Development of an adaptation table to enhance the accuracy of the Predicted Mean Vote model

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Highlights

- The influences of the climate and building type on thermal sensation are more significant than any other variable.
- An adaptation table was developed to reduce the influences of the climate, building type, age group, season and gender.
- The adaptive PMV model is free from serious bias in predicting the average thermal sensation of a large population.
- This is the first study to quantify the effect of categorical variables on the average thermal sensation in buildings.

Abstract

The Predicted Mean Vote (PMV) model is extensively used by current thermal comfort standards, such as ASHRAE 55 and ISO 7730, despite its discrepancy in predicting Thermal Sensation (TS). The implicit assumption is that PMV can be applied for predicting TS of a large population. Our statistical analysis of a subset of ASHRAE global database of thermal comfort field study shows that occupants' expectations towards TS are affected by factors that are not accounted for in the classic PMV model, such as climate, building type, age group, season and gender. The influences of the climate and building type are more determinant. An adaptive PMV (PMVa) model and an adaptation table were developed based on the selected samples to reduce

this discrepancy. After adaptation, the medians of each category corresponding to the discrepancy are zero or near zero. The results also show that the adaptive PMV outperforms the classic PMV in predicting TS, while increasing the overall accuracy from 36% to 39%.

Keywords: Predictive Mean Vote, Thermal sensation, Discrepancy, Adaptive model, Adaptation table, Adaptive thermal comfort

Nomenclature

Am	Tropical monsoon climate
Aw	Tropical wet and dry climate
CA	Correspondence Analysis
BSh	Hot semi-arid climate
Cfa	Humid subtropical climates
Cfb	Oceanic climate
Cwa	Dry-Winter Humid Subtropical
Cwb	Dry winter Oceanic climate
EU	European Union
HVAC	Heating, Ventilation and Air Conditioning
IoT	Internet of Things
MCA	Multiple Correspondence Analysis
PMV	Predicted Mean Vote
PMV_a	adapted PMV
TS	Thermal Sensation

1. Introduction

Buildings are responsible for 40% of the energy consumption in the EU (European Union), with Heating, Ventilation and Air Conditioning (HVAC) equipment used to regulate the indoor climate accounting for approximatively 50% of the building energy consumption [1] [2] [3]. Despite the significant energy footprint spent in controlling the indoor climate, user satisfaction with the indoor comfort is often not met [4]. A large scale survey in North America showed that only 2% of the commercial buildings achieved 80% thermal satisfaction, which is the prescribed minimum requirement by most standards for occupants' thermal comfort [5]. Citizens in industrialized countries spend around 90% of their time indoor [6], and therefore the indoor conditions are important to human health and wellbeing. Thermal comfort has been identified as the most important indicator influencing the overall satisfaction in terms of indoor environmental quality [7] [8]. Several studies have proven that a dissatisfied thermal environment would result in an increased number of problems, such as complaints, absenteeism, and reduced productivity at work [7] [9]. From an energy conservation point of view, indoor comfort can be used to understand the specific demand and requirements of occupants. Such information can inform the design and control of building operation systems to optimize energy efficiency and reduce carbon emission.

Thermal comfort is defined as the concept of mind to express satisfaction towards the thermal environment, and thus it should be evaluated through the direct feedback of the occupants [10]. Human response to Thermal Sensation (TS) is normally measured by asking the subjects to complete a 'comfort vote' on a descriptive scale ranging from '-3' to '3', either a 7-point ordered or continuous scale. '0' is the best condition representing thermal neutrality. Statistical methods are then applied to analyse the results. However, it is not practical for occupants to answer questionnaires on a continuous basis. As a result, other techniques have been developed to correlate TS with the built environment [11] [12].

PMV (Predicted Mean Vote) is the most widely used model to mathematically predict the average TS of a large group of individuals, which is the basis for multiple indoor thermal comfort standards, such as ASHRAE 55 [13] and ISO 7730 [14]. It was developed based on extensive experiments conducted in well-controlled environments of European and North American subjects [15] [16] [17]. It rests on steady state heat transfer conditions between a human body and its surrounding environment. The static heat balance model predicts the mean TS of the occupants exposed to their thermal environment as a function of four thermal environmental parameters (indoor air temperature, radiant temperature, air speed and relative humidity), and two occupant's personal data (metabolic rate and clothing insulation).

Previous studies have revealed that human responses to indoor thermal comfort are affected by non-thermal factors that are not accounted for in the classic PMV model [18]. As a result, a discrepancy exists between the TS votes and PMV model. The evidenced discrepancy triggered an investigation into improving the model's credibility in predicting indoor thermal comfort. Adaptive models have been proposed which assumed that people are able to adapt to their thermal environment through behavioural adjustments, acclimatization to the thermal environment or relaxation of expectations [8]. While the classic PMV model is capable of accounting for some degrees of behavioural adaptation such as adjusting local temperature and changing one's clothes, it overlooks psychological adaptation and acclimatization. Fanger and Toftum [17] extended the PMV model by introducing an expectancy factor for non-air-conditioned buildings in warm climates. They argued that the occupants' TS expectation is lower, and that occupants would slow down their activities to adjust their metabolic rates under warm conditions. Nicol and Humphreys [19] claimed that people are able to adjust themselves to suit the environment, and developed an adaptive thermal comfort model to estimate the acceptable indoor temperature in relation to the outdoor monthly average temperature in free-running buildings. Fanger [17] pointed out that the limitation of the adaptive model proposed by Nicol and Humphreys is that the model does not consider activity level, clothing insulation and the indoor thermal environment, which are believed to have a significant impact on human thermal comfort. Yao et al. [20] proposed an adaptive PMV model based on a "black box" theory to explore the logical and statistical relationships between the variables involved. The established relationship was used to predict thermal comfort, accounting for behavioural and psychological adaptation. They claimed that their model might be important in the context of human interaction with the environment. Humphreys and Nicol [21] discussed the variables affecting the accuracy of PMV model. They advocated that using PMV to predict thermal comfort votes could be misleading and proposed a modified PMV model based on the classic PMV and its discrepancy from the TS votes. The biases were reduced after modification.

The PMV model was developed based on the assumption that if the indoor climate meets the critical requirements for a thermally acceptable comfort condition, the TS is deemed the same for occupants with the same level of clothing insulation and carrying out similar activities, regardless of the demographic and contextual factors. The fact is that the influences of psychological adaptation and physiological acclimatization are well documented [22] [23]. To address this research gap, the proposed study aims to explore the impacts of the variables contributing to this discrepancy. Currently, most of the field and experiment studies are based on a limited number of samples, which cannot be generalized to represent a large population. Thus, our study is derived from the ASHRAE Global Thermal Comfort Database II [24] to investigate the influence of a large sample size. Following this introduction, Section 2 discusses the factors contributing to the PMV discrepancy. The paper then elaborates on the methodology used in this study (Section 3), followed by a presentation of the results (Section 4). An adaptive model and an adaptation table are presented in Section 5 with the aim to compensate the influences caused by the variables identified in Section 2. The results are then discussed in Section 6, followed by concluding remarks.

2. Factors contributing to the discrepancies between PMV and thermal sensation

The PMV model was primarily developed from predefined thermal environmental and personal variables, hence overlooking other factors that may potentially affect the accuracy of the results. However, thermal comfort is a subjective factor, which is closely associated with occupants' thermal expectations and capacity of adaptation. Different occupants may have different perceptions of thermal comfort even when exposed to the same environment [25]. Such differences are associated with the influence of seasonal variations [18] [26] [27] and the general climate [27] [28] [29] [30], as well as lifestyle and socio-cultural factors, including the use of different clothing materials [21], expectations (influenced by the season [31] [32], climate [21] [33], age [34] [35], and gender [36] [37]), and the ability to control the thermal conditions in the actual buildings [38] [39] [40]. This, in turn, involves variations in (a) perceived neutral temperatures, (b) interpretation of the ASHRAE scale categories, and (c) personal judgements [21]. As such, five determinant variables are identified from the literature, namely: season, climate, building type, age group, and gender; and elaborated below.

2.1 Season

Many previous studies have reported the effect of seasonal variations on personal perceived TS [18] [26] [27] [31] [32]. Liu et al. [32] conducted a large-scale thermal comfort survey in a hot summer and cold winter zone of China. Different TS and adaptive responses were detected in different seasons. The results revealed that the significant seasonal variations were due to the individuals' thermal experience and thermal expectations in difference seasons. A higher neutral temperature was expected in warm seasons. Thus, maintaining the same indoor temperature in winter as in summer results in a waste of energy [18]. In addition to the difference in perceived TS, the occupants' physiological reactions are also different. The differences have been recorded from climate chamber experiments by measuring physiological reaction of the participants [41], [42], [43]. Noriko [42] investigated seasonal metabolic rate variation of 6 subjects under identical thermal conditions over the course of one year. Results showed that metabolic rates were higher in winter than in summer. Lee et al. [43] compared sweating responses of 15 male participants in summer and winter. They concluded that sweat volume and evaporative rate were significantly less in winter than in summer.

2.2 Climate

Research studies with regard to thermal comfort have revealed that occupants' thermal adaptation is affected by climate and social custom, mainly reflected by their perceived neutral temperature and their interpretation of ASHRAE comfort vote [21] [33]. Generally, these studies found that neutral indoor temperature in sub-tropical climate is higher than temperate climate, and lowest in cool climate [27] [28]. Although the clothing insulation and metabolic rate are taken into consideration in the classic PMV model, the values are normally assessed from a standard checklist. Clothing in the tropical area may allow great diffusion of moisture and air [21]. The metabolic rate may be lower in the warm climate while conducting the same listed tasks [21]. Thus, the identical clothing level and tasks providing identical assumption of clothing insulation and metabolic rates may result in the same PMV while the TS is different. Meanwhile, evidence suggests that human genome imparted by natural selection is strongly correlated with climate variables [30]. People exposed to certain climate may have higher tolerance for higher temperature and humidity [29] [44]. For example, people living in warm climate prefer a warmer indoor temperature [33].

2.3 Building type

The impact of building type on thermal comfort is much less discussed when compared with other factors [45]. Architects design buildings that address functional requirements while complying with the energy (and other) regulatory landscape [46]. Moreover, the interior design as well as indoor facilities vary from one building type to another. An office building is normally equipped with personal computers and servers, which are responsible for the extra heat gain of the building. Furthermore, the occupants are not passive recipients of their thermal environment regime as they actively interact with the control systems in place (e.g. thermostats and radiator valves) to make themselves comfortable. Different types of buildings affect people's ability to adapt to clothing insulation and control of the environment [38] [39]. For example, occupants in residential buildings tend to adapt their clothing level, and impact on the indoor environment by controlling their HVAC system. Thus, the acceptable temperature range in residential buildings is wider than other types of buildings [40]. Oseland [47] compared 30 subjects' thermal comfort from home, office and a climate chamber. The author concluded that under the same clothing and activity, the participants felt warmer in their home than in their office, and warmer in their office than in the climate chamber. The result was validated by a follow on study from Karjalainen [48], who conducted an investigation to examine the thermal comfort of 3094 respondents. The results showed that the respondents felt warmer at home than in their office.

2.4 *Age group*

Tolerance to cold and hot environments of different age groups is generally considered to decrease with age due to the reduced thermoregulation response [34]. This reduction in thermal sensitivity is caused by aging of the skin and the superficial skin blood flow [49]. Natsume et al. [34] studied 6 older men (71-76 years old) and 6 young men (21-30 years old) to investigate their preferred temperature. The subjects were healthy both physically and mentally. The results indicated that the preferred temperature range of the older people is wider than the younger people. Another study was conducted by Schellen et al. [50] to investigate thermal comfort response of different age groups. 8 seniors (67-73 years old) and 8 young adults (22-25 years old) participated in the investigation. The results revealed that the older people preferred a higher temperature compared with the younger people and their TS was generally 0.5 scale units less than the young people. The results were challenged by some scientists who claimed no significant influence of age on TS. Soebarto et al. [51] investigated the thermal comfort of younger (20 samples) and older (22 samples) subjects under different test conditions. The skin temperature of the subjects was measured at four body parts. No significant difference in thermal preference or thermal sensation was observed for the two different age groups.

2.5 Gender

A large number of studies have examined the effect of gender on TS and yielded conflicting conclusions. A substantial amount of field studies reported a weak or insignificant influence caused by gender difference [36]. Amai et al. [52] studied thermal comfort under three types of tasks. The TS difference between male and female subjects was small. Maykot et al. [53] conducted 116 field studies to investigate the influence of gender on thermal comfort temperature. Total 584 participants were involved in the experiments. Statistical analysis of the collected results showed that the comfort temperature for female is slightly higher (≤ 1°C) than male. Conversely, some studies revealed a noticeable gender difference in terms of thermal comfort [40] [54] [37]. Beshir and Ramsey [54] investigated the TS difference between 31 male and 15 female participants. The subjects were exposed to 23.3 - 43.3°C and were not allowed to adjust the temperature throughout the experiment. The results showed a significant gender difference, with the male subjects preferring a lower comfort temperature than the female subjects. The female participants felt more uncomfortable in both cold and hot temperature extremes. In a way, the results are similar to some field and laboratory studies, which showed that the female participants are more sensitive to deviation from the comfort temperature and more likely to be thermal dissatisfaction than male under the same thermal environment [36] [37]. Thus, it was suggested that female should be used as primary subjects when investigating indoor thermal comfort requirements [55]. However, Kingma and Lichtenbelt [56] and Wang et al. [36] pointed out that the gender differences are derived from the metabolic rate and clothing insulation, and thus the influence might be eliminated once the clothing and metabolic rates are well controlled [45].

3. Methodology

This section describes the data source used in the study, the adopted sampling technique, as well as the analytical methods used to analyse and quantify the relationships between the categorical variables involved, as elaborated below.

3.1 Data source and sampling technique

The ASHRAE Global Thermal Comfort Database II, which consists of thermal comfort data from subjective comfort votes and objective instrumental measurements, is used in this study. Besides the thermal comfort information, the database also includes other related information such as season, climates, building types, age and gender. The samples with PMV, thermal sensation, season, climate (Köppen–Geiger climate classification), building type, age and gender were extracted from the database. Meanwhile, the attributes under the different variables with a sample size of less than 383 were excluded to ensure a confidence level of 95%. This number is obtained by equation (1).

$$Sample\ size = \frac{\frac{Z^2 \cdot SD \cdot (1-SD)}{e^2}}{1+(\frac{Z^2 \cdot SD \cdot (1-SD)}{e^2 N})} \tag{1}$$

Where, Z = 1.96 (95% confidence level), SD (standard deviation) = 0.5, e (margin of error) = 0.05. N is the population size in the database.

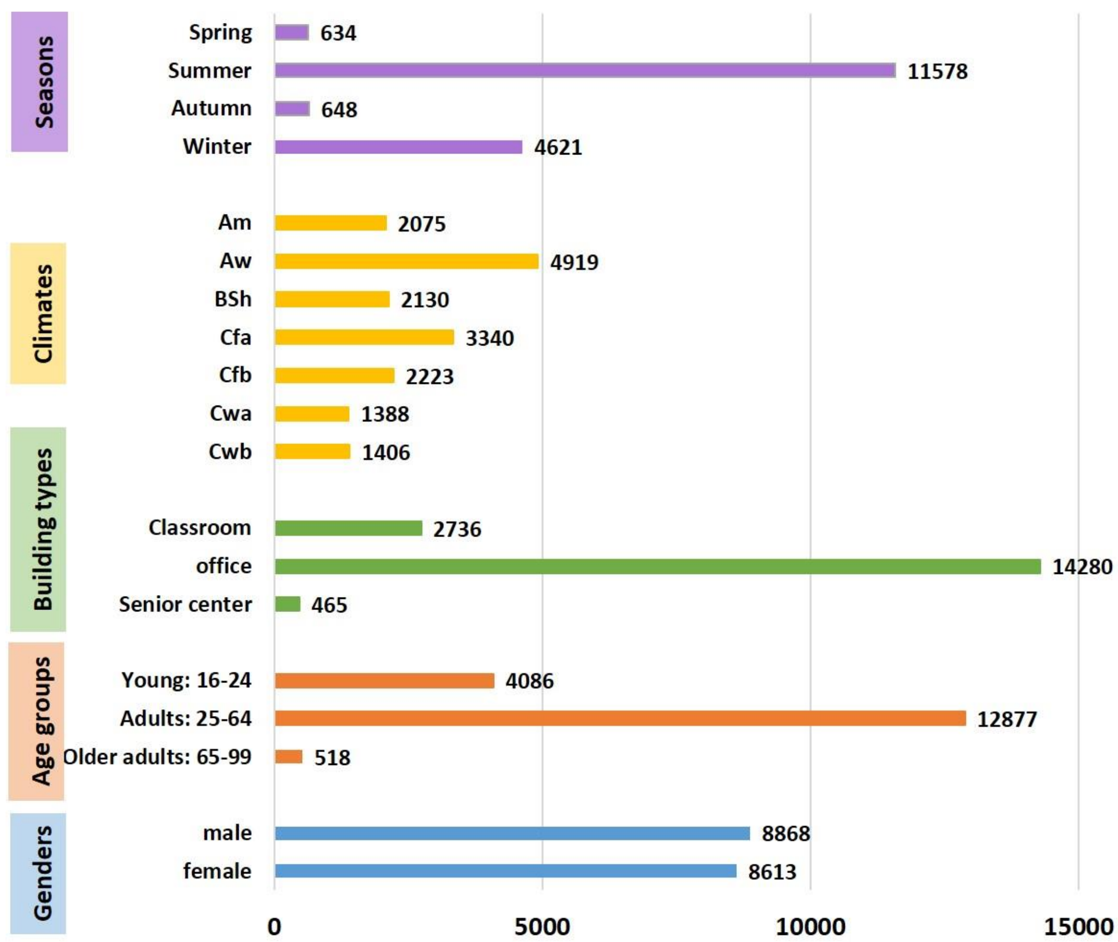


Fig. 1 Distribution of extracted data samples from the database. Am (Tropical monsoon climate), Aw (Tropical wet and dry climate), BSh (Hot semi-arid climate), Cfa (Humid subtropical climates), Cfb (Oceanic climate), Cwa (Dry-Winter Humid Subtropical), Cwb (Dry winter Oceanic climate)

The calculated population size is 383. Finally, a total of 5 variables (Season, Climate, Building Type, Age group, and Gender) consisting of 17841 observations were used in this analysis. A new variable named discrepancy representing the difference between PMV and TS was generated. The extracted age information was a numeric variable ranging from 16 to 99. In this study, the age was grouped into three attributes: Young: 16-24, Adults: 25-64 and Older adults: 65-99. Fig. 1 summarizes the distribution of the extracted samples. A large number of the records were collected from Adults: 25-64 in the office building during summer.

3.2 Analytical methods for categorical variables

The factors contributing to the discrepancy in our analysis are categorical variables. Therefore, the analytical method should be able to analyse the relationships among these categorical variables. Analysis of variance (ANOVA) was applied to explore the association between the discrepancy and the different categorical variables (e.g. season, climate).

A boxplot is a straightforward graphical method to summarize the datasets, which shows whether or not a dataset is symmetric. It was used in this analysis to visually identify the dispersion of samples based on a five-number summary ("minimum", lower quartile (Q1), median, upper quartile (Q3) and "maximum"), as shown in Fig. 2. The difference between lower quartile and upper quartile is the length of the box. A line that divides the box into two parts represents the median of the data. For example, a median of 5 denotes that the number of data higher than 5 is the equal to the number of data lower than 5. The difference between lower quartile and upper quartile is the interquartile range (IQR). The "minimum" and the "maximum" are the Q1-1.5*IQR and Q1+1.5*IQR. Outliers are displayed as individual points.

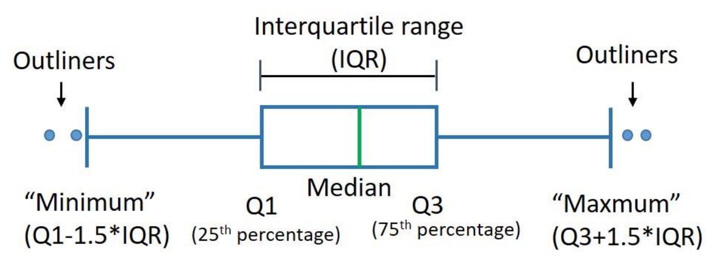


Fig. 2 Interpretation of the boxplot

Correspondence Analysis (CA) and Multiple Correspondence Analysis (MCA) were both used in this study to project the correlation between the discrepancy and the categorical variables in 2D map. The CA is a graphical technique designed specifically for the analysis of categorical variables, which interprets the relationship among categorical variables by identifying their differences and similarities [57] [58] [59]. This technique preserves the categorical nature of the variables and is able to accommodate any type of categorical variable [58]. It is developed from data in a contingency table, which is a two-dimensional table in matrix format showing the frequency of the variables associated attributes. The MCA is similar to CA apart from that it can be used when there are more than two categorical variables. The association distances in CA and MCA are measured by chi-square distance between the response categories. This measurement ensures that the larger population do not dominate the relative distance. Thus, CA exhibits a higher accuracy when compared with other multivariate techniques derived from the correlation coefficient [58]. The chi-square distance between row i and i' is defined by equation (2) [58]:

$$d(i,i') = \sqrt{\sum_j \left(\frac{\left(p_{ij}-p_{i'j}\right)^2}{p_{+j}}\right)} \tag{2}$$

where p_{ij} and $p_{i'j}$ are relative frequencies of row i and i' in column j. p_{+j} is the marginal relative frequency for column j.

3.3 Analytical methods to quantify the relationships

Although categorical variables are widely used in our daily life, they cannot be used directly in regression analysis to establish a statistic relationship. Dummy coding, also known as one-hot coding, is employed to incorporate categorical variables into regression analysis by converting the categorical variables into mutually exclusive binary variables. The dummy variables then can be considered as true values that consist of 0 and 1. Table 1 gives an example for dummy coding of season. After coding, the attributes are converted into binary data.

Table 1 An example of dummy coding for season

		Dummy variables			
	Season	Spring	Summer	Autumn	Winter
Sample 1	Spring	1	0	0	0

Sample 2	Summer	0	1	0	0
Sample 3	Autumn	0	0	1	0
Sample 4	Winter	0	0	0	1

Multivariate linear regression is a linear statistical model with more than one independent predictor. It was applied in this study to establish the relationship between the discrepancy and the dummy coded categorical variables. Linear regression is selected because it is the most extensively used regression model and the coefficients can be easily used to generate a compensatory table for categorical variables.

3.4 Workflow of the methodology

The workflow of the methodology is shown in Fig. 3. The main concept of the paper is to analyse the accuracy of the existing PMV model for TS prediction, identify the reasons for the discrepancy (PMV-TS), and propose an adaptive model (PMV_a) together with an adaptation table to enhance the accuracy of the model.

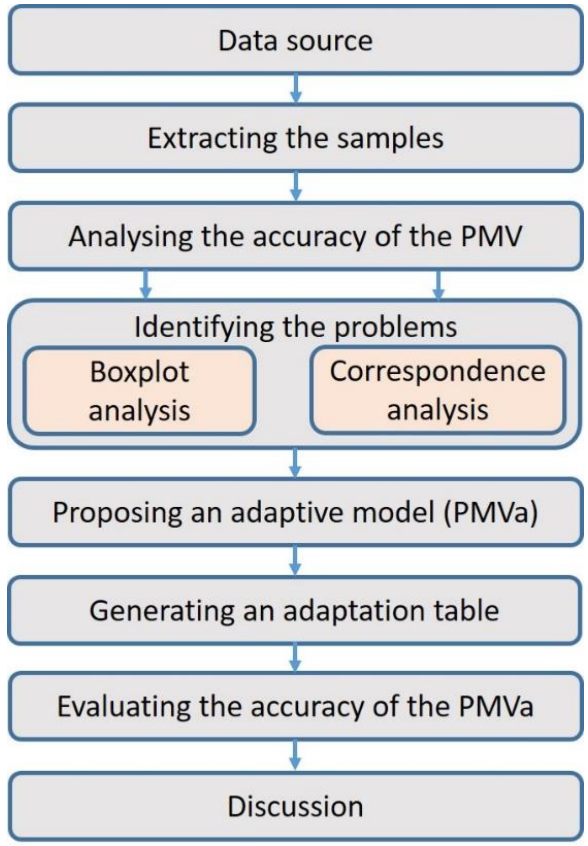


Fig. 3 workflow of the methodology

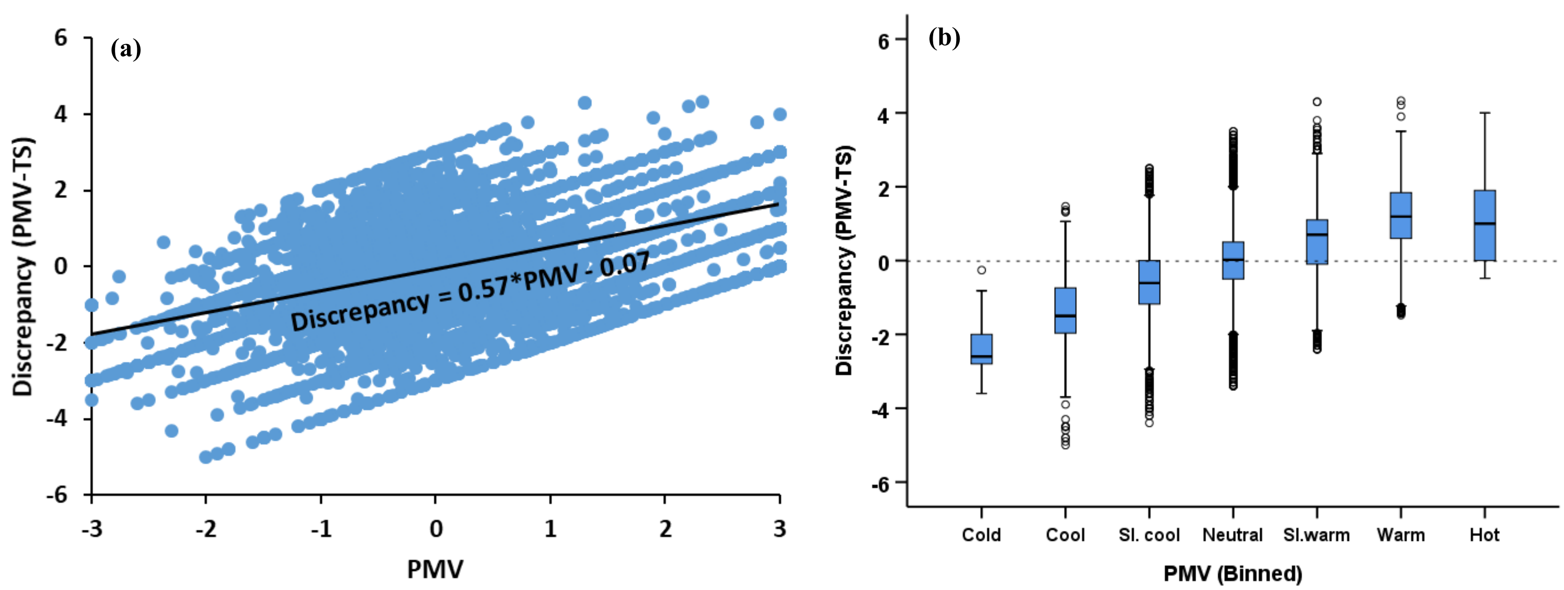
4. Results

This section presents the results related to the accuracy of the PMV model for TS prediction, as well as the effects of the variables involved in the discrepancy based on the extracted samples.

4.1 Accuracy of the PMV model for TS prediction

As people differ in their thermal perceptions, PMV cannot be expected to precisely predict the TS of an individual. The relationship between the PMV and its discrepancy (PMV-TS) is illustrated in Fig. 4. Fig. 4 (a) displays a scatter diagram and a linear relationship of the PMV corresponding to the recorded discrepancy. It can be seen that the discrepancy increases with the increase of the PMV. When the PMV is neutral, the absolute value of the discrepancy is smaller than when the PMV deviates from the neutral. This means that the perceived TS is not as hot or cold as it is predicted from the PMV model in hot or cold environments.

The PMV was binned into 7 categories in Fig. 4 (b): Cold (PMV ≤ -2.5), Cool (-2.5 < PMV ≤ -1.5), Slightly cool (-1.5 < PMV ≤ -0.5), Neutral (-0.5 < PMV ≤ 0.5), Slightly warm (0.5 < PMV ≤ 1.5), Warm (1.5 < PMV ≤ 2.5) and Hot (PMV>2.5). After binning the PMV, the overall sample number for each category is 58 (Cold), 467 (Cool), 3405 (Slightly cool), 7956 (Neutral), 3920 (Slightly warm), 1007 (Warm) and 668 (Hot). The magnitude of the discrepancy quantifies the success of PMV in predicting TS. The median of each boxplot is -2.6, -1.5, -0.61, 0.02, 0.7, 1.19 and 1. The medians are smaller at "Slightly cool", "Neutral" and "Slightly warm" environments. Thus, the PMV model is better for TS prediction under these three circumstances. The ISO 7730 [14] also recommends that the PMV range should be used within ±2 to ensure a higher accuracy. The discrepancy is bigger in "Cold" and "Cool" environments than in "Hot" and "Warm" environments, which indicates that the PMV model is better in predicting "Hot" and "Warm" conditions than in that in "Cold" and "Cool" environments. This could be explained by the access to greater adaptive options for most building occupants in a cooler environment e.g. clothing modification. Thus, they do not feel as cold as predicted from the PMV model.



(a) Scatter plot of PMV corresponding to discrepancy

(b) Boxplots of Binned PMV corresponding to discrepancy

Fig. 4 The correlation between PMV and its discrepancy (PMV-TS)

4.2 The effect of variables on the discrepancy

This section discusses the influence of season, climate, building type, age group and gender on the prediction of the discrepancy based on the extracted samples. The ANOVA test results ($P < 0.001$) indicated that the discrepancy was significantly different for each category. The boxplots categorized by the different variables are displayed in Fig. 5 (a-e). The CA maps and MCA map illustrating the distance between each variable and the discrepancy are shown in Fig. 6 (a-e) and Fig. 7. The origins of the maps correspond to the centroid of each variable. The longer distance from the attributes to the origin, the more discriminating it is. The results are discussed in the following subsections.

4.2.1 Season

Fig. 5 (a) shows the boxplots of the discrepancy observation corresponding to the four seasons. The medians of the discrepancy are -0.115 for spring, 0.09 for summer, -0.58 for autumn, and 0.2 for winter. The negative medians imply that on average the perceived TS is warmer than predicted from the classic PMV model, while the positive medians imply a cooler feedback from the ASHRAE vote when compared with the PMV model. It is apparent that the PMV underestimates the actual TS in autumn. The maximum difference of the discrepancy is 0.78, which occurs between winter and autumn.

The CA map in Fig. 6 (a) demonstrates the distance between season and the categorized discrepancy. Autumn is a highly discriminating attribute indicated by its distance from the origin. It is closer to category 1, category 2 and category 3 ($PMV\text{-}TS \leq -1$), leading to a larger negative median value. The results reveal that autumn has a big impact on occupants' TS. Although spring is also scattered from the origin, it is closer to category 4 and category 5 ($-1 < PMV\text{-}TS \leq 1$).

4.2.2 Climate

The boxplots of the discrepancy observation corresponding to the climate are displayed in Fig. 5 (b). The difference caused by climate is more noticeable when compared with other variables. The medians for the Am, Aw, Bsh, Cfa, Cfb, Cwa and Cwb are 0.1, 0.36, 0.5, -0.4, -0.64, 0.6 and 0.2. The maximum difference is 1.24, which occurs between Cwa and Cfb. It should be noted that the impact of the similar climates on the discrepancy is similar. For example, the tropical climates (Am and Aw) both result in a cooler TS.

On the other hand, the CA map in Fig. 6 (b) indicates the different climates are significantly scattered. Cfa and Cfb are clustered around category 1, 2 and 3 (PMV-TS $\leq$ -1), leading to negative medians. On the contrary, Aw, Bsh and Cwa are clustered around 6, category 7 and 8 (PMV-TS > 1), and thus positive medians are observed.

4.2.3 Building type

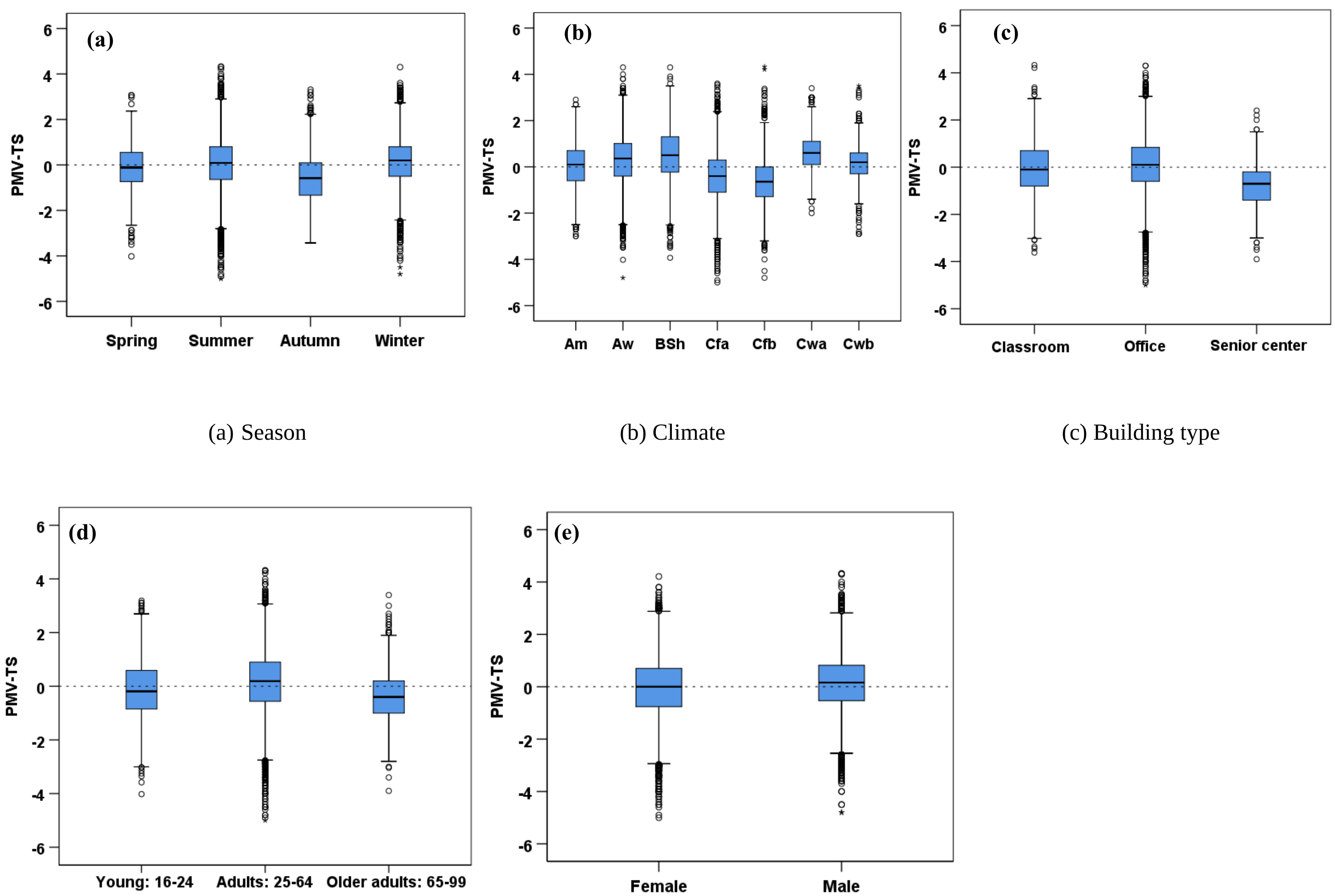
As can be seen from Fig. 5 (c), the influence of classroom and office building on the discrepancy is small, with medians of -0.1 and 0.1, respectively. However, the influence of senior center is more obvious, with a median of -0.7, which means that the perceived thermal comfort is warmer than predicted from the PMV model. The CA map in Fig. 6 (c) shows that the senior center is highly differentiated, reflected in the distance between the senior center and the origin. It is close to category 1, category 2 and category 3. Therefore, a negative median is observed. The classroom and office building are centered around the origin, which is in accordance with the small medians.

4.2.4 Age group

Fig. 5 (d) displays the boxplots of the discrepancy observation corresponding to the age group. The medians for discrepancy are -0.19, 0.19, -0.4 for Young: 16-24, Adult: 25-64 and Older adults: 65-99. The group difference between the Young: 16-24 and Adult: 25-64 is minor when compared with the Older adults: 65-99. The distance between the senior group and the origin in Fig. 6 (d) also indicated that the older group is a more discriminating variable.

4.2.5 Gender

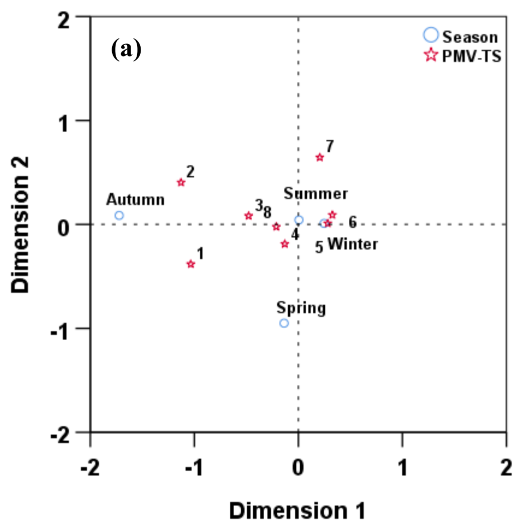
The gender does not have a significant influence on the discrepancy. The median values for discrepancy caused by female (0) and male (0.16) are similar. Fig. 6 (e) clearly demonstrates that female and male are clustered around centroid, and thus the deviation between the two attributes is small. The male occupants are clustered among point 6, point 7 and point 8. The map indicates that the male occupants tend to feel slightly warmer than PMV prediction.



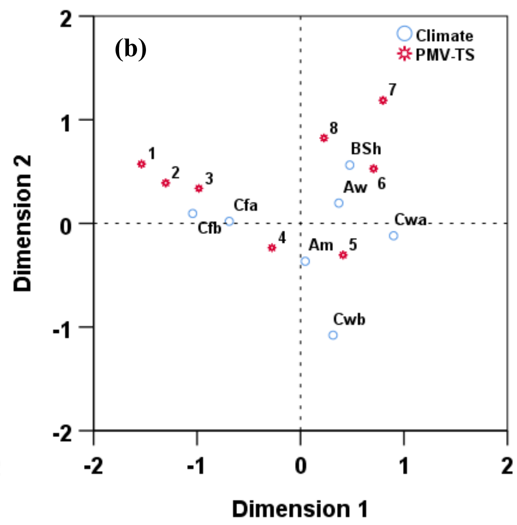
(a) Season (b) Climate (c) Building type

(d) Age group (e) Gender

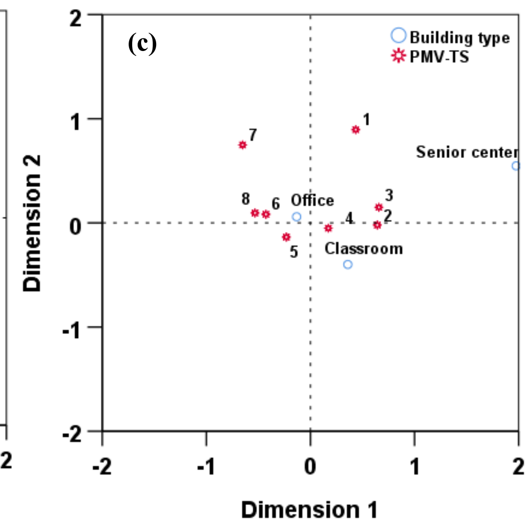
Fig. 5 Boxplots of the discrepancy (PMV-TS) categorized by (a) Season, (b) Climate, (c) Building type, (d) Age group, (e) Gender.



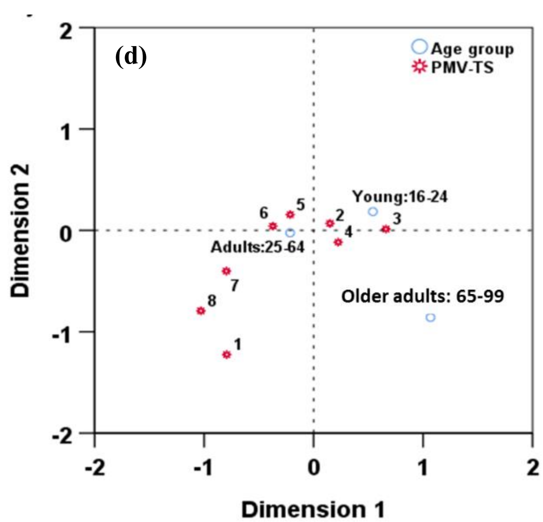
(a) Season



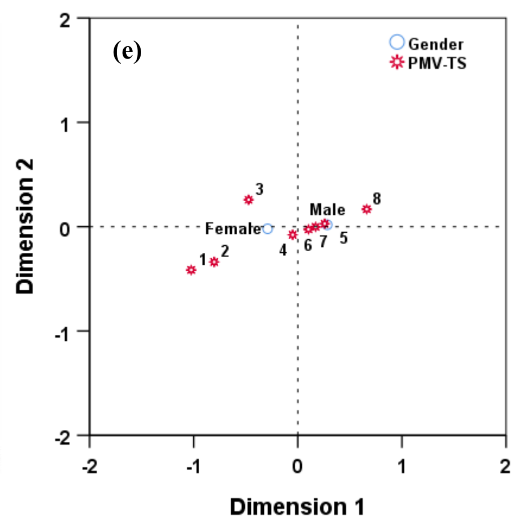
(b) Climate



(c) Building type



(d) Age group



(e) Gender

Fig. 6 Correspondence analysis maps of the discrepancy (PMV-TS) and (a) Season, (b) Climate, (c) Building type, (d) Age group, (e) Gender.

4.2.6 Overall analysis

The results in Fig. 5 and Fig. 6 show that the five categorical variables (season, climate, building type, age group and gender) investigated had an impact on the discrepancy. In order to examine the influence of those variables together, the five variables are mapped into one MCA in Fig. 7. As can be seen from the figure, the climate and building type are more scattered than the other variables, which indicates the two variables are more differentiate than the other variables. The gender is closely located to the origin. The discrepancy categories (from 1 to 8) are primarily clustered by the climate. Thus, the climate has the most significant influence on the discrepancy.

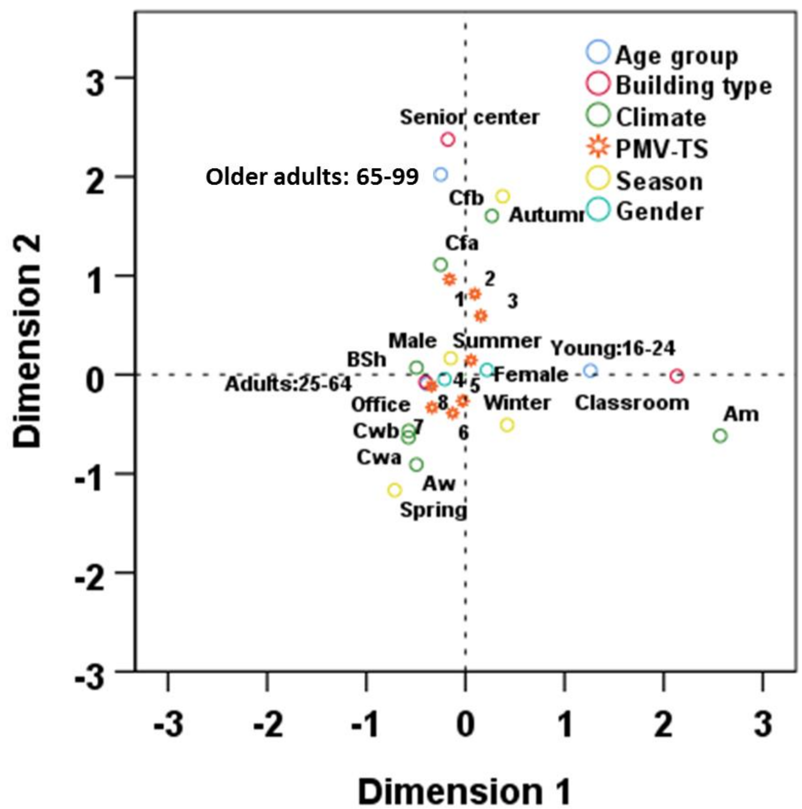


Fig. 7 Multiple correspondence analysis map

5. Improvement in the PMV model

As the PMV model is an aggregated model developed to predict the average TS of a large population, unsurprisingly, its accuracy for predicting individual's thermal comfort response is not high. In fact, for occupants exposed to the same space, sharing the same environment, their thermal comfort perception varies. However, it should be able to predict the mean comfort vote of a large population. The medians shown in Fig. 5 are deviate from zero, and thus there are other factors contributing to the discrepancy, which are not accounted in the classic PMV model. This section attempts to quantify the influence of these factors so that the PMV can better represent the TS of a group of people.

5.1 Adaptative model and adaptation table

A regression model in equation (3) was developed to account for the impact of the categorical variables (season, climate, building type, age group and gender) on the discrepancy.

$$PMV - TS = \beta_0' + \beta_1' Season + \beta_2' Climate + \beta_3' Buildingtype + \beta_4' Agegroup + \beta_5' Gender + \varepsilon \tag{3}$$

Where β_0', β_1', β_2', β_3', β_4', β_5' are coefficients for constant, season, climate, building type, age group and gender. ε is the error term. The categorical variables were then dummy coded. The sample data were fitted into the model ($P < 0.001$). The target was to reduce the difference between PMV prediction and TS from the occupants' feedback. The results are shown in Table 2. Based on the results, we proposed an adapted PMV (PMV_a) model in equations (4). As the range of TS is from -3 to 3, PMVa should also meet the requirement in equation (5).

$$PMV_a = PMV - \beta_0 - \beta_1 Season - \beta_2 Climate - \beta_3 Buildingtype - \beta_4 Agegroup - \beta_5 Gender \tag{4}$$

$$-3 \le PMV_a \le 3 \tag{5}$$

Where β_0, β_1, β_2, β_3, β_4, and β_5 are coefficients for constant, season, climate, building type, age group and gender. The corresponding values are displayed in Table 2. For example, in Summer, in Am climate, in classroom for Young: 16-24 male occupants, the PMVa = PMV -0.362 - 0 - (-0.594) - 0.391-(-0.092) - 0.087 = PMV – 0.154. The standard error of the coefficient is the standard deviation of the coefficient, which measures how precise the coefficient is. Compared with the coefficient, the standard error is small, which indicates the accuracy of the model is high. PMV is the value calculated from Fanger's PMV model. As it can be seen from Table 2, the influence of climate and building type on TS are more significant while the influence of gender is minor. The maximum difference for climate and building type are 1.324 and 0.749.

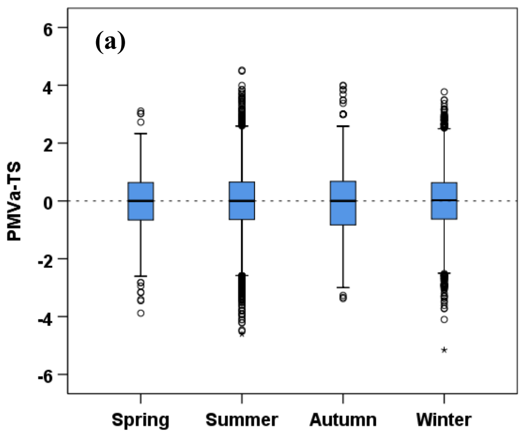
Table 2 Adaptation table for PMV model

		coefficient	Standard error	p
Constant	β_0	0.362	0.019	P < 0.001
Season	β_1-Spring	-0.408	0.044	P < 0.001
	β_1-Autumn	-0.586	0.052	P < 0.001
	β_1 −Winter	-0.093	0.019	P < 0.001
Climate	β_2-Am	-0.594	0.068	P < 0.001
	β_2-BSh	0.170	0.028	P < 0.001
	β_2-Cfa	-0.756	0.025	P < 0.001
	β_2-Cfb	-1.032	0.032	P < 0.001
	β_2-Cwa	0.294	0.032	P < 0.001
	β_2-Cwb	-0.222	0.032	P < 0.001
Buildingtype	β_3-Classroom	0.391	0.057	P < 0.001
	β_3-Senior center	-0.358	0.068	P < 0.001
Agegroup	β_4-Older adults:65-99	0.249	0.063	P < 0.001
	β_4-Young:16-24	-0.092	0.024	P < 0.001
Gender	β_5-Male	0.087	0.016	P < 0.001

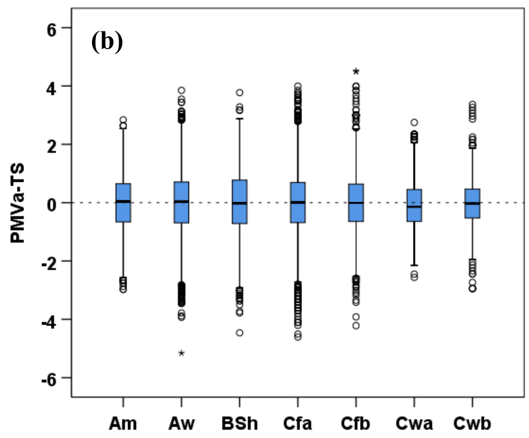
The reference categories are Adult: 25-64; Aw; Female, Summer, Office, which are equal to 0 in the equation.

5.2 Evaluation of the adapted discrepancy

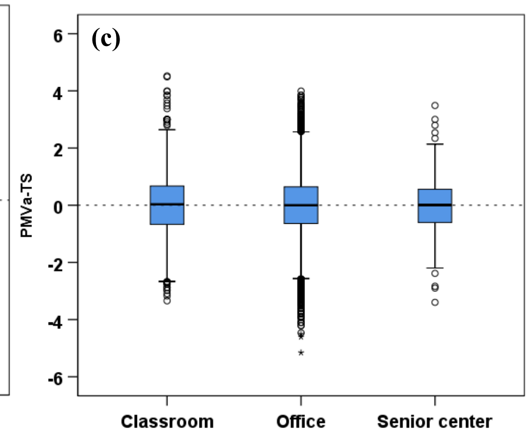
The extracted samples in Fig. 1 together with equations (4)-(5) and the results from Table 2 were used to obtain the adapted discrepancy (PMVa – TS). Boxplots in Fig. 8 show the adapted discrepancy with respect to season, climate, building type, age group and gender. As shown in the boxplots, the median of each attribute is ‘0’ or near ‘0’, which indicates that, on average, the PMVa is free from serious bias. Thus, it is concluded that the PMVa can be used to predict the mean TS of a large population.



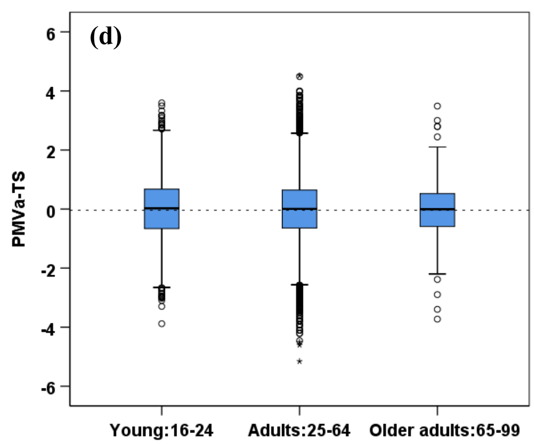
(a) Season



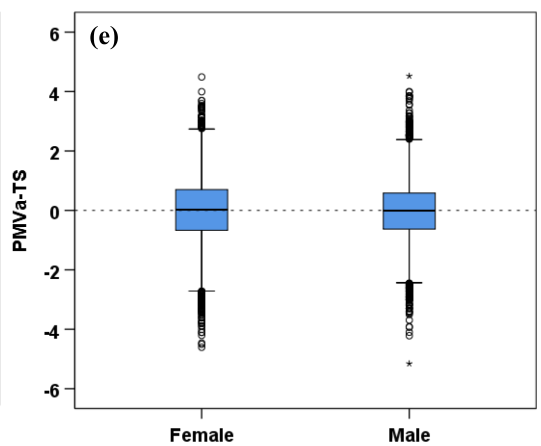
(b) Climate



(c) Building type



(d) Age group



(e) Gender

Fig. 8 Boxplot of the discrepancy (PMV_a - TS) categorized by (a) Season, (b) Climate, (c) Building type, (d) Age group, (e) Gender.

After adaptation, it is also important to ensure the accuracy of PMVa is the same or even better than the classic PMV model when used for individual prediction. To compare the overall accuracy of the PMVa with the classic PMV, the adapted discrepancies and original discrepancies were pooled into distributions in Fig. 9 (a) and Fig. 9 (b), representing 17841 discrepancies for each. The original discrepancy in Fig. 9 (b) follows a normal distribution, with a mean of 0.06 scale units and a standard deviation of 1.13 scale units. The mean value demonstrates that the PMV as a whole is slightly higher than the actual ASHRAE vote by 0.06 scale units, which indicates that on average the discrepancy is small. The distribution of the adapted discrepancy is displayed in Fig. 9 (a), which also follows a normal distribution, with a mean of 0 and a standard deviation of 1.04 scale units. Both the mean value and the standard deviation are decreased. Therefore, the overall accuracy of the adaptive model used for thermal comfort vote prediction has been improved.

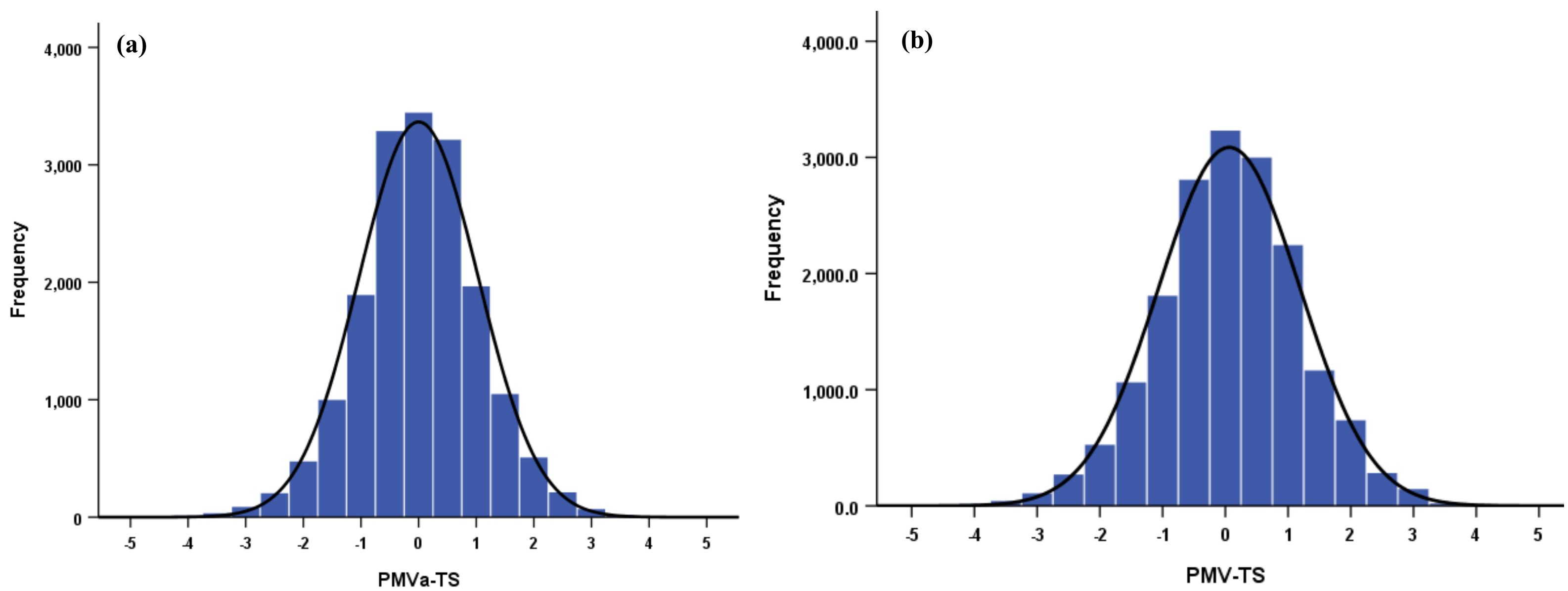


Fig. 9 Frequency distribution of (a) adapted discrepancy and (b) original discrepancy

The PMVa and TS are binned in the same way as the PMV. The PMVa was binned into 7 categories: Cold (PMVa ≤ -2.5), Cool (-2.5 < PMVa ≤ -1.5), Slightly cool (-1.5 < PMVa ≤ -0.5), Neutral (-0.5 < PMVa ≤ 0.5), Slightly warm (0.5 < PMVa ≤ 1.5), Warm (1.5 < PMVa ≤ 2.5) and Hot (PMVa > 2.5). The TS was also binned into 7 categories: Cold (TS ≤ -2.5), Cool (-2.5 < TS ≤ -1.5), Slightly cool (-1.5 < TS ≤ -0.5), Neutral (-0.5 < TS ≤ 0.5), Slightly warm (0.5 < TS ≤ 1.5), Warm (1.5 < TS ≤ 2.5) and Hot (TS > 2.5). After binning the TS, the sample number for each binned TS category is 156 (Cold), 756 (Cool), 3144 (Slightly cool), 8216 (Neutral), 3387 (Slightly warm), 1373 (Warm) and 449 (Hot). The binned PMVa and binned PMV with respect to the binned TS are illustrated in Fig. 10, with the ratio of correct prediction for each category and overall prediction accuracy shown in the top of the figure. When comparing Fig. 10 (a) with Fig. 10 (b), the accuracy for PMVa in “Cool”, “Sl. cool”, “Neutral”, “Sl. warm”, “Warm” is higher than the PMV model. More specifically, in “Neutral” environment, the accuracy has increased by 2%. The most significant increases are observed in “Sl. cool” and “Warm” environment, increasing from 23% and 12% to 33% and 31% respectively. In addition, the overall accuracy for PMVa is 3% higher than PMV model, which indicates the PMVa model is better in predicting TS.

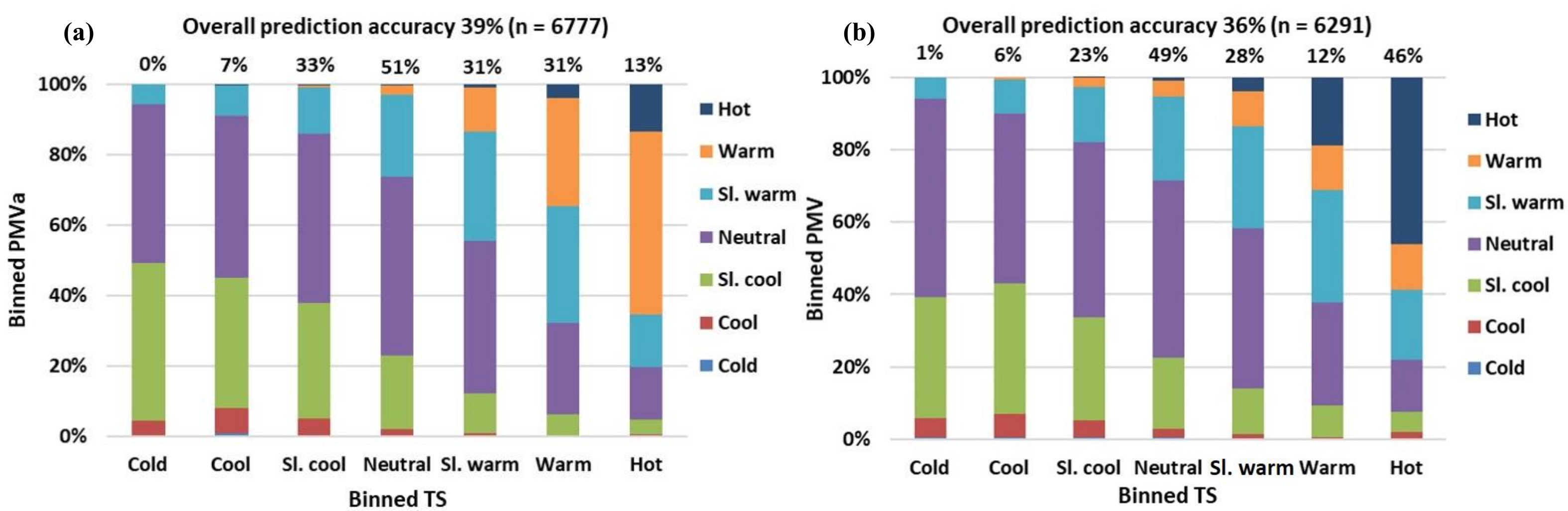


Fig. 10 (a) Binned PMVa and (b) binned PMV distribution corresponding to binned TS

6. Discussion

The PMV model was developed from static heat balance between a human body and its surrounding environment. It illustrates the relationship between the average TS of a large population and the surrounding indoor environment, which assumed that the TS is exclusively affected by four environmental and two personal factors [60]. The occupants are regarded as passive recipients of their thermal environment [33]. In reality, they actively interact with their thermal environment to adapt their own thermal preferences. Demographic and contextual factors are believed to modify the occupants’ thermal preferences and expectations through behavioural, psychological and physiological adjustments [33]. In particular, the behavioural adaptation offers the biggest opportunity for the occupants to play an active role in maintaining thermal comfort.

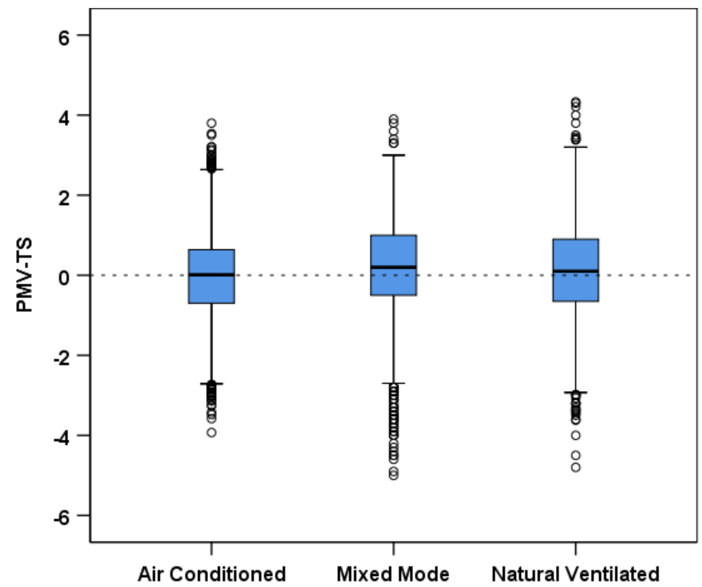


Fig. 11 The effect of cooling strategies at building level on original discrepancy

The literature review in Section 2 and the analysis in Section 4 discussed the effect of season, climate, building type, age group and gender on the discrepancy between PMV and TS. These variables are not used as predictors in the PMV model while evaluating the indoor thermal comfort. The proposed adaptive PMV (PMVa) is able to account for these variables. Although the effect of ventilation system usage (air-conditioned or naturally ventilated) in buildings is recorded [17] [61], it is not used as an indicator in this study. The ventilation information from the building level was included in the database, but it is difficult to identify whether or not the device was on when the subjects were filling the surveys and how often it was used. Fig. 11 shows the original discrepancy of the samples collected from the summer season with respect to the cooling strategies. The medians for the different control strategies are very close to "0". We believe more information is required to identify the effect of air conditioning on PMV accuracy. Furthermore, the use of HVAC systems can be inferred from the climate together with season and building type. For example, the office buildings in tropical areas are normally equipped with air conditioning facilities while in cold area they are equipped with heating devices.

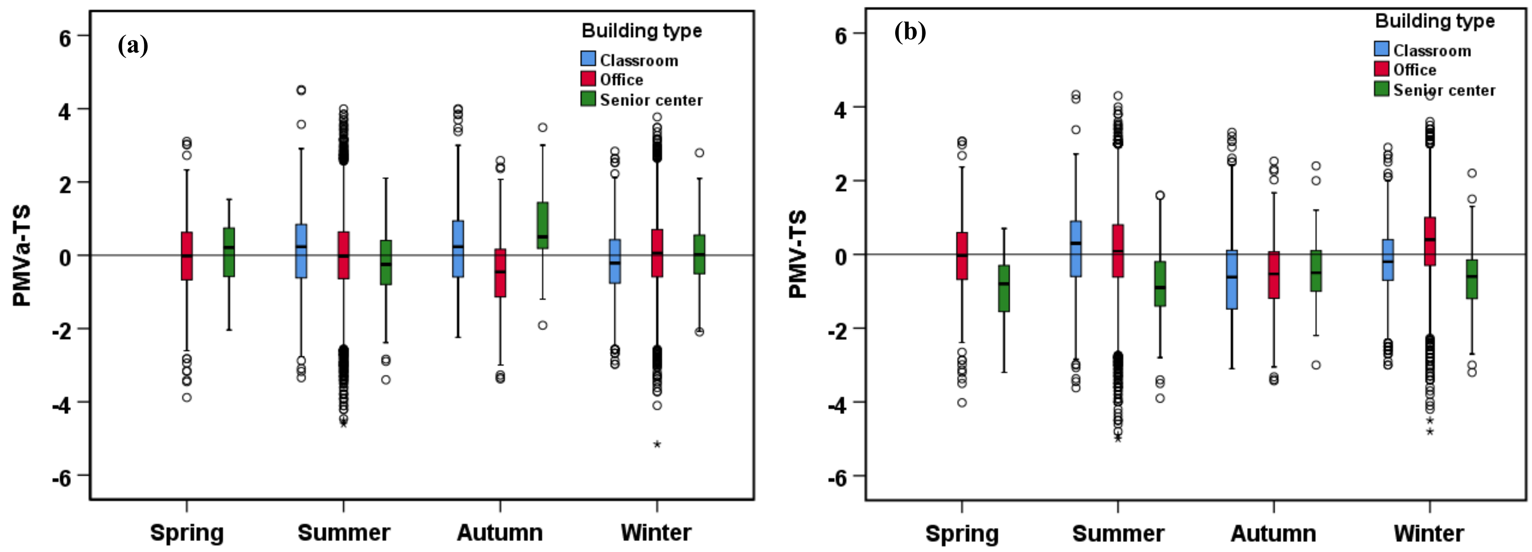


Fig. 12 Boxplots of adapted discrepancy (a) and original discrepancy (b) in different types of buildings and seasons.

Boxplots in Fig. 5 and Fig. 8 compared the medians of the discrepancies with respect to one specific variable. Fig. 12 and Fig. 13 discuss the interaction between the variables. Fig. 12 compared the medians of the adapted discrepancy with the original discrepancy for different building types and seasons. After adaptation, the medians are closer to '0'. The boxplots with significant deviation from '0' for the adapted discrepancy are spring senior center (41 samples), summer senior center (181 samples), autumn office (233 samples) and autumn senior center (41 samples). As discussed in Section 3.1, in order to achieve a 95% confidence, the sample size should be larger than 383. Thus, the significant deviations may be caused by individual differences, while the limited number of observations cannot be scaled to a large population.

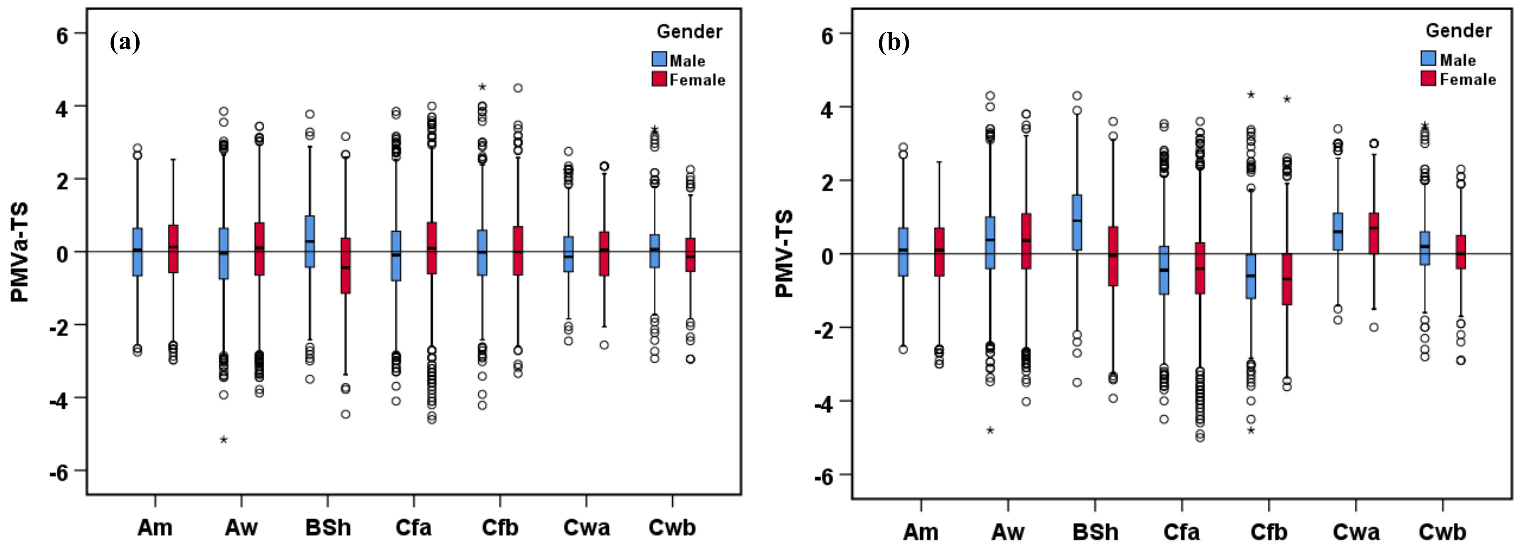


Fig. 13 Boxplots of adapted discrepancy (a) and original discrepancy (b) in different climates and gender.

Boxplots in Fig. 13 compared the medians of adapted discrepancy with the original discrepancy for different climates and gender. The sample size of each attribute is larger than 383 except for female subjects from climate Cwb (345 samples). When compared with the original discrepancy, the medians of the adapted discrepancy are much closer to '0' for male and female participants from the 7 different climates.

It can be concluded from Fig. 12 and Fig. 13 that the universal application of the Fanger's model without any modification is deemed as inappropriate. Researchers proposed multiple adaptive thermal comfort models to improve the prediction accuracy. The models are criticised for their inherent complexity which makes them difficult to be applied again by others [62]. This study is the first one to attempt to quantify the effect of different attributes on the TS of a large population. The model proposed is an extension of the PMV model, which is easy to be utilized by other researchers. We believe this model will be useful to investigate the indoor comfort temperature, which facilitates building energy optimization. The authors also argue that the adaptation table should be incorporated into the current standards to account for the influence of season, climate, building type, age group and gender on TS. Conversely, standards should be adapted to different climates to account for the effect of the categorical variables.

The Fanger's model was developed without considering the influences of the categorical variables. Nevertheless, when it was used for predicting TS of the extracted 17481 samples, the discrepancy is small, which is 0.06 scale unit larger than ASHRAE vote. Based on the results of this study, the authors provide a potential explanation: according to van Hoof [16]: "Fanger derived his comfort equation based on college-age students exposed to steady-state conditions in a climate chamber for a 3 hours period in winter at sea level (1,013 hPa) while wearing standardized clothing and performing standardized activities". According to Alfano et al. [63], extensive experimental studies were carried out in Kansas State University (KSU), which formed the basis of Fanger's finding. Later, a substantial amount of data (including data from Danmarks Tekniske Universitet (DTU)) were integrated the datasets. Fig. 14 shows the calculation of PMVa for Fanger's datasets. The difference between PMVa and PMV for KSU is small, while the difference for DTU is slightly higher. Considering that Fanger's PMV was developed in well-controlled environments at steady-state without local discomfort (PMV=0) [16], and the potential of data collected from other climate, it is reasonable that even when data from DTU were merged to the dataset, the discrepancy for Fanger's model is still small.

$$PMV_a = PMV - \beta_0 - \beta_1 Season - \beta_2 Climate - \beta_3 Buildingtype - \beta_4 Agegroup - \beta_5\ Gender$$

	β_0	β_1	β_2	β_3	β_4	β_5
KSU	Constant 0.362	Winter -0.093	Cfa -0.756	Classroom 0.391	College-age -0.092	Male/female 0.087/0

$$PMV_a = PMV - 0.362 - (-0.093) - (-0.756) - 0.391 - (-0.092) - 0.087/0$$

Male: PMV_a=PMV+0.188

Female: PMV_a=PMV+0.101

	β_0	β_1	β_2	β_3	β_4	β_5
DTU	Constant 0.362	Winter/summer -0.093/0	Cfb -1.032	Classroom 0.391	College-age -0.092	Male/female 0.087/0

$$PMV_a = PMV - 0.362 - (-0.093) - (-1.032) - 0.391 - (-0.092) - 0.087/0$$

Male in winter: PMV_a=PMV+0.377 **Male in summer:** PMV_a=PMV+0.284

Female in winter: PMV_a=PMV+0.464 **Female in summer:** PMV_a=PMV+0.371

Fig. 14 Calculation of PMVa for Fanger's experiments

There are also limitations for the use of the adapted model. Due to a lot of missing information in the database, some demographic and contextual factors, such as educational background, ethnicity, body mass and social status, which may influence thermal sensation are not taken into consideration in the adapted model. With current advances in smart devices and Internet of Things (IoT) in the built environment, understanding the causes of individual difference towards perceived thermal comfort has gained increased popularity. However, this study investigates the occupants' TS as an aggregated model of a group of people, which does not differentiate individual differences. The prediction performance is poor when applied to individuals due to large variations among the occupants. Thus, the model cannot be applied to understand the specific comfort requirements of an individual occupant and characterize a set of conditions to meet personalised conditioning in a given space. The standards should be adapted to different climates.

7. Conclusions

The PMV model has been widely used to predict occupants' thermal comfort. The discrepancy between PMV and TS has been noted and discussed since the model was developed. Extensive studies have investigated the influence of different factors on TS through surveys or field experiments. Understanding the impacts not only contributes to our knowledge on how occupants interact with the built environment, it also provides guidance on how to operate and manage buildings to ensure comfort and health considerations are met, while optimizing energy usage. This study leverages on a global thermal comfort database to quantify the influences of season, climate, building type, age group and gender on the discrepancy. Results indicate that the impacts of climate and building type on the discrepancy are more noticeable than the other variables. An adaptive model was proposed to reduce the discrepancy by the five variables and an adaptation table was generated. The maximum difference for climate and building type are 1.324 and 0.749, respectively. After adaptation, the median of each attribute is '0' or near '0', which indicates that, on average, the PMVa is free from serious bias. The prediction accuracy of the model used for individual TS was improved from 36% to 39%.

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Declarations of interest

None.

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