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Analysis of the accuracy on PMV – PPD model using the ASHRAE Global Thermal Comfort Database II

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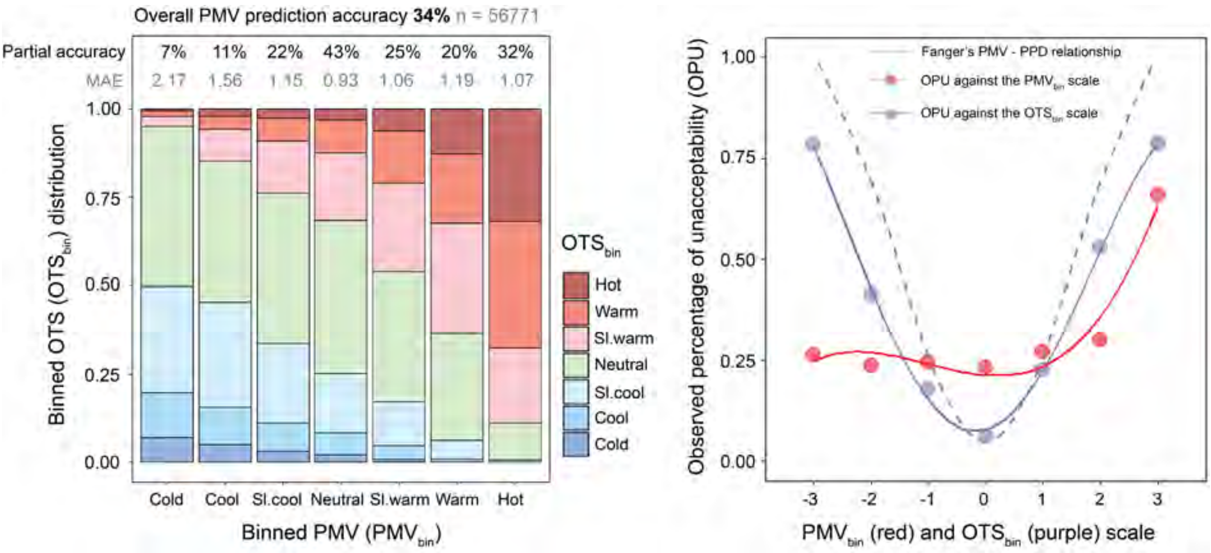
Abstract

The predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD) are the most widely used thermal comfort indices. Yet, their performance remains a contested topic. The ASHRAE Global Thermal Comfort Database II, the largest of its kind, was used to evaluate the prediction accuracy of the PMV/PPD model. We focused on: (i) the accuracy of PMV in predicting both observed thermal sensation (OTS) or observed mean vote (OMV) and (ii) comparing the PMV-PPD relationship with binned OTS – observed percentage of unacceptability (OPU). The accuracy of PMV in predicting OTS was only 34%, meaning that the thermal sensation is incorrectly predicted two out of three times. PMV had a mean absolute error of one unit on the thermal sensation scale and its accuracy decreased towards the ends of the thermal sensation scale. The accuracy of PMV was similarly low for air-conditioned, naturally ventilated and mixed-mode buildings. In addition, the PPD was not able to predict the dissatisfaction rate. If the PMV model would perfectly predict thermal sensation, then PPD accuracy is higher close to neutrality but it would overestimate dissatisfaction by approximately 15-25% outside of it. Furthermore, PMV-PPD accuracy varied strongly between ventilation strategies, building types and climate groups. These findings demonstrate the low prediction accuracy of the PMV–PPD model, indicating the need to develop high prediction accuracy thermal comfort models. For demonstration, we developed a simple thermal prediction model just based on air temperature and its accuracy, for this database, was higher than PMV.

Keywords: Accuracy, ASHRAE Global Thermal Comfort Database II, PMV–PPD model, Prediction, Thermal comfort

Graphical Abstract



1 Introduction

The model developed by Fanger to predict thermal comfort in steady-state conditions is based on climate chamber experiments with 1396 subjects, mainly college-aged students [1,2]. The model outputs two indices: predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD), which respectively refer to occupants' mean thermal sensation vote and the percent of people voting ≥ 2 or ≤ -2 on the thermal sensation scale (i.e., there is an assumption made between thermal sensation and satisfaction). The PMV-PPD model is a widely used design tool incorporated in thermal comfort standards [3–5] that suggest it applies equally to different building types (schools, commercial, hospitals, etc.) and climate. Nevertheless, the accuracy of PMV-PPD model in predicting thermal comfort has been questioned through field studies in real buildings [2,6] as well as in laboratory studies [7–10].

1.1 Validation methods and accuracy of the PMV–PPD model

There are three common methods to assess the prediction accuracy of the PMV-PPD model. The first method graphs the linear relationship between the predicted (PMV or PPD) and observed (thermal sensation or percent of dissatisfied) votes. With this method, the model performance improves as the slope of the regression approaches 1 and the intercept nears 0 [11–13]. Along with the slope and intercept, the coefficient of determination (r^2) and the error terms between the predicted and observed values are used as metrics of model accuracy. The linear relationship between subject's mean thermal sensation and PMV has been shown to vary significantly between country, building types, ventilation strategy, and season [14]. For example, a steeper slope was found in air-conditioned buildings compared to those operating under natural ventilation, presumably due to the narrower comfort range and higher expectations of occupants in air-conditioned space that is often reported in field studies of thermal comfort. In addition, in the naturally ventilated building, observed thermal neutrality (i.e. mean thermal sensation equal to zero) was found at PMV estimated cooler and warmer conditions respectively in winter and summer seasons. Different methods of analysis such as bin widths for PMV or thermal sensation votes may also affect the performance of the linear regression method.

The second method of evaluating model accuracy involves comparing the relationship between "observed thermal sensation – percentage of dissatisfied (PD)" or "PMV – PD" to the original PMV-PPD model [15]. Despite the "satisfaction" scale being adopted by few researcher, for the large majority of studies thermal dissatisfaction is interpreted using the binary "acceptability" votes defined as the ratio of thermal unacceptability to the total votes at each binned thermal sensation scale [16]. A summary of different field studies by van Hoof et al. showed that PPD was weakly related to PD [15].The PPD model was removed in the latest version of Standard 55 (ASHRAE, 2017) for this reason. In van Hoof et al.'s summary, there was no clear distinction between "observed thermal sensation – PD" and "PMV – PD". These two relationships are the same only if PMV and observed thermal sensation are equal. The difference will be discussed in detail later in this paper. In addition, the acronym "PD" is not well defined in the summary, whether it is evaluated by (i) the assumption related to observed thermal sensation (i.e. $-1 \leq$ sensation $\leq +1$ assumes thermally satisfied, else dissatisfied), (ii) observed percentage of subject's responses in satisfaction/dissatisfaction dichotomous scale or (iii) observed percentage of subject's thermal acceptability. The relation of thermal sensation to dissatisfaction changes with different interpretations of "PD".

The third method, proposed by Humphreys and Nicol [6], evaluates the difference between observed thermal sensation and PMV for each building occupant. According to Humphreys and Nicol, the PMV model could be considered free from bias (i.e. accurate) if the distribution mean of the difference between observed thermal sensation and PMV is within -0.25 and +0.25 units on the thermal sensation scale. This approach seems reasonable given that PMV is also used in a space occupied by a single person. However, PMV was designed to predict the mean sensation vote for a group of occupants (without specifying the minimum valid size of the group), so their evaluation method involves an assumption that PMV is equally reliable for individual predictions as it is for groups of occupants. Using this method, they found that the PMV model was free from bias only at predicted "Neutral" conditions while overestimating subjects' thermal sensation on both the cooler and warmer sides. Although the mean difference is helpful to determine unbiased PMV predictions, it does not provide accuracy measures or error terms within the distribution.

Apart from the direct comparison between PMV-PPD and subjects' thermal sensation and acceptability responses, some studies evaluated the accuracy of Fanger's model by including the physical environment conditions along with survey responses, e.g. comparing the predicted and observed neutral temperature and humidity [12,17,18].

This study will focus on the direct comparison between PMV-PPD and subjective evaluations of thermal comfort.

1.2 Factors leading to discrepancy

The discrepancies between PMV-PPD predictions and subjective votes reported in field studies are often attributed to adaptive opportunities afforded to occupants [12,19]. The adaptive comfort theory encompasses various aspects including acclimatization, habituation, expectation, cultural difference, behavioral adjustment and availability of environmental control [7,19–21]. Further compounding the discrepancies are methodological differences or study limitations (sampling protocol, sensor accuracy, clothing and metabolic rate estimation, etc) and inter-individual differences in thermal preferences and expectations [22]. Although these may be a source of error, it is likely that the most significant component of the discrepancies reported in thermal comfort field studies over the past decades arises from adaptive processes. These adaptive opportunities are influenced by several environmental criteria including ventilation strategies, building types and climate conditions [20].

The PMV-PPD model reportedly performs better in air conditioned (AC) than in naturally ventilated (NV) buildings [12,23,24]. Similar results were found in mixed mode (MM) buildings operating under air conditioned and free running strategies [25]. This could be explained by the availability of thermal control options, and adaptation of clothing and expectations to the environment in NV buildings [26]. However, Humphreys and Nicol suggested that PMV was inaccurate regardless of context, and only performs better in AC buildings because of the narrower range of thermal conditions compared to those found in NV buildings [6].

The PMV model was developed using data from climate chamber tests but has been generalized and applied to almost any building type despite reported discrepancies between predicted and observed comfort. In tightly-controlled laboratory environments, numerous studies had reported different prediction results between PMV and observed thermal sensation [7–10]. In real-world settings, building type may hinder occupants' thermal comfort choices due to adaptive opportunities. People tend to be more dissatisfied with their thermal environment when they are unable to exercise adaptive options [20], and the order of initiation of those control options when restoring thermal comfort was found to differ by building type, such as homes [27] compared with classrooms [16].

Considerations of the influence of prevailing weather or climatic factors are ignored by the PMV-PPD model, which only includes indoor parameters as inputs. Yet, the outdoor temperature was found to exert influence over appraisals of thermal comfort in field studies [28]. It is this finding that led to the proposal of adaptive models based on outdoor temperature [12,29]. Mounting evidence in support of the adaptive principle led Fanger and Toftum to suggest an extended PMV model that included an 'expectancy factor' to address the limitations observed in occupants under non-AC buildings in warm climates [24]. It applies as a fraction to the calculated original PMV value, and adjusts the prediction results closer to the observed mean vote. Nevertheless, the expectancy value has been shown to not only apply to non-AC building in warm climates, but also to different building types and locations [30–33].

1.3 Objectives

Despite the reported discrepancies between the PMV-PPD model and field surveys of occupant comfort, relatively small sample sizes, unique contexts and limited comparison approaches are limitations of these comparisons. Some authors have performed comprehensive literature reviews or meta-analyses of combined results from published works [2,20,34], but these too are limited by (i) limited access to raw data from the original studies, and (ii) inconsistent methods across field studies. Humphreys and Nicol attempted to validate the Fanger model using a large open source thermal comfort database (16,762 samples), but validation focused just on the discrepancy between PMV and observed thermal sensation and the scope of discussion was only available between AC and NV buildings [6]. The recently published ASHRAE Global Thermal Comfort Database II [35], referred to as the Comfort Database hereafter) contains approximately 107,000 records from more than 50 field studies around the world and represents the largest thermal comfort database of its kind. We need to reevaluate the reliability of the PMV- PPD model across multiple contexts (building types, ventilation strategies and climates) using this new resource. The aims of this paper, therefore, are as follows:

- Adopt multiple methods to analyze the prediction accuracy of PMV using observed thermal sensation data in the ASHRAE Global Thermal Comfort Database II;
- Compare the relationship between PMV-PPD and the observed thermal sensation – observed percentage of unacceptability by occupants in real buildings;
- Apply consistent method to evaluate PMV-PPD indices accuracy to subset data across combination of ventilation strategies, building types and climate groups.

2 Methods

We used Comfort Database to evaluate the prediction accuracy of the original PMV-PPD model. In our analysis, the observed thermal sensation (OTS) and observed mean vote (OMV) are, respectively, defined as individual's and group mean thermal sensation vote. Thermal satisfaction is not a common psychometric in field evaluations of thermal comfort and it is not included as a parameter in the Comfort Database. The observed percentage of unacceptability (OPU), defines the ratio of unacceptability to total votes, is used as a proxy to compare with the PPD model. In some analyses where the thermal sensation scale had to be binned in discrete scale, i.e. the binned observed thermal sensation (OTS_{bin}) and binned predicted mean vote (PMV_{bin}), we used the follow binning criteria: Cold < -2.5, -2.5 ≤ Cool < -1.5, -1.5 ≤ Slightly cool < -0.5, -0.5 ≤ Neutral ≤ 0.5, 0.5 < Slightly Warm ≤ 1.5, 1.5 < Warm ≤ 2.5, Hot > 2.5.

We gave particular attention to (i) the overall accuracy of PMV to predict both OTS and OMV and (ii) the PMV-PPD relationship compared with the OTS_{bin}-OPU and PMV_{bin}-OPU relationships. We extended the analysis to examine the same relationships in different building types (office, classroom and housing), ventilation strategies (air-conditioned, naturally ventilated and mixed mode), and climate zones (Köppen-Geiger climate classification [36]). Despite the availability of other building types in the database (e.g. elderly home, retail, restaurant, etc.), we considered only the three dominant building types for this analysis. The Köppen -Geiger classification system has five major categories including Tropical (group A), Arid (group B), Temperate (group C), Continental (group D) and Polar (group E); there are no data for group E in the database so it was not included in the analysis. We subset the database by ventilation strategy, building type and climate, and excluded any resulting set with a sample size of OTS less than 500 from further analysis to ensure reliability. This value is estimated by the simple sample size (*SS*) calculation equation below:

$$SS = \frac{Z^2 \cdot SD \cdot (1-SD)}{E^2} \tag{1}$$

where, Z-score (*Z*) = 1.96 (95% confidence level for standard normal distribution), standard deviation (*SD*) = 0.5, margin of error (*E*) = 0.05. The calculated sample size for the present analysis is 384. We added an extra 15% margin for nonparametric calculation based on the rule of thumb by [37]. The required sample size with non-parametric determination was therefore 442, and we decided to round-up to 500 in each data subset to ensure robust results.

All statistical analyses were performed in R (R Development Core Team, 2012; version 3.2.3). We used the mean absolute error (MAE) to measure and compare the difference between the observed and predicted indices, and the Kolmogorov-Smirnov test (KS test) to assess the similarity of two distributions, where $p < 0.05$ indicates a significant difference.

3 Overall database analysis

From the 107,583 records in the Comfort Database, 91,789 included OTS and 56,771 had a corresponding PMV. It is noted the PMV values presented in the Comfort Database were re-calculated using the ISO 7730 standard to ensure consistency. After binning OTS (OTS_{bin}) the overall sample count was 1136 (Cold), 3279 (Cool), 9419 (Slightly cool), 23035 (Neutral), 11301 (Slightly warm), 5994 (Warm) and 2607 (Hot). The sample distribution of OTS_{bin} was not significantly different from a normal distribution ($p > 0.8$, KS-test), and the count of "Neutral" vote contributed 42% of all data.

3.1 Accuracy of the PMV model

The main findings of the present analysis of the performance of the PMV model in predicting thermal sensation are shown in Figure 1. Figure 1a plots the linear relationship of OTS against PMV for each individual case. It demonstrates the widespread of OTS responses, from -3 to 3, across the full PMV scale. The mean absolute error (MAE) of 1.02 means the PMV is, on average, one thermal sensation scale unit different to the OTS of subjects. This is similar to the 1 scale unit bias reported by Humphreys and Nicol [6] and 1.26 scale unit bias observed by Doherty and Arens [8]. In addition, an extremely poor linear relationship between OTS and PMV was found (R^2=0.08), meaning the PMV model was able to explain only 8% of the variance in OTS in the Comfort Database. The slope of the regression line (purple) is less steep than the ideal prediction (yellow) with an almost zero or neutral intercept. According to the regression line, the minimum (-3) and maximum (+3) ends of the PMV scale had a OTS value of -1 and +1.4 respectively. So when PMV predicted "Cold" or "Hot" sensations, the average occupant felt only "Slightly cool" or "Slightly warm".

The poor performance of the PMV model in Figure 1a is based on an analysis of individual sensation votes. However, the PMV model was designed to predict the mean sensation of a group of occupants in the same thermal environment. The boxplot in Figure 1b shows the OMV for each binned PMV (PMV_{bin}). The sample count of OTS (n) is shown along the top. Given that the space is thermally equivalent from the point of view of PMV model, we would expect a good match between PMV_{bin} and OMV. The equation of the linear regression (purple) of OMV and PMV_{bin} is given by:

$$OMV = 0.41 \times PMV_{bin} + 0.16 \qquad (2)$$

Both the slope and the intercept of the regression based on group mean vote is similar to the analysis of individual occupant data presented earlier shown in Figure 1a. The slope of the linear relationship of 0.41 is similar to the expectancy factor proposed by Fanger and Toftum for tropical climates [24]. However, field data from tropical climates only account for 19% of the Comfort Database, suggesting that a similar correction could be universally applied when using the PMV model. Furthermore, a comparison of the OMV and PMV_{bin} had a mean absolute error of 1.06 with significantly different variance (p=0.05, F-test) compared with the ideal prediction (yellow crosses). All OMV values were found within the oft-cited neutral range between slightly cool (-1) and slightly warm (+1) with the exception of the “Hot” PMV_{bin} condition. In both Figure 1a and 1b, the PMV model was found to match OMV only at prediction of neutrality (PMV_{bin} = 0) whilst overestimating on both the cool and warm sides. This suggests that people feel neutral or slightly cool/warm in a larger range of conditions than what is predicted by PMV, with thermal sensation rarely extending out to the cold or hot ends in the sample buildings. The tendency of the PMV model to overestimate thermal sensation, and therefore dissatisfaction, promotes a narrower range of temperatures that carry significant energy penalties [38]. Figure 1b also shows that there is a lack of symmetry in the relationship between PMV_{bin} and OMV for both the warm side and cool sides. In “Cold” conditions people more commonly voted slightly cool or neutral, while in “Hot” conditions more often voted slightly warm to hot. This could perhaps be explained by the greater adaptive options available in cooler temperature to most building occupants e.g. clothing modifications.

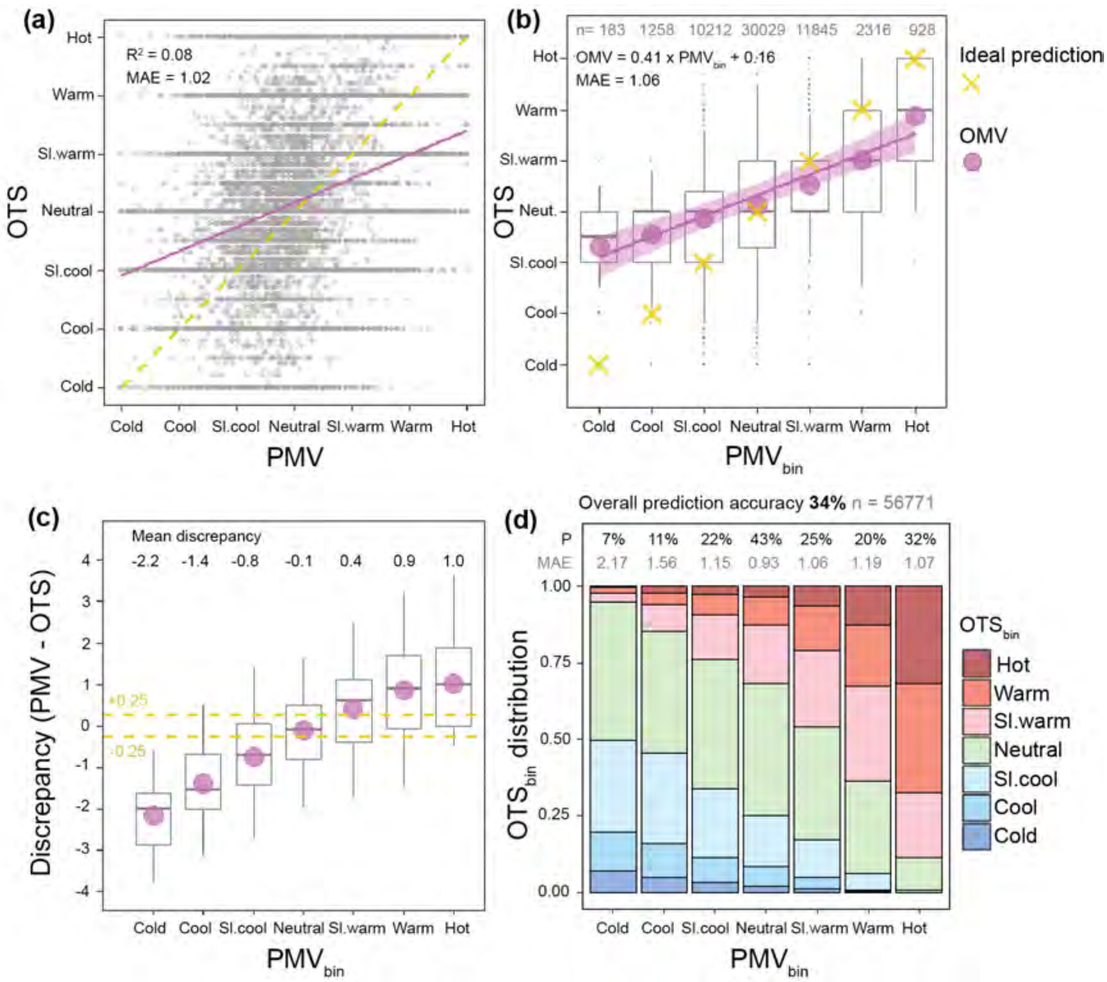


Figure 1 Overall analysis between OTS and PMV. (a) Raw data plot between OTS and PMV; (b) boxplot of OTS against binned PMV (PMV_{bin}) and the OMV to PMV_{bin} linear relationship. In each box, the dot is the mean, the central mark is the median, the box limits denote 25th and 75th percentiles, and the whiskers extend to ±1.5 times the inter-quartile range; (c) boxplot of discrepancy (PMV – OTS) against PMV_{bin} with mean discrepancy (purple dot) at each PMV_{bin}; (d) binned OTS (OTS_{bin}) portions at each PMV_{bin} scale with overall prediction accuracy, and prediction accuracy (P) and mean absolute error (MAE) at each PMV_{bin} scale.

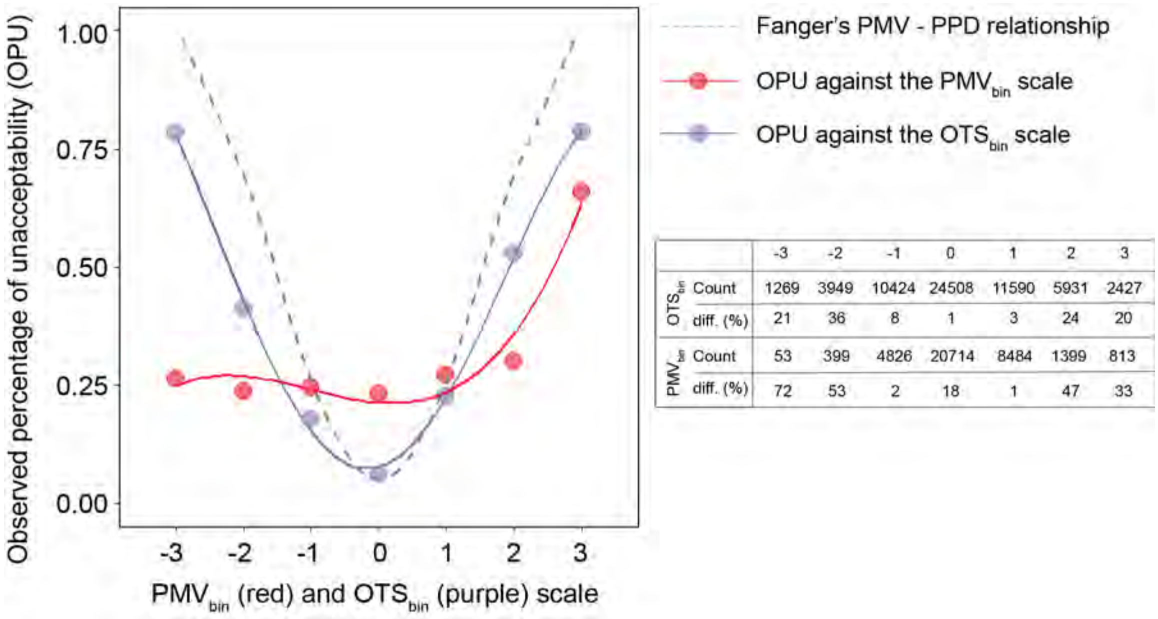
The boxplot in Figure 1c shows the discrepancy between PMV and OTS against PMV_{bin} following the validation method by Humphreys and Nicol [6]. The mean discrepancy is indicated by the purple dot for each PMV_{bin} unit and the corresponding values are summarized along the top. Humphreys and Nicol considered the PMV model free of bias if the mean discrepancy is within ±0.25, a threshold indicated by the dashed yellow lines. According to this criteria, the PMV is valid only for neutral thermal conditions, for the other six categories, including slightly warm and cool, it is not valid. PMV performed poorer at cooler sensations, with a larger mean discrepancy than warmer sensations. These results are consistent with and support the findings of Humphreys and Nicol [6].

Figure 1d shows the ratio of binned thermal sensation vote (OTS_{bin}) for each PMV_{bin} scale. This visualisation is an effective way to assess PMV performance because it shows the OTS_{bin} distribution for each condition that PMV predicts the same sensation. The percentage of correct prediction (P) and mean absolute error (MAE) between the OTS_{bin} and PMV_{bin} data is given along the top. Overall prediction accuracy was 34%, meaning that on average the thermal sensation is incorrectly predicted two out of three times. Although the mean discrepancy (i.e. error) at neutral votes revealed little bias in Figure 1c, the same neutral condition in Figure 1d showed an average prediction error of 0.93 OTS units with the best prediction rate reaching 43%. The accuracies at all other sensations were reported less than 32% with an MAE > 1. When PMV_{bin} was predicting a "Cold" or "Cool" condition, more than 50% of the OTS_{bin} data were voting "Neutral" or at the warmer side. Very low prediction accuracy was found at "Cold" (P=7%, MAE=2.17) and "Cool" (P=11%, MAE=1.56). It's worth noting that this is worse than randomly guessing the thermal sensation (P=1/7=14%).

The plots in Figure 1 clearly demonstrate that PMV has a low OTS and OMV prediction accuracy, regardless of whether the unit of analysis is at the individual or population level. It correctly predicts thermal sensation only one-third of the time, and even at neutrality its accuracy is less than 50%. Such poor performance emphasizes the wide spread of inter-individual difference in real building. It also brings into question the usefulness of PMV as a design tool and highlights its culpability in encouraging both uncomfortable indoor environments and profligate energy waste.

3.2 PMV-PPD relationship

Figure 2 graphs two thermal unacceptability to thermal sensation relationships: PMV_{bin}-OPU (red line) and OTS_{bin}-OPU (purple line). Also the original PMV-PPD (grey dotted line) is added for comparison. The PMV_{bin}-OPU relationship shows the observed thermally unacceptable to total votes percentage at each PMV_{bin}, (i.e. calculated thermal sensation) while the OTS_{bin}–OPU relationship shows percentage of unacceptability at each binned thermal sensation from occupants. The sample sizes in Figure 2 for the PMV_{bin} count are smaller than what was shown in Figure 1b because not all records in the database contained votes of thermal acceptability, which was used in this analysis as a proxy to compare with the PPD model.



		-3	-2	-1	0	1	2	3
OTS_{bin}	Count	1269	3949	10424	24508	11590	5931	2427
	diff. (%)	21	36	8	1	3	24	20
PMV_{bin}	Count	53	399	4826	20714	8484	1399	813
	diff. (%)	72	53	2	18	1	47	33

Figure 2 Regression relationship between thermal unacceptability and thermal sensation: OPU against PMV_{bin} scale (red line); OPU against OTS_{bin} scale (purple line). PMV-PPD relationship (grey dotted line) is added for comparison. The sample count and percentage of difference compares between PPD and OPU at 7-point thermal sensation scale

The results of the Kolmogorov-Smirnov test (p = 0.86) indicate the relationship between OTS_{bin}-OPU and the PMV-PPD are comparable. The PPD model overestimated occupant' thermal dissatisfaction at Cold (21%), Cool (36%), Warm (24%) and Hot (20%) sensations, but the match was very close at Slightly cool (8%), Neutral (1%) and Slightly warm (3%) sensations. Therefore, if the thermal sensation is known and is between -1 and +1 then the PPD metric is an accurate prediction of the observed unacceptability of occupants.

In contrast to the general agreement with OTS_{bin}, the PMV_{bin}-OPU relationship is vastly different from the PMV-PPD model (p = 0.16, KS-test) meaning that PPD cannot predict subject's unacceptability under the same thermal condition defined by PMV model. The PPD overestimated the observed unacceptable votes of occupants at predicted sensations of Cold (72%), Cool (53%), Warm (47%) and Hot (33%), and underestimated OPU when predicted to be Neutral (18%). From the performance of the PMV model in the earlier analysis showed, the possible reason for such a difference between the predicted dissatisfaction and observed unacceptability of occupants is likely due to the inability of the PMV model to correctly estimate OTS or OMV. Another possible reason could be the fact that PPD (derived by satisfaction) and OPU (estimated by acceptability) are two metrics that very much different from each other. Close to 75% of the acceptability votes were acceptable in PMV_{bin} predicted Cold and Cool conditions (supposed to be dissatisfied), whilst 25% of the votes were unacceptable in predicted Neutral conditions (supposed satisfied with only 5% of dissatisfaction).

The key finding from Figure 2 is that the discrepancies observed between the predicted thermal dissatisfaction and observed unacceptability of occupants is likely to result from the poor performance of the PMV model rather than the lab-based empirically derived relationship between thermal sensation and satisfaction (i.e, PMV-PPD). PPD was shown to be unreliable when the PMV is used to predict thermal sensation. However, if the observed mean vote is known then the PPD curve is not very accurate but still a useful predictive tool. The reported inaccuracies in this study, therefore, lie in the PMV model rather than the ability to predict occupant unacceptability using the PPD function.

4 Subset environmental factors analysis

The Comfort Database is comprised of field studies with varying contextual factors that may exert some influence over the prediction accuracy of the PMV model as well as the PMV-PPD and OTS_{bin}-OPU relationships. In order to test the performance of PMV-PPD model across these different contexts, the database was divided into 47 subsets, summarized in Table 1, based on ventilation strategy (AC, NV and MM), building type (Office, Classroom and Housing) and climate classification (Tropical (A), Arid (B), Temperate (C) and Continental (D)).

In Table 1, the prediction performance of the PMV-PPD model in each case is summarized by the indices presented in Figure 1b, Figure 1d and Figure 2. The PMV model was assessed based on: (1) the prediction accuracy (%) for all OTS values; (2) the prediction accuracy (%) at Cold, Neutral and Hot sensations; and (3) the OMV-PMV_{bin} relationship i.e. the slope and intercept of the regression, and the mean absolute error (MAE) between OMV and PMV_{bin}. The Kolmogorov-Smirnov test (KS) was used to compare the difference between OTS_{bin}-OPU relationship to the PMV-PPD model. The MAE between PPD and OPU at cooler ($OTS_{bin} \leq -2$), neutral ($-1 \leq OTS_{bin} \leq 1$) and warmer ($OTS_{bin} \geq 2$) sensations were also evaluated.

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escholarship.org/uc/item/2kd0135t

Table 1 PMV-PPD model performance subsets by ventilations, buildings and climate groups

Case	Ventilation types			Building types			Climate groups				OTS Sample size	PMV accuracy % (refer to Figure 1d)				OMV–PMV$_{bin}$ relationship (refers to Figure 1b)			OPU to PPD comparison (refers to Figure 2)			
	AC	NV	MM	O	C	H	gA	gB	gC	gD		Overall	Cold	Neutral	Hot	Slope	Int.	MAE	KS.p	MAE (≤ -2) %	MAE (±1) %	MAE (≥2) %
1	x	x	x	x	x	x	x	x	x	x	91789	34	7	43	32	0.41	0.16	1.06	0.86	28	4	22
2	x			x	x	x	x	x	x	x	29552	35	5	42	44	0.53	0.42	0.85	0.86	28	5	17
3		x		x	x	x	x	x	x	x	41571	34	1	44	33	0.37	0.43	1.11	0.44	24	3	26
4			x	x	x	x	x	x	x	x	20666	31	31	44	30	0.44	0.11	1.04	0.14	39	5	22
5	x	x	x	x			x	x	x	x	64606	34	1	43	31	0.37	0.36	1.12	0.86	20	3	17
6	x	x	x		x		x	x	x	x	17410	34	18	46	79	0.58	0.41	0.82	0.14	51	8	31
7	x	x	x			x	x	x	x	x	9773	25	0	51	30	0.35	0.50	1.2	0.03	73	7	56
8	x	x	x	x	x	x	x				17817	31	0	41	40	0.40	0.30	1.05	0.15	59	7	36
9	x	x	x	x	x	x		x			11138	32	0	44	32	0.33	0.30	1.17	0.43	59	8	20
10	x	x	x	x	x	x			x		55124	35	12	44	26	0.41	0.31	1.04	0.88	16	4	19
11	x	x	x	x	x	x				x	8437	33	6	42	-	0.45	0.33	0.99	0.12	29	23	14
12	x			x			x				5247	34	0	41	46	0.48	0.34	0.94	0.15	43	11	18
13	x				x		x				1363	-	-	-	-	-	-	-	0.09	79	16	23
14	x					x	x				0	-	-	-	-	-	-	-	-	-	-	-
15		x		x			x				1877	30	0	50	40	0.50	0.13	0.85	0.16	58	13	40
16		x			x		x				4256	37	0	55	-	0.25	0.34	1.14	0.40	71	11	26
17		x				x	x				1319	-	-	-	-	-	-	-	0.03	88	11	63
18			x	x			x				2695	23	-	29	33	0.50	0.04	0.86	0.17	57	11	42
19			x		x		x				0	-	-	-	-	-	-	-	-	-	-	-
20			x			x	x				1060	-	-	-	-	-	-	-	-	-	-	-
21	x			x				x			1438	33	0	39	-	0.37	0.63	1.07	0.41	23	8	48
22	x				x			x			94	-	-	-	-	-	-	-	-	-	-	-
23	x					x		x			15	-	-	-	-	-	-	-	-	-	-	-
24		x		x				x			1225	31	0	50	36	0.33	0.31	1.18	0.84	56	12	9
25		x			x			x			0	-	-	-	-	-	-	-	-	-	-	-
26		x				x		x			560	30	0	58	54	0.48	0.64	0.93	-	-	-	-
27			x	x				x			4483	31	0	43	27	0.27	0.24	1.16	0.43	58	11	18
28			x		x			x			0	-	-	-	-	-	-	-	-	-	-	-
29			x			x		x			836	-	-	-	-	-	-	-	0.16	74	10	37
30	x			x					x		18000	34	6	41	0	0.47	0.45	0.99	0.89	16	5	16
31	x				x				x		146	39	-	34	-	0.72	-0.34	0.83	-	-	-	-
32	x					x			x		11	18	0	100	-	0.08	0.02	1.42	-	-	-	-
33		x		x					x		19501	36	0	44	5	0.31	0.33	1.17	0.86	14	3	15
34		x			x				x		3726	34	5	51	71	0.54	0.37	0.83	0.14	21	4	28
35		x				x			x		2219	15	0	28	15	0.28	0.55	1.45	0.47	24	7	54
36			x	x					x		7737	37	0	55	30	0.22	0.42	1.42	0.86	5	10	4
37			x		x				x		3273	29	50	44	100	0.84	-0.08	0.43	0.14	43	11	32
38			x			x			x		511	-	-	-	-	-	-	-	0.51	23	12	39
39	x			x						x	2332	40	-	44	-	0.15	0.16	0.88	0.86	29	22	46
40	x				x					x	906	45	7	60	-	0.51	-0.06	0.71	-	-	-	-
41	x					x				x	0	-	-	-	-	-	-	-	-	-	-	-
42		x		x						x	0	-	-	-	-	-	-	-	-	-	-	-
43		x			x					x	3646	29	0	39	-	0.24	0.49	1.37	-	-	-	-
44		x				x				x	755	-	-	-	-	-	-	-	-	-	-	-
45			x	x						x	71	-	-	-	-	-	-	-	-	-	-	-
46			x		x					x	0	-	-	-	-	-	-	-	-	-	-	-
47			x			x				x	0	-	-	-	-	-	-	-	-	-	-	-

Note:
Case 1 is the entire database. Data subsets are listed as ‘cases’ in the first column by ventilation strategy (cases 2 to 4), building type (cases 5 to 7), climate (cases 8 to 11), and subsequent cases (cases 12 to 47) are combinations of the three factors. Conditions with OTS sample size < 500 or missing PMV or thermal acceptability data are printed in grey. “-” denotes no data available or insufficient sample size for corresponding analysis.

Sample size:	Define the number of sample includes the observed thermal sensation (OTS) data in each category
Building types:	O (office), C (classroom), H (housings)
Ventilation types:	AC (air conditioned), NV (naturally ventilated), MM (mixed mode)
Climate groups:	gA (group A, Tropical), gB (group B, Arid), gC (group C, Temperate), gD (group D, Continental (Cold))
KS.p: (test distribution)	*p*-value in KS-test ($p<0.05$, different in distribution)
MAE (≤-2)	Mean absolute error between OPU and PPD (%) for $OTS_{bin} \leq -2$
MAE (±1)	Mean absolute error between OPU and PPD (%) for $-1 \leq OTS_{bin} \leq 1$
MAE (≥2)	Mean absolute error between OPU and PPD (%) for $OTS_{bin} \geq 2$

4.1 PMV prediction accuracy

As shown in Table 1, the accuracy of the PMV model in predicting OTS across the datasets categorized by ventilations, buildings and climates (case 2 to 11) were all similarly low, ranging mostly between 31-35%. The worst case was in residential buildings (25% correct), possibly because at home occupants have more adaptive opportunities available [39]. Cases with higher PMV accuracy (between 36-45% correct) are generally subsets with smaller sample sizes (cases 16, 33, 36, 39, 40); the relative success of the PMV model in predicting

OTS is likely due to the narrow thermal conditions observed in these environments which limit predictions mostly to the neutral sensations where the model performs best.

Despite the mean discrepancy between PMV and OTS being close to zero at neutral votes in Figure 1c, the prediction accuracy of PMV at neutral remains less than half in most cases regardless of ventilation, building and climate types (cases 2 to 11). Surprisingly, in all climates where data was available (cases 12 & 15, 21 & 24 and 30 & 33), we found a higher PMV prediction accuracy for neutrality in NV compared to AC offices. It is important to note that higher prediction accuracy in NV offices was only observed for neutral and not across the entire range of thermal sensations.

The accuracy of PMV in predicting Cold sensations was very weak in all cases except one (case 37), demonstrating an overestimation of cool conditions on thermal sensations. In many cases, such as in residential settings and buildings in tropical and arid climates, the accuracy was at or near zero. Such poor model performance in hot and humid climates may be the result of occupants' preference for and lower sensitivity to warmer conditions due to adaptation [40,41]. Prediction accuracy of Cold sensations was slightly improved in the temperate (12%) and continental (6%) climates.

4.2 OMV to PMV_{bin} relationship

The relationship between OMV and PMV_{bin} for different ventilation, building and climate types is presented in Figure 3. When analysing by ventilation strategy (Figure 3a), NV buildings had the weakest relationship between OMV and PMV_{bin} evidenced by a flatter slope (coefficient of 0.37) and a larger MAE (1.11). For all ventilation strategies, PMV prediction accuracy was highest at Neutral and reduced towards either end of the thermal sensation scale, overestimating occupants' OMV at predicted Cold (MAE_{AC} = 1.94, MAE_{NV} = 2.40, MAE_{MM} = 1.73), Cool (1.38, 1.67, 1.69), Warm (1.05, 1.11, 1.43) and Hot (0.60, 1.05, 1.11) sensations. Despite a slightly steeper slope and smaller error observed in AC buildings (slope = 0.53, MAE = 0.85) than in NV buildings, the overall PMV prediction accuracy was found to be low in both ventilation strategies (35% in AC and 34% in NV).

PMV performed slightly better in classrooms compared to offices and homes (Figure 3b), with the stronger association between OMV and PMV_{bin} in classrooms (slope = 0.58, MAE = 0.82) buoyed by better predictions outside of neutrality. Figures 3c and 3d show the performance of the PMV model is similar across the four climate group classifications. PMV prediction accuracy at cooler sensations is weaker in tropical climates and low at warmer sensations in continental climates. Possible reasons for these discrepancies have been discussed in Section 4.1.

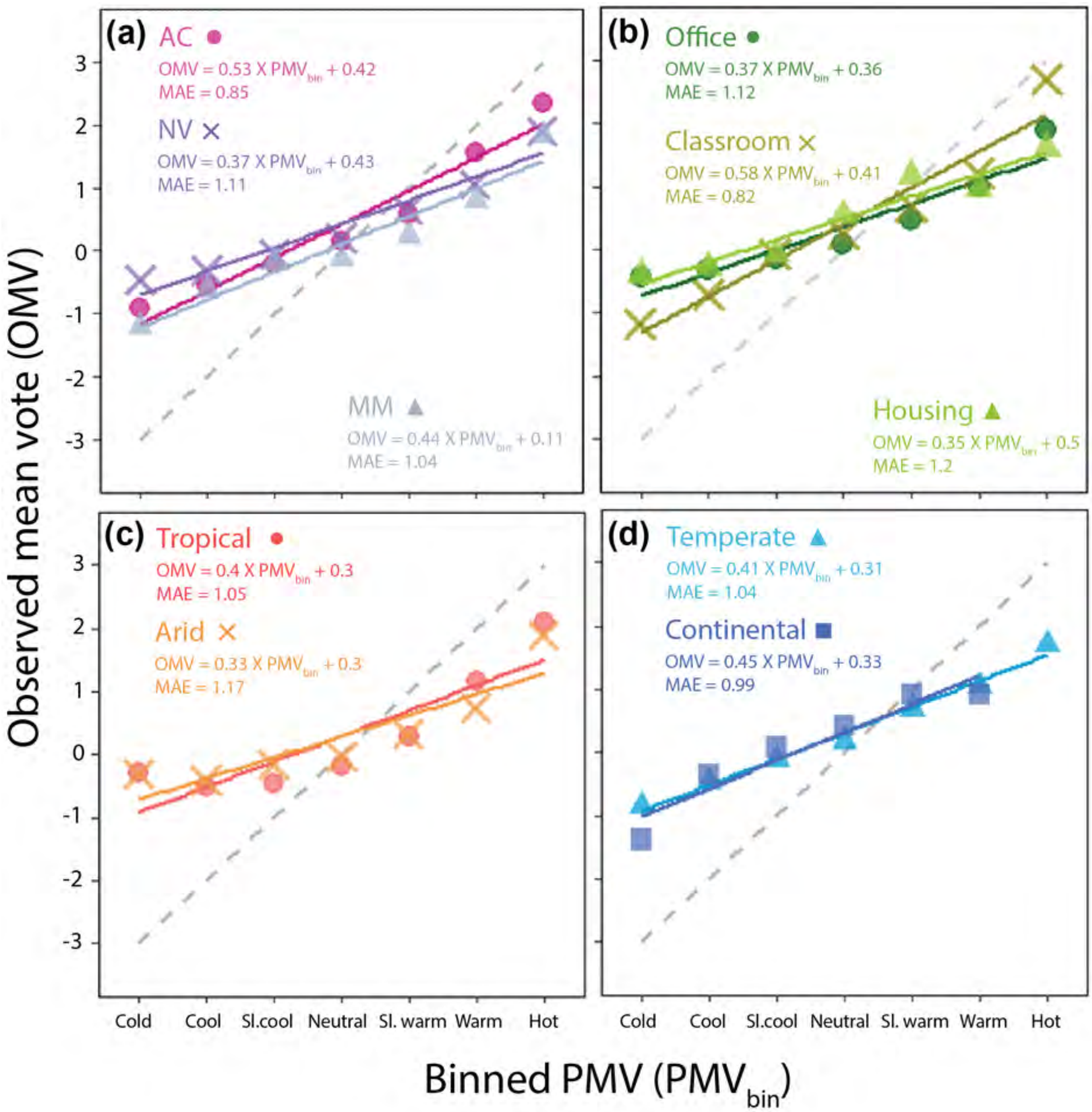

Figure 3 OMV – PMV_{bin} relationship by (a) ventilation strategies (air conditioned (AC), naturally ventilated (NV) and mixed mode (MM)); (b) building types (office, classroom and housing); (c) and (d) climate classifications (Tropical, Arid, Temperate and Continental)

The findings presented in Figure 3 classified by either ventilation, building or climate type could be biased by the interaction effects of the two other factors. To address this, the statistical relationship between OMV and PMV_{bin} with detailed classification on each contextual factor is shown in Figure 4. Air conditioned office buildings is the only case with data from all four climate groups. PMV model performance was slightly more reliable in tropical and temperate climates compared to arid and continental climates, but the prediction accuracy was still low at cooler and warmer sensations. The PMV prediction accuracy of occupants in offices in temperate climates was lower in buildings with NV and MM strategies compared with AC offices. This is in line with the adaptive comfort theory put forward by Brager and de Dear [40]. However, PMV had equal performance measures for occupants in office buildings in tropical climates regardless of ventilation strategy. In fact, the PMV model had the highest performance in office buildings in tropical climates compared to other climate types. These findings are different from the claims by Fanger and Toftum [24], that the PMV model was less accurate or relevant to occupants of buildings in tropical climates.

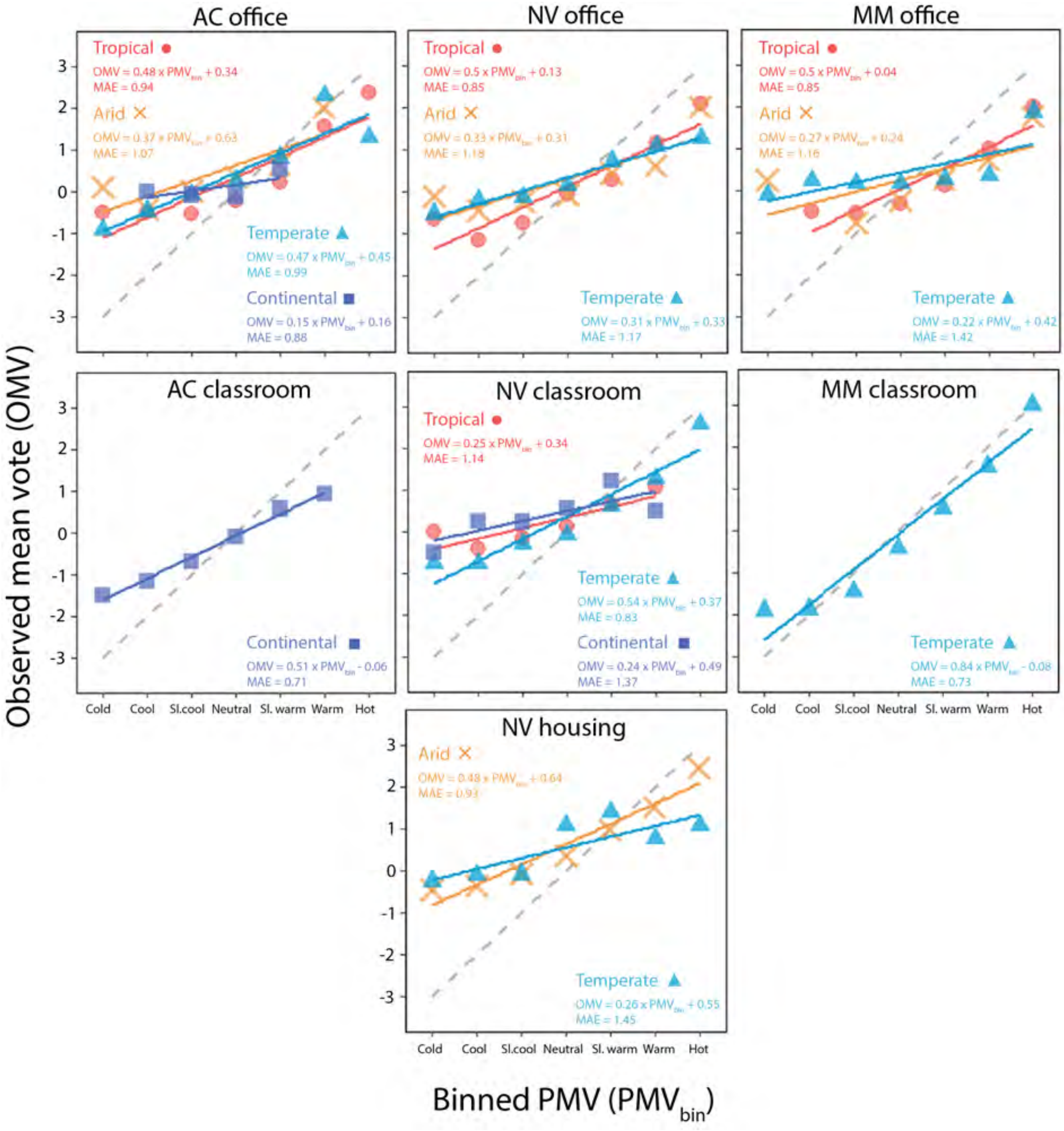

Figure 4 OMV – PMV_{bin} relationship by detailed classification of ventilations (left to right: AC, NV and MM) and buildings (top to bottom: office, classroom and housing) at different climate groups (Tropical, Arid, Temperate and Continental). AC and MM housing data are excluded due to insufficient sample for discussion.

The available data was relatively limited across climate groups and ventilation strategies for classrooms and homes (see Figure 4). We found a higher PMV prediction accuracy in classrooms compared to offices in temperate and continental climates but not in tropical climates. The accuracy was highest for mixed mode classrooms in temperate climates (Case 37, slope = 0.84, MAE = 0.43), followed by naturally ventilated classrooms under the same climate group. Figure 3b shows better prediction accuracy overall in classrooms compared to office and residential buildings. It is unclear why PMV performs better in classrooms, but there are two possible hypotheses. First, depending on the culture and institution type, students in a classroom may have limited adaptation possibilities since the indoor environment is largely under the control of the teacher, similar to subjects of the climate chamber experiments forming the empirical basis of the PMV model. Second, students are closer in age to the predominantly college-age students used by Fanger in laboratory testing [1]. The hypotheses are not verified in this paper, yet it would be worthwhile to conduct further thermal comfort research in classroom environments to re-confirm the findings reported in this study.

4.3 Thermal acceptability to sensation relationship

Similar to the previous analysis, we compared the PMV-PPD model with OTS_{bin}-OPU relationship for different ventilation, building and climate types (see Figure 5). Figure 5a shows the PPD model correctly predicts unacceptability for neutral sensations (~5%) for different ventilation strategies, but overestimates it at both the cold and hot ends of the sensation scale, especially in MM buildings (+41% at Cold and +26% at Hot). Overestimation of thermal unacceptability may be explained by the availability of different adaptive opportunities in buildings which may improve satisfaction at self-reported cooler and warmer sensations [15]. This overestimation was lowest at Hot sensation votes in AC buildings (+8%), increasing to +26% for both NV and MM buildings. The better performance of the PPD in predicting lower acceptability levels in AC buildings is likely due to the higher expectation of occupants in fully conditioned spaces.

Figure 5b shows the PPD model reliably estimating OPU in offices, but is less successful in classrooms and poor when applied to residential settings. In all building types, PPD accurately predicted the lowest unacceptability rate (5%) at neutral sensation votes. Lower PPD prediction accuracy was expected in residential buildings due to the availability of adaptive control options and the different expectations of occupants in homes [16,27,42,43]. The lowest OPU value in classrooms was slightly shifted towards the cooler sensation, perhaps due to the overriding impact of climatic conditions rather than the building type.

The OTS_{bin}-OPU relationship across the four different climate classifications are plotted in Figure 5c and 5d. The PPD model performed well in buildings at temperate climates, with only small discrepancies (+10 to +15%) across both the warmer and cooler sensation ranges. However, the lowest OPU value in the other three climate groups were all shifted towards the slightly cool sensation vote (not at thermal neutrality). Furthermore, the PPD model overestimated occupants' unacceptability at cold sensation votes in tropical, arid and continental climates by +59%, +68% and +55% respectively, and at hot sensation votes by +42%, +20% and +30% respectively. Building occupants in these three climate groups (tropical, arid, continental) seem to express less dissatisfaction in cooler environments compared to counterparts in temperate climates. In other words, the PPD model is less accurate in these climate groups even though occupants' thermal sensation is known. Breaking down the available data into detailed Köppen climate classifications reveals measurements from buildings in hot semi-arid (Bsh), warm summer humid continental (Dfb), and hot summer humid continental (Dwa) types. This may explain the similar OTS_{bin}-OPU relationships seen in Figure 5c and 5d, and echo findings of other studies showing occupant preference for cooler environments in hot-humid regions [18,41].

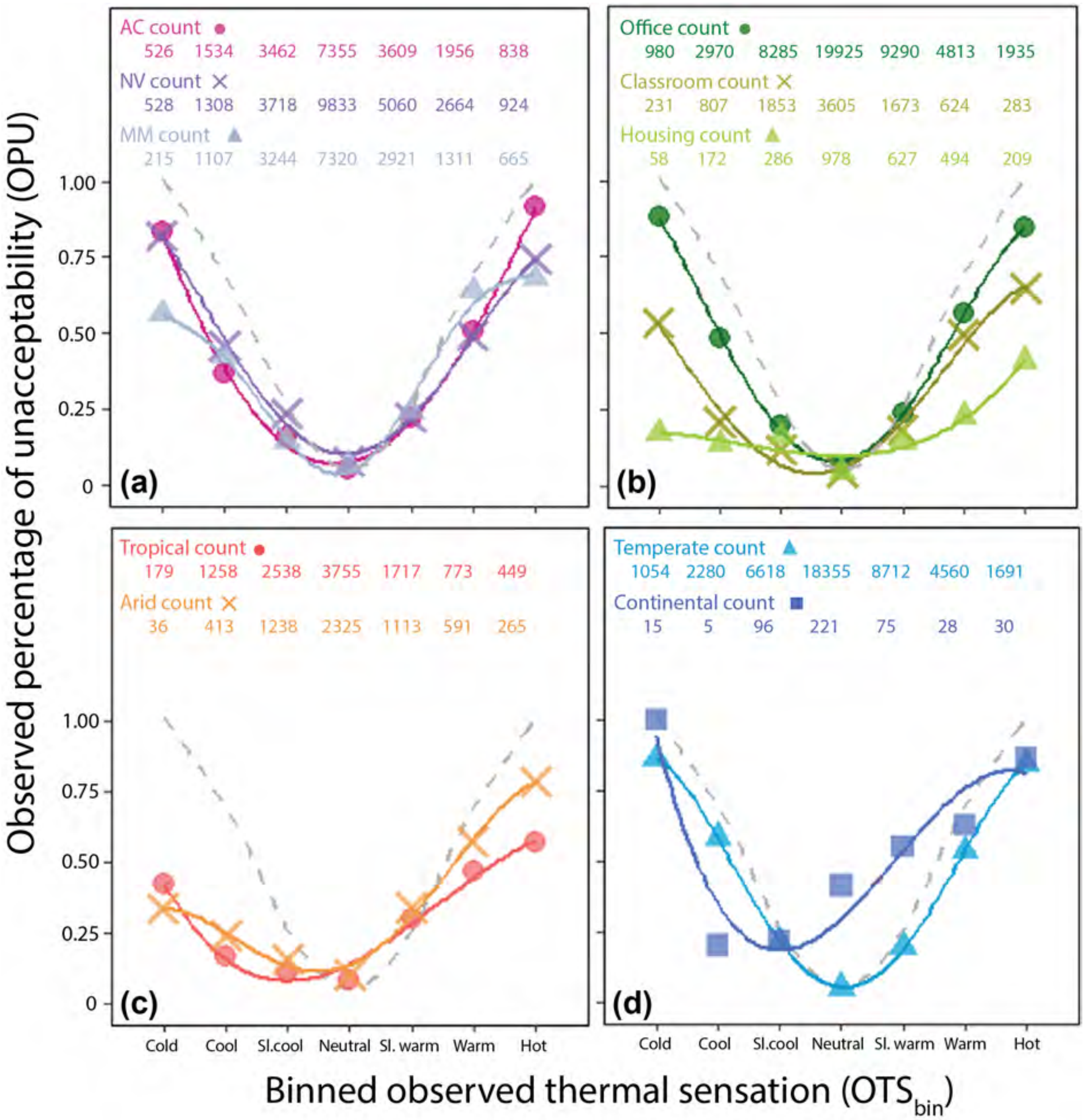

Figure 5 OTS_{bin} –OPU relationship by (a) ventilation strategies (air conditioned (AC), naturally ventilated (NV) and mixed mode (MM)); (b) building types (office, classroom and housing); (c) and (d) climate classifications (Tropical, Arid, Temperate and Continental)

The OTS_{bin}-OPU regressions for every combination of ventilation, building and climate type is shown in Figure 6. In temperate climates, the OTS_{bin}-OPU relationship did not vary much across different ventilation strategies, but was markedly different between the three building types (offices, classrooms and homes). The PPD model (when PMV predicts OTS_{bin} perfectly) performed best in temperate climates, with almost perfect prediction in office buildings, small to moderate discrepancy at the more extreme sensations in classrooms, and a larger discrepancy at warmer sensations in naturally ventilated residential buildings. The results suggest that PPD is actually a reliable model for offices in temperate climates regardless of the ventilation strategy only if occupants' mean thermal sensation is predicated accurately or known. These results suggest that the reliability of PMV-PPD model is biased towards the thermal expectations of building occupants in temperate climates. Unfortunately, there is insufficient data to assess PPD performance for buildings in continental climates.

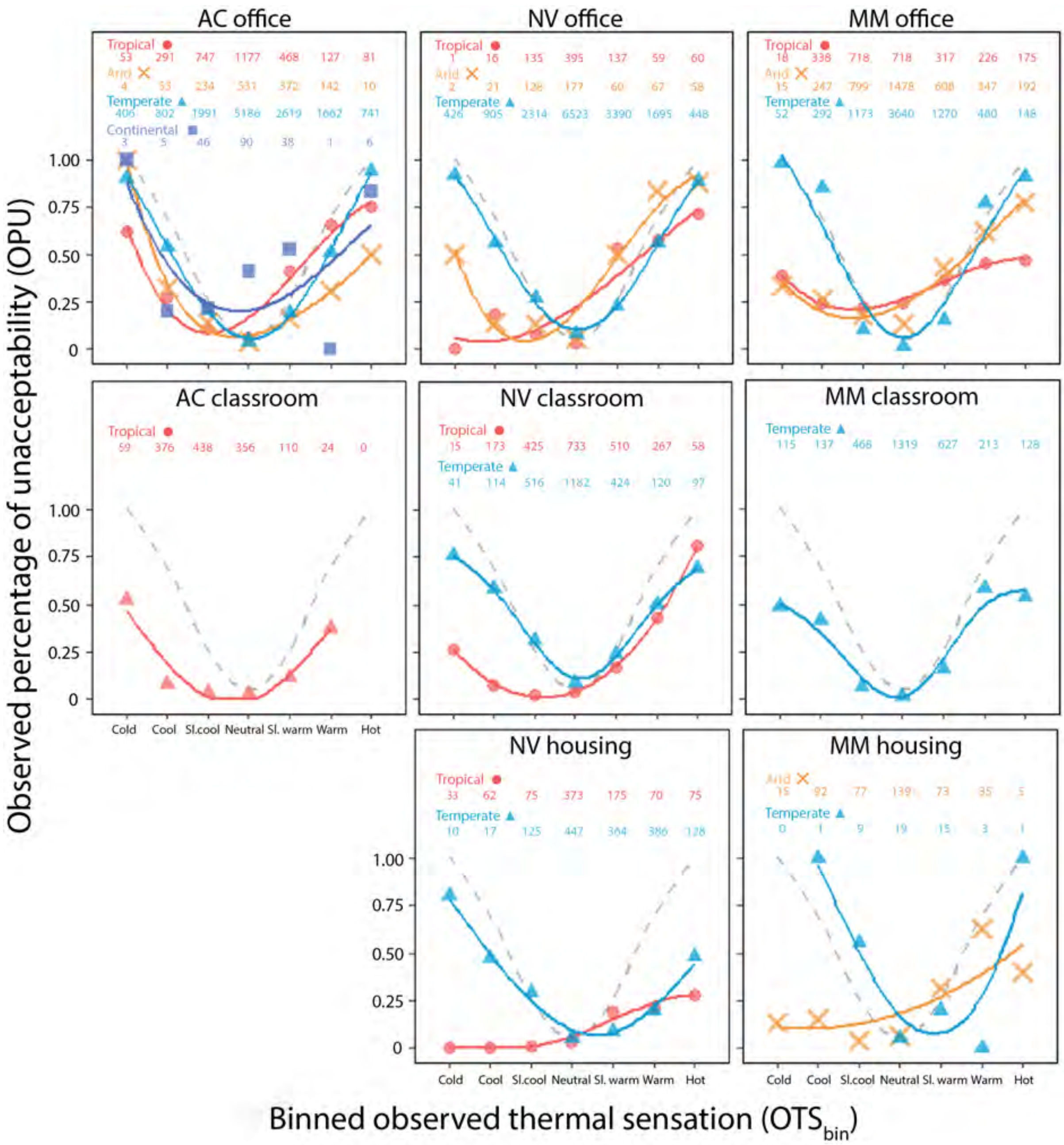

Figure 6 OTS_{bin}-OPU relationship by detailed classification of ventilations (left to right: AC, NV and MM) and buildings (top to bottom: office, classroom and housing) at different climate groups (Tropical, Arid, Temperate and Continental). MM housing data is luded due to too insufficient sample for discussion.

Despite achieving reasonable performance measures for buildings in temperate climates, the PPD model has a low prediction accuracy in offices in tropical and arid climates (Figure 6), where the lowest OPU value is shifted towards cooler sensations and generally higher unacceptability was reported on the warmer side. In addition, the PPD model underestimated OPU by -18% and -13% at Neutral and Slightly warm sensations in tropical MM offices. Similar levels of underestimation at Slightly Warm sensations were also reported in AC (-15%) and NV offices (-27%). It is possible that overcooling in AC offices led to the increased OPU at the Cold sensation to 62%, which was higher than in NV (0%) and MM (38%) offices. The OTS_{bin}-OPU relationships for classrooms in tropical climates were similar to that observed in offices, but underestimation of OPU by the PPD model was not observed.

5 A simpler thermal sensation model

The present analysis shows that the PMV model has low prediction accuracy for both individual's and group mean thermal sensation in buildings. To reinforce these findings and contextualise them in the realm of modelling, we compared the PMV predictions with a much simpler approach. A thermal sensation prediction model was built using just the air temperature (t_a, °C) measurements in the Comfort Database as the sole input parameter (see Figure 7a_i). The cut-off temperature between sensations were informed by engineering judgement. This simple model had an overall prediction accuracy of 35% (Figure 7a_{ii}), comparable to the 34% PMV accuracy reported despite using only one of the six input parameters (air temperature). The random forest machine learning algorithm was used to develop another set of prediction models with different cut-off temperatures (Figure 7b_i). The temperature ranges were determined by maximizing model accuracy, and resulted in surprisingly wide ranges for "Neutral" sensation (i.e. 18 – 30°C). This simple model had an overall prediction accuracy of 43%, higher than the value reported for the PMV model. The purpose of this analysis is not to introduce a new model to replace PMV, but to demonstrate that a simpler model (i.e. just using air temperature as a predictor) does not necessarily perform worse than a more detailed approach. It suggests that the PMV model may be too complex for the prediction of thermal sensation in real buildings, and a simple model based on readily-available inputs may be of greater use.

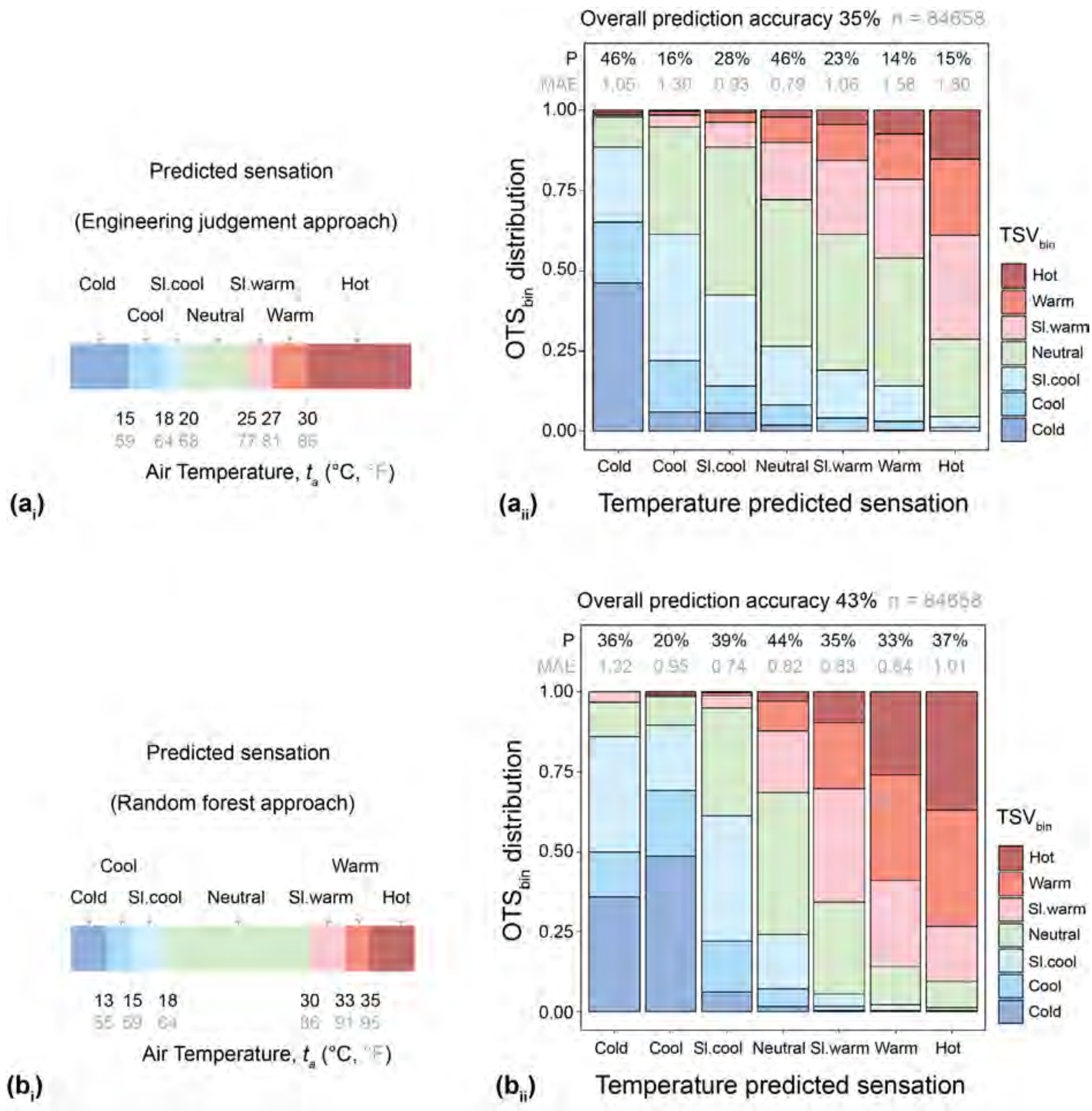

Figure 7 Simple thermal sensation prediction model based only on air temperature, t_a (°C, °F) (a$_i$) Cut-off temperature (determined by an engineering judgement approach) for different sensation outputs; (a$_{ii}$) Model prediction performance (determined by an engineering judgement approach and detail identical to Figure 1d); (b$_i$) Cut-off temperature (determined by machine learning random forest approach) for different sensation outputs; (b$_{ii}$) Model prediction performance (determined by random forest approach).

6 Discussion

Detailed analyses of field measurements in the Comfort Database revealed that the PMV-PPD model has a low accuracy in predicting both individual observed thermal sensation (OTS) as well as the observed mean vote (OMV), and the observed percentage of unacceptability (OPU) across a wide range of contexts. The overall accuracy of the PMV model is 34%, with slightly better performance in buildings in temperate climates and classrooms but still below 40%. Even at neutrality, when PMV is purported to be most reliable, accuracy in all subset cases is below

60%, leading to the conclusion that such poor reliability is unacceptable for a widely-used and endorsed index [6]. The results of the present analysis suggest that the PMV model has to be modified in order to be useful for designing and predicting occupant thermal comfort in real buildings. Ideally, this would include utilizing improved metrics in predicting thermal sensation, or using observed metrics such as the OMV, allowing for a OMV-PMV_{bin} relationship that varies with context, similar to the expectancy factor proposed by Fanger and Toftum [24]. In addition, even if we assume that thermal sensation is perfectly predicted or is known, the PPD model would only be reliable in temperate climates and of little relevance to buildings in tropical climates, particularly at cooler sensations.

The conventional approach of validating the PMV-PPD model performance using one-dimensional comparisons of contextual factors (e.g. AC vs NV building or office vs classroom) may lead to misleading interpretations or unexplainable observations masked by other confounders. The strategy used here of clustering factors by ventilation strategy, building types and climate can reduce the confounding effect and provide more robust comparisons between subsets. This approach has only been possible with the recent release of the Comfort Database. Other factors beyond the three used in this paper (and beyond what the Comfort Database includes), may also have an important influence on the PMV-PPD model accuracy in real buildings, such as cultural variation or the availability of personal environmental control options.

The Comfort Database is an ensemble of data collected from different researchers using different instruments and procedures. The heterogeneity of physical measurement sensors, sampling procedures, and estimations of occupants' metabolic rate and clothing insulation are all possible sources of error contributing to the inaccuracy of the PMV-PPD model. We cannot verify to what extent these errors affect the overall prediction accuracy, and if the inaccuracy of the PMV-PPD model is due to the model itself or the uncertainty in the input values. Nevertheless, we can critically question the practicality and robustness of the PMV-PPD model if the input variables cannot be collected by trained researchers in real buildings with sufficient accuracy. If the conclusion that the PMV-PPD model is not sufficiently accurate is to be made, then the question becomes which alternative is available to both thermal comfort researchers and practitioners? One option is to use a more simplistic model based on air temperature as in the example reported in Figure 7. This is already a common approach used in the building sector where many of the PMV inputs cannot be practically measured (e.g. air velocity, clothing insulation and metabolic activity). Another alternative is to use personal comfort models [44] which predict individual thermal comfort responses rather than the average response of a larger population e.g. a floor or a whole building. Personal comfort systems may leverage the Internet of Things paradigm and machine learning techniques to evaluate thermal comfort requirements based on data collected in everyday environments. Such an approach has demonstrated very high prediction accuracy well beyond that of the PMV-PPD model [45].

7 Conclusion

This paper used the ASHRAE Global Thermal Comfort Database II to evaluate the prediction accuracy of the popular PMV-PPD thermal comfort model. We focused on: (i) the accuracy of PMV to predict individual observed thermal sensation (OTS) and group observed mean vote (OMV), and (ii) comparing the relationships between the PMV-PPD and binned OTS (OTS_{bin})

to the observed percentage of unacceptability (OPU). These analyses were performed across different building types (offices, classrooms and homes), ventilation strategies (air conditioned, naturally ventilated and mixed mode) and climate classifications (tropical, arid, temperate and continental). It was found that PMV has a low prediction accuracy based on three different methods used in other works to assess the performance of the PMV model. The overall prediction accuracy was measured at 34%. The PMV model had a slightly higher prediction accuracy at sensation votes close to neutrality, but never exceeded 60% in any building types, ventilation strategies and climate classifications. Its accuracy declined towards either end of the thermal sensation scale and overestimated OTS at both hot and cold sensations. The tendency of overestimation results a narrower range of temperatures that carry significant energy penalties. We developed a simple model based solely on air temperature and achieved an accuracy of 43% in thermal sensation prediction, which is higher than the PMV model requiring four environmental parameters and two personal parameters as inputs.

The PPD model has been removed in ASHRAE Standard 55-2017 due to its low prediction accuracy. However, the results presented here demonstrate that in many contexts the inaccuracies are not in the PPD model itself but rather the PMV model and its prediction of thermal sensation. If OMV is known then the PPD model accuracy improved significantly in many contexts. In general, PPD overestimated subject's unacceptability outside the range of thermal neutrality (i.e. OTS $\leq$ -2 or OTS $\geq$ +2). Larger discrepancies between the predicted satisfaction and observed unacceptability were found in non-AC offices in tropical climates, while PPD was underestimating unacceptability at neutral and slightly warm sensations. It had a high prediction accuracy in temperate climates in offices and classrooms for all ventilation strategies.

Considering the complexity of the PMV-PPD model, it provides unacceptably low prediction accuracy. It is important for the advancement of the thermal comfort research discipline to look beyond deterministic heat-balance models by developing either simpler models that are easier to implement or personal thermal comfort models that are able to respond to the diverse expectations and requirements of building occupants.

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