Project acronym	B4B
Project full name	Brains for Building's Energy Systems
Grant No	MOOI32004
Project duration	4 year (Starting date May 1, 2021)

Deliverable 3.5
Comfort and occupancy data for FDD system
Olivia Guerra-Santin (TU/e) Nitant Upasani (TU/e)

Work package	3
Result	5
Lead beneficiary	TU/e
Due Date	31/10/2023
Deliverable Status	Final
File name	B4B-WP3-D3.5-Comfort and occupancy data-231215_clean.docx
Reviewers	TUD-BK, TUe, Avans

This project received funding from Dutch Ministry of Economic Affairs and Climate Policy and Ministry of the Interior and Kingdom Relations under the MOOI program

SUMMARY

This deliverable focuses on the research activities carried out in task 3.2.3. The task results will contribute to the research carried out in WP1, and therefore, a second version of the deliverable will be produced at the end of the B4B project. This task explored the possibilities and limitations of integrating occupant-related data to fault detection and diagnosis systems. For this, we use crowdsourced, self-reporting, and sensor data to determine the occupants' comfort, taking into account personal and subjective comfort preferences and needs and objective/measured data.

The research was conducted in the HHS living lab (campus Den Haag). The main objective was to define and set up the (self-reporting) data collection methods and to explore the use of the data in thermal comfort models.

A machine-learning model based on self-reporting of thermal comfort was developed. The modem predictions were compared with those based on the Predicted Mean Vote model, the current method to establish thermal comfort in office buildings. The self-reported model was better at predicting the thermal comfort reported by the study participants. A further study was carried out on the personal and contextual variables that influence thermal comfort, showing which variables contribute the most to it in this building. The full results of the analysis will be published in a journal paper (currently in preparation).

The following steps in the research are the integration of heart rate into the thermal comfort model, as well as the development of individual thermal comfort models. These will be published in an accompanying journal paper.

Furthermore, to be able to integrate the thermal comfort model in the FDD system, as well as for (energy flexible) building control, we will investigate the application of the same methodology in different contexts (living labs), as we will investigate the practical application of this approach with WP1 partners. These results will be presented in the final version of this deliverable.

TABLE OF CONTENT

1 INTRODUCTION

Within this task, we explored the possibilities and limitations of employing occupant-related data, such as occupancy, occupant behaviour and subjective data related to comfort and satisfaction based on self-reports to contribute to fault detection and diagnosis systems. For this, the first step is to examine how far crowdsourced, self-reporting and sensor data can be used to determine the occupants' comfort. This will allow us to differentiate between a complaint related to dissatisfaction with the building's indoor conditions that may indicate a fault in the building systems (thus, for FDD), and personal and subjective comfort preferences and needs that could be used to inform building control.

This task contributes to the development of task 1.1 (WP1) *Smart optimised operation*, where we look into how subjective comfort and/or health indicators can be integrated into fault detection and diagnosis systems. Thus, in this report (version a), we will be reporting on the first three activities outlined below, while the last activity will be reported in the last version in M48, after the implementation and testing of the results in the WP3 use cases.

This task consists of the following activities:

- Use of occupant-related data for fault detection and diagnosis systems.
- Data collection in Living Lab HHS.
- Analysis of data into reliable and relevant health and comfort data input.
- Integration of building monitoring data and self-reporting data for health, comfort and occupancy.

These activities have been reframed into the following research questions:

PHASE 1

- RQ1 How do self-reported occupant-related variables contribute to a predictive/explanatory comfort model?
- RQ2 How do measured (occupant-related) variables contribute to a predictive/explanatory comfort model?
- RQ3 Can these models improve the accuracy of prediction in comparison to existing comfort models?

PHASE 2

- RQ4 How can we ensure maximum predictability with minimum effort from the occupants? (part of Task 3.3)
- RQ5 How can we distinguish between occupants' input given as a complaint vs. discomfort? How can we make this clear to the system or to the occupant? (part of Task 3.3)

PHASE 3

- RQ6 What are the practical applications of data-driven comfort models for FDD?
- RQ7 What are the challenges associated to gathering occupant-related data in relation to data management, ethics, and practicability?

The first three questions are the focus of this deliverable and based on the data collection an analysis in the HHS living lab (campus Den Haag). This part of the research was intended to define and set up the (self-reporting) data collection methods and explore the data's use in thermal comfort models.

In the coming stages of the research project (linked to Task 3.3), RQ4 and RQ5 will be answered by integrating other types of occupant-related data into the models with other data collected in the HHS living lab. In this phase, we investigate the role of heart rate data in the comfort model (which requires less effort from the occupants but is more intrusive and requires careful data management), and the development of individual comfort models. Measured occupant parameters and individual comfort models were originally intended to be developed in task 3.3 for (flexible) building control, but given the strong link between the topics, its relevance for FDD will also be discussed in the final version of the deliverable.

RQ6 and RQ7 will be answered in the following stage of the deliverable after the implementation/testing of the results in Spectral and HHS (Delft) living labs. The Spectral living lab focuses on building control, management, and user-centric interfaces (to be fully reported in Deliverable 3.7), while the HHS living lab focuses on FDD.

This report is organized as follows: Section 2 discusses integrating occupant-related data into FDD systems within the B4B context, framing this research. This discussion is based on a non-systematic literature review and, more importantly, on the lessons learned from previous projects and work of WP partners. Thus, not only reflecting the state of the art but also relevant parties' views on the topic. Section 3 focuses on existing comfort models and their challenges and opportunities in the context of FDD systems. Section 4 presents a quick overview of self-reporting occupant data in the literature and within the B4B project. Section 5 shows the thermal comfort investigation and development of the (first) thermal comfort model based on the case study in the HHS living lab. Sections 6 and 7 focus on the conclusions from this first phase, and the next steps within the B4B project.

2 INTEGRATION OF OCCUPANT-RELATED DATA INTO FAULT DETECTION AND DIAGNOSIS SYSTEMS.

The Brains4Buildings project aims to increase buildings' energy efficiency through two different strategies: fault detection and diagnosis and flexible energy management and control. An important component in both strategies is the role of the occupants. In this report, we focus on fault detection and diagnosis, although we will return to the second strategy in the final version of the deliverable.

Fault detection and diagnosis aims to increase energy efficiency and improve indoor conditions in buildings. According to previous studies, as building systems become more complex, a large share of HVAC system components need to operate at optimal levels [1]. There are many causes for it, including unbalanced airflow, malfunctioning operation of dampers, insufficient evaporator airflow, valve leakages, air-cooled condenser fouling [2], duct leakage, HVAC or lights left on when space unoccupied, airflow not balanced, improper refrigerant change, dampers not working properly, improper controls setup/commissioning, control component failure or degradation, software programming error, improper controls hardware installation, air-cooled condenser fouling, valve leakage, wrongly configured building equipment, misplaced or wrongly wired sensors or actuators [3].

Different FDD methods are used to identify these faults. FDD has been categorised in different ways; for example Yang et al. [4] classified them as data-driven models, grey box models, and prior knowledge-based (rule-based) methods; Katipamula et al. [5] classified them as history-based, quantitative model-based and qualitative model-based methods; and Nojodehi et al. [6] classify them as a knowledge-driven and data-driven. These reviews agree that although precise modelling is vital for FDD, it is also challenging and time-consuming [3]. This makes grey box, model-based and rule-based methods more complex to use [7].

Data-driven methods, on the other hand, show potential because they do not depend on a physical model. These data-driven models, however, require good quality historical data. Additional challenges in these models have been recognised, including the necessity for pre-processing data and evaluating and selecting features. This is crucial to mitigate the risk of overfitting, especially when operationally unrelated or redundant attributes in large datasets are utilized. Moreover, issues linked to high dimensionality and redundancy of attribute data have also been identified [2].

2.1 Occupant behaviour in smart buildings

The use of occupant-related data within the B4B project is twofold. Firstly, occupant-related data can be used as input in FDD systems to help identifying faults in the system. Secondly, in (flexible) energy control systems to determine the thermal comfort of the occupants to increase energy efficiency while maintaining good indoor conditions.

There are several methods to investigate occupants' behaviour in buildings. Many of these techniques have been developed for building performance monitoring and building assessments. These methods can be employed right away to monitor some aspects of occupants' behaviour, for example movement sensors can be used to determine the presence of people (occupancy), but occupant-related data could also be integrated into virtual sensors (also called soft or proxy sensing) to determine occupant-related variables indirectly [8]. Analytic virtual sensors use data gathered through different means (e.g. CO_2 measurements) to calculate or estimate another parameter (e.g. presence of people, thermal comfort), while empirical virtual sensors estimate a new parameter based on historical data.

Past research has already focused on ways to model occupant behaviour in buildings using building data. For an overview of these methods, refer to Deliverable 3.8 (TNO). These ways to model occupants' behaviour could be used as input in FDD systems to determine whether there is a fault in the system, based on the assumption that if occupants interact with building interfaces (thermostats, windows), it is because they are trying to restore their comfort. In the same way, information of the actual occupants' behaviour in buildings can help facility managers and control systems to improve the energy efficiency of the building by identifying instances in which 'unexpected' or 'wrong' behaviours are observed that are leading to a loss in efficiency. These are however out of the scope of this deliverable.

On the other hand, building sensor data can also be used to calculate occupants' thermal comfort in buildings through the use of well-established thermal comfort models such as the Predicted Mean Vote (PMV) and the adaptive model (see Section 3). The inputs of these models are indoor or outdoor temperature, relative humidity, wind speed and a few contextual variables (insulation provided by clothing level and activity rate).

However, research has shown that thermal comfort is also affected by other factors, such as the occupants' needs and (comfort) preferences, as well as by their interaction with their physical environment (i.e., the building itself and its systems and interfaces). Therefore, in this task, we look into the role of occupant-related data (physiological and self-reporting data) for FDD and building control.

2.2 The relevance of occupants' data for FDD

Due to the increase in the capabilities of smartphones and smartwatches to collect data, we see an increase in the possibilities to use occupants' feedback as a new layer of information in FDD systems and in building management systems. For example, since some devices allow to track users location, gather sensor data (light, temperature), subjective feedback, users' health and activity data (heart rate, steps taken) and other personal data (skin temperature), there has been an increase in interest in using occupant data for FDD, where participants can contribute passively or actively in the data collection [3, 6]. These types of studies are also called crowdsourcing, participatory sensing [9], people-centric sensing [10], and ecological momentary assessment (EMA) [6].

The main contribution that occupant-related data could have in FDD is using occupant feedback as a sign of a fault in the building, such as a faulty sensor. For example, Nojodehi et al. [6] developed a method to integrate occupants' feedback to enhance the performance of fault detection and diagnosis technology, where occupant input is used to confirm alarms raised by the system. In their method, the system flags alarms that are inconsistent with occupants' votes. In their research, they claim that the feedback accurately proved or disproved alarms, and that by the end of the study occupants were more likely to report discomfort sooner.

2.2.1 The challenges of using occupant data for FDD

Based on previous research monitoring the performance of buildings, both in terms of occupant comfort and energy efficiency, we can hypothesize which challenges might be encountered when trying to incorporate occupant-related data into FDD systems.

The challenge in the use of complaints reports as input data for FDD might be the assumption that an average occupant feedback) might be reliable enough to detect faults that affect comfort. Thus, it would be essential to assess how accurate occupant inputs are, and whether they are compatible with the assumptions that building operators normally make [6].

However, as Nojodehi et al. [6] acknowledges, occupants do not always report poor indoor environments. Previous studies have suggested that collecting self-report data on behaviours in real-time using mobile devices is associated to higher compliance, completion and first prompt response rates while being perceived as less disruptive [11]. However, it is still necessary to determine what exactly would be the data needs (frequency, duration) and consequences (disruptions to occupants) involved in using self-reporting data in buildings for FDD or management, especially if both uses are to be employed in the same building. This is important because while for FDD the occupants are asked to report (i.e. complain) when they feel discomfort, for building control it is important also to know when they are comfortable.

Furthermore, there might be a risk of classifying as a building fault something related to personal preferences, especially when more than one person is in the space, or when the occupants do not have control over their environment. For example, users might complain of a room being too warm because it is impossible to open a window. In addition, misclassification of a fault might also occur when occupants report a complaint not knowing exactly the source of their discomfort. For example, it has been observed in previous research that occupants sometimes complain about bad air quality or high levels of CO_2, when their discomfort is caused by air dryness. Therefore, the integration of sensor data might be crucial for the proper implementation of FDD systems.

A second crucial matter would be the role of contextual variables. These could be those related to the building itself, for example, presence of openable windows, orientation of room and windows, presence of heating sources, number of occupants in each room, presence of drafts, solar shading, etc. These building-related characteristics might affect comfort and might be very local (from room to room and even from one side of the room to the other). Furthermore, contextual variables related to the users might also affect comfort and occupants' complaints, for example their thermal preferences, health condition, activity level, clothing level, mood, etc.

Finally, as Nojodehi et al. [6] mentions, while one or a few complaints cannot be treated as ground truth, frequent reporting/complaints about an issue could be treated as symptoms for a fault. However, the baseline conditions (e.g., indoor conditions) must be predefined. This predefinition might have to be dynamic, especially if we look for energy flexibility in buildings, which could add complexity in the meaning of the occupants' input. For example, if a lower indoor temperature could be expected on Monday mornings, either the occupants in their self-reporting or the FDD systems in the rules it follows, would have to take into account the discrepancy with the temperature and comfort levels on other days' mornings. The same can be expected when considering occupants' capacity for adaptive comfort.

2.2.2 Limitations of using occupants' data for FDD

Studies such as Lazarova-Molnar et al. [3] claim that using occupant-related data in FDD provides further insight to FDD systems at no additional cost. However, they assume that all building users will have either a smartphone with these functionalities (gps, hearth rate measurement, skin temperature measurement, options to self-report), or a smart watch, which is only sometimes the case. More importantly, these studies assume that the occupants will be willing to give access to their data, which not only might not be the case for a large part of building occupants, but also entails working with data privacy issues, for example where the data is stored, how to store it safely, how to deal with the data when the occupants are not in the office buildings, etc. Especially when we consider the use of smart watches that count steps, measure heart rate or skin temperature, these types of data can be categorized as sensitive personal data, since they indicate the health condition of the user. Furthermore, employees might not be comfortable with data related to their health or location being constantly available to their employers.

3 THERMAL COMFORT MODELS

3.1 PMV and adaptive model

Standards for thermal comfort in buildings are defined in the EN 15251 and the ASHRAE 55-2020 [12, 13]. These standards are defined based on two thermal comfort models: the predicted mean vote (PMV) method (defined in ISO 7730:2005 [14]) and the adaptive method. The standards can be used for building design, to evaluate building performance, and more recently we have seen efforts to integrate these comfort models in building control systems. The advantage of these models is that they are widely accepted and known. Still, the certainty of these models to predict thermal comfort has long been questioned, even when adapted to other climate conditions.

3.1.1 PMV model

The Predicted Mean Vote (PMV) model, developed by Fanger [15], considers various aspects of indoor environments, including certain elements of user context. This model employs heat balance principles to establish a relationship between six factors affecting thermal comfort and the average responses of individuals on a seven-point thermal sensation scale [12]. The Predicted Percentage of Dissatisfied (PPD) index is closely tied to PMV and assumes that individuals who vote +3, +2, -2, or -3 on the thermal sensation scale experience discomfort. This assumption simplifies PPD as symmetric around a neutral PMV point [12]. The parameters used in PMV calculations encompass air temperature, mean radiant temperature, relative humidity, air speed, clothing level, and activity level. The PMV standard primarily caters to building occupants with sedentary to moderately elevated activity levels, as it was originally developed for office buildings.

The PMV method has faced several criticisms [16-20], with the most relevant ones for Fault Detection and Diagnostics (FDD) and building control being:

1. The narrow range of comfort: The model's assumption that only votes within the -1 to +1 range denote comfort has been challenged. It has been observed that categorizing a building as Class A, aiming for this narrow temperature range, does not necessarily lead to greater satisfaction and is less energy-efficient compared to broader comfort ranges.
2. Weak correlation with actual comfort votes: Studies have shown that PMV is less correlated with actual comfort assessments compared to air temperature and globe temperature [21]. For instance, Cheung et al. [22] found that the PMV accuracy in predicting actual occupants'comfort (based on self-reports) is only correct on 34% of the cases.

3.1.2 Adaptive model

The adaptive model relies solely on outdoor temperature as an input for its calculations. It was developed based on the assumption that thermal comfort is a result of dynamic equilibrium, in contrast to the static balance assumed by the PMV model [23, 24]. Additionally, the adaptive model acknowledges the influence of social context and the interaction between people and buildings on comfort [25]. It posits that individuals will adapt to maintain comfort in response to changes in indoor conditions. Those with greater control over their environment, either through personal adjustments (e.g., clothing, activity) or modifying indoor settings (ventilation, thermostat), are less likely to experience discomfort [19]. This approach is best suited for buildings with occupants capable of adapting themselves to the environment and making adjustments as needed.

Occupants of air-conditioned spaces expect homogeneoustemperatures regardless of the weather conditions, while occupants of naturally ventilated buildings expect temperature fluctuations reflecting local patterns of daily and seasonal climate variability, and are thus more forgiving of higher or lower, and fluctuating temperatures . Thus, according to the ASHRAE Standard 55, adaptive models should only be used in buildings with natural ventilation or buildings with air conditioning systems when these are not in operation. However, the possibility of users to make such adaptations, such as opening windows, should also be considered, especially in environments with multiple users, where it might be impossible to meet all individual requirements, like in open-plan offices. The primary advantage of adaptive models is their relative simplicity compared to the PMV/PPD model [20]. However, they come with certain disadvantages [20, 26]:

- they narrowly focus on temperature, neglecting the effects of air velocity and humidity;
- they ignore local thermal discomfort and the factors influencing human heat balance;
- they have limited application range, mostly suitable for offices and workplaces;
- they are valid only for specific metabolic and clothing insulation levels;

- they are inapplicable in winter due to low outdoor temperatures.

There are several indices to calculate the adaptive temperature [26]. The statistical approach of the adaptive model allows indices for other climates to be developed.

3.2 Personalised thermal comfort models

With the possibilities to gather more information from the user (real time or not), we see a trend to develop personalised thermal comfort models. This comes from the idea that personalised models are better, since general (aggregated) models (e.g., the PMV model) assume that all occupants within a building (or area in a building) share the same comfort preferences [27] while in reality thermal comfort varies in people according to their metabolic rate, preferences and tolerance for comfort, which poses a "challenge when conditioning a workplace to meet the requirements of all occupants' [28]. In building performance evaluations, it is considered impossible to specify a thermal environment that will satisfy everybody all the time [29]; if the criteria ranges for the PMV–PPD and operative temperature are to be met at all times, the heating and cooling capacity of the HVAC systems would be relatively high. In HVAC system design, it is acceptable for indoor conditions to be out of the comfort ranges for 3–5% of the time [14]. Thus, the need for a personalized comfort model (at least in office buildings) might not be necessary for building control. However, other uses can be found for personalized comfort models, for example to cluster occupants based on their thermal comfort preferences to suggest a suitable better place (when available) [27].

In personalized thermal comfort models, data from sensors measuring physiological parameters and/or self-reporting data obtained through smartphone or web applications are fed into the models [6, 27, 30]. The advantage of personal comfort models is the opportunity to add physiological variables from sensors and wearables to improve model accuracy [31]. This is an advantage to the PMV model that only estimates activity rate, while heart rate can be used as a more accurate measurement of activity level. In the same way, skin temperature could reflect objectively the thermal comfort perception.

4 SELF-REPORTING DATA AND PHYSIOLOGICAL DATA

Self-reporting data can be obtained from different means, for example, simple paper or online surveys to real-time smartphone applications, smartwatches or websites. Each has disadvantages and advantages related to return rates and sample sizes. For example, a phone survey has a higher response rate than a mailed questionnaire, and an internet questionnaire might be used when only a sub-section of a sample is required (i.e. people more likely to use internet regularly) [32]. However, the disadvantages of the media can disappear when the owner/facilities manager or occupant of the building is involved in the study. Comfort surveys can be retrospective or real time, and one-off, seasonal or longitudinal [32]. In retrospective questionnaires, participants are asked to rate their comfort (or describe their behaviour) on a regular winter/summer day. These questionnaires are used to evaluate buildings' performance or link specific behaviours with building performance. In real-time questionnaires, participants are asked to rate their comfort (or report their behaviour) "right now". These questionnaires are intended to be linked to sensor data on building indoor parameters, outdoor conditions, etc.. They are intended to investigate further relationships between comfort/behaviour, and building parameters/energy use, often to improve the building performance. Thermal comfort questionnaires can be applied at different intervals. One-off or seasonal questionnaires are often used to evaluate performance, while with the new availability of gathering self-reporting data through smart devices, longitudinal questionnaires (e.g., daily reports) can be used for applications related to smart buildings. Since the objective of this task is the use of self-reporting data for FDD, we limit this report only to data collection methods intended for their use in smart applications.

Cozie, a clock-face originally designed for Fitbit but also available for Apple Watch, has been developed to collect subjective comfort feedback, in a more scalable and non-intrusive manner [27]. Cozie gathers data on users' location (GPS), heart rate, steps walked since the last log, and self-reported comfort data (e.g., prefer warmer, neutral, prefer cooler). It also allows additional questions via a phone application, for example to give further explanations on thermal, light or noise preferences, mood and whether the user is at the office. Cozie can prompt users at a desired interval/time with a gentle vibration to give feedback.

Several groups of researchers have presented their research using Cozie for different building applications, for example to develop personalized thermal comfort models [27], to be used within FDD systems [6], and to predict how occupants perceive their thermal environment [31]. For example, Jayathissa et al. [27] used Cozie in a study in office buildings, where they paired the data with an on-body sensor for temperature and light, and off-body sensor (in users' bags) for temperature and humidity. They prompted users to report 5 times during each working day. They found that 55% of the responses came from the prompting times. Using hierarchical k-means clustering they found 4 distinct clusters of users which could be used to recommend spaces that may be better suited to their thermal comfort needs.

In another example, Tartarini et al. [31] used Cozie to develop personalized comfort models in a study with 20 participants for 180 days, collecting more than 1080 field-based surveys per participant (the participants received a monetary reward for their participation). They matched the Cozie self-reported data with environmental and physiological data. The seven ML models produced per participant had a median prediction accuracy of 0.78 (F1-score), however not all personal models performed equally. They found that skin, indoor and near body temperatures and heart rate were the most valuable variables, but there were some differences on which variables were important for each personal model. They also found that 250-300 data points were needed per participant for an accurate prediction. Through Cozie, they asked whether the occupants would prefer to be warmer, cooler or neutral, which of four types of clothing levels they were wearing, their air movement perception, activity in the last 10 minutes and location change in the last 10 minutes. They also integrated weather data.

In the example also presented above, Nojodehi et al. [6] integrated occupants' feedback to enhance the performance of fault detection and diagnosis technology. They linked comfort votes indicating discomfort ("I want my office to be cooler/warmer") with pre-determined rules related to temperature measurements, to flag when a fault produced by the FDD system should be verified.

Within the Brains4Building project, several partners have been employing self-reporting thermal comfort methods for different objectives. The table below presents a short overview of these efforts. In further stages of the B4B project, we will seek to link the knowledge gathered in this task with the FDD method followed partners in WP1 (TUe and TUDelft). This will be added in the second version of this report.

Table 1. Overview within B4B to utilise self-reporting data

Partner	Living Lab		Objective	Used in WP/Task
TUe / Kropman	Breda – Kropman building	Mobile phone application for hourly input data from users.	Develop and test a self-learning continuous monitoring (CM) & detection and diagnosis module as an add-on for BMS of offices, supplemented with the perceived comfort and indoor air quality of the users.	WP1
DWA	Gouda - DWA building	Mobile application to request decrease or increase in temperature.	Using app to add personal control to buildings class B. Identifying consistent patterns, interference of app with regular operation, relation of votes with objective KPI's (Adaptive Thermal Comfort standard), effectiveness of the app to fulfil requests. See [33, 34].	WP1/WP2
TNO / Spie / Unica / TUD	Son - Spie building	User feedback was gathered with both self-standing vote boxes and QR codes placed on tables in the rooms.	Method to evaluate the performance of building (Indoor climate label). See deliverable 3.1.1.	WP3
TUD / OfficeVitae TNO / (VLA / Spie / DWA	Gouda – DWA building	Extensive online survey conducted once per year.	Method for integrating building performance, subjective comfort scores, and sensor data using rules to create a single end score indoor comfort score ranging from A to D. See deliverable 3.1.2.	WP3

5 SELF-REPORTING DATA FOR FDD AND BUILDING CONTROL - CASE STUDY: LIVING LAB HHS-DEN HAAG

Based on the opportunities and limitations of smart technologies to gather occupant-related data outlined in the previous sections we have developed a methodology for self-reporting data collection and analysis. This methodology is used, in this first phase of development, to answer the following research questions:

– How do self-reported occupants-related variables contribute to a predictive/explanatory comfort model?
– How do measured occupant-related variables contribute to a predictive/explanatory comfort model?
– Can these models improve the accuracy of prediction in comparison to existing comfort models?

For this task, research has been conducted in the HHS-The Hague Living Lab in collaboration with Unica, HHS and Avans. The living lab is located in the Haagse Hogeschool, Hague campus, specifically, the area belonging to the Department of Faculty Management Studies. This part of the building (Figure 1) contains 21 rooms of different types such as classrooms, meeting rooms, open office spaces and closed office spaces.

5.1 Data collection methods

For the study, objective data measuring indoor environment parameters and subjective occupant data related to thermal comfort were collected. The following methods were used to collect the data:

(i) Indoor Environment – To monitor the indoor environment conditions, Unica developed an open dashboard (webpage), where, based on the real-time values of the sensors in each room, indoor environment conditions like temperature, humidity, CO_2 levels, window status (open/closed), lighting levels, occupancy level (occupant presence), can be seen in near real-time. In addition, historical values of these sensors can also be seen and downloaded via the dashboard. Figure 1 shows a screenshot of the dashboard, where rooms and sensors can be selected from a list (on the left), data and time can be selected from the top, and the data can be seen/downloaded according to the set filters. The location and type of sensors can be seen in Figure 2.

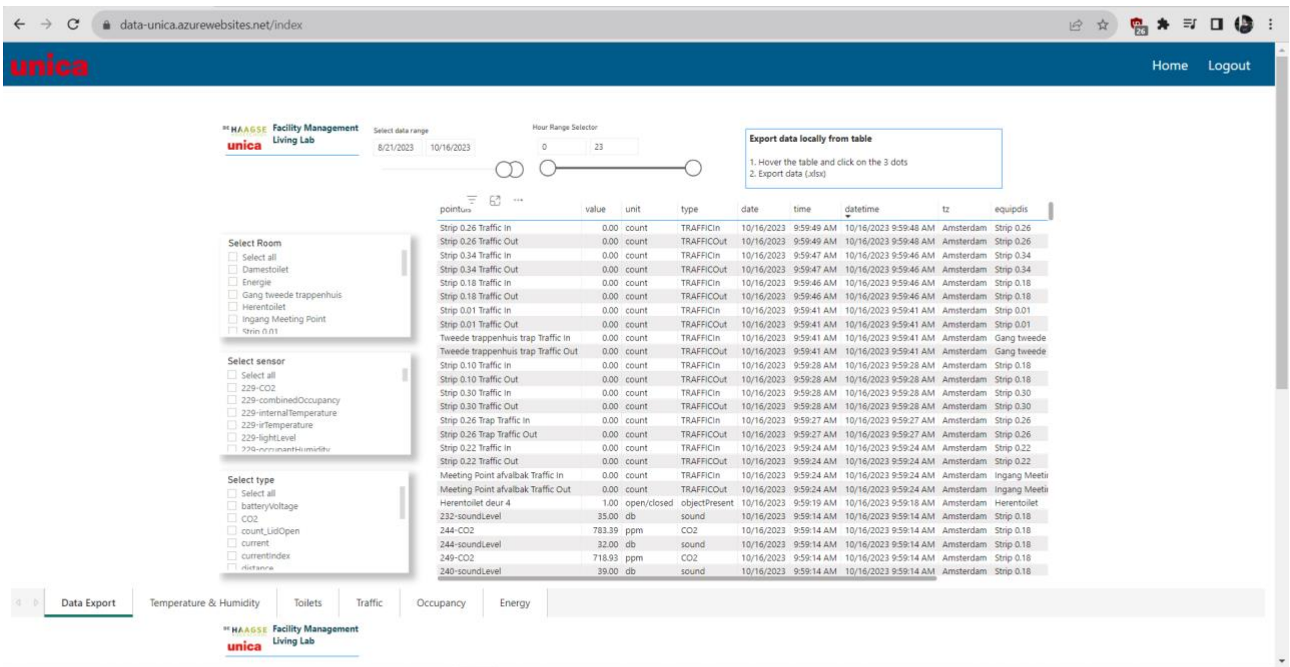

Figure 1: Dashboard created by Unica.

Figure 2: Use-case: Department of Faculty Management Studies, HHS Hague.

(ii) Comfort evaluation – Collecting data on people's comfort and their individual contextual differences is important to study what factors affect occupants' satisfaction the most. When discussing indoor comfort, thermal comfort has been most important in literature for decades. Present literature studies agree with the highly subjective nature of thermal comfort. Thus, self-reporting comfort preference and contextual variables were collected from the occupants. The subjective and contextual data collection was carried in two ways – (a) mobile application and (b) smartwatch application.

(a) Mobile application – A mobile application was developed using Flutter, an open-source UI SDK created by Google. One of the major reasons to use Flutter is that it supports Android and iOS app development from a single codebase. Figure 3 shows screenshots of the comfort app. Occupants who used the app were notified three times per day using push notifications to self-report. As a result, around 250 self-reporting votes were collected in a period of four weeks by 23 distinct users.

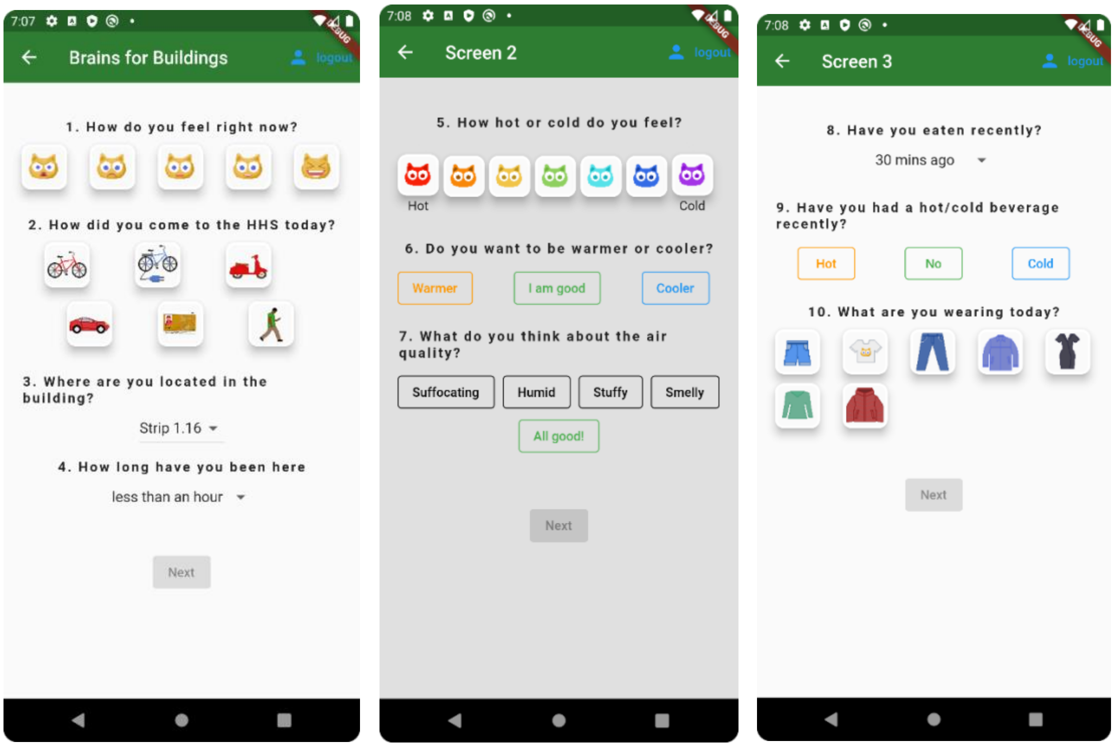

Figure 3: Screenshots of the Comfort App

(b) Smartwatch application – Self-reporting data was also collected using smartwatches, which not only provided an additional feature of heartrate to model thermal comfort, but also was more accessible way of self-reporting. The application, called Experiencer was developed the Future Everyday Group (Industrial Design Department) at TU/e. The smartwatch application also notified the user to report 3 times per day. The use of smartwatches also saw an increase in participation. 10 smartwatches were handed over to the teachers (not students) for the month of June 2023. Figure 4 shows the images of smartwatch application.

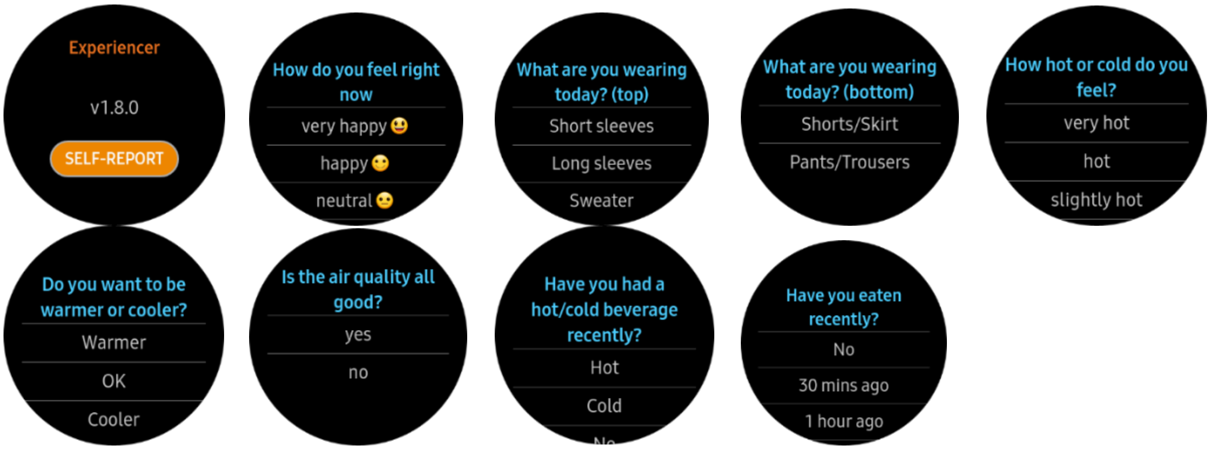

Figure 4: Screenshots of the smartwatch application

(iii) Outdoor conditions - The data for the outdoor conditions, such as outside temperature, outside humidity, and rainfall, were downloaded from the Royal Netherlands Meteorological Institute (KNMI) database. KNMI collects data from the numerous weather stations installed across the Netherlands and makes it available publicly. The weather station closest to the HHS Hague (i.e., the station in Voorschoten) was chosen as a reference for the outdoor conditions, and its data was used in the model.

The mobile phone app designed was based on the previous research project Suslab. The first version of the app was a physical device with which people could self-report their current thermal comfort in real time [35]. The “comfort dial” data was then paired with the indoor parameter data monitored in the building. The first digital version was developed by TUD, and consisted of a webpage that could be opened from a mobile phone. The method of self-reporting via a mobile application was chosen in this study, as application features such as faster loading of pages and push notifications make it more convenient for a user to self-report. The second part of the study employed an application on smartwatches for ease of accessibility. While mobile phones are typically kept in pockets or purses, a push notification may not always lead to a self-report, whereas since smartwatches are worn on the wrist, there is a higher probability that a push notification on the watch will lead to a self-report.

5.1.1 Ethical procedure

To ensure data privacy, the data collected from the occupants was pseudonymized. From the beginning, the participants were given a personal code they could use both for the questionnaire and for the app. No names were collected.

A detailed ethical procedure was sent to the Ethical Review Board of TU Eindhoven, which approved the current research.

5.2 Analysis of data into reliable and relevant health and comfort data input

While various thermal comfort models, including the Predicted Mean Vote (PMV), account for human-related factors such as metabolic rate and clothing, determining precise values for these parameters proves challenging. Often, they are assigned constant values due to the complexity of accurately determining their context. Even though thermal comfort is considered highly subjective, we hypothesize that considering these occupant-related factors can give insights and help in building a more accurate thermal comfort model. Thus, instead of just asking occupants about their thermal comfort and preference, we ask more contextual questions about their mood, activities in the near past, and clothing. We also ask how they feel about the indoor air quality. A list of all the questions asked in the app is described below.

(1) How are you feeling today? – This is the first question which is aimed at capturing the mood of the occupant at the time of self-reporting as mood is suspected to affect one's thermal comfort.
(2) How did you come to the HHS? – Riding a bike or walking will lead to a higher metabolic rate and this is considered to affect one's thermal comfort.
(3) Where are you located? – This information is needed to gather data in the indoor environmental sensors of the space where the occupant is located.
(4) How long have you been here? – If the occupant has recently entered a space, they might still be under the influence of their previous environment. Hence, we want to know if this affects their thermal comfort vote.
(5) How hot or cold do you feel? – A 7-point scale for the occupant to report their thermal comfort as used in the PMV scale.
(6) Do you want to be warmer or cooler? – Thermal preference of the user in a 3-point (warm, OK, cool) choice. This is asked as a person feeling warm/cool (in the previous question) might prefer it that way and we want to know that.
(7) What do you think about the air quality? – A multichoice question for the user to report how they feel about the air quality, as this is one parameter that may also affect one's comfort.
(8) Have you eaten recently? – To assess what impact meals have on one's metabolic rate and hence thermal comfort.
(9) Have you had a hot or a cold beverage recently? – To assess what impact beverages have on one's metabolic rate and hence thermal comfort.
(10) What are you wearing? – To know the clothing value of the occupant at the time of self-reporting.

5.2.1 Encoding variables

To use the variables as input in the models, there were encoded in the following manner:

Mood was reported through icons indicating the mood level: very upset, upset, neutral, happy/content and very happy. These were translated into a numerical variable as follows, as it is considered that upset and happy feelings would probably have opposite impact on one's thermal comfort.

Very Upset	Upset	Neutral	Happy	Very Happy
-1	-0.5	0	0.5	1

Mode of transport – Users were asked to select from one of the icons of biking, e-bike, scooter, car, public transport, or walking. One hot encoding was used to incorporate this categorical variable into the dataset. It essentially considers all the modes of transport as separate binary variables.

Location – Not a variable in the dataset, as this information is used only to reference the room the occupant is in at the time of self-report, so the sensor values of that room can be used to determine the indoor conditions to which the occupant is subjected.

Time spent at location – Occupants had a dropdown to choose the duration of their stay in a particular room. This was encoded as an ordinal variable as the less time they were in the room, the greater the impact the external conditions are expected to have on them.

Less than an hour	1-2 hours	more than 3 hours
1	0.5	0

Thermal comfort is translated as a numerical variable ranging from -3 to +3, as done in previous thermal comfort models such as the PMV.

Very Cold	Cold	Cool	Neutral	Warm	Hot	Very Hot
-3	-2	-1	0	1	2	3

Thermal preference is encoded again as a numerical variable where -1 indicated that the user wants to be cooler, 0 indicates they prefer neither warmer or cooler thermal environment and +1 indicates that they prefer warmer conditions.

Cooler	OK	Warmer

-1	0	+1

Air quality – All available responses (Humid, Smelly, Suffocating, Dry and All good) are translated as distinct categorical binary variables.

Eaten recently – This variable is translated as a numerical variable as follows, as recent eating is projected to have a higher impact on one's thermal comfort.

No	30 mins ago	1 hour ago	2 hours ago
0	1	0.75	0.25

Beverage – This variable has been translated into a numerical variable as follows, because hot and cold beverages are thought to have opposite impacts pertaining to one's thermal comfort.

Hot	No	Cold
-1	0	+1

Clothing – The clothing value (CLO) is calculated by adding all the distinct pieces of clothing selected. These values are taken from the CLO values chart in the ANSI/ASHRAE Standard 55-2010, Standard Thermal Environmental Conditions for Human Occupancy [13].

Shorts	T-shirt	Pants	Full Sleeves	Short Dress	Long Dress	Winter coat
0.08	0.09	0.25	0.3	0.25	0.4	0.45

5.2.2 Descriptive Statistics

A total of 239 responses were collected in two 2-week long sessions (one in January 2023 and one in March 2023) from 23 different users. Out of 239 responses, 220 responses were recorded where indoor conditions were known, i.e., where environmental sensors were present. According to Tartarini et al. [31], a minimum of 250-300 datapoints are necessary for a reliable model.

	Mood	Bike	Scooter	Car	OV_chipkaar	Walking	Duration Loc	Suffocating	Humid	Stuffy	Smelly	aten recentl	Beverage	CLO	Temperature	Humidity	Outside T	Preference	T Comfort
Mood	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Bike	0.034	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Scooter	-0.007	-0.452	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Car	-0.034	-0.358	-0.059	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OV_chipkaart	-0.009	-0.692	-0.113	-0.09	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Walking	-0.044	-0.117	-0.019	-0.015	-0.029	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Duration of Location	0.142	0.022	0.001	-0.074	0.011	0.023	1	0	0	0	0	0	0	0	0	0	0	0	0
Suffocating	-0.131	-0.053	-0.027	0.221	-0.042	-0.007	0.033	1	0	0	0	0	0	0	0	0	0	0	0
Humid	-0.167	-0.249	0.508	-0.046	-0.022	-0.015	-0.002	-0.021	1	0	0	0	0	0	0	0	0	0	0
Stuffy	-0.175	-0.128	-0.077	-0.061	0.201	0.249	0.036	-0.028	-0.061	1	0	0	0	0	0	0	0	0	0
Smelly	0.07	0.053	0.055	-0.041	-0.079	-0.013	0.021	0.254	-0.041	-0.053	1	0	0	0	0	0	0	0	0
Eaten recently	0.134	-0.024	-0.085	0.014	0.068	0.075	-0.071	-0.054	0.029	-0.002	-0.042	1	0	0	0	0	0	0	0
Beverage	0.079	-0.242	0.135	-0.103	0.233	0.159	0.006	-0.102	0.171	0.112	0.249	0.001	1	0	0	0	0	0	0
CLO	0.041	0.049	-0.155	0.117	-0.021	0.014	-0.11	-0.018	-0.052	-0.11	0.037	0.042	0.049	1	0	0	0	0	0
Temperature	0.232	0.036	-0.036	0.117	-0.093	0.032	0.133	-0.011	-0.063	-0.012	-0.01	0.211	-0.038	0.064	1	0	0	0	0
Humidity	-0.089	-0.046	-0.022	0.062	0.019	0.092	-0.105	-0.006	-0.162	0.051	-0.04	-0.095	-0.114	-0.064	-0.172	1	0	0	0
Outside Temperature	-0.086	-0.236	0.224	0.089	0.065	0.085	-0.1	-0.037	0.134	0.082	0.018	0.024	0.095	-0.14	0.139	0.598	1	0	0
Thermal Preference	-0.373	0.096	0.22	-0.171	-0.196	0.091	-0.043	-0.127	0.198	-0.02	-0.078	-0.129	-0.134	-0.198	-0.288	0.06	-0.068	1	0
Thermal Comfort	0.468	-0.066	-0.101	0.215	0.065	-0.178	0.004	0.057	-0.137	-0.087	0.024	0.023	0.083	0.326	0.312	-0.033	-0.019	-0.737	1

Figure 5: Correlation matrix

The correlation matrix is shown in Figure 5. As expected, large negative correlation is found between thermal comfort and thermal preference. Also, positive correlations are found between clothing values, temperature and thermal comfort, which also makes sense as more temperature and clothing will possibly mean a warmer (higher) thermal comfort value. It's interesting to note that high correlation between thermal comfort (and thermal preference) and mood were also found, in fact higher than temperature itself. Other high correlations between outside temperature and humidity were observed (lower outside temperature implying lower humidity), which also makes sense. However, no significant correlation was found between outside temperature and thermal preference/comfort.

5.3 Modelling Thermal Comfort

We treat modelling thermal comfort as a classification problem with 7 classes. We approach this problem in the following three steps:

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

Train-test split – The dataset was split in two groups: 70% of the datapoints 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.

5.3.1 Comparing different models

Figure 6 shows a comparison of various models fitting the training data and the average of their performance in the 10-fold cross validation.

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
rf	Random Forest Classifier	0.6283	0.0000	0.6433	0.6152	0.6092	0.5106	0.5283	0.0490
lightgbm	Light Gradient Boosting Machine	0.5849	0.0000	0.6078	0.5926	0.5834	0.4586	0.4734	0.1310
xgboost	Extreme Gradient Boosting	0.5783	0.0000	0.5908	0.5880	0.5709	0.4525	0.4667	0.1380
gbc	Gradient Boosting Classifier	0.5724	0.0000	0.5933	0.5997	0.5744	0.4445	0.4575	0.1460
et	Extra Trees Classifier	0.5599	0.0000	0.5858	0.5820	0.5544	0.4194	0.4434	0.0460
dt	Decision Tree Classifier	0.5353	0.0000	0.5382	0.5784	0.5199	0.4087	0.4237	0.0100
svm	SVM - Linear Kernel	0.5353	0.0000	0.5578	0.5062	0.5180	0.3907	0.4034	0.0130
lr	Logistic Regression	0.4908	0.0000	0.4846	0.4810	0.4698	0.3273	0.3389	0.6790
ada	Ada Boost Classifier	0.4787	0.0000	0.5583	0.3490	0.4174	0.2776	0.3227	0.0240
ridge	Ridge Classifier	0.4783	0.0000	0.4929	0.4640	0.4630	0.2984	0.3124	0.0100
lda	Linear Discriminant Analysis	0.4662	0.0000	0.4662	0.4653	0.4495	0.2976	0.3077	0.0100
dummy	Dummy Classifier	0.3107	0.0000	0.3607	0.1122	0.1711	0.0000	0.0000	0.0090
qda	Quadratic Discriminant Analysis	0.2173	0.0000	0.2031	0.0469	0.0761	0.0000	0.0000	0.0110
nb	Naive Bayes	0.1923	0.0000	0.1506	0.1836	0.1426	0.1008	0.1382	0.0110

Figure 6: Comparing different classification models

Figure 6 clearly shows that the random forest classifier (RF) performed the best compared to other models and hence was used in this study (yellow values indicate better performance). RF has the highest training accuracy of 62.83%, which is higher than any other model. The hyperparameters in the random forest classifier were tuned and the model was evaluated on the entire dataset once again. The resulting confusion matrix is shown in Figure 7. The values populated in the leading diagonal of the matrix show the number of predictions which were correctly predicted by the model. . It can be easily deduced that most of the predictions matched the actual values. For example, when the prediction of '-2 (feeling cold)' was made - 50 times the users were actually feeling cold, 3 times the users were feeling slightly cold, 2 times neutral, 2 times slightly warm and 3 times hot. This shows that the model we developed was able to predict most of the votes accurately with a reasonable margin of error.

The importance of features in this model was calculated using the method of Mean Decrease in Impurity. Figure 8 shows the plot of importance of all the features. It can be observed that temperature of the room was the most important in predicting thermal comfort, followed by clothing value of the person. Humidity and Mood are shown to have a similar amount of impact on one's thermal comfort in this case study. Moreover, outside temperature and CO_2 have even less impact than the aforementioned variables. And lastly, variables like eaten recently, beverage and modes of transport are shown to have very little impact.

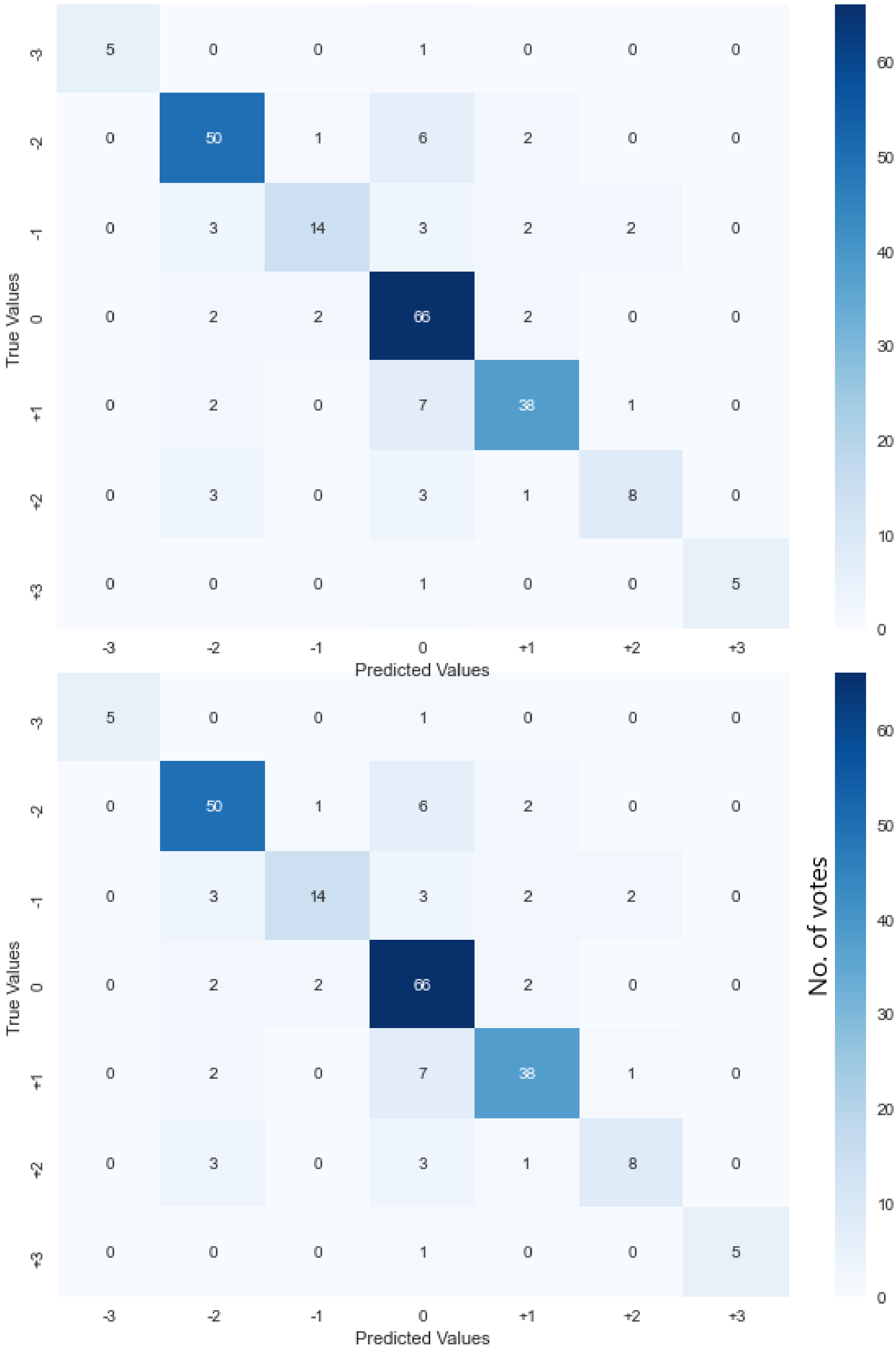

Figure 7: Confusion matrix for Random Forest classification model for thermal comfort

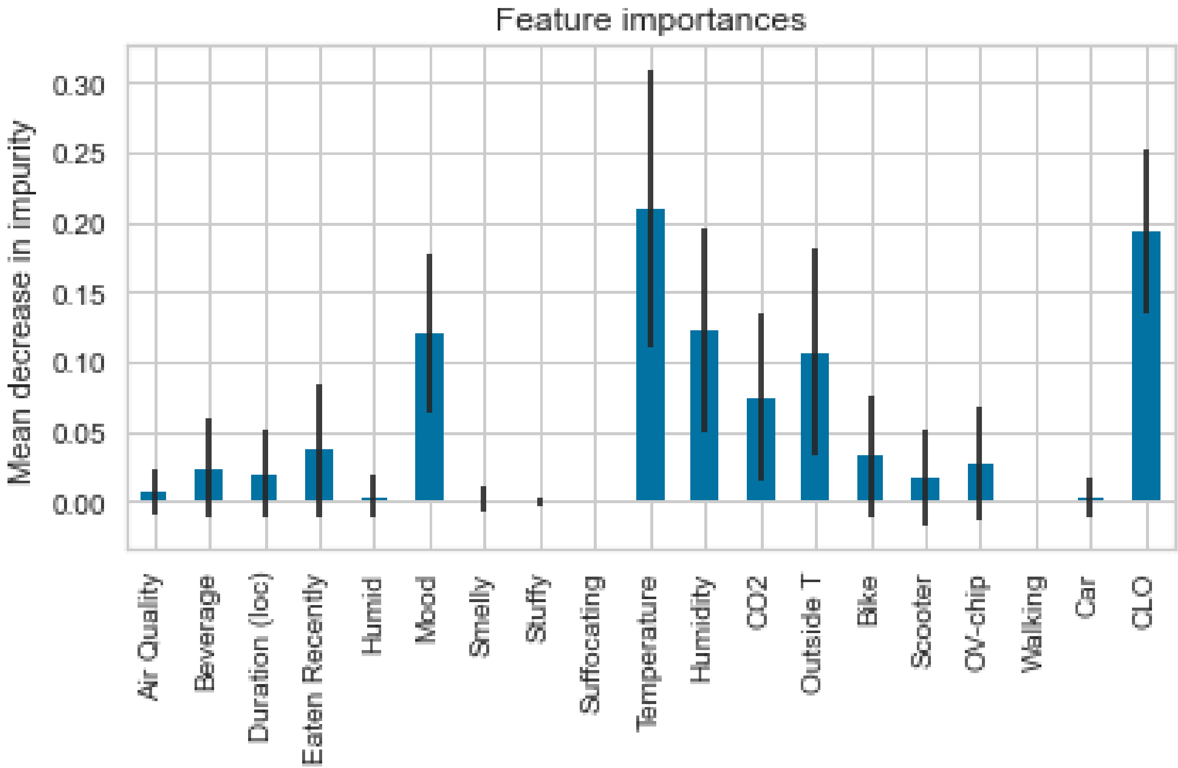

Figure 8a: Feature Importance plots showing the impact of each feature on the RF model

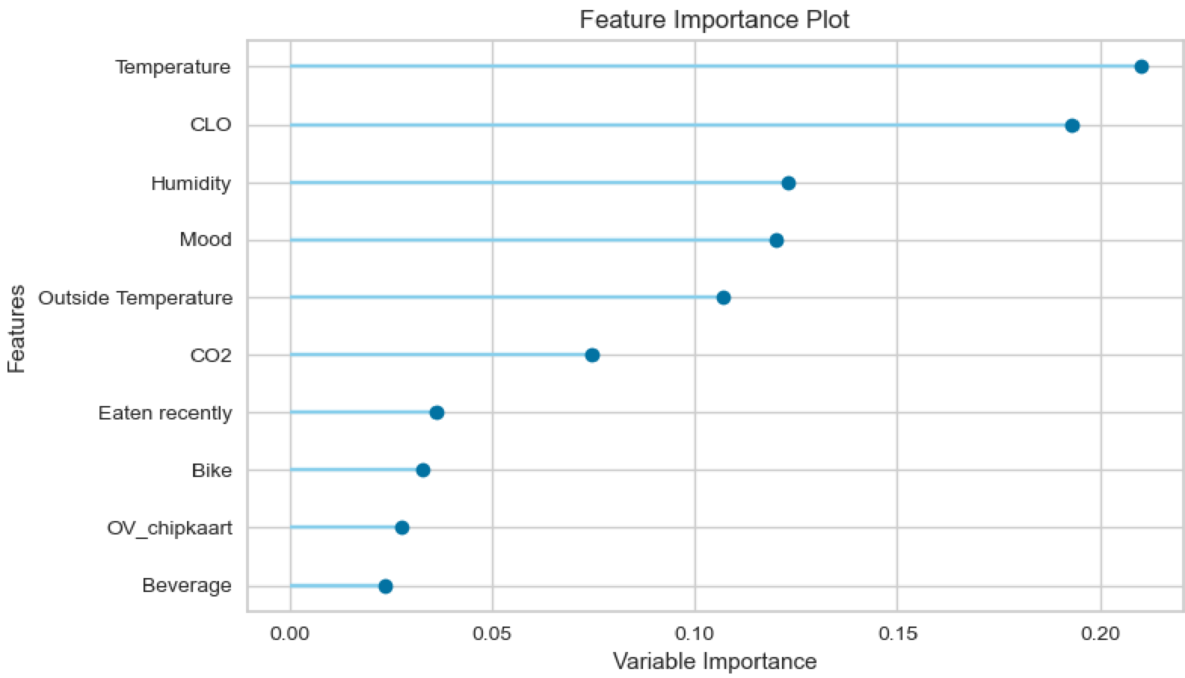

Figure 8b: Feature Importance plots showing the impact of each feature on the RF model

5.4 Comparison with the PMV Model

Fanger's PMV Model is arguably the most widely used thermal comfort model since it was introduced in 1970. Several studies, however, have shown that it is not an accurate representation of thermal sensations for a lot of people. In this section, we compare our model based on self-reporting to the PMV and observe the differences. The PMV requires the following parameters to evaluate thermal comfort, some of which will be used as constants (according to ANSI/ASHRAE-55 Standard 2020) owing to the lack of expensive sensor technology in most buildings:

(i) Ambient air temperature – The value of this parameter was taken from the temperature sensors in the room that the occupant self-reported, at the time of self-reporting.

(ii) Mean radiant temperature – Assumed as equal to ambient air temperature.

(iii) Relative humidity – The value of this parameter was taken from the humidity sensors in the room that the occupant self-reported, at the time of self-reporting.

(iv) Relative air velocity - Assumed as equal to 0.1 m/s (assuming no discomfort due to draft).

(v) Metabolic rate – Assumed as a constant of 1.2 for sedentary office work.

(vi) Clothing value – Clothing values are extracted and calculated from each self-report.

With these parameter values as input, the thermal comfort values according to the PMV are calculated. Figure 9 shows the difference between actual thermal comfort values (self-reported values) and predicted thermal comfort values according to PMV, for each data point or self-report vote. For comparison, the same difference (actual – predicted (by RF)) is shown for each data point in Figure 10. In both, the figures' blue lines indicate a prediction when a cooler prediction was made and red lines indicate a warmer prediction. Moreover, the length of the lines indicates the difference between the actual and predicted vote. And when no line is present for a data point, it means that the prediction was correct. For example, a blue line of length two indicates that a difference of two units in the thermal sensation scale was made and the prediction was cooler than what the occupant actually felt according to their self-report. It can be observed by the Figures 9 and 10 that the RF model developed based on self-reporting votes is far more accurate than the PMV model (more coloured lines indicate more error in prediction), with the self-reporting model giving an accuracy of 75% as compared to PMV model's accuracy of 35%.

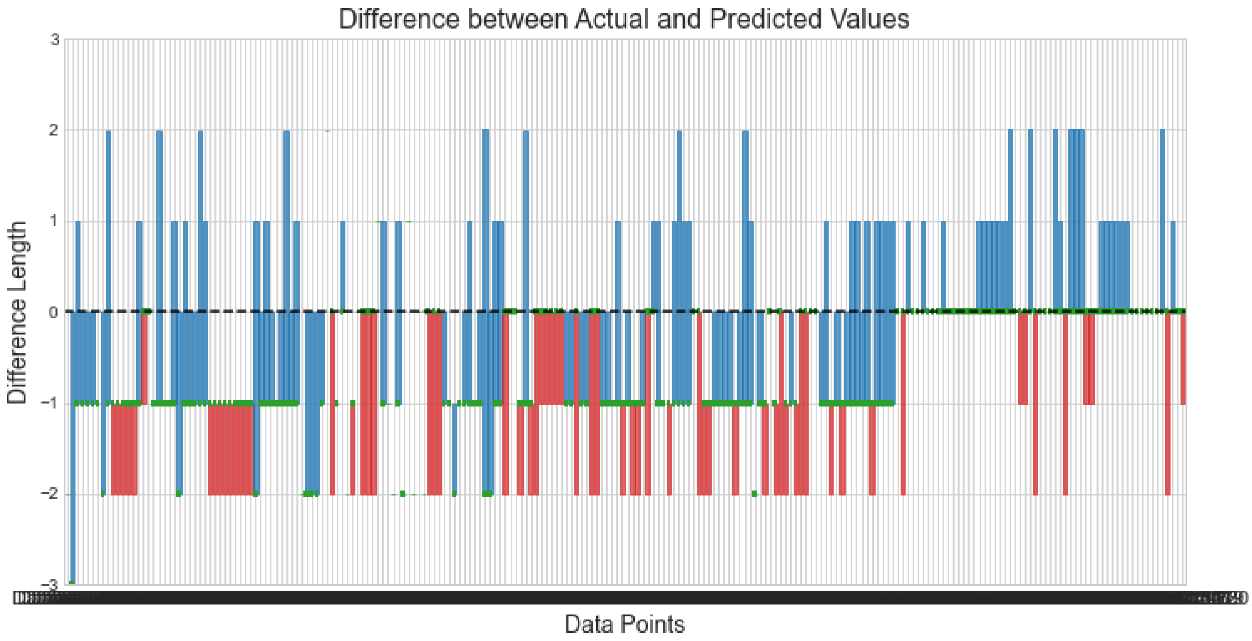

Figure 9: Difference plot: actual – predicted (PMV) vs self-reports

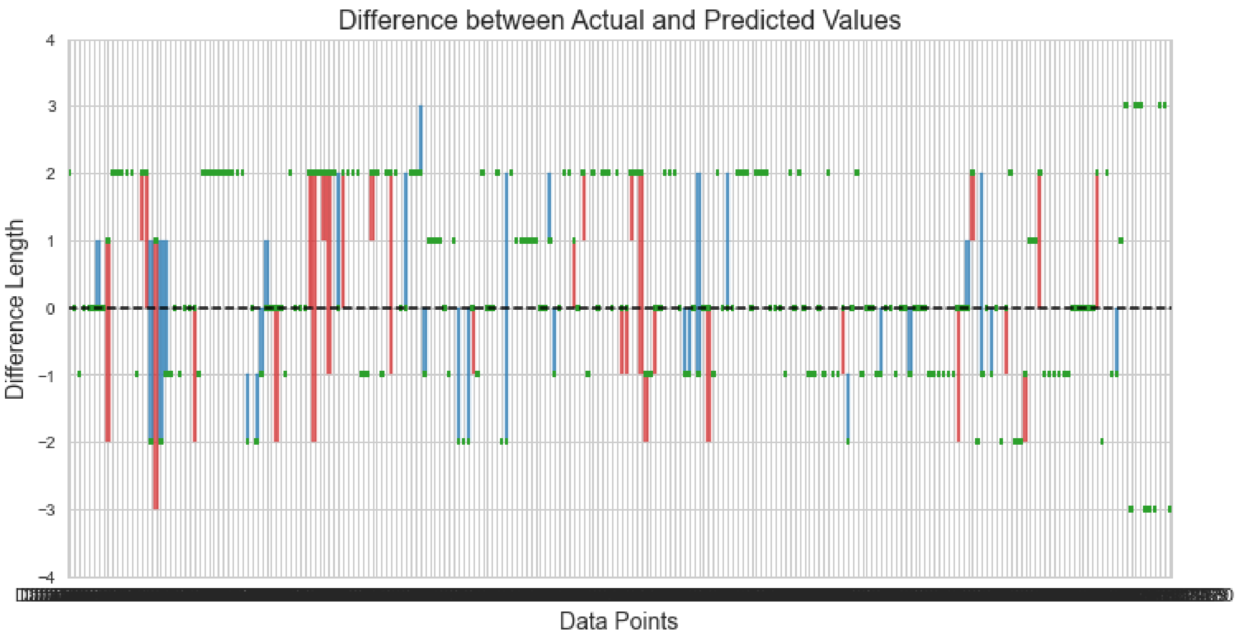

Figure 10: Difference plot: actual – predicted (RF) vs self-reports

5.5 Conclusions from the thermal comfort model

Based on the observations made in the previous sections, some inferences can be made. A machine-learning model based on self-reporting of thermal comfort provides significantly higher accuracies than pre-existing empirical models like PMV. In this RF model based on self-reporting, occupant-related variables such as clothing and mood rank high in importance as seen in Figure 8. Since this model performs quite well (75%), it implies that human variables indeed affect one's thermal comfort greatly. Thus, high importance to such variables should be given in further studies dealing with thermal comfort. While no significant impact of eating/drinking to thermal comfort is observed in this model, such questions should not be omitted as they could give different insights into thermal sensations of occupants in other cases. However, it is not claimed that the RF model developed will prove effective and accurate in all buildings across different geographies. It merely demonstrates that by knowing a user's indoor conditions (temperature, humidity etc.) and asking certain human contextual questions (clothing, activities, mood etc.), an accurate enough thermal comfort model could be developed for their building (or particular indoor spaces). When trying to use this model in a different building, several problems could arise. For example, if a building is located in a place warmer than The Hague (Netherlands), occupants would adapt and react differently to the indoor conditions present in this study. Moreover, a different building layout, crowded (or empty) spaces, different sensor locations or a different façade could similarly affect the occupants' thermal sensations. Hence, it is recommended that a self-reporting model be a characteristic of a building and its occupants, rather than all buildings and all occupants.

6 NEXT STEPS

The next steps in the research are the integration of heart rate into the thermal comfort model, as well as the development of individual thermal comfort models. The heart rate integration in the model will be investigated to determine whether the model can be improved with occupant variables requiring less user effort. Furthermore, through the implementation of the method in other living labs, we will investigate the amount of data required (e.g., self-reporting periods) to ensure maximum predictability with minimum effort from the occupants (RQ4).

Furthermore, to be able to integrate the thermal comfort model in the FDD system, as well as for (energy flexible) building control, we will apply the same methodology in different contexts (living labs) to further understand how we can distinguish between occupants' input given as a complaint vs. comfort, and how can we make this clear either to the system or to the occupant (RQ5).

Last, we will define, in collaboration with WP1 partners, the practical applications of data-driven comfort models for FDD (RQ6). Linked to this, and in association with our living lab partners, the results will be discussed to determine the challenges associated to gathering occupant-related data in relation to data management, ethics, and practicability, answering RQ7.

7 REFERENCES

[1] Y. Zhao, T. Li, X. Zhang, C. Zhang, Artificial intelligence-based fault detection and diagnosis methods for building energy systems: advantages, challenges and the future, Renew. Sustain. Energy Rev. 109 (2019) 85–101.

[2] M. S. Mirnaghi, F. Haghighat. Fault detection and diagnosis of large-scale HVAC systems in buildings using data-driven methods: A comprehensive review. Energy & Buildings 229 (2020) 110492

[3] S. Lazarova-Molnar, H. R. Shaker, N. Mohamed, and B. Nørregaard Jørgensen. Fault Detection and Diagnosis for Smart Buildings: State of the Art, Trends and Challenges. 2016 3rd MEC International Conference on Big Data and Smart City.

[4] H. Yang, T. Zhang, H. Li, D. Woradechjumroen, and X. Liu, ''HVAC Equipment, Unitary: Fault Detection and Diagnosis,'' in Encyclopedia of Energy Engineering and Technology, Second Edi., no. November, Taylor & Francis, Ed. CRC Press, 2014, pp. 854–864.

[5] S. Katipamula, M. R. Brambley, and M. R. Brambley, ''Review Article: Methods for Fault Detection , Diagnostics, and Prognostics for Building Systems — A Review Part I,'' vol. 11, no. 1, pp. 3–25, 2011, doi: 10.1080/ 10789669.2005.10391123.

[6] P. Nojedehi, B. Gunay, W. O'Brien. Deployment of crowdsourced occupant data to support fault detection and diagnosis in buildings. Building and Environment 242 (2023) 110612

[7] G. Xu, ''HVAC system study: A data-driven approach,'' ProQuest Diss. Thesis, vol. 1514516, p. 102, 2012.

[8] O. Guerra-Santin & A.C. Tweed. In-use monitoring of buildings: An overview and classification of evaluation methods. Energy and Buildings 86 (2015) 176–189

[9] J. A. Burke, D. Estrin, M. Hansen, A. Parker, N. Ramanathan, S. Reddy, et al., "Participatory sensing, UCLA: Center for Embedded Network Sensing," ed, 2006.

[10] G. S. Tuncay, G. Benincasa, and A. Helmy, "Autonomous and distributed recruitment and data collection framework for opportunistic sensing," *ACM SIGMOBILE Mobile Computing and Communications Review,* vol. 16, pp. 50-53, 2013.

[11] S. Intille, C. Haynes, D. Maniar, A. Ponnada, J. Manjourides, μEMA: microinteraction-based ecological momentary assessment (EMA) using a smartwatch, in: UbiComp 2016 - Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing, Sep. 2016, pp. 1124–1135, https://doi.org/10.1145/2971648.2971717.

[12] CEN, Standard EN 15251, Indoor Environmental Input Parameters for Design and Assessment of Energy Performance of Buildings—Addressing Indoor Air Quality, Thermal Environment, Lighting and Acoustics, CEN, Standard EN 15251, Brussels, 2007.

[13] ASHRAE, Thermal environment conditions for human occupancy, in: ASHRAE Standard 55-2007, ASHRAE, Atlanta, 2007.

[14] CEN, Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort, in: Standard ISO EN 7730, Brussels, 2005.

[15] P. Fanger, Thermal Comfort: Analysis and Applications in Environmental Engineering, Danish Technical Press, Copenhagen, 1970

[16] E. Arens, M. Humphreys, R. de Dear, H. Zhang, Are 'class A' temperature requirements realistic or desirable? Building and Environment 45 (2010) 4–10.

[17] F.R. d'Ambrosio Alfano, B.I. Palella, G. Riccio, The role of measurement accuracy on the thermal environment assessment by means of PMV index, Building and Environment 46 (2011) 1361–1369.

[18] F.R. d'Ambrosio Alfano, M. Dell'Isola, B.I. Palella, G. Riccio, A. Russi, On the measurement of the mean radiant temperature and its influence on the indoor thermal environmental assessment, Building and Environment 63 (2013) 78–88.

[19] M.A. Humpreys, J.F. Nicol, The validity of ISO PMV for predicting comfort votes in every day thermal environments, Energy and Buildings 34 (2002) 667–684.

[20] J. van Hoof, J.L.M. Hensen, Quantifying the relevance of adaptive thermal comfort models in moderate thermal climate zones, Building and Environment 42 (2007) 156–170.

[21] M.A. Humpreys, J.F. Nicol, The validity of ISO PMV for predicting comfort votes in every day thermal environments, Energy and Buildings 34 (2002) 667–684.

[22] T. Cheung, S. Schiavon, T. Parkinson, P., Li, G. Brager, Analysis of the accuracy on PMV–PPD model using the ASHRAE Global Thermal Comfort Database II. Building and Environment 153 (2019) 205-217.

[23] F. Nicol, S. Roaf, Post-occupancy evaluation and field studies of thermal comfort, Building Research & Information 33 (4) (2005) 228–346.

[24] R.J. de Dear, G.S. Brager, Thermal Comfort in naturally ventilated buildings: revisions to ASHRAE standard 55, Energy and Buildings 34 (2002) 549–561.

[25] A.K. Melikov, J. Kaczmarczyk, Air movement and perceived air quality, Building and Environment 47 (2012) 400–409.

[26] S. Ferrari, V. Zanotto, Adaptive Comfort: analysis and application of the main indices, Building and Environment 49 (2012) 25–32.

[27] P. Jayathissa, M. Quintana, T. Sood, N. Nazarian, C. Miller. Is your clock-face cozie? A smartwatch methodology for the in-situ collection of occupant comfort data. Journal of Physics: Conference Series 1343 (2019) 012145

[28] J. Kim, S. Schiavon, G. Brager, Personal comfort models – a new paradigm in thermal comfort for occupant-centric environmental control, Building and Environment 132 (2018) 114–124.

[29] CEN, Standard EN 15251, Indoor Environmental Input Parameters for Design and Assessment of Energy Performance of Buildings—Addressing Indoor Air Quality, Thermal Environment, Lighting and Acoustics, CEN, Standard EN 15251, Brussels, 2007.

[30] S. Liu, Personal thermal comfort models based on physiological parameters measured by wearable sensors, Rethinking Comfort.

[31] F. Tartarini, S. Schiavon, M. Quintana, C. Miller. Personal comfort models based on a 6-month experiment using environmental parameters and data from wearables. Indoor Air. 32 (2022) e13160

[32] O. Guerra-Santin & A.C. Tweed. In-use monitoring of buildings: An overview of data collection methods. Energy and Buildings 93 (2015) 189–207.

[33] K. Wisse. Evaluatie klimaatklasse A in de praktijk. Tvvl magazine 06 (2022) 10-15.

[34] K. Wisse. Comfort-apps: hoe vaak gebruiken we ze? Tvvl magazine 01 (2023) 42-46.

[35] O. Guerra-Santin, N.R. Herrera, E. Cuerda, D. Keyson, Mixed methods approach to determine occupants' behaviour–Analysis of two case studies. Energy and Buildings 130 (2016) 546-566.