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Journal

Building and Environment, 161

ISSN

03601323

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Publication Date

2019-08-01

DOI

10.1016/j.buildenv.2019.106231

Predicting older people's thermal sensation in building environment through a machine learning approach: modelling, interpretation, and application

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Keywords: Thermal comfort; Machine learning; Random forests; Skin temperature; Older people; Building environment

Abstract

There is insufficient knowledge on how environmental and physiological factors affect older people's thermal perceptions. In this paper, we present two data-driven models (a field study model and a lab study model) using the algorithm of random forests to predict older people's thermal sensation. These two models were developed from a field study dataset and a lab study dataset separately. The field study dataset was collected from 1040 old subjects (70+ years) who lived in 19 aged-care homes, which contains multi-dimension factors such as environmental parameters, subjects' demographic information, health condition, acclimatization degrees, living habits and thermal perceptions' votes. The lab study dataset was collected from a lab study and contains 18 old subjects' (65+ years) eight local skin temperatures and thermal perceptions' votes under five thermal environments (21/23/26/29/32°C). After the procedure of feature selection, the field study model was developed with four environmental variables (air temperature, velocity, CO_2 concentration, illuminance) plus two human-related variables (health condition and living time in aged-care homes) as inputs. It produced an overall accuracy of 56.6%, which was 24.9% higher than that of the PMV model. The lab study model was built on five local skin temperatures including head, lower arm, upper leg, chest and back temperatures, which demonstrated an overall accuracy of 76.7%, 30.1% higher than UC Berkeley thermal sensation model's accuracy. We then interpreted how these inputs distinguish thermal sensations by applying a partial dependence analysis. Finally, we proposed two applications of the above models and present older people's seasonally neutral indoor temperature zones.

1. Introduction

Our world is facing great challenge of population aging. Based on the United Nations Population Division's World Population Prospects (2019 version) [1], the percentage of people aged 65 or above will rapidly increase from 9.3% in 2020 to 18.9 % in 2070. By the end of 2070, there will be 1.98 billion older people in this world. Figure 1 demonstrates the global aging trend we will face in the next 50 years. For older people, they tend to or have to live in aged-care homes or nursing homes due to their poor health conditions, physical disabilities and other concerns. According to our previous investigations[2], the older people who live in aged-care homes spend more than 90% of their daily time staying indoors. So, it is important to provide them a healthy and comfortable indoor thermal environment. The current building environment standards like ASHRAE 55 [3], European EN15251[4] and Chinese GB/T 50785

[5] recommend comfort zones, but they are based on young people's thermal comfort perception which may not suitable for older people.

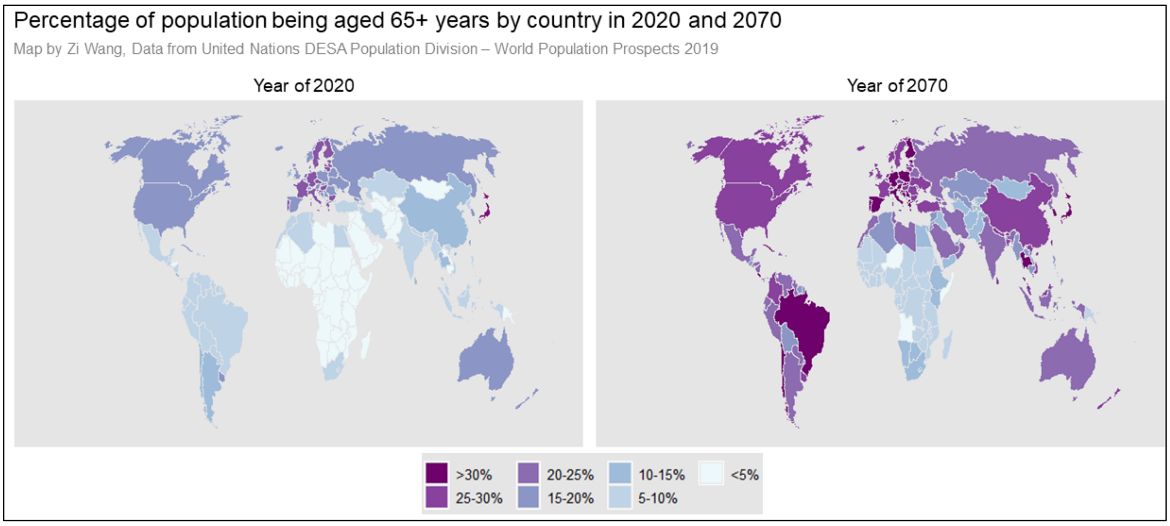

Figure 1 Global aging trends

Comparing young and older people's subjective and physiological responses to different thermal conditions have been broadly studied. For example, Stevens et al. [6] conducted a series of lab studies to measure young people (18-28 years old), mid-age people (40-60 years old) and older people's (above 65 years old) local thermal sensation thresholds. They found that older people had higher perception thresholds and less sensitivities to both coldness and warmness than young people. Tsuzuki et al. [7] conducted a study with older and young subjects exposed to 23/25/27/29/31 ℃ conditions. They found that older people expressed less warm thermal sensations than their young counterparts at warm condition of 31℃ and felt colder than what PMV (Predicted Mean Vote) predicted in temperatures below 27℃. Schellen et al. [8] compared young (22-25years old) and older adults' (67-73 years old) thermal comfort response to moderate temperature step changes. They found older subjects' thermal sensations were generally 0.5 scale units lower than those of young subjects in both warm and cool environments. This indicated that older people had different responses to thermal stimuli. Novieto[9] reviewed older people's physiological parameters related to human body thermoregulation system. He found that typical older people's basal metabolic rate (-26.4%), cardiac output (-14.4%), and body surface area (-5.0%) decreased than those of typical young adults but their percentage of body fat greatly increased by 78.6%. Wang[2] developed an adaptive thermal comfort model for older people based on a four-year field study in aged-care homes and compared the new model with those in current standards. He found that older people's neutral (or comfortable) temperature is lower in cold environments while higher in warm conditions than the models in the current standards. There are also studies which did not find significant thermal comfort difference between older and young people. Veronica[10] recently reported that they did not find any statistical difference on older and young people's thermal sensation, comfort and acceptability in a climate chamber study in slight cool or slight warm environment. Based on the above literature, age difference in thermal comfort may exist between young and older people, but more studies are yet to be produced to validate this point.

Thermal sensation is a subjective response to thermal environment. Having an accurate thermal sensation model is essential for predicting occupants' thermal responses and therefore is important for indoor environment design. Among the existing sensation models, the PMV model [11] is widely used by standards like ISO 7730[12], ASHRAE 55[3] and EN 15251[4]. It can predict occupants' averaged thermal sensation via six parameters including air temperature, relative humidity, mean radiation temperature, air velocity, metabolic rate and cloth insulation. Normally, the comfort zone is defined as the PMV being within -0.5 to +0.5[3]. Recently, Cheung[13] compared the actual thermal sensation votes in ASHRAE Database II with its corresponding PMV values. They found that the PMV model is not reliable and only shows 34% prediction accuracy[13]. Jiao[14] validated the accuracy of the PMV model when it was used to predict older people's thermal sensation in summer. She found that the PMV model would overestimate old people's thermal sensation, and the discrepancy increases as air temperature go up.

In addition to the PMV model, another approach is using physiological data like skin and/or core temperatures to derive regression model. Two classic examples are Hui's [15] and Fiala's [16] thermal sensation models. Their models were developed on local body skin temperatures and core temperature. This approach is theoretically reasonable because human brain does not directly sense air temperatures, but instead to the signals from thermoreceptors located in skin and other organs. Therefore, the skin and core temperatures can largely reflect human body thermal status and its corresponding thermal sensations. However, either Hui's or Fiala's model has its own deficiencies when applying to older people. First, the above models usually require many inputs. For example, 16 local skin temperatures are needed in Hui's model. Second, some inputs are difficult to obtain in practice. To run Hui's[15] or Fiala's [16] model, users need to input a core temperature which is not easy to measure. A common way of using these comfort models is to use a human thermoregulation model to obtain predicted core and skin temperatures. However, by now, we have not found a suitable thermoregulation model which can reflect older people' physical and physiological characters, and therefore we could not get accurately predicted temperatures through existing models.

To fill in this gap, our goal is to develop two older people's thermal sensation models to predict their thermal responses under different thermal conditions. These two models can be applied to two scenarios respectively. The first scenario is when basic environmental information and basic human-related information are acquirable. We built this model based on our field study data, so we call the first model the *field study model* in the following context. The second scenario is when older people's local skin temperatures are accessible either by measuring or predicting. We developed this model based on our lab study data and consequently, we call it the *lab study model*. A data-driven approach (random forest algorithm) was applied to establish these two models. The field study model was built on the data of environmental parameters, subjects' demographic information, health conditions, acclimatization degrees, and living habits, which were collected from a large-scale field survey [2]. The lab study model was developed with older people's local skin temperatures collected from lab experiments [17]. The prediction accuracies of these two models were assessed and were compared with the PMV [11] model and the UCB thermal sensation model[15], respectively. We analyzed selected variables' partial dependence to visualize the interactions between different variables and their thermal sensation effects. Finally, we utilized the new models in two real applications: 1) developing seasonal characterized older people's neutral temperature zones, and 2) evaluating the feasibility of using only one easily detected skin temperature to predict older people's thermal sensation.

2. Methodology

2.1 Data collecting

Data set 1 (field study data)

Data set 1 were collected from 1040 older persons (33.7% male and 66.3% female) aged 70 to 97 years old in 19 aged-care homes located at Shanghai through January 2014 to April 2017[2]. A total of 342, 330 and 368 older subjects were surveyed in winter, summer, and mid-seasons. The study was carried out in their living rooms, where subjects remained seating during the survey. Their demographic information (age, gender), health condition (self-evaluated health status), acclimatization degree (living time in local sites) and living habits (time spent on exercise per day and sleeping hours per day) were obtained through a questionnaire-based method. Indoor environmental parameters (air temperature, relative humidity, air velocity, black-bulb temperature, illuminance, sound level, CO_2 concentration) were measured based on the protocol in ASHRAE Standard 55[3] and GB50785[5]. Table 1 lists the information of equipment that was used in the field study and the lab study. Meanwhile, subjects' thermal sensation votes (TSV) were gathered using a seven-point scale (+3,+2,+1,0,-1,-2,-3 corresponding to hot, warm, slightly warm, neutral, slightly cool, cool and cold, respectively) [3].

Table 1 Information of equipment

Measurement	Instrument	Range	Accuracy
Air temperature	WSZY-1,Tian Jian Hua Yi, China	0~+50℃	±0.1 ℃
Relative humidity		10~90%	±2 %
Black-bulb temperature	TM200, KIMO, France	-50~+250℃	±0.2 ℃
Air velocity	Air velocity meter 9515, TSI, USA	0~20m/s	±0.025 m/s
Illuminance	ZDS-10F-3D, Xinnuo, China	0-20000lx	≤±(4% reading)
CO_2 concentration	Testo 535, TESTO, Germany	0-5000ppm	±(50ppm+2% reading)
Sound level	TES-1350A, TES, Taiwan China	35-130dB	±2 dB
Skin temperature	Pyrobutton-L, OPULUS, USA	-40~+85℃	±0.2 ℃

Data set 2 (lab study data)

Data set 2 has 413 data samples collected from a lab study with 18 (9 males and 9 females) older people aged 65 to 83 years old [17]. The study was conducted in a climate chamber with two rooms (Room A and Room B). Room A was kept at 26℃, while Room B varied its air temperature (21℃, 23℃, 29℃, 32℃). Therefore, four temperature step changes were conducted between the two rooms (C3:26℃-23℃-26℃, C5:26℃-21℃-26℃, W3:26℃-29℃-26℃, W6:26℃-32℃-26℃). For each case, every subject first experienced a 30-minute preparing period, then a 40-minute in Room A, followed by a 50-minute's in Room B, and then another 50 minutes in Room A. Subjects' eight local skin temperatures (forehead, left chest, left back, left forearm, left hand, left upper leg, left lower leg and left foot) were recorded by wireless pyrobuttons with an interval of 1 minute during all the time, and their thermal sensations were also surveyed with the seven-point scale at the 1st, 4th, 7th, 10th, 20th, 30th, 40th minute after each temperature step change. In data analysis, we only used subjects' skin temperatures and corresponding TSV gathered after (and at) the 20th minute when their TSV tended to be relatively stable. During the tests, subjects were allowed to read newspaper or listen to music or Chinese opera. The experiment would stop whenever subjects reported they were not willing to do it anymore. The test protocol has been reviewed and approved by Tongji University's Committee for the Protection of Human Subjects.

In this paper, we rescaled subjects' original thermal sensation votes (TSV) from the seven-point scale to a three-point scale as 'Cool'(TSV<0), 'Neutral'(TSV=0) and 'Warm'(TSV>0). That is because we concern on older people's overall thermal status, but not the degrees of their coolness or warmness.

2.2 Data cleaning and balancing

Figure 2 illustrates the flowchart of data processing, modeling and testing. Missing data existed in both data set 1 and data set 2. Instead of replacing missing data with the mean or median value of the corresponding variable, we deleted all missing data from the raw dataset. In our data sets, we found the numbers of three classes were imbalanced with 'Neutral' always being the majority. And imbalanced training data set may reduce a model's prediction performance[18]. Normally, there are three ways to rebalance data, which are down-sampling(D), balance(B) and over-sampling(O). In short, down-sampling is a way to randomly reduce the majorities' sample sizes to match the number of the least prevalent class. By contrast, over-sampling randomly synthesizes the minorities by applying K-Nearest Neighbor (KNN) algorithm until their numbers are equal to that of the majority class[18]. While balance is an approach that combines over-sampling the minority class and under-sampling the majority class. In this study, we used all of the above three methods to rebalance data and then build models and further select the model with the highest prediction accuracy.

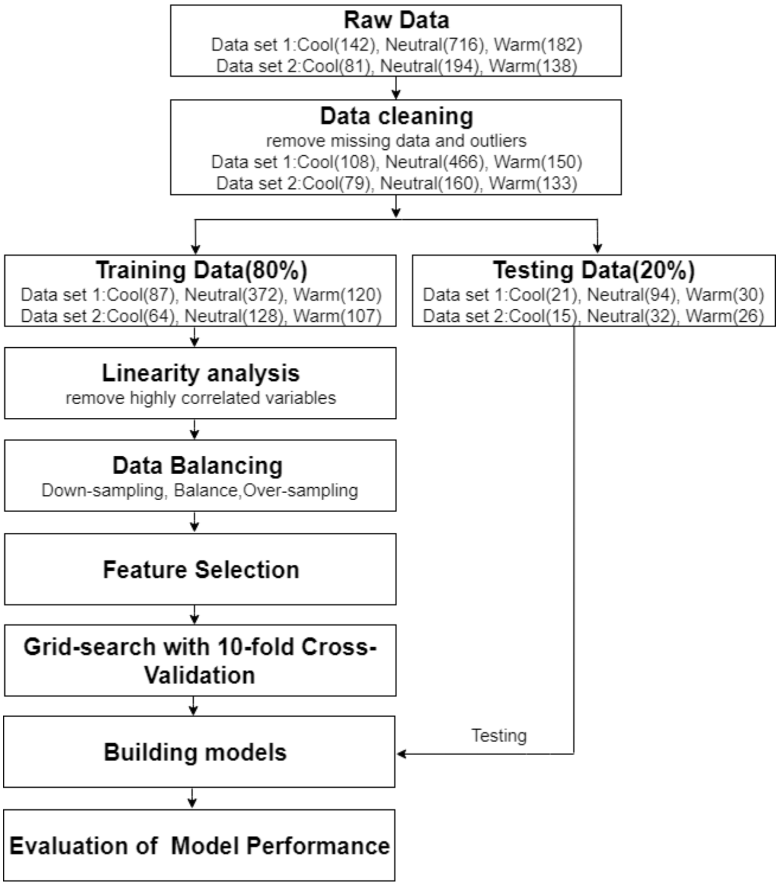

Figure 2 Framework of developing thermal sensation models

2.3 Algorithm of random forests

A decision tree is a decision tool and is used to divide a specific dataset into smaller datasets with descriptive features until one label or response variable being assigned at the end of the route. However, a single decision tree sometimes may not make the optimal decision at the final node and may be overfitting when a tree is too deep. In order to overcome these drawbacks, the concept of random forests was introduced by Breiman[19] in 2001. This algorithm is a useful nonparametric statistical method to deal with regression and classification tasks. As the name implies, random forests are an ensemble of tree-structured classifiers whose final decisions are aggregated and weighted into a final result. To be specific, each tree in the forests gives a vote to a task, and the forest takes the classification with the most votes as the final decision. Figure 3 shows the schematic of random forests. For an individual tree in the forest, the growing procedures as follows[19]:

1) Randomly select around two-third of cases from training dataset with N cases, which is called a bootstrap sample and is used to build a tree. The rest data is called Out-of-Bag (OOB) data which is used to calculate the prediction error, denoted by errOOB.

2) Randomly select m (m<<M) variables (mtry) from the total M variables. The number of mtry is related to the correlations between any two trees in the forest and the strength of each tree. Consequently, mtry could influence the prediction error.
3) Extent each tree as large as possible.

For a classification task, adding each case in OOB data into the tree and get a classification. Based on the above descriptions, each case can be classified by about one-third of the total trees. In the end, the class with the most votes predicted by all trees is the final output of the forest. And the percentage of wrong predictions is errOOB.

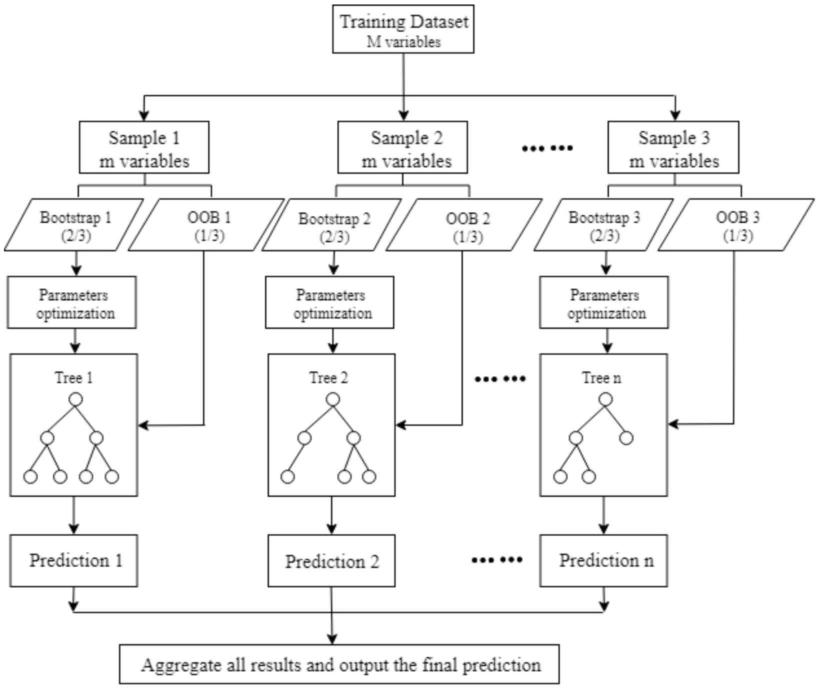

Figure 3 A schematic of random forests

2.4 Feature selection

A model's performance may benefit from removing highly correlated variables[20]. In this study, the Pearson correlation coefficients of each two variables were computed. The pairs whose absolute coefficients being larger than 0.8 was marked as highly correlated, and only one variable of a highly correlated pair remained. Then, we selected qualified variables being high-importance and non-redundancy with a three-step method proposed by Genuer in VSURF package for R[21], which included the threshold step, the interpretation step and the prediction step. Note that this method is also random forests algorithm based and fully data-driven. The threshold step includes ranking variables by the variable importance (VI), calculated by Equation (1), and eliminating useless variables being failed to decrease the model's error rate. The interpretation step eliminates the variables being failed to decrease the model's error rate by a specific amount (the VI standard deviation of the useless variables). The prediction step is trying to minimize the number of variables retained from the previous step as well as maintain predictive power. More detailed information can be obtained from Genuer's papers[21, 22].

$$\mathrm{VI}(\mathrm{X}^{\mathrm{j}}) = \frac{1}{\mathrm{ntree}} \sum_{\mathrm{t}} (\mathrm{err}\widetilde{\mathrm{OOB}}_{\mathrm{t}}^{J} - \mathrm{errOOB}_{\mathrm{t}}) \quad (1)$$

Where X^{j} means a specific variable. $\mathrm{errOOB}_{\mathrm{t}}$ is the prediction error for a specific tree predictor *t*. $\mathrm{err}\widetilde{\mathrm{OOB}}_{\mathrm{t}}^{J}$ means the error rate of a perturbed OOB data after randomly permuting the values of X^{j}. ntree is the number of trees in the forest. In short, $\mathrm{VI}(\mathrm{X}^{\mathrm{j}})$ means the average change of the prediction error rate after a specific variable being added into the model. The higher the value is, the more importance the variable has.

2.5 Parameter optimization and cross-validation

As mentioned above, the number of randomly selected variables (mtry) can influence the prediction accuracy of the final results. In this study, we used a grid search to capture the optimal mtry together with a 10-fold cross-validation. This method works with four steps. First, selecting a specific mtry from all possible values (from 1 to the number of qualified independent variables). Second, randomly splitting the entire training data into 10 folds and fitting a model with 9 folds and validate the model with the remaining 1 fold. Third, repeating the second step and averaging all the possible validating results. That is the final performance metric for the model using a specific mtry. Fourth, selecting the model coupling with the optimal mtry that shows the best final performance. In this study, the best performance means the highest prediction accuracy.

2.6 Evaluation of model performance

To evaluate the model performance, we used 20% of the data that haven't been included in model development to validate prediction accuracy, as shown in Figure 2. The prediction accuracy was assessed by the percentage of correctively predicted cases.

The predictions of PMV model and UCB thermal sensation model were also calculated for comparison. Subjects' metabolic rates were estimated by ASHRAE Handbook Fundamental[23]. In our field study, subjects were always seated and quiet, which corresponds to the metabolic level as 1.0 met. However, considering that older people may have a lower metabolic rate than what the standard indicated [24-26], we calculated PMV with both 1.0 met and 0.8 met. Also, it's noteworthy that the whole UCB thermal sensation model consists of a static term and a dynamic term [27, 28]. In this study, we only calculated the static overall thermal sensation because the ambient conditions were relatively stable, and we assumed that the subjects' skin temperatures did not change much during the survey. Further, running UCB thermal sensation model requires 16 local skin temperatures (forehead, chest, right upper arm, left upper arm, right lower arm, left lower arm, right hand, left hand, left thigh, right thigh, right lower leg, left lower leg, right foot, left foot, back, pelvis), but our lab survey data only has 8 local skin temperatures. So we further assumed symmetrical distributions of skin temperatures for left, right, anterior and posterior body parts. In the UCB model, one inevitable setting is determining local body parts' temperature setpoints, which stand for neutral local skin temperatures when local thermal sensations are 'Neutral'. In this study, we used the data collected from our lab study to deduce each local body part's setpoint by selecting and averaging all of the subjects' neutral skin temperatures when both their local and overall thermal sensations were 'Neutral'. The comparisons of the default setpoints in the UCB model and our study's setpoints for older people were listed in Table 2. In addition, because both the PMV model and UCB model produce continuous outputs, we rescaled their outputs of predicted thermal sensation (PTS) into three categorical classes as 'Cool' (PTS<-0.5), 'Neutral' (-0.5≤PTS≤+0.5) and 'Warm' (PTS>+0.5).

Table 2 Setpoints of local body parts

	Head	Chest	Upper arm	Lower arm	Hand	Thigh	Lower leg	Foot	Back	Pelvis
UCB model defaults	35.8	35.1	34.2	34.6	34.4	34.3	32.7	33.3	35.3	35.3
This study	33.8	33.8	32.9	32.9	32.8	33.3	33.1	32.9	33.4	33.4

2.7 Partial dependence

To provide insights into the black-box model, partial dependence plots were represented. It can provide a simple solution to illustrate the relationship between a specific variable and a target class. For a classification problem, the partial dependence function is defined as a logit function based Equation 3[29].

$$f_k(x) = \log[p_k(x)] - \frac{1}{K}\sum_{k=1}^{K}\log[p_k(x)]\,,\mathrm{k} = 1,2,\ldots\mathrm{K} \quad (3)$$

Where k is the number of target classes. x is the variable for which partial dependence is searched. $p_k(x)$ is the probability predicted by a model for the k-th class. As the definition of the above equation, a positive and larger log-odds$f_k(x)$ means a larger probability for the k-th target class to be predicated by the specific value of variable x. In contrast, a negative log-odds indicates less possibility for the k-th target class to be predicted by the value[30].

2.8 Software

All analysis conducted in this study was based on R language version 3.3.2[31] and the platform of RStudio (RStudio, USA). R packages of 'outliers'[32], 'VSURF'[33], 'smotefamily'[34], 'caret'[35] were applied to prepare data and build models, while packages of 'pdp'[36], 'corrplot'[37], 'ggplot2'[38], 'rworldmap'[39], 'mapproj'[40], 'rgeos'[41] and 'viridis'[42] were used for mapping and visualizing associated data.

3. Results and discussion

3.1 Variable description and selection

Table 3 Subjects' anthropometric information

Dataset	Age(years) Mean±S.D.	Height(cm) Mean±S.D.	Weight(kg) Mean±S.D.
Field study	83.8±6.0	159.7±8.8	59.4±11.1
Lab study	67.4±4.4	161.6±7.6	60.7±9.2

Subjects' anthropometric information is listed in Table 3.Table 4 describes the variables collected in data set 1 and data set 2, which includes variables' categories, units and ranges. Except for 'Self-evaluated health condition' and 'Gender' which are categorical, other variables are continuous. Figure 4 displays the distributions of the 16 variables in data set 1 under 'Cool', 'Neutral', 'Warm' thermal sensation categories and overall of the three, which are corresponding to the red area, green area, blue area, and white area with black contour lines in the figure. These distributions are presented as the form of either scaled densities for continuous variables or histograms for discrete variables. The scaled density is computed by the method of smoothed kernel density estimate[43], the higher the scaled density value, the higher frequency happened at the observed value. Taking Figure 4(c) as an example, the highest density of air temperature under 'Cool' occurs at near 13℃, which means that the major votes of cool feelings were gathered when the air temperature was around 13℃. The highest density of air temperature under 'Warm' concentrated at 30℃ temperature. For 'Neutral' thermal sensation's profile, it peaks at two temperatures, near 14℃ and 28℃. This indicates that air temperature could be a good indicator to forecast older people's thermal sensation. Following the above analysis, the distributions of relative humidity, black-bulb temperature, air velocity, CO_2 concentration, health condition, living time in aged-care homes, cloth insulation, illuminance and sleeping hour under three thermal sensations also exhibit different extents of differences, as shown in Figure 4.

Table 4 Descriptions of variables

Dataset	Categories	Variables	Units	Ranges
Data set 1	Demographic information	Age(x1)	years	70-97
		Gender(x2)	-	Male=0; Female=1
	Environmental parameters	Air temperature(x3)	℃	6.4-32.5
		Relative humidity(x4)	%	21.3-83.2
		Black-bulb temperature(x5)	℃	6.3-32.5
		Air speed(x6)	m/s	0.00-0.60
		Illuminance(x7)	lux	15.8-879.8
		A-weighted sound level(x8)	db	35.53-89.60
		CO2(x9)	ppm	281.2-785.2
	Health Condition	Self-evaluated health condition(x10)	-	1-Very bad; 2-Bad; 3-Normal; 4-Good; 5-Very Good
	Acclimatization	Time living in Shanghai(x11)	years	3-94
		Time living in aged-care home(x12)	months	0.2-90.0
		Time spent indoor per day(x13)	hours	10.5-24.0
		Cloth insulation(x14)	clo	0.22-2.34
	Living habits	Exercise(x15)	min	0.0-180
		Sleeping hours per day(x16)	hours	3-18
Data set 2	Local skin temperature	Head, Chest, Back, Lower arm, Hand, Upper leg, Lower leg, Foot	℃	Head:29.64-36.14 Chest:28.78-36.46 Back:30.02-35.73 Lower arm:28.94-35.33 Hand:25.65-36.39 Upper leg:27.71-35.19 Lower leg:28.28-35.39 Foot:27.34-35.83

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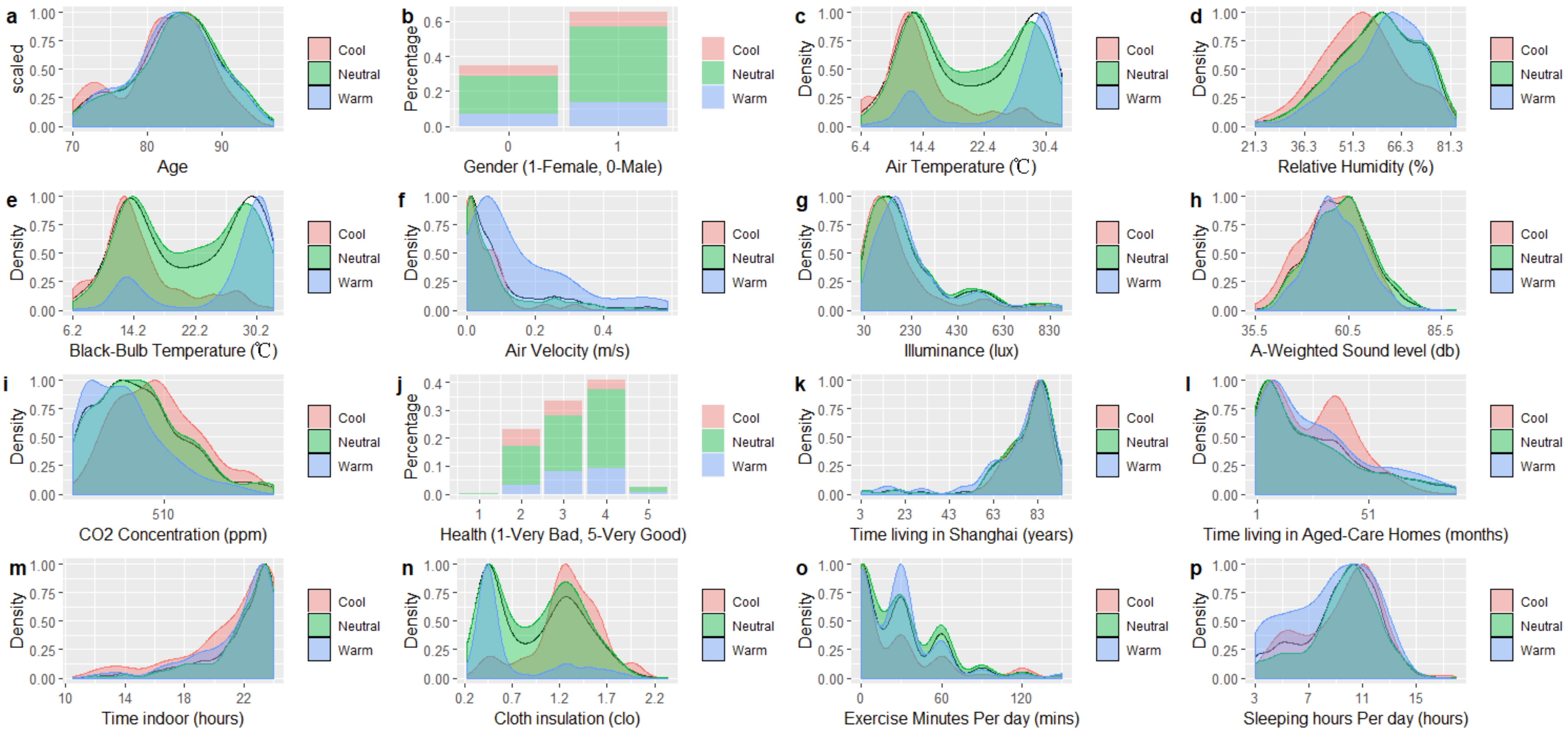

Figure 4 Distributions of variables in field study data

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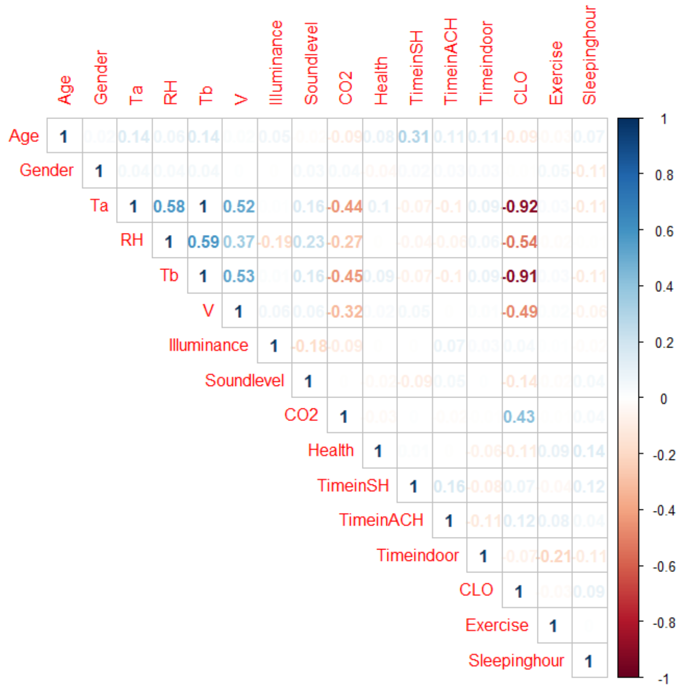

Figure 5 Correlation coefficients of variables in field study data

Figure 5 lists Pearson correlation coefficients of every two variables in data set 1. In the figure, blue and red numbers respectively represent positive and negative correlations. Note that only those high correlation coefficients are exhibited clearly, while other small values are set to be invisible or fade away. That is because we intend to select highly correlated variables and ignore other correlations. Black-bulb temperature (Tb) and cloth insulation (CLO) are found to be highly correlated with air temperature (Ta), having coefficients of 0.91 and -0.92 respectively. We therefore excluded Tb and CLO from qualified input variables to avoid linear dependence.

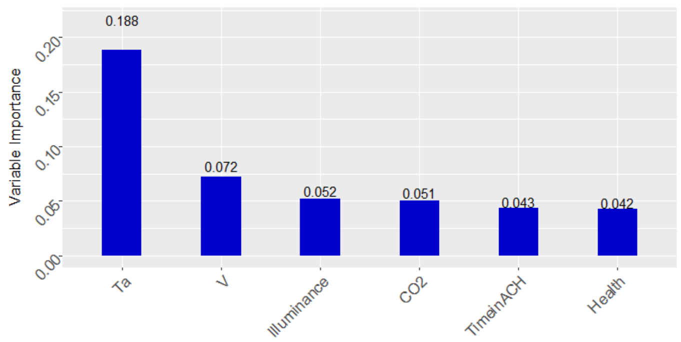

Figure 6 Variable importance of selected features in field study model

Figure 6 shows the importance of finally selected variables from field study data based on the proposed feature selection algorithm. Air temperature is the dominating factor, followed by air velocity, illuminance, CO_2 concentration, time in aged-care home and self-evaluated health condition.

Figure 7 presents the distributions of eight local skin temperatures in data set 2. The violin plots (a combination of box plot and density plot) display the temperature distributions of a specific local body part under 'Cool', 'Neutral' and 'Warm' thermal sensations with the red dots and the red lines representing the means and the standard deviations. The most frequently observed temperature in each category corresponds to the widest part in the violin plot. Taking

Figure 7(a) as an example, the distributions of head skin temperature under different thermal sensation categories are 32.8℃ under ‘Cool’, 34.3℃ under ‘Neutral’, and 34.7℃ under ‘Warm’. As in the field study data analysis, Pearson’s correlation coefficients of every two local skin temperatures were computed and presented in Figure 8. Local skin temperatures are positively correlated, which is reasonable because the thermal environments in our experiments were uniform with no local heating or cooling strategy. For those highly correlated local skin temperatures with a coefficient higher than 0.8, we only kept one of them as model input. In the end, skin temperatures of head, lower arm, upper leg, chest and back were selected as qualified inputs. Figure 9 shows the variable importance of finally selected local skin temperatures. Skin temperatures of head and lower arm have relative higher VI (above 0.1) than those of upper leg, chest and back.

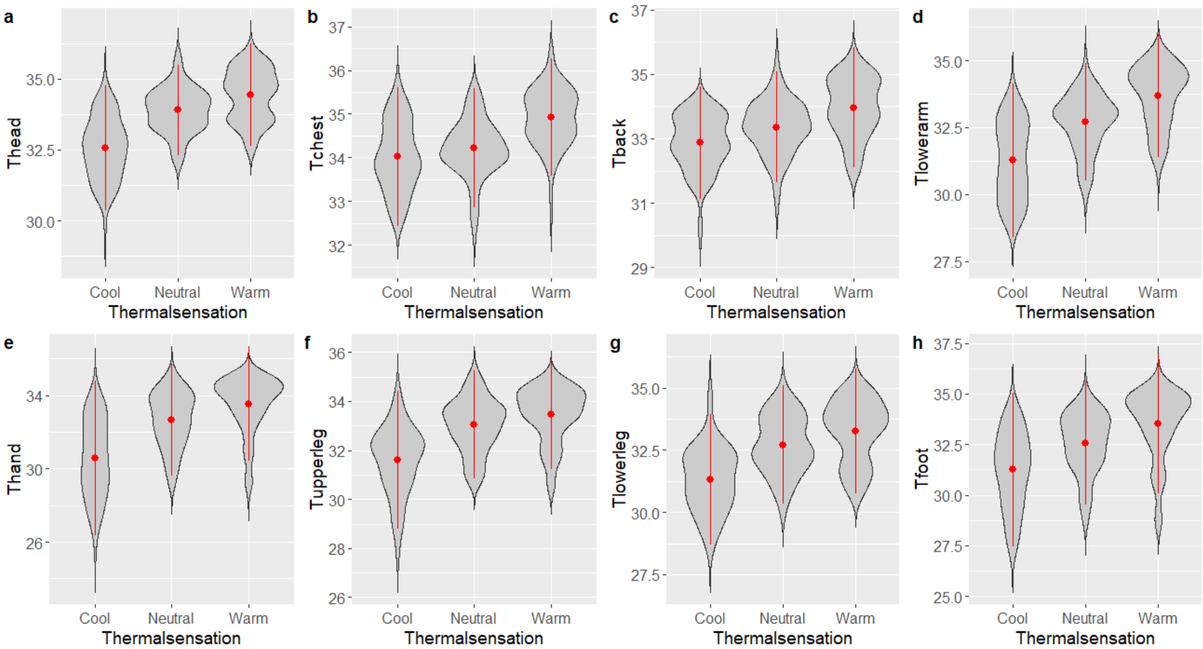

Figure 7 Distributions of local skin temperatures in lab study data

	Thead	Tchest	Tback	Tlowerarm	Thand	Tupperleg	Tlowerleg	Tfoot
Thead	1	0.56	0.69	0.72	0.7	0.7	0.71	0.65
Tchest		1	0.65	0.6	0.49	0.46	0.45	0.46
Tback			1	0.57	0.49	0.58	0.58	0.42
Tlowerarm				1	0.86	0.72	0.75	0.74
Thand					1	0.74	0.77	0.77
Tupperleg						1	0.88	0.84
Tlowerleg							1	0.86
Tfoot								1

Figure 8 Correlation coefficients of variables in lab study data

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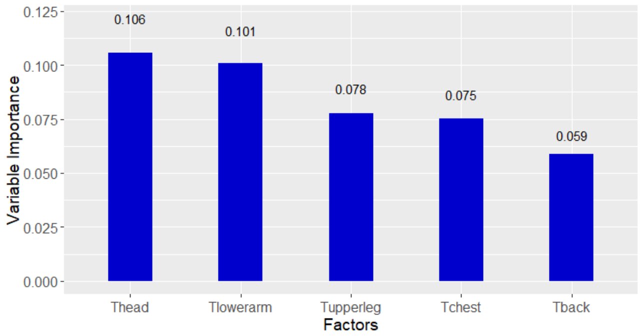

Figure 9 Variable importance of selected features in lab study model

3.2 Model performance

Table 5 shows the accuracy performance of field study model (Model 1), lab study model (Model 2), PMV model and UCB static thermal sensation model. For Model 1 and Model 2, we separately evaluated their accuracies by applying raw data set and three rebalanced datasets, which were expressed as raw datasets (R), over-sampling datasets (O), balance datasets (B) and down-sampling datasets (D). The series of Model 1 and the PMV model are considered as the same type models because they are predicted by multiple environmental and human-related parameters. While the series of Model 2 and UCB thermal sensation model are categorized as the other type because they are all skin temperature-based models.

Model 1(R) was found to have the highest overall accuracy among the series of Model 1, with enhancement of 2.7-6.9%. However, the performance of Model 1(R) was not balanced. It sacrificed its accuracy on two minor categories of ‘Cool’ and ‘Warm’ so that enhanced the overall accuracy. Model 1(B) produces a much balanced performance on each category (all above 55.0%), and it has an overall accuracy of 56.6%. Generally, no matter which data balancing strategy was applied, Model 1 always has a better performance on predicting older people’s thermal sensation than the PMV model does, with 15.8%-27.6% enhancement on the overall prediction accuracy. The PMV model turned out to be strongly biased to cool side thermal sensation and, therefore, failed to provide reliable predictions on the other two thermal sensation categories, especially on ‘Neutral’ sensation with less than 22% accuracy.

For the models built on lab study data, Model 2(O) has the highest overall accuracy with the overall accuracy as high as 76.7%. The results of UCB static thermal sensation model are extremely imbalanced with the accuracy of 78.7% and 84.6% accuracy on ‘Cool’ and ‘Warm’ sensations respectively, while the prediction accuracy on ‘Neutral’ is only 3.1%. This strong bias comes out because we rescaled UCB model’s predicted thermal sensation (PTS) from continuous values ranging within $\pm$4 into three discrete votes (Cool: PTS<-0.5; Neutral: -0.5 $\leqslant$PTS$\leqslant$+0.5; Warm: PTS>+0.5). There is only 1 scale of PTS in the category of ‘Neutral’, while there are 3.5 scales of PTS in ‘Cool’ and ‘Warm’. That is one main reason why UCB model performs badly on predicting ‘Neutral’.

Table 5 Performances of different thermal sensation models on testing data

Data	Models	Optimal mtry	Features	Accuracy			
				Cool	Neutral	Warm	Overall
Field study data	Model 1(R)	5	Air temperature	9.5%	83.0%	20.0%	59.3%
	Model 1(O)	2	Air velocity	52.4%	56.4%	50.0%	54.5%
	Model 1(B)	3	Illuminance	**57.1%**	**55.3%**	**60.0%**	**56.6%**
			Health condition				
	Model 1(D)	1	CO_2 concentration	81.0 %	40.4%	70.0%	52.4%
			Time in aged-care home				
	PMV-1.0 met	-	Air temperature	76.2%	21.3%	56.7%	36.6%

	PMV- 0.8 met	-	Black-bulb Temperature Relative humidity Air velocity Metabolic rate Cloth insulation	95.2%	14.9%	40.0%	31.7%
Lab study data	Model 2(R)	2	5 local skin temperatures: forehead, lower arm, upper leg, chest, back	66.7%	78.1%	73.1%	74.0%
	Model 2(O)	1		**73.3%**	**78.1%**	**76.9%**	**76.7%**
	Model 2(B)	2		73.3%	68.8%	80.8%	74.0%
	Model 2(D)	1		80.0%	56.3%	73.1%	67.1%
	UCB TS model (static state)	-	16 local skin temperatures	73.3%	3.1%	84.6%	46.6%

*R-Raw data, O-Over-sampling, B-Balance, D-Down-sampling

3.3 Interpretations of selected variables

Here we would like to further dissect the underlying reasons why the above qualified variables were selected to build the field study model and the lab study model. Taking variable ‘Air temperature (Ta)’ in Model 1(B) and variable ‘Head skin temperature (Thead)’ in Model 2(O) as two examples, we interpret how these variables affect subjects’ expressions on thermal sensation. Figure 10 and 11 show their partial dependence plots. Other variables’ partial dependence plots are attached in Appendix A. In these plots, the black lines indicate the variation of log probability along with the values of a specific variable, while the blue lines are smoothed curves of log probability computed by the method of LOESS (Local Weighted Smoothing)[44], the higher the log-odds value, the higher the probability. In Figure 10, the left plot shows that the further the air temperature is lower than 20℃, the higher the possibility of older people expressing ‘Cool’ thermal sensation would be. The middle and right plots indicate that when the air temperature is above 22.5℃, the probabilities of getting ‘Neutral’ and ‘Warm’ sensations will greatly increase. Figure 11 suggested that head skin temperature is a good predictor to categorize ‘Cool’ and ‘Warm’ when it is lower than 32.5℃ or higher than 33.2℃, respectively.

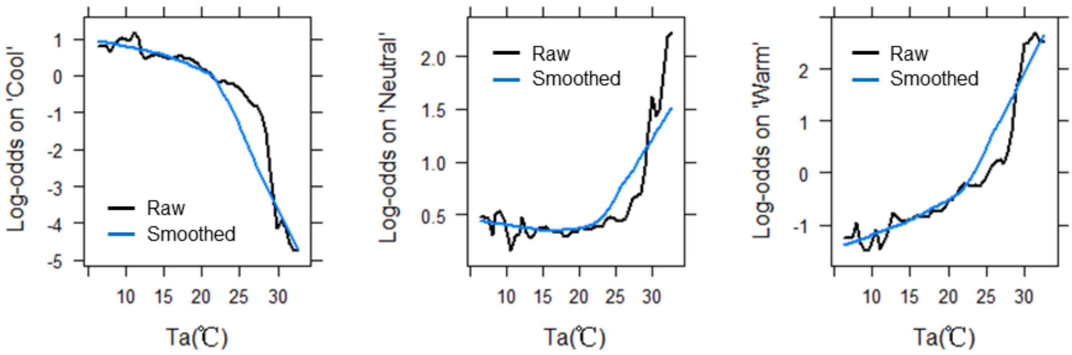

Figure 10 Partial dependence plot of air temperature in field study model

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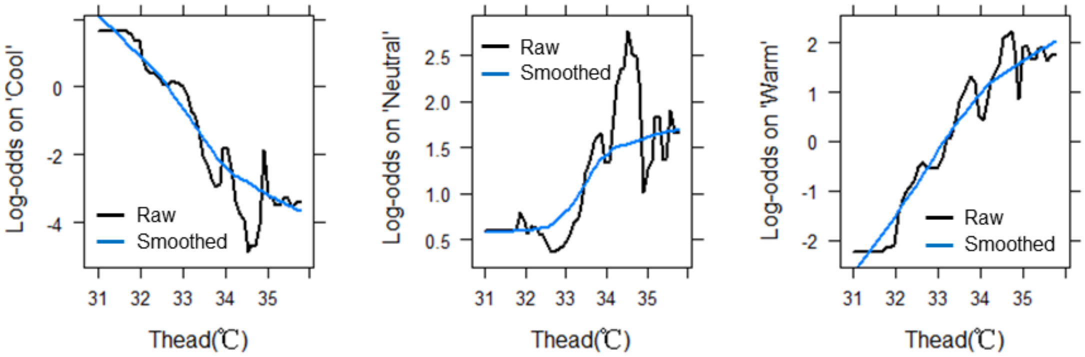

Figure 11 Partial dependence plot of head temperature in lab study model

Table 6 summarizes the contributors of each category in field study model and lab study model based on the results of partial dependence plots (shown in Figure 10, 11 and Appendix A). The six variables that contribute to field study model actually can be further classified as four categories, basic environmental factors (air temperature, air velocity and illuminance), indoor air quality (CO_2 concentration), acclimatization (time in aged-care homes) and health (self-evaluated health condition).

To date, many studies have validated the influences of the above basic environmental factors on human thermal responses. Air temperature is one of the most widely studied factors in thermal comfort field because it is practical to measure and its thermal comfort effects have been demonstrated by many previous researches [2-4, 13, 45-51]. In this paper, air temperature was also found to be the major contributor of field study model with the highest variable importance. And it is also highly correlated with older people's clothing insulation. That pattern is in agree with what Liu[47] found in her study with young people as subjects.

Table 6 Contributors of target thermal sensation in field study model and lab study model

Model	Cool	Neutral	Warm
Field study model	Air temperature	Air temperature Air velocity Illuminance CO_2 concentration Time in aged-care home Health	Air temperature Air velocity Illuminance Time in aged-care home Health
Lab study model	Head temperature Lower arm temperature Back temperature	Head temperature Lower arm temperature Upper leg temperature Chest temperature Back temperature	Head temperature Lower arm temperature Upper leg temperature Chest temperature Back temperature

Air velocity helps to distinguish 'Neutral' and 'Warm' in field study model. The highest probability for older people to feel 'Warm' happened when the air velocity was around 0.25 m/s. In data set 1, air velocities of 0.25m/s and above were detected in summer and generally corresponded to air temperatures of 30°C or above. Figure A1 in Appendix A shows that when air velocity was higher than 0.25m/s, the probability of older people feeling 'Warm' in fact decreased rather than increased. This indicates the air speed of 0.25m/s may be a boundary value. That means when indoor air movement is beyond 0.25m/s, it is very likely for older people to adopt adaptive behavior, like using fans or open windows to increase their rooms' air movement and, therefore, to enhance heat dissipation. That also implies only using air temperature to predict subjects' thermal sensation or simply considering the relationship between air temperature and thermal sensation as linear is not adequate. That would overlook the potential influences of subjects' adaptive behaviors on adjusting their thermal sensations.

Illumination also plays an important role in maintaining older people's thermal comfort. We found that older people were more likely to feel 'Neutral' or 'Warm' when their surrounding illuminance levels were relatively high, which is consistent with previous studies[52, 53] that reported the links between illuminance and thermal comfort. Badia[53] found that the brighter light (5000lux) elevated subjects' body temperature during the night time, which may be caused by a higher melatonin level stimulated by light. Candas [52] observed that subjects preferred to wear more clothing in 70lux than in 700lux, indicating that higher illuminance may make subjects feel warmer.

Indoor air quality is represented by CO_2 concentration in this study. Figure A3 in Appendix A clearly shows that CO_2 concentration helps to distinguish older people's 'Neutral' sensation from other two sensation categories. Older people who were exposed to low CO_2 concentration were more likely to feel 'Neutral'. That conclusion partially agrees with Zhang's [54] finding that a negative perception of air quality, higher CO_2 concentration, may trigger a negative thermal response or a feeling of discomfort.

Acclimatization is one of physiological feedbacks to the local thermal environment and a vital component in the thermal adaptation theory [55, 56]. In this study, we took subjects' living time in aged-care homes as an evaluation index of acclimatization. Generally, those who lived in an aged-care home for a long time were more likely to feel 'Neutral' and 'Warm', while this index has no effect on 'Cool' sensation. This observation matches what Brager and de Dear's finding [55] that acclimatization is more easily to be found for heat exposure than cold exposure because '*adaptation to the cold is primarily behavioral*'.

Self-evaluated health condition used in this study is a comprehensive index, by which subjects made self-judgments on their health status. We found subjects who had better health conditions ('Good' or 'Very good') were more likely to feel 'Neutral' and 'Warm' than those who evaluated themselves as 'Normal', 'Bad' and 'Very bad' health condition. Diseases have been shown to affect human thermal perceptions. Taking diabetes as an example, diabetes-related metabolic disorders will affect peripheral nerves and bring neuropathic symptoms, which results in decreased sensitivity to the ambient thermal environment [24, 57].

The connection between skin temperature and human thermal perception has been widely studied by many researchers [15, 16, 58-61]. Dai [60] summarized the related studies over the last ten years. He found that the statistical regression model is the most common method and the number of selected local skin temperatures varied case by case. In our model, the machine learning algorithm only selected head, lower arm, upper leg, chest and back skin temperatures as inputs. Although it is based on a data-driven approach, the result is coincident with what Stevens[6] and Hui[15] found in their physiology studies. As shown in Figure B1 in Appendix B, Stevens mapped 20 older people and 20 young people's 13 local body parts' cold and warm thresholds. Four of the five local body parts (head, lower arm, upper leg and back) selected in our model are marked with red rectangles in Figure B1 by Stevens[6], which are proved to be highly sensitive to both warmness and coldness. Generally, a high thermal sensitivity corresponds to a low thermal threshold. Although Stevens did not test the thermal sensitivity on chest, Hui[15] reported that chest is one of three dominant parts (chest, pelvis and back) to determine human cold side sensation. All the above literature suggest that the selected input skin temperatures and the modeling framework used in this paper are rational and consistent with previous findings.

3.4 Application of the proposed models

In this section, we applied the proposed models in real application scenarios. Based on the field study model, we would like to present indoor neutral indoor temperature zones of the older people who live in aged-care homes.

Neutral temperature zone is defined as the indoor temperature ranges in which people would feel ‘Neutral’ [4, 51]. Here, we used a backward method to deduce neutral zones for older people with different health conditions and degrees of acclimatization. It is accomplished by fixing the values of independent variables of velocity, CO_2 concentration, illuminance at the median values in each season and selecting the air temperatures with which the field study model would output the predicted thermal sensations as ‘Neutral’. The older people are characterized by health conditions (‘Good’ and ‘Bad’) and two types of acclimatization (‘Shorter-stay’ and ‘Longer-stay’). Noted that the periods of shorter-stay and longer-stay are defined as the first and third quartiles of ‘living time in aged-care homes’ in data set 1, which are 6 months and 36 months respectively. Table 7 lists the inputs in three seasons.

Table 7 Inputs of independent variables to calculate neutral temperature zones

Features	Summer	Mid-season	Winter
Air velocity(m/s)	0.17	0.01	0.02
CO2(ppm)	357.1	453.3	495.3
Illuminance(lux)	185.8	158.2	169.0
Living time in Aged-care homes(months)	Shorter-stay(6 months), Longer-stay(36 months)		
Health	Good-4, Bad-2		
Air temperature range (℃)	25.3-32.5	9.2-27.6	6.4-19.9

Figure 12 illustrates older people’s neutral temperature zones in summer, winter and mid-season by health conditions and living time in aged-care homes. The numbers shown in the figures are upper or lower limits of neutral temperature zones. Generally, older people’s neutral temperature zones exhibit discrepancies in three seasons. Their neutral temperature zones are narrower in summer than those in the other two seasons. In summer, except for the older people being as longer-stay and healthy, other older people have a similar neutral temperature zone ranging from 25.3°C to 28.5°C, while the diversities of neutral temperature zones become larger in mid-season and winter. In winter and mid-season, those older people who are longer-stay and healthy generally have lower limits of neutral temperature: 11.7℃ in winter and 9.2℃ in mid-season. That implies these people have better abilities to adjust themselves to feel neutral in relatively cool environments. Besides, those older people who have bad health condition show higher upper limits (both above 27.0℃) of neutral temperature than those with good health in mid-season, meaning that these people are not as sensitive as healthy older people in response to warmness. The above knowledge can help aged-care administrators and nurses to identify if a specific type of older people is in or out of thermally neutral zones by measuring their indoor air temperatures. As the neutral temperature zones described above have taken older people’s thermal adaptations into consideration, Figure 12 can also be a useful reference for HVAC engineers to properly design a comfort-based HVAC operation strategy for the facilities where the elderly live.

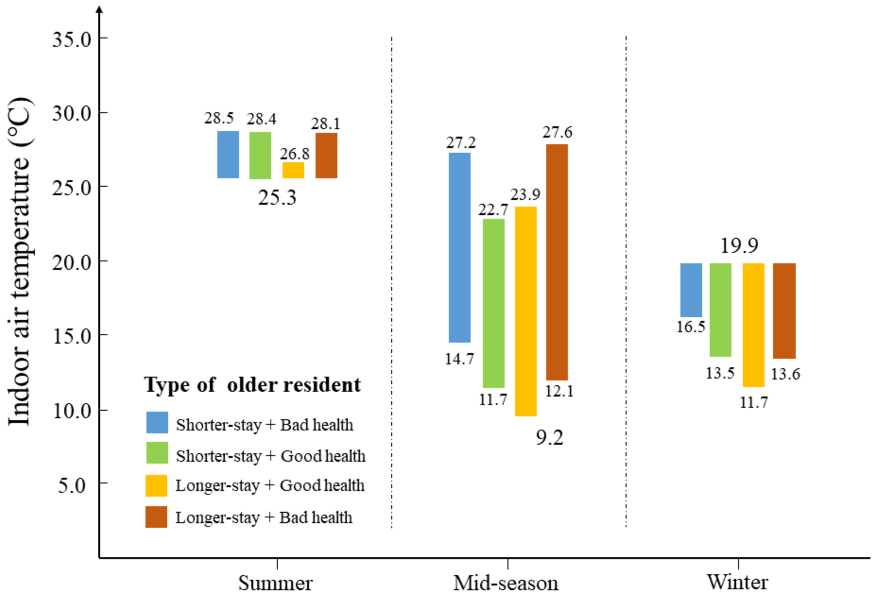

Figure 12 Predicted neutral temperature zones for older residents in aged-care homes

The lab study model has a relatively higher prediction accuracy (76.7%) to distinguish older people's thermal sensation than the field study model (56.6%). However, to run the lab study model, we need to acquire five local skin temperatures which are actually not easy to be measured in the real world. One of the two possible applications of the lab study model is combining it with an older people-based thermoregulation model, by which their local skin temperatures can be predicted based on surrounding thermal environment and human body related factors (body shape, basal metabolic rate, cardiac output and percentage body fat)[4]. Some excellent previous studies have been conducted by Stolwijk[62, 63], Tanabe[64], Fiala[16], Huizenga[65] to develop numerical human physiology models. However, the common problem of the above models is that all of them were developed based on young people's parameters. This constrains these models' capabilities to accurately predict older people's skin temperatures. Modelling an older people-based thermoregulation model is beyond the content of this paper and deserves to be studied in the future. Compared with the above approach, a more practical way is to only use forehead skin temperature to predict older people's thermal sensation. That is reasonable because head skin temperature has been validated to be as the highest importance, and this area of skin is generally uncovered and can be easily detected by an infrared thermometer or camera installed in living rooms. It needs to be noted that we did not acquire head skin temperature data via an infrared thermometer or camera but we explored the possibility of using a solo head skin temperature in data set 2 to predict older people's thermal sensation. After using the over-sampling method to rebalance head skin temperature, we applied the random forests algorithm again to predict older people's thermal sensation. This simplified model's overall prediction accuracy is 53.4%. Previously, Dai[60] also proposed a head skin temperature-based model, using Hui Zhang's data collected from intensive lab studies[15], to predict young people's thermal sensation by using Gaussian support vector machine (SVM) algorithm. Table 8 lists the prediction accuracies of the above two models. Dai's model has much higher prediction accuracies on 'Cool', 'Neutral' and overall sensation than those of our simplified model.

Table 8 Results of using head skin temperature to predict thermal sensation

Studies	Subjects	Accuracy			
		Cool	Neutral	Warm	Overall

Our study	Older people	60.0%	40.6%	65.4%	53.4%
Dai[60]	Young people	85.3%	82.3%	50.8%	72.8%

The above results indicate that the head skin temperature alone can perform reasonably well in predicting older people's thermal sensation. And the possible reasons that Dai's model produces a much higher overall accuracy than that of our model can be attributed to two explanations. The first one is about data. Dai's data was collected from strong local heating and cooling experiments, so their subjects might experience strong cold or hot feelings with relative wider skin temperature variations. While our data was collected from stable and uniform thermal environments, and subjects' feelings may not be as strong as theirs. The second explanation is that older people's reducing thermal sensitivity may weaken skin temperatures' indicative effects on their thermal sensations. Older people lose thermal sensitivities to both warmness and coldness. Stevens[6] pointed out that older people have increased cold and warm thresholds on many local body parts (see as Figure B1 in Appendix B) especially on body extremities, like toes and soles, which indicates older people's thermal sensitivity get deteriorated. The underlying mechanisms of their reduced thermal sensitivity were summarized and discussed by Slava and André[24], which are related to the changes in the density of sensory epidermal nerve fibers and its functional properties.

3.5 Limitations

This study has its own limitations, which come from the following sources.

1) The proposed models, either the field study model or the lab study model, are built based on the data collected from Chinese older people who lived in hot summer and cold winter climate zone. For those older people who live in different climate zones or countries, or with different culture backgrounds, their thermal perceptions may be different from what we observed.
2) All the subjects were keep seated during our experiments, and the influence of metabolic rate was not considered.
3) The field study data was collected from aged-care homes. For those who live in their own homes, this model and its results may be not applicable. Also, we avoided doing field surveys in raining days so we missed much data with high relative humidity.
4) We didn't observe that any subject was sweating even in a 32℃ thermal environment, so we didn't consider the possible effects of sweating on older people's thermal sensation in lab study model.
5) The neutral temperature zones proposed in this study focus more on older people's thermal comfort but not healthy issues. The relationship and trade-off between health and thermal environment deserve to be further discussed.

4. Conclusions

In this paper, we proposed two data-driven models with a random forests algorithm to predict older people's thermal sensation in the building environment. The field study model was built based on multi-dimension data collected from our large-scale field studies conducted in aged-care homes, while the lab study model was built based on local skin temperatures recorded from our lab studies.

The six input variables of air temperature, air velocity, CO_2 concentration, illuminance, health condition and living time in aged-care homes were selected as high-importance features to establish the field study model. After rebalancing the data, the model's overall prediction accuracy could achieve at 56.6%, which is 24.9% higher than the prediction accuracy of the PMV model. Five local skin temperatures including head, lower arm, upper leg, chest and back skin temperatures were found to be important features in lab study model to predict elderly's thermal state. The combination of the above skin temperatures can produce an overall accuracy of 76.7%, which is 30.1% higher than that of UCB thermal sensation model (static).

Further, we proposed two practical applications of the above two models. By applying the field study model, we presented older people's neutral indoor temperature zones in different seasons. Based on the analysis of the lab study model, we derived a simplified model by using an easily detected skin temperature, head skin temperature, as the only input, which could produce an accuracy of 53.4%. The above applications provided two pathways for the architectures, administrators or healthcare providers whose work is related to aged-care homes to design a comfortable thermal environment for older residents. They can use the above ways to monitor or predict older residents' thermal sensations. When their thermal sensations are found to be cool or warm, further actions, like running heating or cooling system, should be applied to their living environment. In the next step, future studies could consider the synergistic effects of health and comfort concerns on older people's indoor thermal environment design and operation.

Acknowledgment

This work was supported by the National Natural Science Foundation of China [No.51578386] and China Scholarship Council [No.201806260135].

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Appendix A – Partial dependence plots

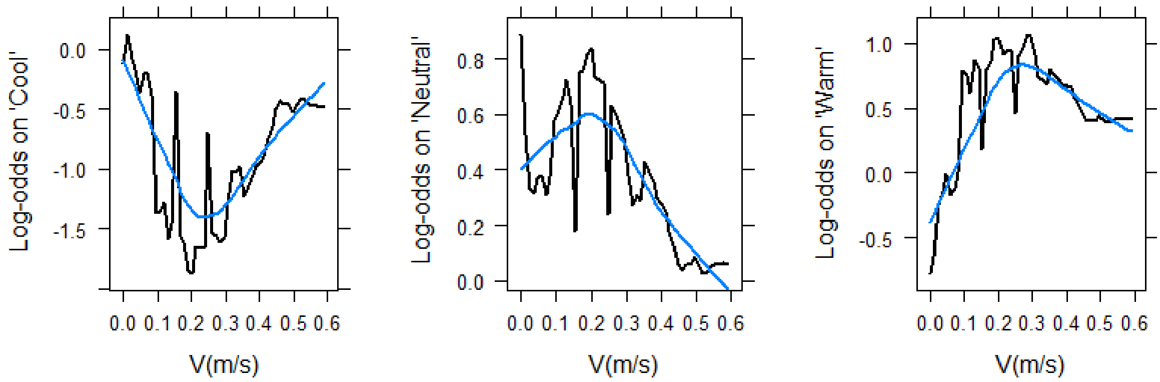


Figure A1 Partial dependence plot of air velovity in field study model

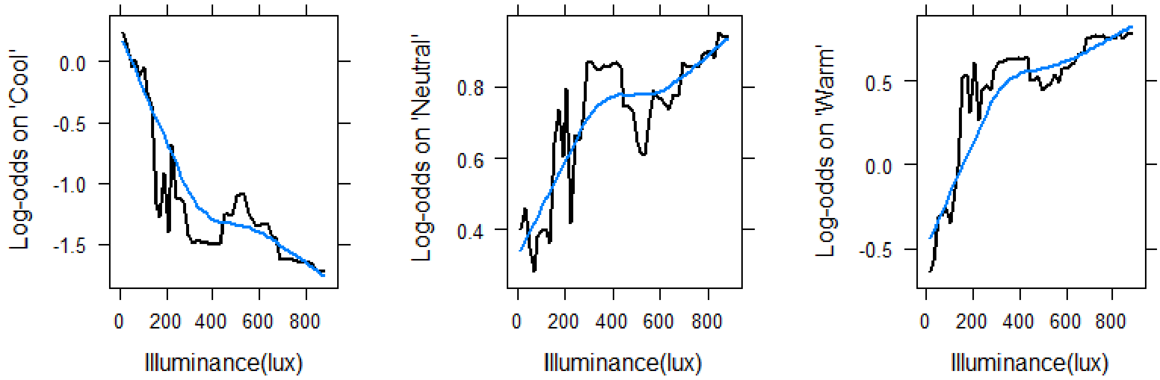


Figure A2 Partial dependence plot of illuminance in field study model

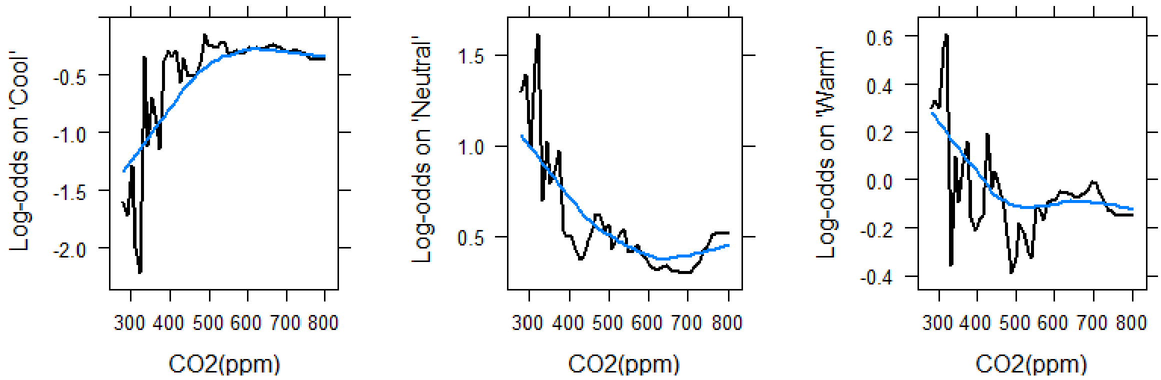
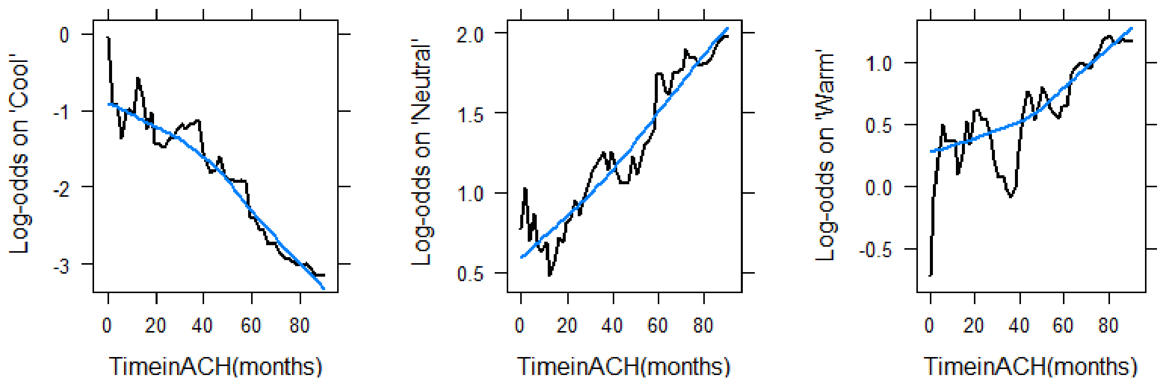


Figure A3 Partial dependence plot of CO_2 in field study model



https://doi.org/10.1016/j.buildenv.2019.106231
http://escholarship.org/uc/item/9wq674bp

Figure A4 Partial dependence plot of living time in aged-care homes in field study model

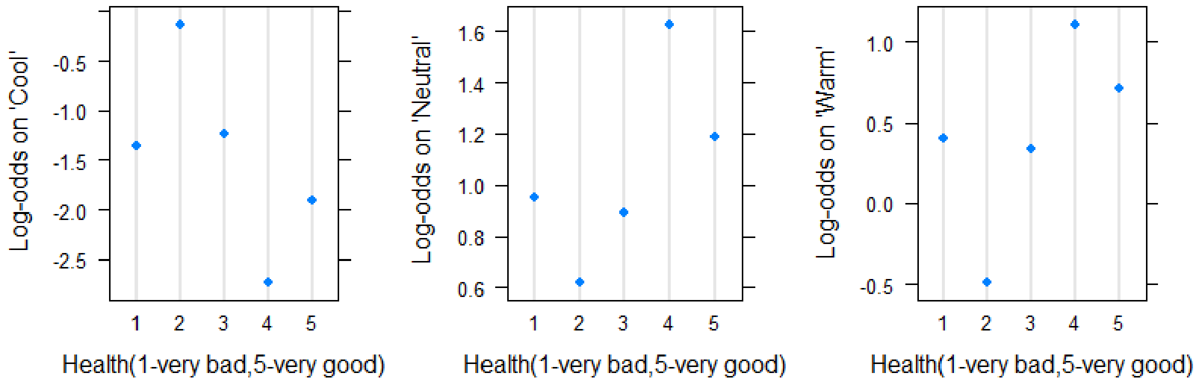


Figure A5 Partial dependence plot of health condition in field study model

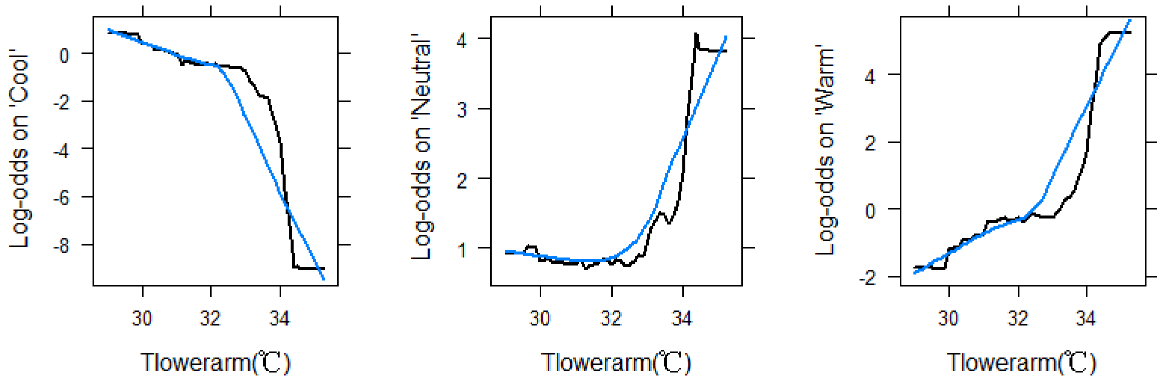


Figure A6 Partial dependence plot of lower arm temperature in lab study model

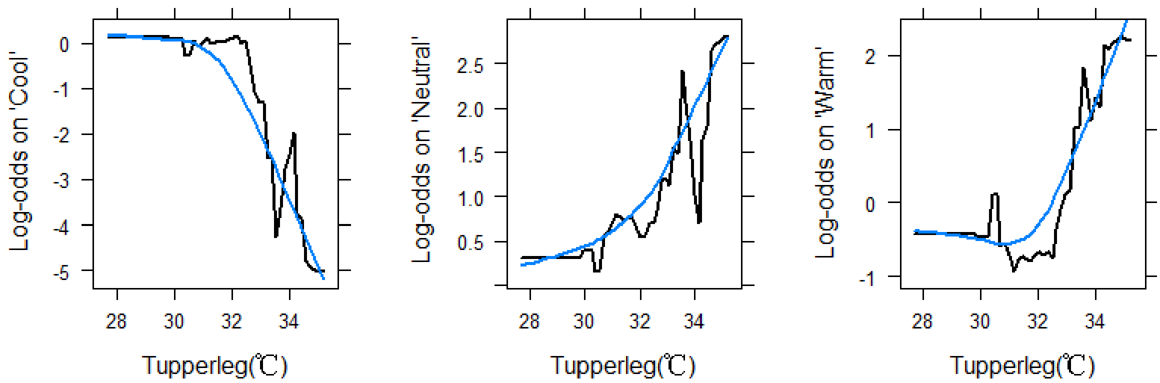


Figure A7 Partial dependence plot of upper leg temperature in lab study model

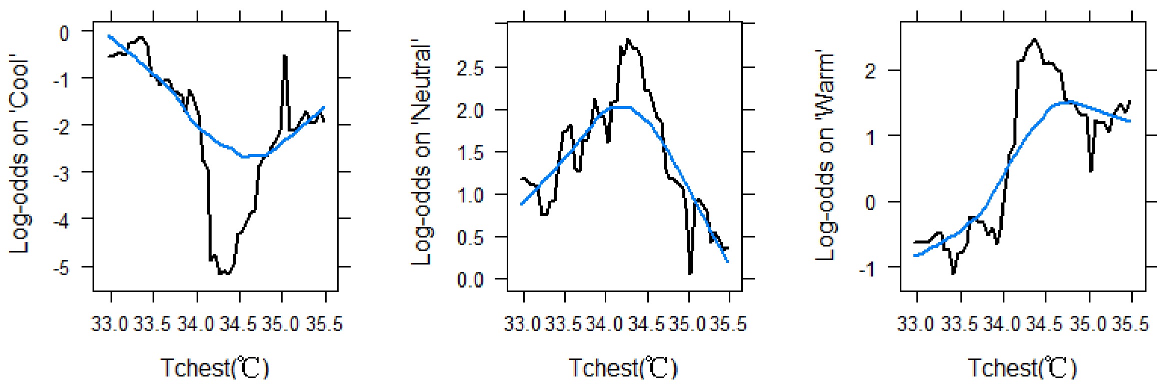


Figure A8 Partial dependence plot of chest temperature in lab study model

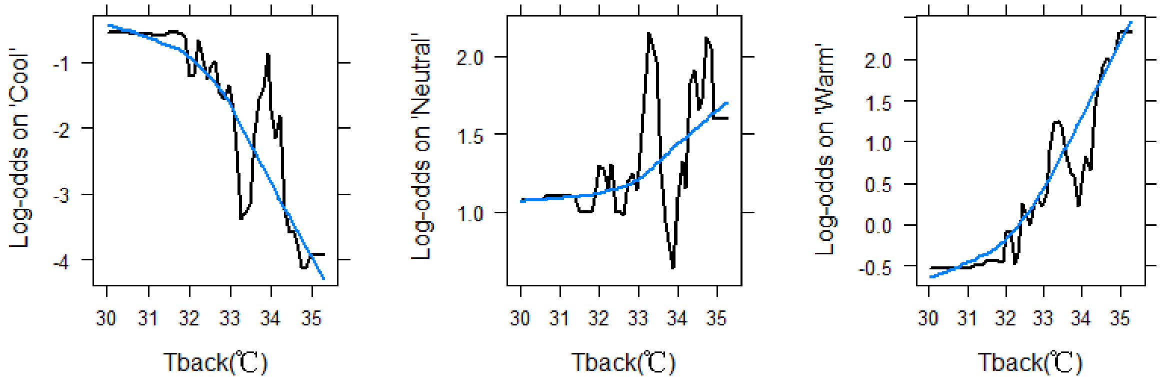


Figure A9 Partial dependence plot of back temperature in lab study model

Appendix B – Human thermal sensitivity map

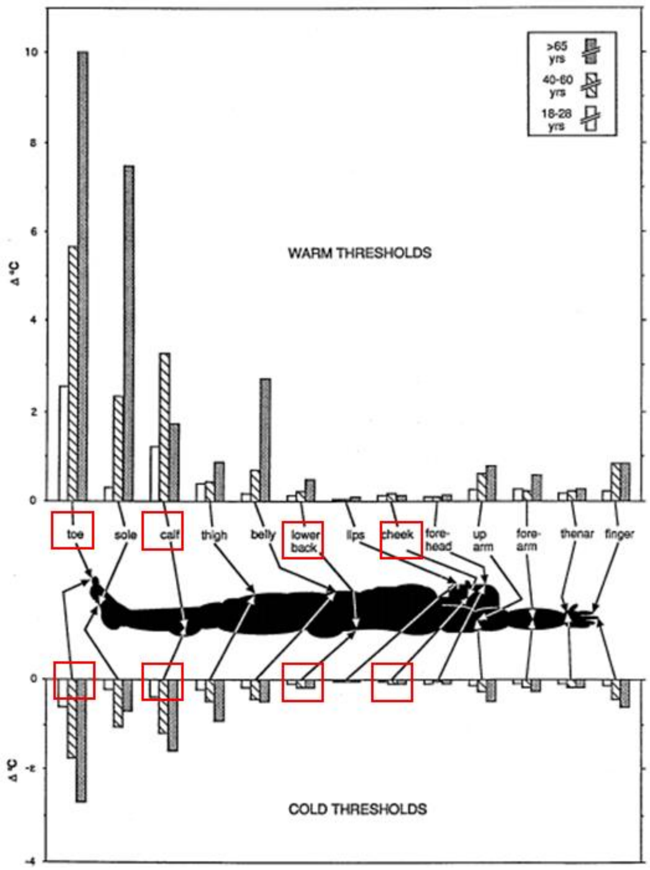


Figure B1 Body maps of regional warm (upper bars) and cold (lower bars) thresholds[6]