Exploring Contextual Feature Combinations for Prediction of Subjective Thermal Perceptions

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ABSTRACT

Thermal attributes in the environment impact well-being, but their inclusion in standard well-being monitoring is challenging due to complex measurement requirements. Industry standards like the Predicted Mean Vote (PMV) index need numerous measures and specialized setups, making large-scale applications impractical. This study investigates predicting thermal perception ratings using only contextual factors. We conducted an ablation study using the Chinese Thermal Comfort Dataset (CTCD) and a Random Forest (RF) classifier to evaluate prediction performance with different contextual feature combinations on five labeling scales. Results showed that omitting measures required for PMV index calculation and relying on contextual features exclusively achieved F_1 scores similar to those when including PMV measures. Key predictive factors included daily outdoor temperature and a person's clothing, weight, and age. These findings suggest that leveraging more accessible contextual data to estimate thermal perception ratings is promising, and further research should explore more contextual factors to enhance prediction accuracy and support well-being assessments.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing design and evaluation methods**; Collaborative and social computing systems and tools; • **Computing methodologies →** *Classification and regression trees.*

KEYWORDS

Thermal Perception; Context-based Estimation; Ubiquitous Computing

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1 INTRODUCTION

The evaluation of thermal environments has been a long-standing research focus in the field of building ergonomics [23]. A common topic within these fields is the prediction of subjective ratings surrounding individuals' perceptions of thermal environments. Thermal environmental conditions and subjective perceptions of them greatly impact physical well-being [21] and regulatory cognitive processes, such as emotion regulation [26]. The rating scales that are commonly used measure concepts such as thermal sensation, thermal comfort, or thermal acceptability [28]. Due to their impact on physical and mental well-being, individuals' subjective perceptions of the thermal attributes in their environments represent a relevant source of information for well-being monitoring, yet it is currently impractical to incorporate subjective thermal perception ratings (STPRs) as parameters in standard well-being monitoring scenarios [24]. This is primarily because established methods for predicting STPSs, such as Fanger's Predicted Mean Vote (PMV) index [9, 10], require numerous measures, which in turn require specialized sensors that are likely unavailable in field scenarios. Concerning this issue, prior research has investigated how the addition of contextual factors, such as personal attributes, building type, building ventilation, and outdoor contextual information (e.g., outdoor temperature, relative humidity, climate zone, and season), can support STPR prediction (e.g., [4, 18]). While prior studies have found that the inclusion of such contextual information can improve prediction performance [7, 14], research investigating to what extent contextual information can serve as sufficient input to predict STPRs without PMV index measures (i.e., indoor temperature, relative indoor humidity, clothing insulation, mean radiant temperature and metabolic rate) has been underaddressed. The growing availability of publicly accessible thermal comfort datasets, which include personal, location-based, and outdoor contextual features (e.g., [6, 11, 22, 27]), presents an opportunity to explore how combinations of contextual information features can be leveraged to infer users' STPRs without relying on PMV features as a basis. A deeper understanding of the role contextual features can play in STPR prediction may facilitate the inclusion of thermal sensation, comfort, and acceptability measures as monitoring variables in future research, allowing for a more exhaustive analysis of users' well-being. In this paper, we conduct an exploratory examination of an existing thermal comfort dataset [27], which includes subjective thermal comfort ratings across three scales: *Thermal Sensation Vote - TSV ([-3,-2,-1,0,1,2,3]), Thermal Comfort Vote - TCV ([0,1,2,3,4,5]), and Thermal Acceptability Vote - TAV ([-1, -0.01, 0.01, 1])*. This dataset also includes thermal comfort states estimated using the PMV index and contextual factors such as building information, personal information, and outdoor environmental parameters. Our main goal is to investigate to what extent more easily accessible input features represent a feasible basis for thermal comfort prediction in future research. We explore the achievable performance of different feature combinations using a Random Forest (RF) classifier and compare them to two baselines. The first is the null model, which always predicts the majority class, and the second is the PMV index, which is the primary metric in the ASHRAE55 [15] standard. We further conducted a feature importance analysis across 16 features. Using only contextual factors, we achieved a higher F_1 score than the one achieved using PMV measures. Additionally, we were able to achieve F_1 scores comparable to using a full feature set. We discuss the broader implications of these results and identify open questions that should be investigated further in upcoming research.

2 RELATED WORK

2.1 Thermal Comfort and Well-being

Thermal conditions such as outdoor or indoor temperature affect one's well-being as physiological processes in the human body regulate themselves in response to changes in temperature and humidity [8, 13, 25]. This has relevant implications for research in the fields of building ergonomics and well-being monitoring. For instance, numerous studies have shown that the perceived level of thermal comfort impacts employees' overall satisfaction and productivity in office buildings [3, 17]. Further, cognitive processes such as emotion regulation have been shown in previous work to affect how individuals perceive the thermal environment to be acceptable [26]. Because of this, perceiving the thermal environment as far too warm or cool can lead individuals to experience amplified emotions due to thermal stress. Moreover, thermal comfort is intricately linked to thermal sensation and thermal acceptability. As these concepts depict different levels of granularity (see Section 1) of subjective thermal perception, each of them is evaluated using distinct rating scales (i.e., thermal sensation, thermal comfort, and thermal acceptability scale [30]).

2.2 Thermal Comfort Estimation

Given the substantial impact of thermal comfort on various aspects of health, mental well-being, productivity, and energy efficiency, a large body of work focuses on deriving algorithms and models to estimate individuals' STPRs, most prominently thermal comfort. In their work, Fanger et al. [10] proposed the PMV index, which predicts the mean value of thermal sensation votes of a large group [15]. The factors involved in the calculation of the PMV index are the air temperature, relative humidity, metabolic rate, air velocity, mean radiant temperature, and clothing insulation [10]. The PMV index is considered the standard metric for estimating thermal sensation in mechanically ventilated buildings and therefore included in the ASHRAE Standard 55 [19] as well as the ISO 7730 [20], however, prior work has been critical of the PMV method as it has led to over or underestimation of perceived thermal sensations in past studies (i.e., [2, 16]). Recent research more frequently leverages machine learning methods to explore alternative methods of thermal comfort modeling (e.g., [4, 24, 29]). In particular, supervised learning methods that use either the measures as the PMV index or physiological signals as input to classify individuals' thermal comfort make up a considerable portion of previous work. For instance, Somu et al. [24] were able to predict the thermal comfort states of study participants in a laboratory setup with an accuracy of over 55%. In addition to six measures for PMV calculation, personal context information (e.g., age, gender, weight, and height) and outdoor environmental factors (e.g., mean outdoor temperature, relative outdoor humidity, and air velocity) were found to affect thermal comfort prediction performance [14]. Prior work investigating machine learning architectures for thermal comfort prediction oftentimes uses contextual information in addition to the PMV features and compares the baseline PMV performance against feature combinations that leverage contextual information alongside PMV features to demonstrate a prediction performance increase (e.g. [14]). While this has produced improvements in thermal comfort prediction models, leveraging PMV features for estimation presents constraints for continuous thermal comfort monitoring in buildings not equipped with the required sensory components. This reduces the feasibility of including thermal comfort as a monitoring variable in studies investigating physical and mental well-being. Contrarily, contextual factors such as personal attributes, outdoor environmental measures, and building information are more easily accessible without prior instrumentalization of study sites. For instance, outdoor environmental measures are accessible via online weather APIs, while information about the building type can be accessed via mapping and navigation APIs or through self-reports. Nevertheless, as previously described, such contextual factors have traditionally been used as additional features to predict thermal comfort. Yet, investigations of the prediction performance that can be achieved using these contextual factors alone have thus far been sparse. In this paper, we, therefore, conduct an exploratory feature combination experiment to explore the feasibility of predicting STPRs across five different labeling scales.

2.3 Datasets

Various thermal comfort datasets have been made public in the past, such as the ASHRAE Global Thermal Comfort Database II [11], which includes extensive data on thermal comfort from different climatic regions worldwide, and the SCATs dataset [22], which focuses on thermal comfort in naturally ventilated buildings in Europe. Our investigation used the Chinese Thermal Comfort Dataset (CTCD) [27] due to its coverage of personal, location, building, and outdoor input features over a large sample size, provides more robust and diverse information across multiple contexts, and is well-aligned with the study goal of investigating the feasibility of various feature combinations to predict STPRs. The CTCD consists of 41,977 data sets collected from numerous field studies across diverse climate zones, building types, and occupant profiles [27, 28]. While similar feature combination studies have recently been conducted on the CTCD (e.g., [28]), to the best of the authors' knowledge, no work has investigated combinations that do not include the features necessary for PMV calculation. The subjective thermal perception self-reports included in the dataset were measured using three scales (TSV, TCV, and TAV).

Group	Features
Location Features	Building Type, Building Operation Mode, City
Outdoor Features	Season, Climate Zone, Mean Daily Outdoor Temperature (°C)
Personal Features	Gender, Age, Height (cm), Weight (kg)
PMV Features	Indoor Air Temperature (°C), Indoor Relative Humidity (%), Indoor Air Velocity (m/s), Globe Temperature (°C), Clothing Insulation (clo), Metabolic Rate (met)

Table 1: This table shows the features included in the experiment. We grouped the features into four parent groups, which we used to derive the possible combinations for the experiment.

3 METHOD

3.1 Data Preparation

As a first step, we identified relevant contextual input features for inclusion in our analysis and derived overarching groups. In our analysis, we used 16 features in total, which were grouped into four categories. Table 1 shows the defined groups and included features, along with a short description explaining the meaning of each feature. The features included in the first group provide general information about the location and building type. The features in the second group describe the outdoor environment via features such as mean outdoor air temperature, climate zone, and the current season. The third group describes personal factors such as gender, age, height, and weight. The last group includes all the features relevant to calculating the PMV index. After defining the required feature set, we screened the data for missing entries and employed outlier detection for each numerical input feature. We filtered lines with missing entries or outliers, defining outliers as values three standard deviations greater or smaller than the feature's mean value. After filtering, we normalized all numerical features and encoded categorical features such as gender or building type using one-hot encoding. Numerical feature normalization was performed using min-max normalization. As discussed in Section 2.3, the CTCD includes subjective ratings for thermal sensation, comfort, and acceptability, which serve as labels in our classification tasks. Following related work (e.g., [5]), we transformed the original 7-level TSV ratings into a simplified 3-level scale (*Too Cold, Comfortable, Too Warm*). This transformation, referred to as TSV3, was achieved by mapping TSv labels as follows: $TSV < -0.5 \rightarrow -1$ (Too Cold); $-0.5 \leq TSV \leq 0.5 \rightarrow 0$ (Comfortable); $TSV > 0.5 \rightarrow 1$ (Too Warm). Similarly, TAV ratings in the CTCD were initially recorded using a 4-point scale (see Section 1) ranging from perceived acceptability levels: acceptable, just acceptable, just unacceptable, and unacceptable. This scale was simplified to a binary format denoted as TAV2, representing either acceptable or unacceptable conditions. The initial 4-point TAV scale was denoted TAV4 for clarity. TSV3 and TAV2 are additional ratings in our analysis, potentially useful for future well-being research. As a final step in our data preparation, we examined the class distributions for each included labeling scale. As Table 2 depicts, ratings were primarily distributed around neutral thermal perception states, leading to an underrepresentation of states at the extremes of the labeling scales.

Label Type	Distribution
TSV	**Comfortable**: 43.60%, **Sligthly Warm**: 17.96%, **Slightly Cool**: 16.22%, **Warm**: 8.38%, **Hot**: 8.31%, **Cool**: 4.41%, **Cold**: 1.11%
TCV	**Very Comfortable**: 52.67%, **Comfortable**: 34.71%, **Just Comfortable**: 10.24%, **Just Uncomfortable**: 2.20%, **Uncomfortable**: 0.19%
TAV4	**Acceptable**: 48.05%, **Just Acceptable**: 42.38%, **Just Unacceptable**: 5.78%, **Unacceptable**: 3.79%
TSV3	**Comfortable**: 40.71%, **Too Warm**: 35.49%, **Too Cold**: 23.81%
TAV2	**Acceptable**: 90.43%, **Unacceptable**: 9.57%

Table 2: Label distributions for each scale included in the analysis. It can be observed that labels for thermal perceptions at the extremes of the chosen scales are generally underrepresented, leading to imbalanced class labels.

3.2 Models and Procedure

We conducted a combinatorial analysis between the four feature groups to investigate the performance of various contextual feature combinations in the CTCD. We derived all possible combinations, excluding duplicates, resulting in 15 combinations. We decided to group similar features before deriving combinations. This allows us to capture the interactions and dependencies between related features, providing a more holistic understanding of their collective impact on thermal comfort prediction. For model selection, we initially included Support Vector Machine (SVM), KNNeighbors (KNN), Decision Tree (DT), and Extreme Gradient Boosting (XGBoost) in addition to RF as possible candidates, all with their default hyperparameters. The listed models were chosen based on prior work on STPRs [14]. We then conducted a 10-fold grid search cross-validation on the full input feature set with all five labeling scales. Given the imbalances in our dataset, we used the F_1 score as our evaluation metric. Our data processing and model evaluation pipeline was built using the Scikit-learn python library [1]. RF achieved the highest F_1 score and was consequently selected for further evaluation. We evaluated the RF model using 10-fold cross-validation across all previously derived input feature combinations and the labeling scales described in Section 2.3. After fitting the model for each configuration, we extracted the relative feature importance for later evaluation. Feature importances were calculated based on the mean decrease in Gini-impurity. To further contextualize the achieved F_1 scores and provide an estimate for the expected F_1 scores if a model always predicted the majority class, we included a majority class predictor in our evaluation.

4 RESULTS

4.1 Prediction Performance

We evaluated the performance of various feature combinations on five labeling scales. For configurations involving a single feature group, the PMV features alone achieved the highest F_1 scores across most scales, with scores of 0.27 for TSV, 0.42 for TCV, and 0.6 for TAV4, indicating the robust predictive power of the PMV features in isolation. In contrast, the location and building features alone had the lowest scores, with 0.18 for TSV, 0.27 for TCV, and 0.5 for TAV4. For TSV ratings, the best overall configuration based on the achieved F_1 scores was using the full feature set. Similar to using the PMV index calculation, this configuration achieved F_1 scores of 0.34 for TSV, 0.44 for TCV, and 0.58 for TAV4. The best configuration for the prediction of labels on the TSV scale that did not include PMV features was the combination of outdoor and personal features, with F_1 scores of 0.31 for TSV, 0.39 for TCV, and 0.52 for TAV4. For the prediction of TSV3 and TAV2 labels, it can be seen that all configurations performed similarly in most cases, regardless of the feature combination, although using only features surrounding building and location information again led to the lowest F_1 scores. While PMV features alone are effective, the inclusion of outdoor and personal features considerably enhances predictive performance, especially when PMV data is not used. The most accurate predictions are achieved with a comprehensive feature set that includes PMV, outdoor, building, and personal features. The null model, represented by the majority class predictor, consistently yielded the lowest F_1 scores across all labeling tasks. For instance, the majority class predictor scores 0.09 for TSV, while the best feature combination achieves 0.34. However, for the 2-point TAV2 tasks, the majority class predictor achieved an F_1 score of 0.49, similar to the RF model using only location features, likely due to the large class imbalance in TAV2 ratings.

Feature Groups				Classification				
PMV	O	L	P	TSV	TCV	TAV4	TSV3	TAV2
		X		0.18	0.27	0.5	0.44	0.48
	X			0.23	0.29	0.5	0.5	0.59
			X	0.23	0.3	0.5	0.48	0.57
X				0.27	0.42	0.6	0.55	0.61
	X	X		0.29	0.35	0.5	0.54	0.61
		X	X	0.26	0.33	0.55	0.52	0.6
X		X		0.28	0.42	0.59	0.56	0.62
	X		X	0.31	0.39	0.52	0.54	0.6
X	X			0.3	0.4	0.59	0.56	0.63
X			X	0.31	0.41	0.58	0.59	0.62
	X	X	X	0.34	0.4	0.55	0.58	0.62
X	X	X		0.29	0.4	0.62	0.57	0.63
X		X	X	0.32	0.43	0.58	0.6	0.61
X	X		X	0.32	0.42	0.58	0.6	0.63
X	X	X	X	0.34	0.44	0.58	0.61	0.63
PMV Index				0.34	-	-	-	-
Majority Class Predictor				0.09	0.14	0.16	0.19	0.46

Table 3: F_1 scores for various feature group combinations on five different labeling tasks (TSV=7-point, TCV=6-point, TAV4=4-point, TSV3=3-point, TAV2=2-point).

4.2 Feature Importances

Using the mean decrease in Gini impurity, we extracted the relative feature importances of all features included in our feature groups. Figure 1 shows that the feature with the most relative importance in predictions, including all feature groups as input, was the mean daily outdoor temperature, followed by individuals' clothing, weight, and age. While not all PMV features were among the most important features, they still contributed considerably to the prediction. Further, some PMV features, such as indoor temperature, globe temperature, and relative humidity, are correlated. This high degree of correlation implies that these features provide overlapping information. As a result, their individual importance scores may be lower, but their collective contribution to the model's predictive power remains significant. Features surrounding location and building attributes such as the city of measurement, building type, and building operation mode achieved a lower relative importance score using the RF classifier. This indicates that while these attributes provide some relevant information, they are less critical to the model's performance compared to environmental and personal features.

5 DISCUSSION

5.1 Performance and Practical Implications of Feature Combinations

Our analysis demonstrates that various combinations of contextual features can predict STPRs across various subjective rating scales. In line with prior work (e.g., [14, 24]), our results indicate that the performance of different feature combinations varies largely depending on whether PMV features are used or not. However, the combination of PMV, outdoor, building, and personal features yielded the highest prediction performance across all five labeling scales. Interestingly, even when PMV features were excluded, the combination of outdoor, personal, and location features performed comparably well, even in comparison to the ratings calculated using the PMV index. Looking at the performance scores for TSV3 and TAV2 ratings, it becomes apparent that the performance across all combinations was higher due to the reduced classification complexity. Here, relying exclusively on contextual factors without PMV features also achieved comparable results. For well-being research, preferences, as captured on the TSV3 scale or perceptions of thermal acceptability (TAV2), may represent feasible metrics based on our results. The feature importance analysis further reinforces these findings. The mean daily outdoor temperature emerged as the most important feature, followed by individuals' clothing and weight. While individual PMV features like globe temperature and relative humidity were not among the most relevant features, their collective contribution was still substantial. In line with prior work that already suggests that PMV features should be supported with additional contextual information (e.g., [7, 14, 23]), our findings further indicate that relying more heavily on contextual factors achieves prediction performance comparable to the standard PMV index and using a full feature set. Especially for less complex STPR prediction tasks such as the binary thermal acceptability prediction, estimation of STPRs without PMV features may represent a feasible approach. Further, we encourage the exploration of alternative

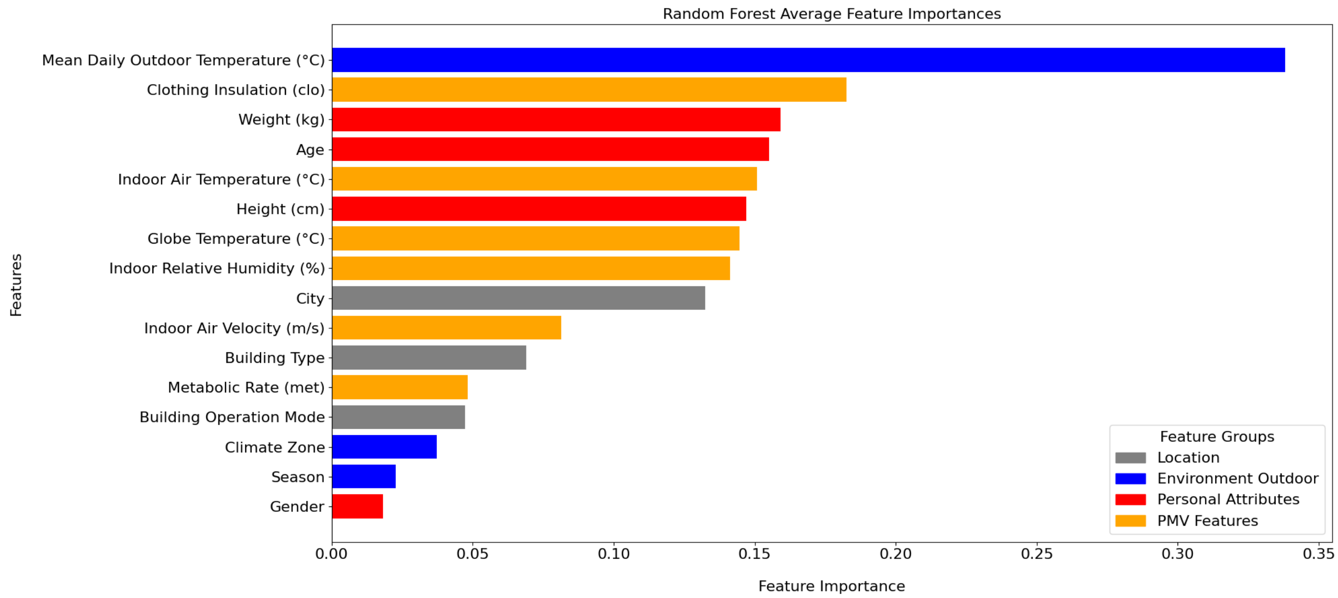

Figure 1: The calculated mean feature importance across all combinations. It can be seen that factors relevant to PMV calculation generally achieved high importance scores. Likewise, outdoor temperature and individuals' clothing, weight, and age were shown to be the most important features.

methods for STPR estimation, such as camera-based approaches that infer thermal comfort from facial expressions [29] or body movements [12].

5.2 Limitations and Future Work

While our study demonstrates the feasibility of using easily accessible contextual features for thermal comfort estimation, several limitations should be noted. First, the reliance on the CTCD may limit the generalizability of our findings to other geographic regions and climates. Future research should validate these results using diverse datasets from different locations and environmental conditions. Another limitation is the exclusion of potential real-time data sources, such as wearable sensors or smart building technologies, which could provide more dynamic and precise measurements. Integrating these technologies could enhance prediction accuracy and offer insights into thermal comfort variations with increased granularity. Finally, while our study focused on an RF classifier, exploring deep learning models and hybrid approaches could further optimize performance, as related research has shown (e.g., [24]). Future research should also investigate the long-term deployment of these models in real-world settings, assessing their robustness and adaptability over time.

6 CONCLUSION

This study investigated the feasibility of predicting STPRs using readily accessible contextual features from the existing CTCD dataset. We evaluated the performance of various feature combinations across five labeling scales. Using an RF classifier as our model for evaluation, we found that combining outdoor and personal features can achieve F_1 scores comparable to including features necessary for PMV index calculation. We conducted a feature importance analysis that underlined the importance of outdoor and personal factors, with mean daily outdoor temperature, weight, and age emerging as key predictors. Our work thus supports more inclusive and scalable subjective thermal perception monitoring methods for future well-being research.

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