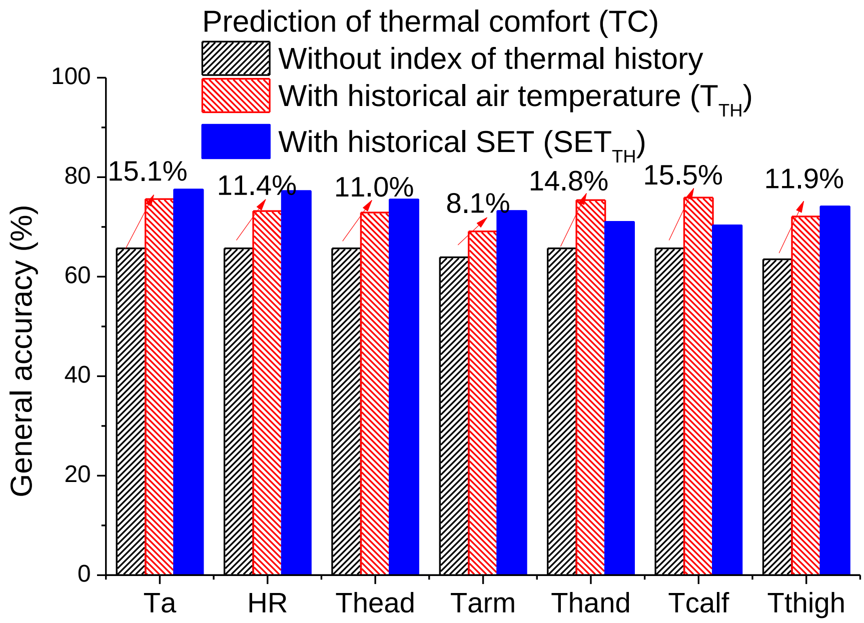
Table 5: Sensitivity and reliability tests of physiological parameters with subjective responses

	Thermal comfort (TC = -1 or 0).				Thermal demand (TD = -1 or 0).			
Parameter	r_s	P	d	RA	r_s	P	d	RA
$\boldsymbol{BP_{max}}$ (mmHg)	-0.087	**0.31**	0.06	0.43	-0.023	0.56	0.07	0.47
$\boldsymbol{BP_{min}}$ (mmHg)	-0.162	**0.01**	0.21	1.04	-0.196	**	0.28	1.40
HR (bpm)	**0.331**	**	0.31	4.56	0.214	**	0.33	4.90
$\boldsymbol{T_{head}}$ (°C)	**0.405**	**	**0.53**	11.41	**0.473**	**	**0.64**	12.95
$\boldsymbol{T_{chest}}$ (°C)	0.248	**	0.23	3.75	0.272	**	0.35	5.64
$\boldsymbol{T_{arm}}$ (°C)	**0.385**	**	**0.53**	9.52	**0.354**	**	**0.46**	8.28
$\boldsymbol{T_{hand}}$ (°C)	**0.482**	**	**0.73**	28.57	**0.537**	**	**0.83**	32.33
$\boldsymbol{T_{thigh}}$ (°C)	**0.321**	**	0.35	6.85	0.212	**	0.27	5.17
$\boldsymbol{T_{calf}}$ (°C)	**0.386**	**	**0.53**	12.06	**0.430**	**	**0.55**	12.84

Note: **P<0.001

3.5 Prediction performance of the classification model

Figure 11 shows the general prediction accuracies with different physiological parameters. With the thermal history temperature as an additional input, the general accuracies using a single parameter in the classification tree model C5.0 increased up to 15.5% for thermal comfort prediction and 29.8% for thermal demand prediction. The general prediction accuracy for TC was lowest when using local skin temperature of the arm, and higher when using other physiological parameters. For the TD, the general prediction accuracy was lowest when using heart rate, and not quite different among other physiological parameters. Generally, the prediction accuracy based on physiological parameter was higher by using the historical SET (SET_H) than the historical air temperature (T_H). However, when the skin temperature of the hands and calves (feet) was used as an input to predict thermal comfort, the models with historical air temperature performed better. This result implied that the local body parts of hands/feet were affected more significantly by air temperature rather than SET which also included the effect of clothing insulations and so on.



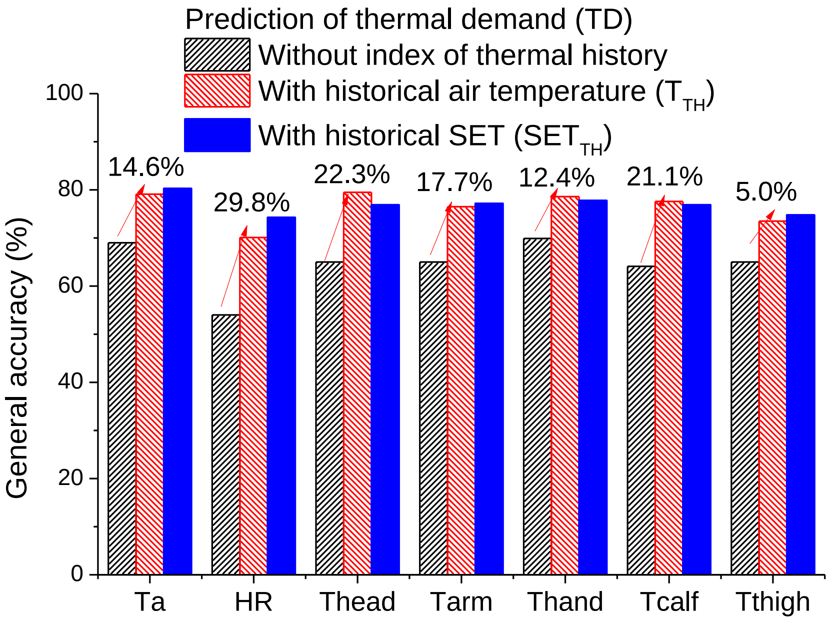


Figure 11: General accuracies of thermal comfort and thermal demand prediction with or without indexes of thermal history

Figure 12 shows the performance evaluation for the thermal comfort prediction model with historical air temperature. With a single physiological parameter, the accuracies for predicting both TC and TD were ranging between 72% and 82%. However, the precision and recall of TC prediction were much unstable, with the worst when using local skin temperature of the arm (T_{arm}). The local skin temperatures of the calf (T_{calf}) and hand (T_{hand}) were more stable than other parameters, regarding accuracy, precision, and recall of TC prediction, and they were the only two parameters with all indices higher than 60%. For TD prediction, the local skin temperatures of the head (T_{head}) and hand (T_{hand}) were the only two parameters with all accuracy, precision, and recall of TD prediction higher than 75%. Therefore, the local skin temperatures of the calf (T_{calf}) and hand (T_{hand}) could be used for predicting thermal comfort, and the local skin temperatures of the head (T_{head}) and hand (T_{hand}) are best for predicting thermal demand.

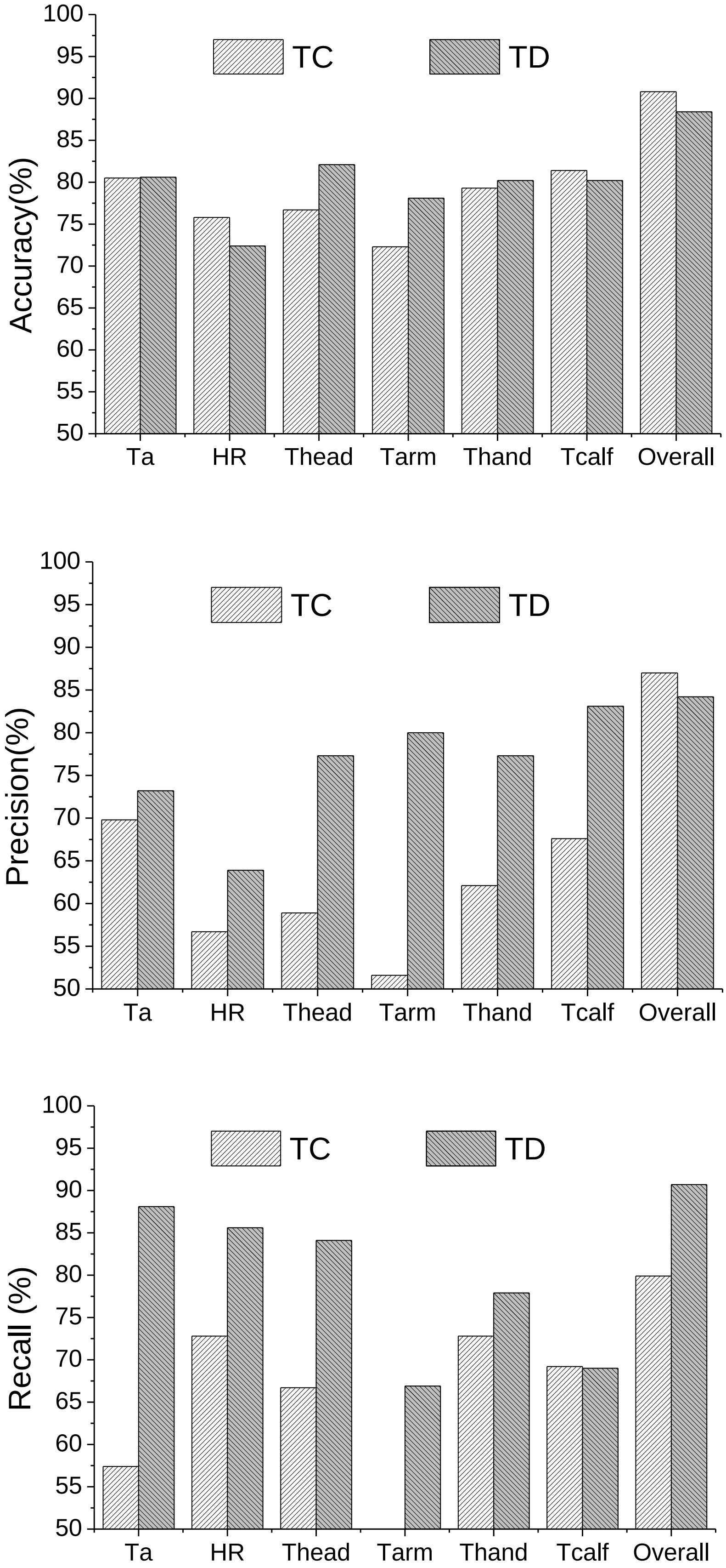


Figure 12: Performance evaluation of different parameters with historical air temperature.

4 Discussions

4.1 The underlying significance of thermal history and physiological parameters

Results showed that thermal history plays an important role in the thermal comfort prediction models. In view of human thermal physiology, these physiological parameters are related to the cold mitigation functions of the human body (Jessen, 2012). The vasoconstriction in cold environments could affect the blood pressure of subjects, and a higher blood pressure means a more intense vasoconstriction. The heart rate is related to the blood flowrate and aerobic thermogenesis of the human body. Thermal perception is affected by skin temperature (Wu et al., 2021a), which is recognized by thermosensitive afferents expression ion channels in thermosensitive nerves of skin (Mckemy, 2005; Story et al., 2003). Besides that, the thermal history of indoor conditions also affected subjects' expectations. Thus, the higher thermal sensation of occupants with thermal history of low temperature might cause by the insensitivity of thermosensitive nerves and lower thermal expectations due to cold adaptation.

In the previous studies about thermal history, either the study (Ji et al., 2017) did not measure the physiological parameters or most of them only measured the skin temperatures (Li et al., 2010; Wu et al., 2018; Zhang et al., 2016). It is still difficult to build a universal individual thermal comfort model based on these physiological parameters. Because cold adaptation was a long process, the conclusions about the significance of thermal history could be quite different in different studies. A study (Wu et al., 2019c) showed that warm indoor thermal history only affects thermal sensation but not affects the physiological responses. But the effect of thermal history on the relationships between TSVs and physiological responses were similar in different studies. Thus, the methods of this study are believed to be suitable for occupants with thermal history in cold conditions.

4.2 Practical application and limitations

In the previous studies about personal thermal comfort predictions (Chaudhuri et al., 2020; Chaudhuri et al., 2018a, b; Choi and Yeom, 2017; Dai et al., 2017; Li et al., 2018b; Liu et al., 2019; Salehi et al., 2020), the average prediction accuracies are between 70% and 90%. However, the thermal history levels of test subjects in these studies were not reported, and it is highly possible that the test subjects with the similar thermal history level were recruited in each study. Thus, the accuracies of these methods could reduce due to the variety of thermal histories of the occupants in the “real-world” buildings (Luo et al., 2016a; Luo et al., 2016b; Luo et al., 2018; Ning et al., 2016a; Ning et al., 2016b). This study reveals that the accuracy of thermal comfort prediction could be improved if we consider thermal history as an input. That means that when the thermal comfort models were applied to the occupants with different thermal histories, revisions needed to be made. Thus, more sophisticated thermal comfort models that include index reflect thermal history could be more applicable. However, it is still difficult to accurately quantify the actual thermal history in reality by using available data.

In most cases, the models using the historical thermal comfort might perform better than the models with historical air temperatures. However, using historical air temperature is much more convenient. Results show the skin temperature of the hands and calves (feet) in a cold environment could be used as a good index to predict thermal sensation, as these are the body parts most sensitive to cold (Hong et al., 2018). When the skin temperature of the hands and calves (feet) was used as an input, the models with historical temperature performed better. This result implied that the local body segments of hands/feet were affected more significantly by air temperature rather than SET. That’s because the hands were directly exposed to the surrounding air in most time, but the values of SET indeed reflected the effect of clothing insulations and whole-body thermal stress. These parameters were also easier to be measured, e.g. by devices being attached to the wrist or ankle, which should be adopted first. From the view of the practical application, the heart rate (Choi et al., 2012) (Nkurikiyeyezu et al., 2018) could be a good monitoring parameter to predict thermal comfort which worth to be further studied.

The accuracy of predicted individual thermal comfort could be interfered with by many factors such as body mass, gender, health conditions, psychological difference of occupants and so on. Because the individual prediction model in this study was only tested in winter conditions in the range of 12 -24°C. The application of this model in other seasons or thermal conditions remains to be verified in the future. Besides that, thermal comfort/demand in relatively short-time climate chamber tests might also be different to that in “real-world” buildings where occupants stay a longer time. Other factors, such as occupation, age, culture, and so on, might also affect the conclusions (Wu et al., 2019a). Those are needed to be further studied.

5 Conclusions

In this study, experiments in the climate chamber were conducted to investigate the thermal responses of human subjects in cold environments during winter. Thirty-two subjects with different indoor and outdoor thermal history were studied. A simplified method by using historical air temperature to quantify the individual thermal history was proposed and used to predict thermal comfort and thermal demand from physical or physiological parameters.

Results show the accuracies of individual thermal sensation prediction was low to about 30% by using the PMV index in cold environments of this study. With the historical air temperature as an additional input, the general accuracies using classification tree model C5.0 were increased up to 15.5% for thermal comfort prediction and up to 29.8% for thermal demand prediction. The analysis shows the local skin temperatures of calf and hand could be the optimal parameters to predict thermal comfort, while the local skin temperatures of head and hand were the optimal parameters to predict thermal demand.

Thus, the proposed quantification of historical temperature is recommended to be used in the thermal comfort model when predicting thermal demands from physical or physiological parameters in winter.

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