Understanding thermal comfort using self-reporting and interpretable machine learning

Nitant Upasani	-	PhD Candidate,
Dr. Olivia Guerra-Santin	-	Assistant Professor,
Masi Mohammadi	-	Full Professor,

Department of the Built Environment, Eindhoven University of Technology,
Eindhoven, Netherlands.

B4B: Brains for Building's Energy Systems

- B4B is a multi-stakeholder project that aims to add operational intelligence to smart buildings.
- By developing scalable and modular solutions to achieve the transition to energy efficiency and flexibility in smart buildings.
- Divided in *five* work packages
    - WP1 - Self-diagnostic installations for energy efficiency and smart maintenance
    - WP2 - Intelligent management strategies for energy flexibility
    - WP3 - Smart user-oriented interfaces and feedback
    - WP4 - Data integration for smart communication
    - WP5 - Learning communities for smart buildings

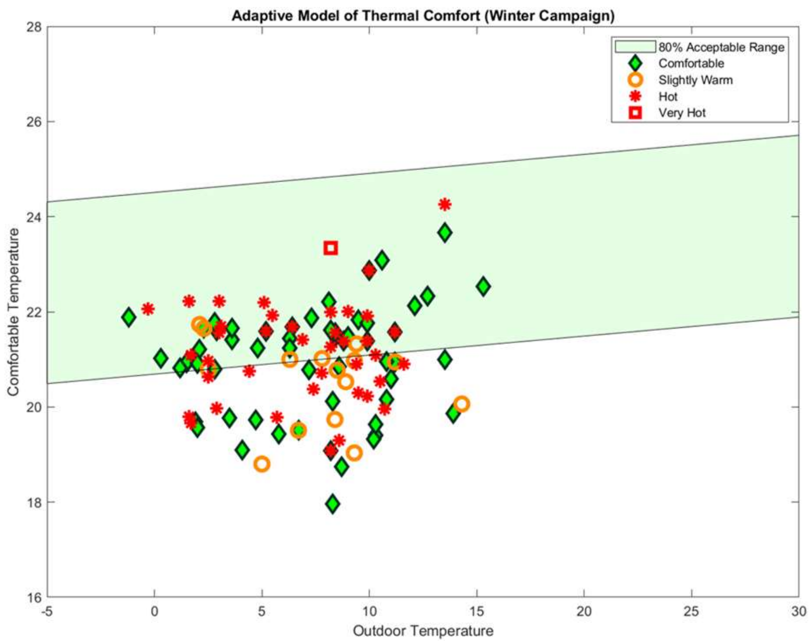
WP3 - User-centric interfaces and feedback

Objectives

- To integrate occupancy real-time data into Fault-Detection and Diagnosis and Predictive Smart Maintenance -> WP1
- To develop dynamic occupancy profiles based on monitoring and self-reporting data to support energy flexibility -> WP2
- To develop user-centric interfaces which empower the occupants with comprehendible knowledge of control strategies of the Building Management System (BMS).

In this presentation, I will talk about

Thermal Comfort Models



- A thermal comfort model is a framework used to predict the comfort level of people in a specific environment, based on various environmental and personal factors.
- Traditional popular thermal comfort models are the PMV model and the Adaptive model perform poorly at times as they fail to incorporate various factors of gender, age, culture, geography.
- These days, thermal comfort models based on self-reporting are being developed, where occupants are asked about their comfort instead of using pre-existing models.

Use-Case

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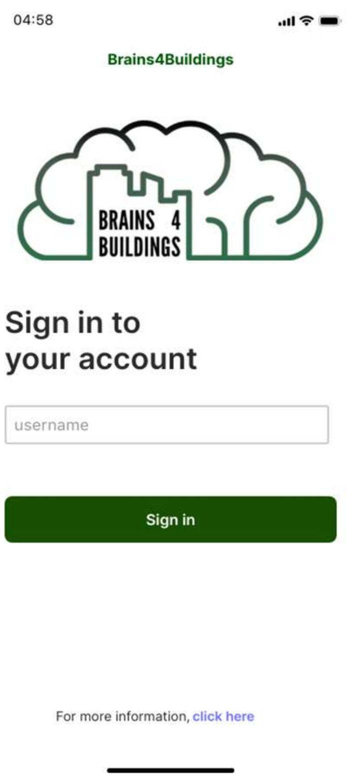
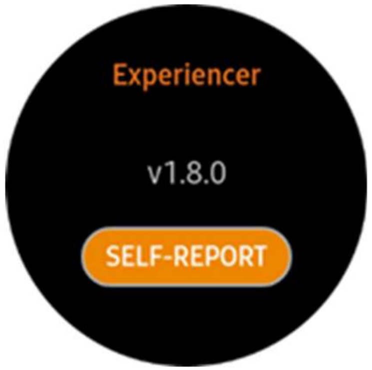
Types of sensors in every room

- Temperature
- CO_2
- Humidity
- Occupancy (presence)
- Sound/Light
- Window open/closed

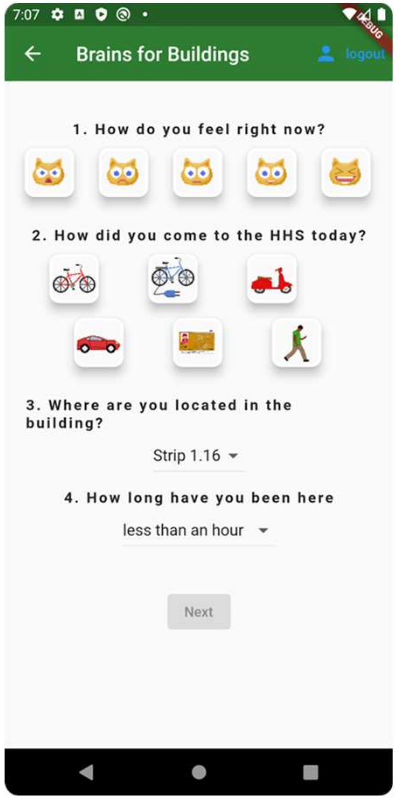
Self-Reporting

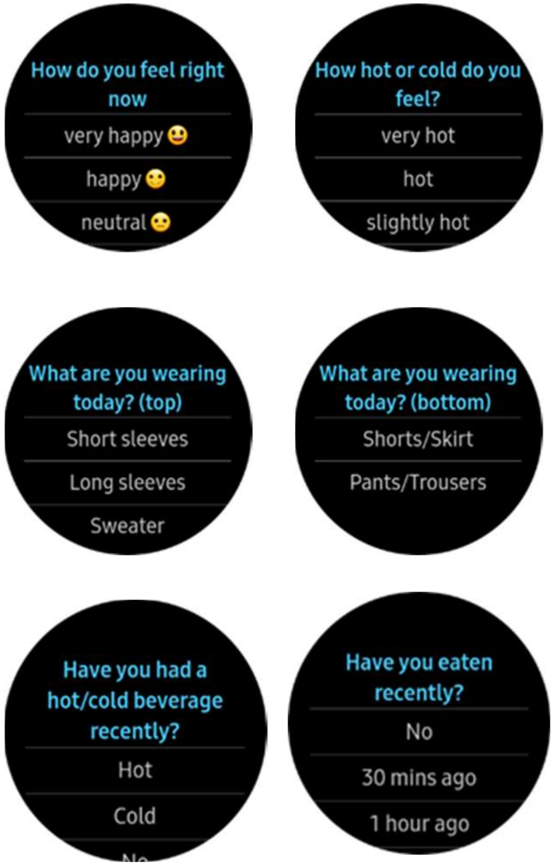
Mobile Application





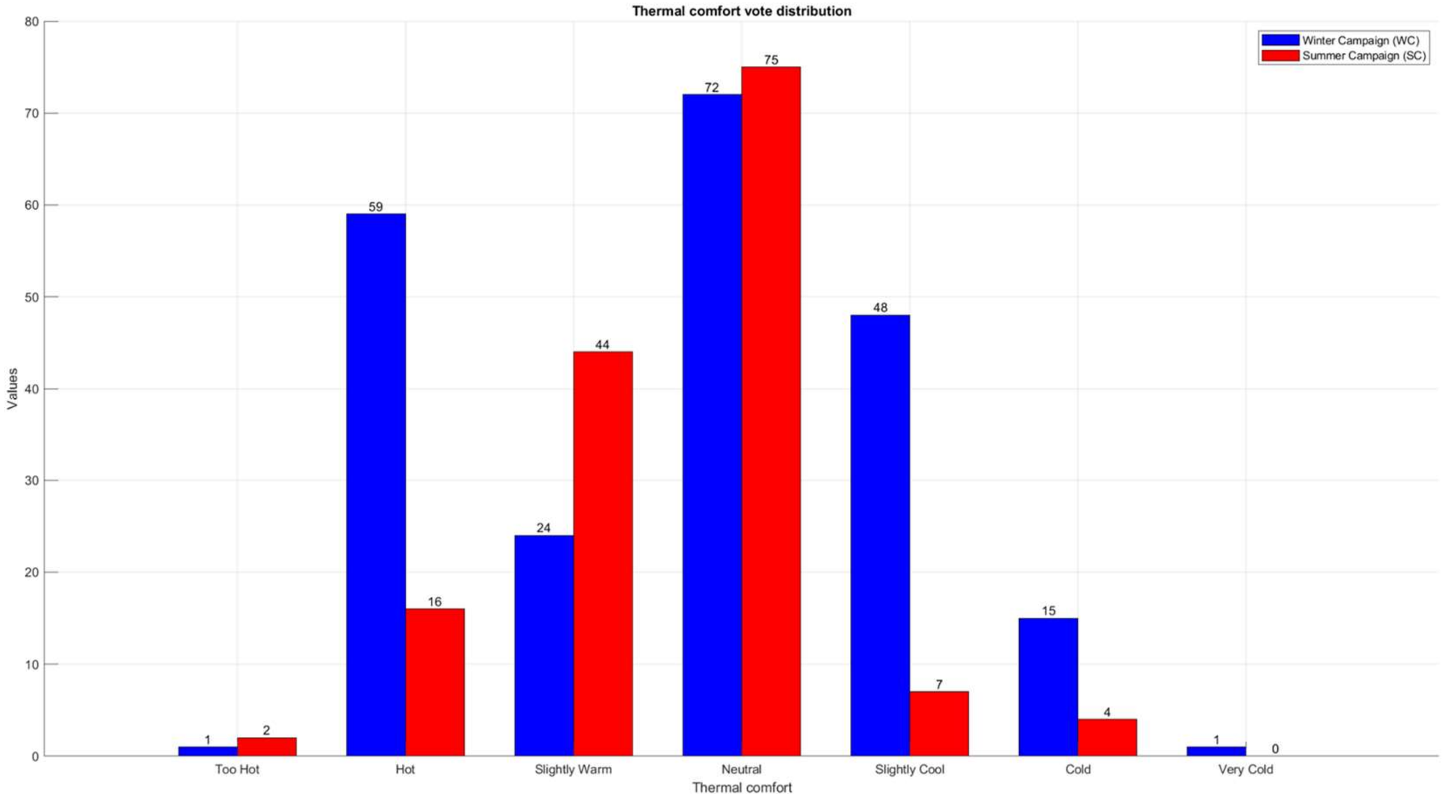
Smartwatch Application





- Mood
- Mode of Transport
- Duration
- Thermal Comfort
- Thermal Preference
- Air Quality
- Eat/Drink
- Clothing

Descriptive Statistics - 377 votes over a period of 4 weeks.



Modeling Thermal Comfort

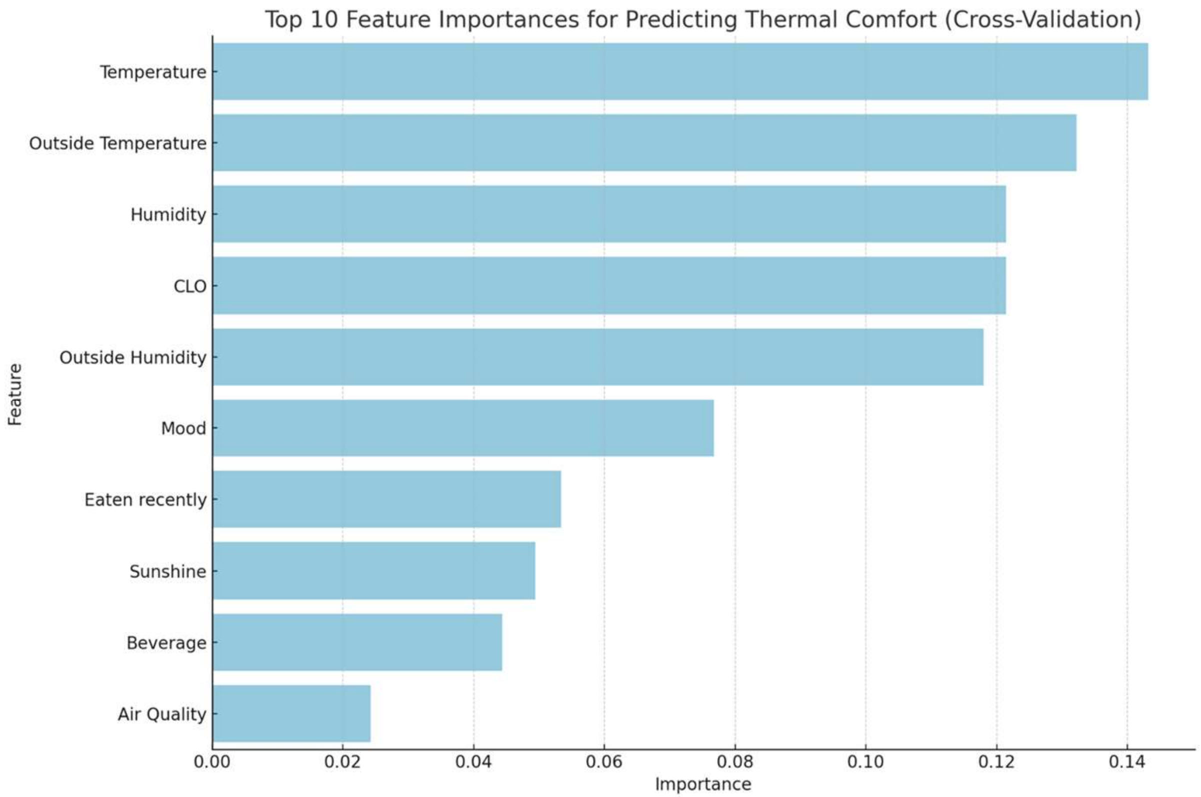
We treat modeling thermal comfort as a regression problem. We approach this problem in the following four steps.

Feature Selection – For determining which features explain and impact thermal comfort of occupants the most, this model does not omit any features in this initial model, thus all features shown in figure 5 are considered for predicting thermal comfort (except thermal preference).

Train-test split – The dataset was split in two groups. 70% of the data points were grouped in the training set and 30% in the testing set. The sampling method used for this segregation was stratified, meaning the prediction class in each group had the same ratio to one another, as in the original dataset. The test set is not looked at while training the model for a good evaluation of the model.

Training – For training the dataset with different models, a 10-fold cross validation was used to avoid overfitting and allow all parts of the dataset in the training process.

Feature Selection



Top 6 features selected for modeling

- Temperature (Indoor)
- Temperature (Outdoor)
- Humidity
- Clothing Levels
- Outside Humidity
- Mood

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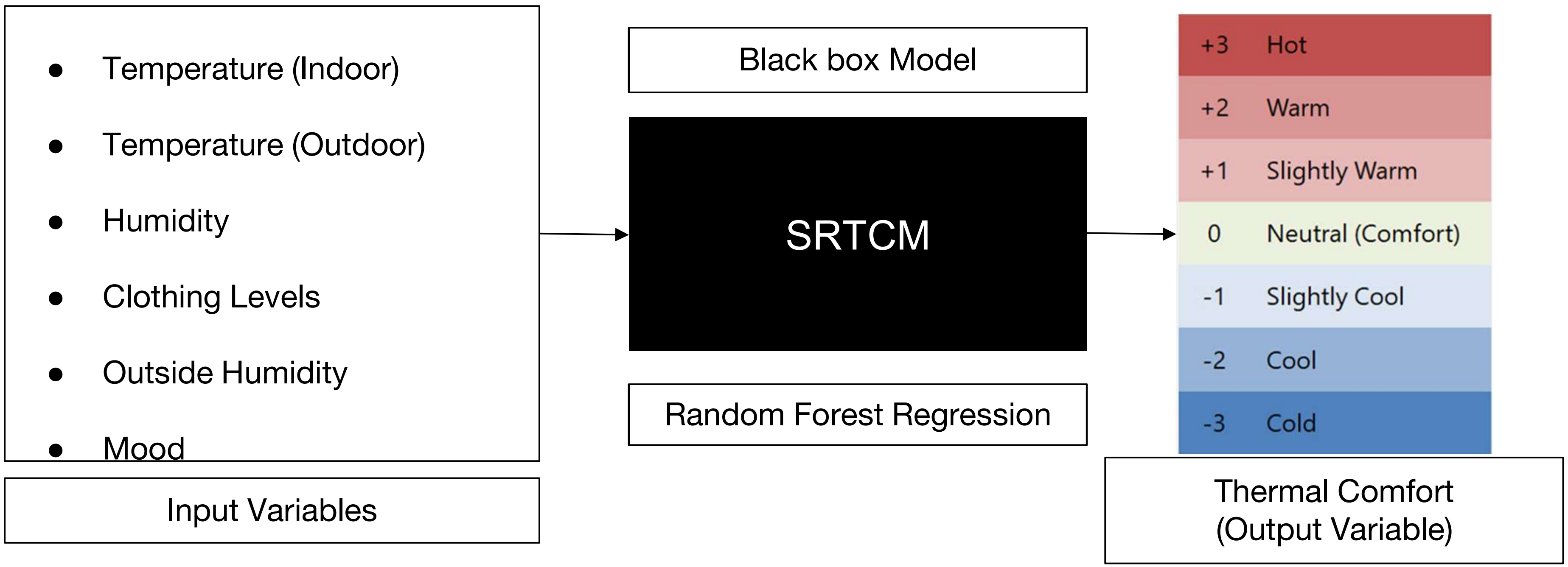
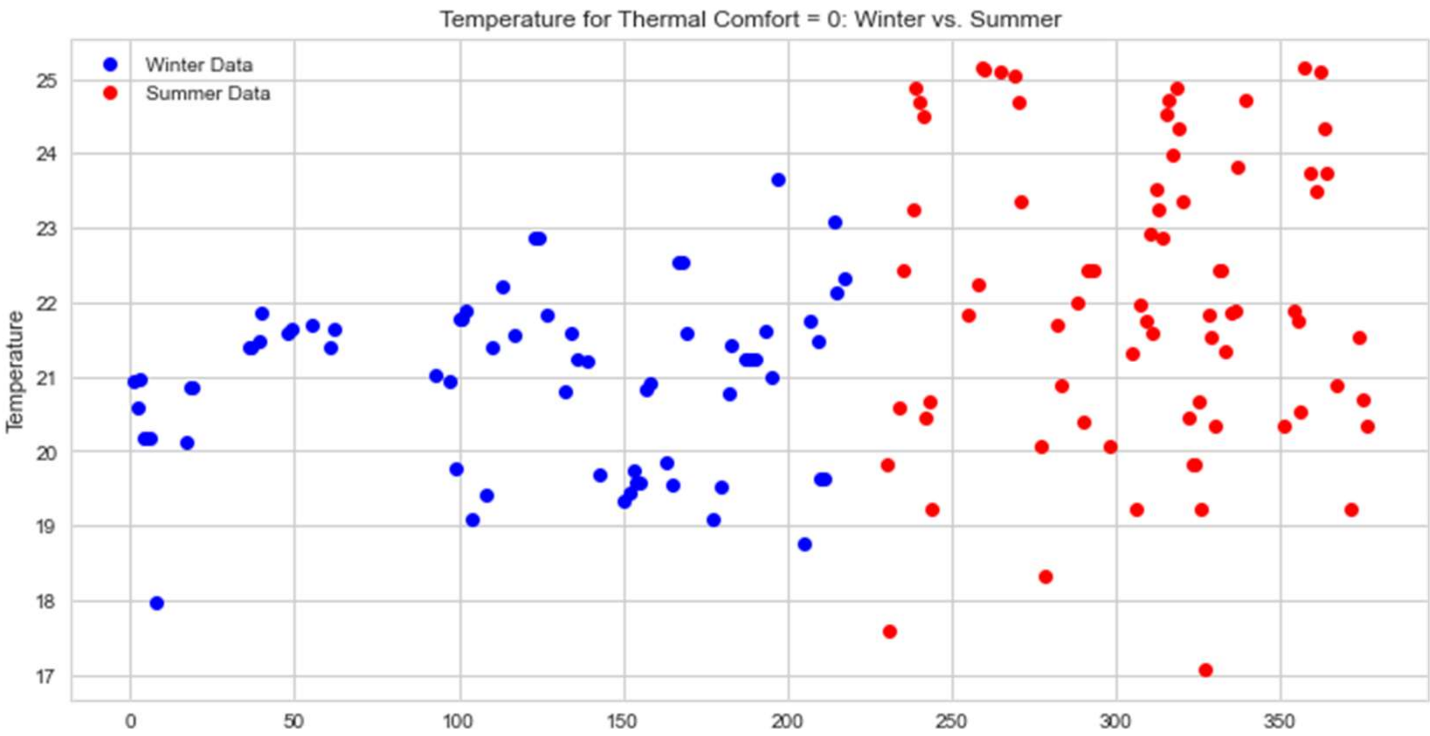
Self-reporting based thermal comfort model (SRTCM)



Performance of SRTCM vs PMV Model

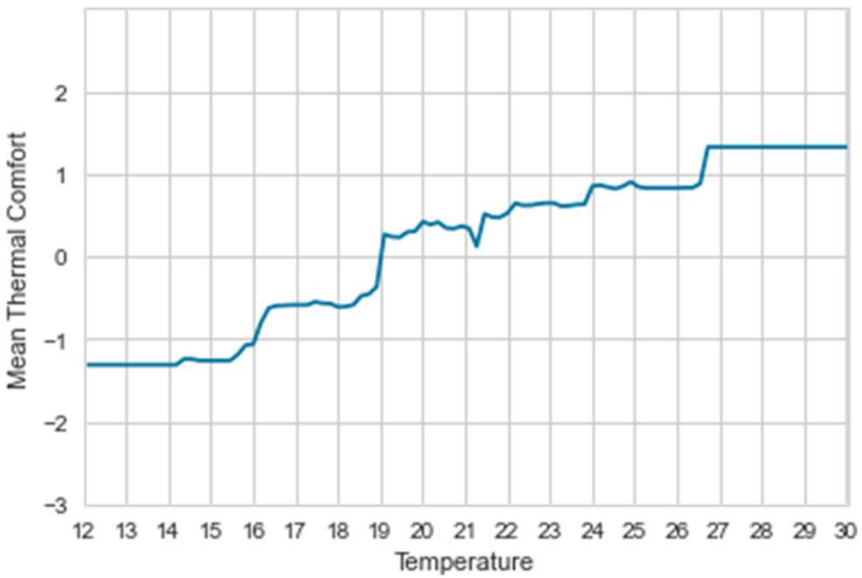
Model	Correct Prediction	Margin error = ±1	Margin error = ±2	Final accuracy	Error = ±1 Accuracy
SRTCM	271	360	376	72%	95.49%
PMV	88	211	304	25%	79.31%

Indoor Temperatures when occupants voted TC as Comfortable



Very difficult to set temperature as the range is big! > 8°C

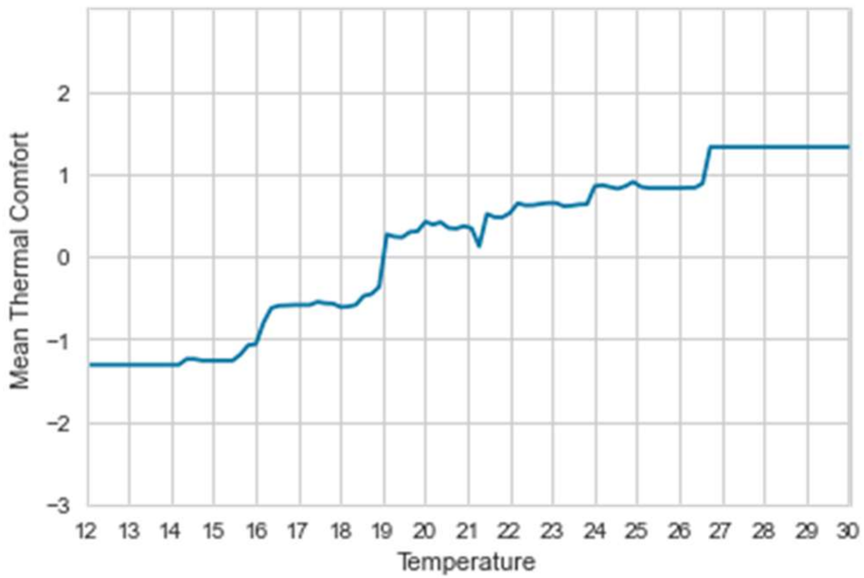
Understanding the SRTCM (BLACK BOX) Model

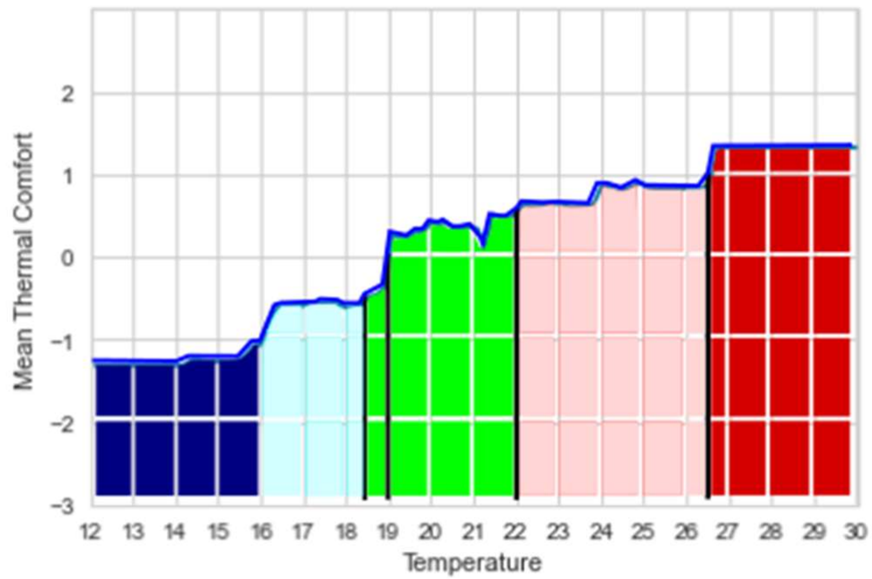


- A PDP is a tool used to visualize the importance of a feature on the output of a complex model
- It is calculated by averaging out the effects of all other features except the feature in consideration for the PDP (in this case, temperature).
- Can be used for any (thermal comfort) model, even PMV.

Partial Dependence Plots

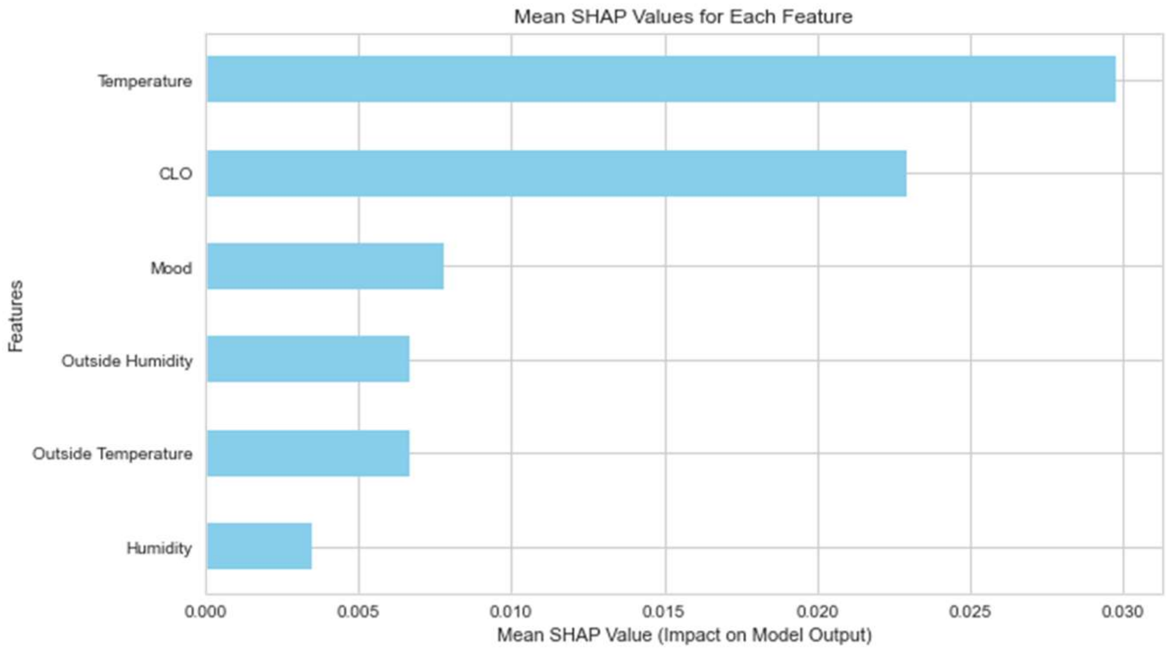
Understanding the SRTCM (BLACK BOX) Model





Partial Dependence Plots

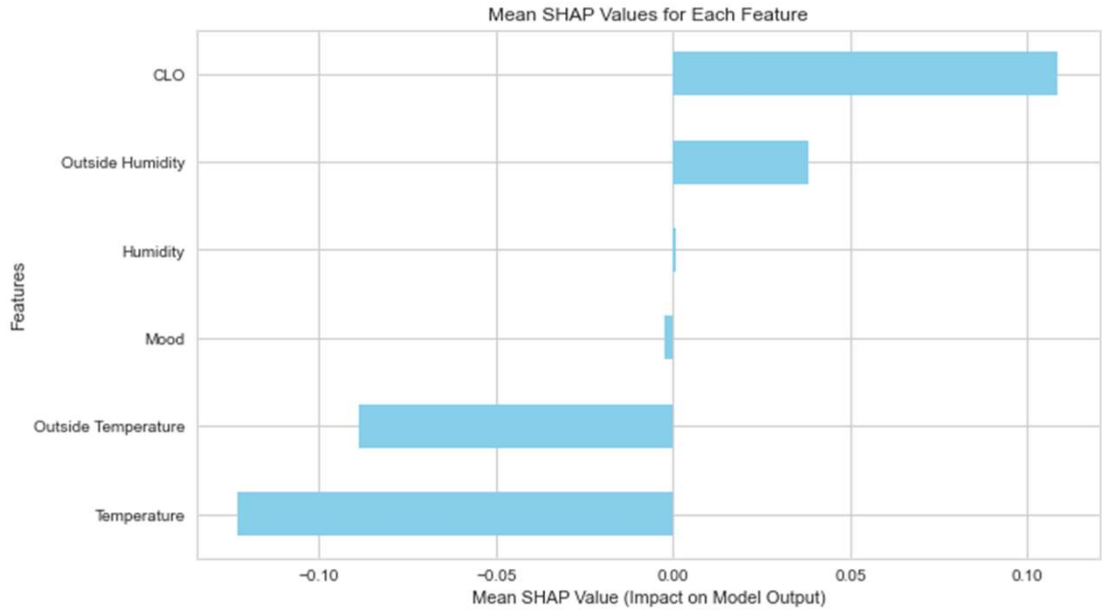
Understanding the SRTCM (BLACK BOX) Model



SHAP Values

- SHAP values can be calculated for any data point, are model agnostic.
- For any specific prediction, SHAP values precisely calculate the contribution of each feature to the final result.
- For a localized dataset, can be seen as feature importance for the local data.

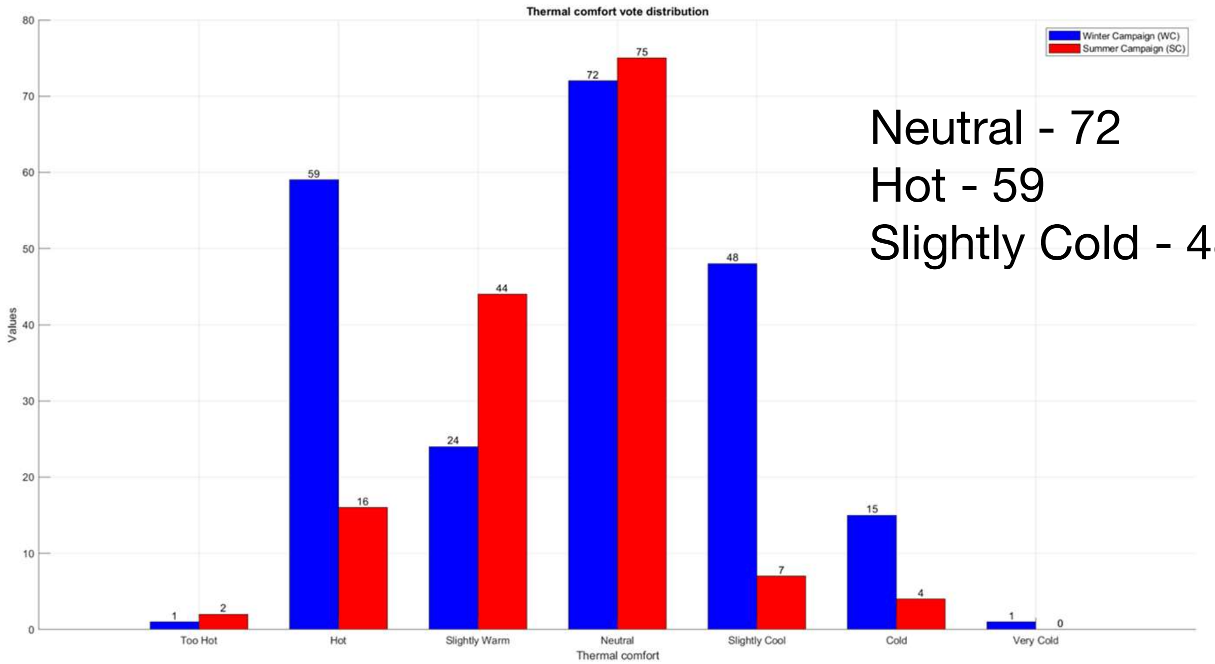
Understanding the SRTCM (BLACK BOX) Model



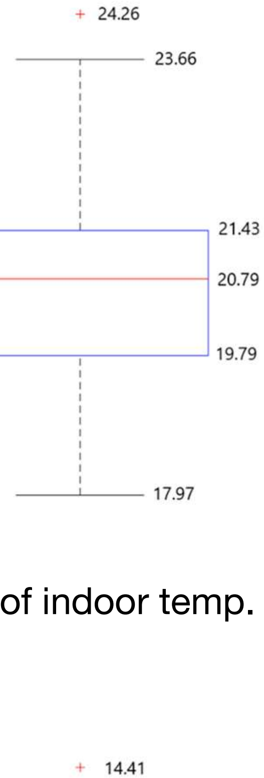
SHAP Values for Winter data

- Baseline prediction is important to interpret the SHAP values! (Here, the baseline is 0.325 - slightlyyyy warm)
- In winters, clothing values are contributing to occupants feeling even warmer.
- Indoor temperature is contributing negatively for the winter data. (Negative from the baseline, i.e. 0.325)

Understanding the SRTCM (BLACK BOX) Model



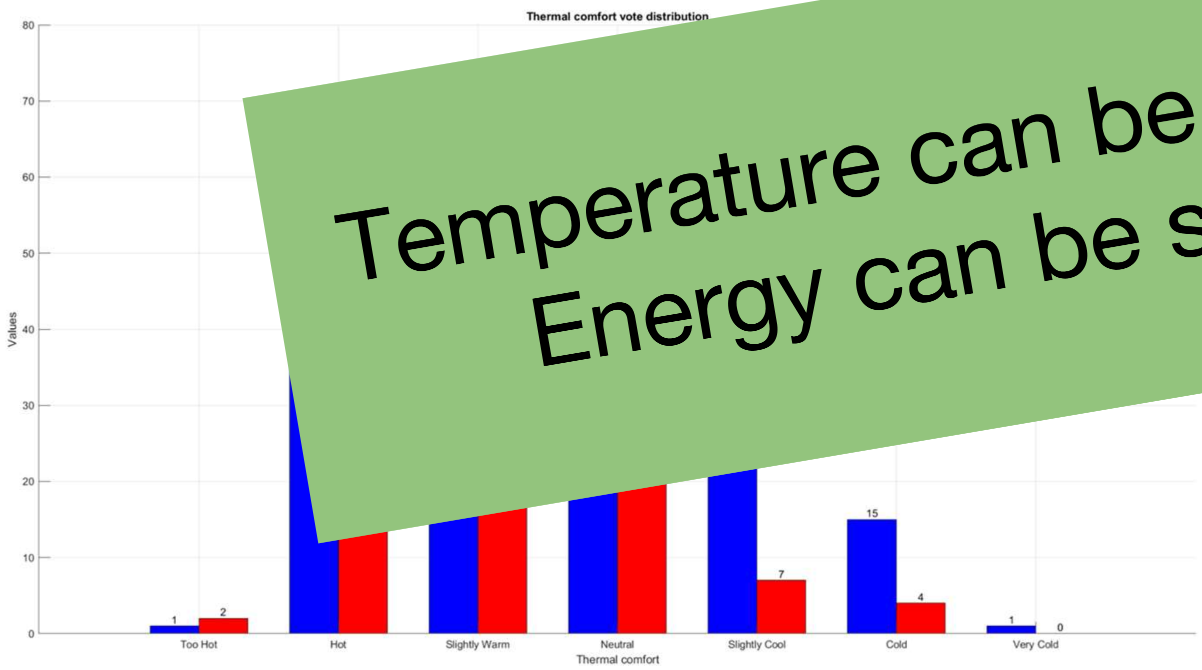
Neutral - 72
Hot - 59
Slightly Cold - 48

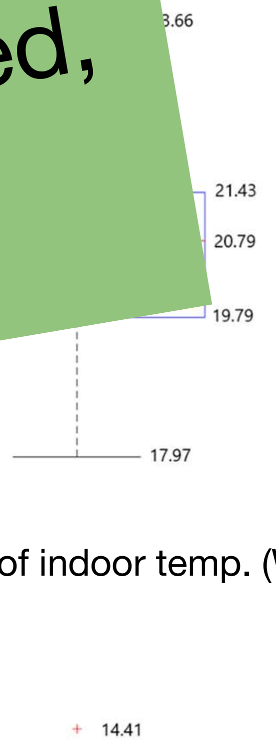


Box Plot of indoor temp. (WC)

Takeaways

Temperature can be reduced,
Energy can be saved!





Box Plot of indoor temp. (WC)

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Takeaways

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If we can save energy in this little part of one building, we should aim to do so in most parts of many buildings :)

Thank you!