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Enhancing personal comfort: A machine learning approach using physiological and environmental signals measurements

Gloria Cosoli [a,*], Silvia Angela Mansi [b], Ilaria Pigliautile [c], Anna Laura Pisello [c,d], Gian Marco Revel [a], Marco Arnesano [b]

[a] Department of Industrial Engineering and Mathematical Sciences, Università Politecnica delle Marche, Ancona, Italy
[b] Università Telematica eCampus, Novedrate, Italy
[c] Department of Engineering, Department of Excellence 2023-2027, via G. Duranti 93, Università degli Studi di Perugia, Italy
[d] Centro interuniversitario sull'inquinamento e l'ambiente M. Felli, via G. Duranti 67, Università degli Studi di Perugia, Italy

A R T I C L E I N F O

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A B S T R A C T

The assessment of the occupants' thermal sensation (TS) in a living environment is fundamental to enhance well-being and optimize building energy consumption. Machine Learning (ML)-based approaches can be adopted for TS prediction exploiting physiological and environmental parameters, but identifying an optimal features subset is fundamental. This work aims at assessing the correlation between physiological parameters and TS, hence selecting the optimal feature subset for ML-based TS prediction. A dedicated experimental campaign was designed to gather signals through wearable sensors; the actual TS was collected via a specific questionnaire. The results prove the weight of physiological features on the TS determination; ML classifiers achieved an accuracy of up to ≈90% by using physiological and environmental parameters. The strategic potential of personalized comfort systems enables the optimization of both comfort and energy efficiency of a building according to a human-centric approach.

1. Introduction

The measurement of thermal sensation (TS) can provide very relevant information on buildings occupants' well-being; in fact, the subjective perception of thermal conditions leads to changes in vital parameters, hence modifying the human's status and reflecting into her/his comfort and, more in general, well-being. Thermal comfort is a crucial aspect of the built environment, due to its effect on the occupants' health [1], well-being, and work efficiency [2], as well as on buildings energy consumption [3]. This can be observed from a twofold perspective: on the one side, a subject's physiological status is affected (among others) by indoor thermal conditions, hence changes in thermal perception of the surrounding environment and the related TS are correlated with changes in physiological responses [4]; on the other side, the individual response to certain ambient conditions can be interpreted and exploited for control purposes, in particular in the context of Personal Comfort Models (PCMs) [5,6]. At present, PCMs are being studied to actually take account of the real needs of a building occupant, and they generally outperform conventional models [7,8]. For example, Williamson et al. [9] investigated the relationship between thermal comfort and well-being of elderly occupants in order to provide some recommendations for policymakers as well as guidelines for living environments design, given that the built environment affects also the health outcomes [10]. Moreover, it should be considered that such models can be beneficial to optimize the buildings energy demand (with energy savings from 4% to 60% [11]), which has a huge impact on the environment (the building and construction sector accounts for the 36% of the total energy consumption and for the 37% of energy-related CO_2 emissions [3]).

At present, the literature encompasses different methods for the assessment of TS. Survey-based investigations are performed very often [12,13], without complementing them with sensor-based assessments; indeed, subjectivity plays a dominant role in these procedures, leading to non-fully reliable results. Both physical and mental state can affect the results from survey-based investigations; the discrepancy observed between the perceived and the observed sensation could come from psychological adaptation processes, so depending on previous thermal experiences [14]. Moreover, the survey-based methods can be used only

* Corresponding author.
E-mail address: g.cosoli@staff.univpm.it (G. Cosoli).

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with a-posteriori control, without having the possibility to anticipate the upcoming change of TS. Also the Predictive Mean Vote (PMV) scale is commonly exploited for the assessment of indoor pleasantness, but its accuracy is not always so high [15] in environments different from air-conditioned rooms (e.g., workspaces), with limited metabolic activity and no personal control. Furthermore, its validity is often questioned [16], representing a mean vote of a large sample of subjects, and not individual perceptions. Actually, most of literature studies (>62%) deal with group-based comfort models [7], showing limited applicability in the real comfort-building management because of their aggregate model nature.

Hence, objective measurements should be considered in combination with surveys (still representing a pivotal means in thermal comfort assessment), to better contextualize the subject's perceptions. Physiological parameters can be considered for this aim, being influenced by the subject's thermal sensation (as well as thermal comfort) and not suffering significantly from the subject's mental state. Jung et al. [17] evidenced that the inclusion of vital parameters in comfort models enhances their accuracy by up to 97%. This is particularly relevant in many applications, since thermal comfort affects, among others, productivity and efficiency in occupational and educational environments. For example, Li et al. [18] found that thermal discomfort reduces performance and intensifies the sick-building syndrome symptoms. Fang et al. [19] underlined that both physical and mental conditions of workers are significantly affected by environmental conditions, impacting on efficiency; these results are useful in terms of actions to implement for occupational safety and risks management. Concerning the measurement of thermal comfort, literature presents a large amount of research conducted through the measurement of environmental parameters. However, such procedures often involve quite cumbersome instruments, making the assessment not practical in everyday life environments. Contrarily, wearable devices are constantly spreading thanks to multiple advantages, from being minimally intrusive to their relatively low-cost, through user-friendly functioning and interface. They can acquire a plethora of physiological quantities: from heart rate (HR) and its variability (HRV) to energy expenditure and activity, as well as indirectly estimated quantities, such as blood pressure (BP) or respiration rate. Currently there are also wearable sensors to measure environmental parameters, such as pollutants, contaminant, dangerous gases, etc; they are particularly useful both to contextualize physiological monitoring and to monitor hazardous situations [20]. Also, this type of sensors could result useful for thermal comfort determination.

Concerning surveys dispensed to the participants of an experimental campaign, there is a still open issue on their reliability and on the possibility of a perceptual bias in the responses. In fact, collecting the occupants' perception via survey fulfilment implies people's evaluation that may be affected by personal understating of the task, inaccurate questions or explanation of investigated quantities, or other personal bias in interpreting the scale. The uncertainty related to subjective measures of the occupants' comfort could be limited through the application of good practices in survey design and experimental procedures. Wang et al. [21] identified repeated-measures (longitudinal) research design and discrete scales of multiple points (Likert scale) as the best choices for reducing uncertainties in subjective estimation of thermal comfort. Moreover, Raccuglia et al. [22] defined the "anchoring bias" as that bias occurring in environmental judgment when subjects repeatedly express their sensorial scores in a single experimental session: subsequent votes may be given based on previous ones, resulting in a higher magnitude of sensation as compared to votes given one time under the same environmental conditions. In the same study, the authors provided insights to identify, quantify, and mitigate the anchoring bias, thus improving the quality of the personal comfort investigation including transient conditions and repeated measures. In line with previous contribution, Wang et al. [23] proposed a method for cleaning a dataset of subjective measures of environmental comfort from outliers, defined as "those thermal comfort votes that are substantially and illegitimately different from others that are comparable". Here identified outliers differ from inter-individual variabilities in preferences and thermal demand that, conversely, must be accounted in the development of PCMs [24]. Indeed, both physiological and psychological factors have been recognized as drivers of diversity in thermal perception [25]; these differences may be pivotal for the achievement of optimal comfort conditions at minimum energy expenditure through personalized systems. Nevertheless, in view of the development of personalized models, the reliability of perceptual responses needs to be verified through objective measures (e.g., the physiological ones), which can be collected through wearable sensors. These devices are very user-friendly, considering that the most diffuse type is represented by the so-called smartwatches, seeming just as common watches; hence, people wear them almost without perceiving of being monitored. This results in more reliable results, since no "white coat" effect is present. Their growth is exponential, with an attended Compound Annual Growth Rate (CAGR) of 11.8% between 2019 and 2026 [26]. Furthermore, using wearable sensors can make the user aware of different aspects: her/his own health status, environmental conditions, mental well-being, and also thermal comfort, enabling a better management of the energy demand and also an improved productivity [27].

In recent years the use of both Internet of Things (IoT) and Artificial Intelligence (AI) technologies has spread in multiple fields, finding a particularly fertile ground in the analysis of "big data" acquired 24 h a day, 7 days a week by wearable sensors. In literature the occupants' TS has already been modelled [28] and ML-based algorithms have been exploited with the objective of predicting a subject's thermal comfort; for example, Chaudhuri et al. [29] fed Random Forest model with gender-specific physiological features to predict thermal comfort, evidencing the great potential of wearable sensors in this field. Similarly, Liu et al. [30] exploited the Support Vector Classifier to predict TS, but their features were focused on environmental parameters, clothing insulation, and metabolic rate. Wearable sensors were combined to ML algorithms also by Lee and Ham [31], who defined personal thermal comfort models considering diverse human activities. Also deep learning algorithms have been exploited to this aim; Somu et al. [32] used a CNN-LSTM model for modelling thermal comfort, highlighting the better accuracy of data-driven models with respect to PMV-based assessment.

Diverse physiological signals have been correlated to the subject's comfort state [33]. Electroencephalographic (EEG) data have been used for the real-time classification of thermal comfort [34]; in particular, the EEG power spectrum density (PSD) has been demonstrated to be correlated to the subjects' TS [35]. For example, gamma waves (>30 Hz) amplitude seems to increase with negative emotions [36,37]. Also, skin temperature (ST) is surely affected by the environmental conditions; for this reason, it can be exploited for the realization of models predicting TS. This parameter is correlated also to productivity and cognitive performance, both varying with the thermal conditions of the environment [38]. Furthermore, the signals related to cardiovascular activity are definitely correlated with TS; in fact, temperature conditions have a direct effect on vasoconstriction and vasodilation phenomena, which reflect into photoplethysmography (PPG) signal, depending on the blood volume pulse measured underneath the PPG-based sensor. The environmental conditions affect the activity of the Autonomic Nervous System (ANS), which can be investigated through the analysis of HRV, thus reflecting somehow the subject's TS [39,40]; also, thermal discomfort can cause stress, which is another aspect that can be analysed through HRV analysis [41]. Indeed, some of the present authors have already proved the relevance of HRV in the human thermal comfort assessment and thermal sensation vote (TSV) prediction (with prediction accuracy up to 92% [42,43]).

Many features can be extracted from multimodal signals; however, to optimize the classification performance of ML-based models, it is generally recommended to select a proper subset of features [44]. In fact, even if we can think that the more input parameters are ingested by the ML classifier, the better the classification performance will be, this is not always the case. Indeed, increasing the input group size will enhance the correlation with the class to be predicted, but it is unlikely to have variables not correlated with the others [45]. When there is redundant information, or similarly when data are very noisy, the training process of the model is hard and the learning approach can be compromised [46], also with possible overfitting issues [47]. Hence, it is very advisable to limit the number of inputs, preferring those attributes showing a greater correlation to the class to be predicted, along with being uncorrelated with the other parameters to be ingested by the algorithm. To this aim, a "feature subset selection" method was used to reduce the data size and to facilitate a faster and more efficient learning phase. In this way, non-justifiable complex models can be avoided, for the sake of reduced computational load (which is also beneficial for portable applications, such an in wearable sensors).

The main aims of this paper are summarized hereafter:

- To evaluate the correlation between features extracted from physiological signals acquired through wearable sensors and TS;
- To identify an optimal physiological features subset for TS prediction, exploiting the correlation feature selection approach;
- To combine the selected physiological features to a few environmental quantities and boundary conditions to feed ML classifiers for TS prediction, considering the questionnaire results as the ground truth.

Indeed, this paves the way to the development and exploitation of measurement systems for thermal comfort assessment.

The analysis was performed on 24 subjects exposed to three fixed ambient temperatures (supposed to be cold, neutral, and warm) in a controlled environment. Wearable sensors were used to acquire physiological data and surveys were administered to the participants to address their perception of the environmental boundaries in terms of thermal comfort and sensation. Data were analysed in terms of correlation between physiological parameters and TS and different ML algorithms were tested for classification purposes.

The paper is organized as follows: Section 2 presents the study materials and methods, describing the test protocol, the data processing techniques, the feature selection method, and the classification of TS based on ML models. The results are reported in Section 3, whereas in Section 4 the authors make their final considerations and propose future advancements.

2. Materials and methods

2.1. Experimental equipment and environment

The experimental campaign took place in the NEXT.ROOM [48,49], a human comfort test environment located at the Environmental Applied Physics Lab (www.eaplab.net) at the University of Perugia in Italy (Fig. 1). This laboratory features a realistic, full-scale room measuring 4 m × 4 m × 2.7 m, which allows for the analysis of personal responses from real building occupants under multidomain stimuli. The sensors installed in the room enable the monitoring and control of various environmental parameters, which are outlined in Table 1, along with the technical specifications and positions of the sensors.

2.2. Physiological measurement devices

Two distinct wearable sensors were used to measure physiological parameters, namely MUSE Interaxon headband [50] and Empatica E4 [51] (see Fig. 2(a) and (b), respectively).

MUSE Interaxon headband allows to measure the EEG signal (sampling frequency: 256 Hz) through 4 input electrodes, 2 silver-made on the forehead (AF7 and AF8, on the right and on the left, respectively) and 2 in conductive rubber above ears (TP9 and TP10); the reference electrode is placed on the forehead (FPz).

Empatica E4 (classified as a medical device, Class IIA, according to 93/42/EEC Directive) is equipped with four different sensors: a PPG sensor for cardiac activities parameters (e.g., heart rate and related variability; sampling frequency: 64 Hz, resolution: 0.9 nW/digit), a sensor for electrodermal activity (EDA; measurement range: 0.01–100

Table 1
Sensors for environmental data monitoring.

Sensor	Measured parameters	Technical specification	Position
Thermal-hygrometer	Air temperature Relative humidity	Accuracy: ± 0.1 °C	Height: 0.10/0.60/1.10/1.60 m
		Accuracy: ± 1.5%	Height: 1.10 m
Hotwire anemometer	Air velocity	Accuracy: ± 0.2 m/s	Height: 1.10 m
CO_2 sensor	CO_2 concentration	Accuracy: ± 50 ppm	Height: 1.10 m
Luxmeter	Illuminance	Range: 20 ÷ 2000 lx	On the desk surface

Fig. 1. NEXT.ROOM outdoors (left) and indoors (right).

Fig. 2. Physiological monitoring - acquisition devices: (a) MUSE Interaxon headband and (b) Empatica E4.

μS; resolution: 900 pS; electric current applied: 100 μA max, 8 Hz), an IR thermometer for skin temperature (ST, measurement range: −40–115 °C; accuracy: ±0.2 °C in the range 36–39 °C), and a 3-axial MEMS accelerometer (sampling frequency: 32 Hz; measurement range: ±2 g).

2.3. Experimental procedure

The experimental campaign was carried out in accordance with the WMA Declaration of Helsinki – Ethical Principles for Medical Research Involving Human Subjects [52] and in compliance with the statute of the Ethics Committee of the University of Perugia. Regarding the test population, the investigated sample included 24 healthy subjects (10 females and 14 males, aged 24.0 ± 1.8 years – reported as mean ± standard deviation). Before starting the acquisitions, personal data were provided just after entering the NEXT.ROOM by filling in a first questionnaire, where they also confirmed to have no specific clinical histories potentially influencing (and biasing) the results. Furthermore, all the subjects were made sign an informed consent module. The General Data Protection Regulation (GDPR) was considered for data privacy and confidentiality and all the gathered information was managed according to it; moreover, all the data were anonymised before their processing. The tests (entirely conducted in springtime) were designed with three pre-determined temperatures, as follows: (i) (24.3 ± 0.9, reported as mean ± standard deviation) °C as representative of the thermally neutral scenario in accordance with ISO 7730:2005 [53] by assuming a clothing resistance level equal to 0.6 clo, and a low metabolic rate (i.e., equal to 58 W/m^2 for sedentary activities); (ii) (19.4 ± 0.9) °C representative of the cold environment; (iii) (32.2 ± 0.6) °C representative of the warm thermal environment. Moreover, lighting conditions were modified throughout the tests, providing three different lighting scenes for each thermal environment. RGB reflectors were used to characterize three different lighting scenes in terms of Correlated Colour Temperature (CCT); CCT was measured on the vertical plane at the sight height with a portable spectroradiometer (JETI specbos 1211-2), as follows: whitish (4114 K), bluish (178,000 K), and reddish (2,010 K). The test setup in the three different lightning conditions is reported in Fig. 3. The whitish light was always the first to which the subject was exposed, whereas the other two were randomized in the order of exposure. The other environmental parameters were kept constant as reported in Table 2.

The tests were scheduled from 10:00 a.m. to 1:00 p.m. and from 3:00 p.m. to 6:30 p.m. All the participants were instructed to not smoke, perform physical activity, and not eat or drink anything at least one hour before their test, to avoid the metabolic process alteration. Subjects were asked to sit down and keep relaxed; no activity was allowed to reduce artifact movements in the physiological measurements. Each test lasted at least 20 min; a minimum of 15 min was considered for thermal adaptation (until the achievement of the target TS) and the subsequent 5 for data recording. At the end of each session, they filled out a second questionnaire. The details about the survey are discussed in the next section.

2.4. Survey structure and submission

All study participants were required to complete two surveys. The first survey was designed to gather personal information, including gender, age, height, weight (and subsequently Body Mass Index, BMI), and clothing, which could affect thermal sensation according to previous literature. Participants completed this survey at the beginning of the test, once they had entered the NEXT.ROOM. After at least 20 min of exposure to the designed environmental conditions, the second survey was presented to the subjects to collect their evaluation of the surroundings in terms of perceived thermal sensation and comfort, following ISO 10551 [54].

The judgment scales were designed as follows:

- Thermal sensation (TS): the scale ranged from −2 (cold) to +2 (warm) with intermediate ratings of −1 (slightly cold), 0 (neutral), and +1 (slightly warm);
- Thermal comfort (TC): the scale ranged from −2 (very uncomfortable) to +2 (very comfortable) with intermediate ratings of −1 (slightly uncomfortable), 0 (neutral), and +1 (slightly comfortable).

We used 5-point scales as our study aimed to distinguish between hot and cold thermal sensation without focusing on intensity details.

2.5. Data processing

Data processing was performed in Python environment (as fully described in [33]), whereas the feature selection and the ML-based classification were conducted through the WEKA toolbox [55].

The first step of the processing pipeline consisted in synchronising the signals (considering the timestamps provided by the two acquisition devices) and dividing them according to the different testing conditions. Hence, signals were properly filtered before proceeding with the computation of the features of interest. In particular, in order to remove the contribution of noise sources (e.g., eye blink and jaw clench), the EEG signal was filtered with a band-pass filter (0.1–45.0 Hz); this procedure was made exploiting an onboard digital signal processing module [56]. Then, the Fast Fourier Transform (FFT) algorithm was employed to compute the power in the different frequency bands of interest, namely:

- Delta (δ) band (0.1–4.0 Hz): these are the slowest but highest brain waves; in some studies, delta waves were reported to be dominant in warm conditions [35].
- Theta (ϑ) band (4.0–7.5 Hz): these are slow waves and are not common in adults, even if sometimes they have been reported to decrease in a warm environment [57].
- Alpha (α) band (7.5–12.0 Hz): these waves prevail in relaxed conditions [58], whereas disappear in case of concentration [59].

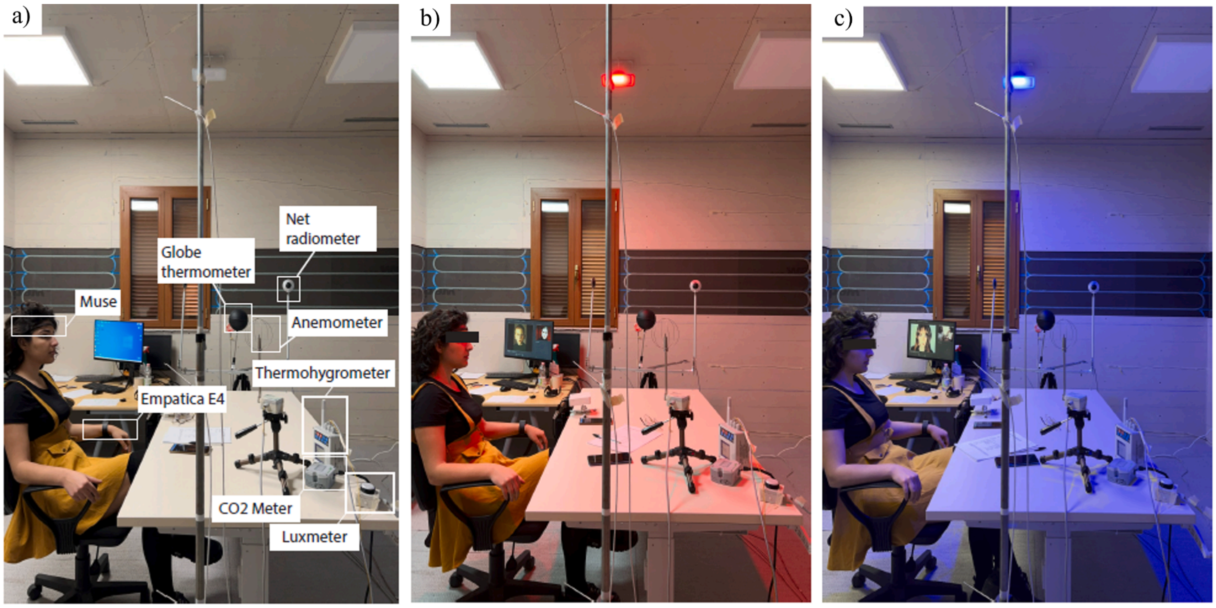

Fig. 3. Test setup with (A) reddish light, (B) bluish light, and (C) whitish light.

Table 2
Mean values ± SD of the environmental parameters monitored during experimental sessions.

Measured Parameters	Cold	Neutral	Warm
Relative humidity [%]	52.4 ± 8.1	44.2 ± 4.4	28.7 ± 3.9
Air velocity [m/s]	0.20 ± 0.07	0.10 ± 0.03	0.10 ± 0.02
CO_2 concentration [ppm]	450.8 ± 9.8	490 ± 8.7	509.0 ± 7.6
Illuminance [lx]	490 ± 19	488 ± 18	501 ± 17

- Beta (β) band (12–30 Hz): these waves are common in alert/anxious people. Their content is higher in cold/warm conditions than in neutral thermal environment [60].
- Gamma (γ) band (>30 Hz): these waves increase in complex and high attention-demanding tasks [61].

Regarding the cardiac related activity, the HRV analysis was conducted on the basis of the inter-beat intervals (IBIs) signal provided by Empatica E4 (after having cleaned up artefacts); the "hrvanalysis" Python module [62] was exploited, considering both time and frequency domain parameters.

Concerning EDA signal, after having removed the artefacts (EDA toolkit 11), tonic and phasic components were discriminated (cvxEDA tool 13 [63]).

A total of 110 features were extracted from the acquired physiological signals, averaging each of them on the whole test duration, i.e., 5 min). A dedicated code, developed in Python programming language, was exploited and specific features were extracted from each signal channel, namely:

- EEG: average relative power in delta, theta, alpha, beta, and gamma bands for each channel, power ratios, and frontal and temporal asymmetry;
- PPG: HRV parameters in both time and frequency domains;
- EDA: tonic and phasic components.

A detailed description of the extracted features and calculation procedures is reported in [33].

The obtained dataset was composed by 149 instances, each one containing the 110 physiological features extracted from EEG, PPG, and EDA signals, plus environmental parameters and test conditions. It is worthy to underline that only the instances with a hot or cold reported TS were considered, since the final aim was the binary classification between hot and cold perceptions.

The dataset with features was then subjected to an attribute selection process in order to extract an optimal features subset to be exploited for ML-based classification purposes.

2.6. Features correlation and subset selection

The WEKA toolbox developed by the University of Waikato [55] was used to analyse the correlation between thermal sensation and physiological parameters and to understand which parameters lead to the perception of thermal conditions.

In particular, the attribute selection procedure was used with a dual purpose: i) to evaluate the correlation of physiological features with the thermal condition to which the subject was exposed and ii) to identify a features subset to be used for the ML-based classification of TS. The authors exploited the CfsSubsetEval tool; it is a correlation-based approach, based on the Correlation-based Feature Selection (CFS) algorithm, able to quickly identify irrelevant and redundant features (which could degrade the classifier performance), as well as distinguish relevant features not related to each other [64]. A well-performing features subset is constituted by features highly correlated with the class to predict, but uncorrelated to each other. The measurement of the "merit" of a features subset can be performed through the Pearson's correlation coefficient; considering a heuristic evaluation function based on correlation, a CFS algorithm can rank feature subsets. The evaluation function is reported in Eq. (1) [65]:

$$M_s = \frac{k \bullet \overline{r_{cf}}}{\sqrt{k + k(k-1)\overline{r_{ff}}}} \tag{1}$$

where k is the number of features, $\overline{r_{cf}}$ is the mean feature-class correlation, and $\overline{r_{ff}}$ is the average feature-feature inter-correlation. This means that M_s increases with the subset predictivity power (numerator), whereas decreases with redundancy (denominator). Three heuristic search strategies are available:

- Forward selection: starting from an empty subset, one feature at a time is added, until no higher evaluation is obtained;

- Backward elimination: starting from the whole set, one feature at a time is removed, until the evaluation does not degrade;
- Best first: it can start both from a full or an empty subset and moves backward or forward, respectively. The search terminates when 5 consecutive subsets do not show improvement.

The subset with the highest merit is used to limit the feature set size and can be used for training a ML model, as it will be described in detail in the next subsection.

The CfsSubsetEval attribute evaluator was used, exploiting the GreedyStepwise search method (with forward selection). The ranking was generated and the authors selected the first 10 physiological features that was coherent with the findings of previous studies on physiological signals for thermal comfort assessment (but conducted with diverse test protocol and methodology [33]). This new subset (formed by relevant features in the TS classification, whose relevance does not depend on other features) was exploited for the ML-based classification part, performed again within the WEKA toolbox. The same subset was used as input for all the considered ML classifiers.

2.7. *Thermal sensation prediction with Machine learning*

Different ML algorithms were considered to predict the TS value from the computed features. The TS scores were considered as labels for a binary classification between the following classes related to the thermal sensation:

- Hot (TS $>$ 0): this class includes both warm (TS $= +1$) and hot (TS $= +2$) scores;
- Cold (TS $<$ 0): this class includes both slightly cold (TS $= -1$) and cold (TS $= -2$) scores.

Neutral TS was not considered, as mentioned above.

The pipeline of the procedure is reported in Fig. 4.

The following supervised classifiers were considered, being suitable for a binary classification as well as being widely employed in literature:

- Gaussian Naïve Bayes (GNB): it models continuous features through Gaussian distribution.
- Logistic regression (LR): given a variable of input, it derives the probability of a certain output. It results particularly suitable for dichotomic variables.
- Simple logistic (SL): this classifier builds a linear logistic regression model and can be used to fit logistic models. It can be used to predict a single binary variable or to determine the relationship between two variables.
- Support Vector Machine (SVM): it is based on statistical learning frameworks to build a non-probabilistic binary classifier.
- Bagging (BAG): this method generates more predictor versions to obtain an aggregated predictor. It is suitable both for classification and regression.
- Decision Table (DT): it is a classification model based on a concise visual representation, which foresees actions based on given conditions.
- J48: it generates a decision tree, able to analyse data in a continuous and categorical manner.
- Random Forest (RF): it uses decision trees for both classification and prediction purposes. Both the majority and the average are considered.

10-fold cross-validation method was adopted; in particular, validation was carried out dividing the dataset into 10 subsets: 9 for training, 1 for validation (hence, with a ratio of 90:10 for training and validation). With 10 iterations each of the subset was considered alternatively for testing, exploiting the remaining 9 for training, and the results from the 10 iterations were averaged to obtain the metrics related to the algorithm classification performance.

Standard metrics [66] were computed in order to evaluate the classification performance of the tested ML classifiers, namely Accuracy (Eq. (1)), Recall (or Sensitivity, Eq. (2)), Precision (Eq. (3)), and F-measure (Eq. (4)).

$$Accuracy = \left(1 - \frac{|N_{cci} - N_{ti}|}{N_{ti}}\right) \bullet 100 \tag{1}$$

N_{cci} is the number of the correctly classified instances, whereas N_{ti} is the number of the total instances.

Recall is the ratio between the number of true positive (TP) and the total instances number (i.e., the sum of TP and false negatives, FN).

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

Precision is the ratio between the number of true positive (TP) and the total positives number (i.e., the sum of TP and false positives, FP).

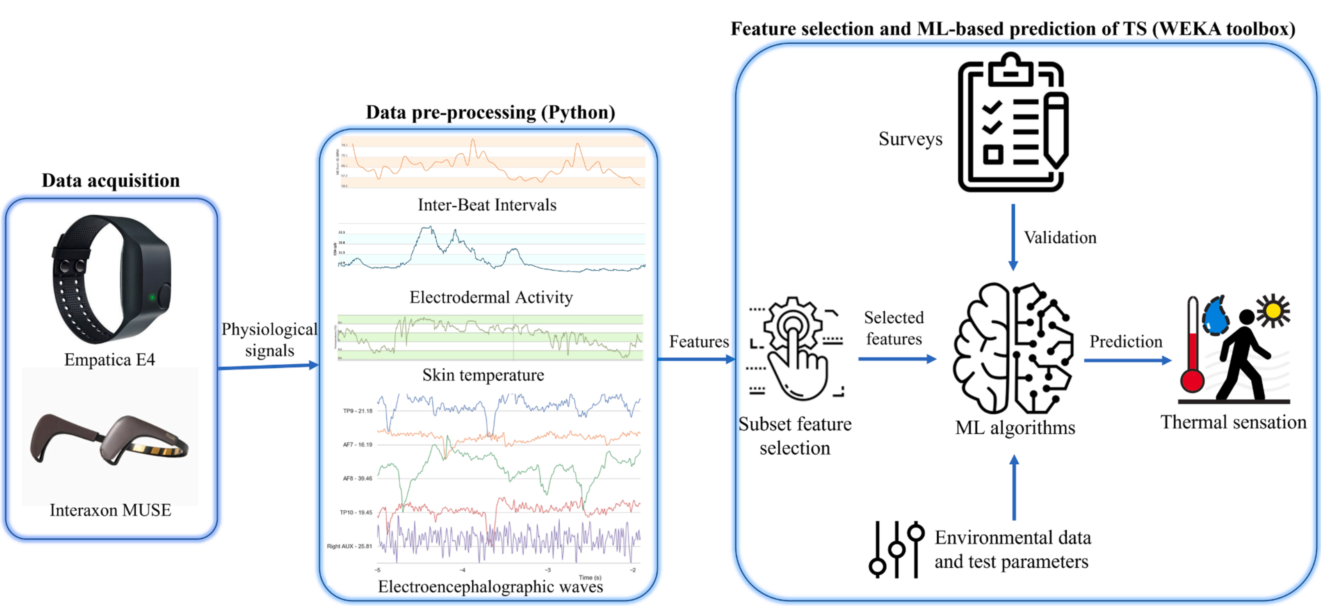

Fig. 4. Pipeline of data processing for ML-based classification of thermal sensation.

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

F-measure is the harmonic mean of Recall and Precision, with a weight coefficient (β, which in Weka toolbox is considered equal to 1).

$$F - measure = \frac{(1+\beta)^2 \bullet Sensitivity \bullet Precision}{\beta^2 \bullet Sensitivity + Precision} \tag{4}$$

3. Results and discussion

The acquired signals reflect the different thermal sensations perceived in hot/cold conditions. Concerning the IBIs signal, in Fig. 5 it is possible to observe the RR duration decrease at higher temperatures (TS > 0), equivalent to a HR increase aimed at dissipating thermal energy (increasing skin blood flow [67]), whereas HR is lower in a cold environment [68]. EDA signal (Fig. 6) intensity increases with TS > 0, since the thermoregulation systems tries to dissipate energy through sweat production, resulting in a higher tonic component [33] (EDA is correlated to skin electrical conductivity [69]). This happens also with ST signal (Fig. 7), which directly follows the ambient temperature variations. Regarding EEG signals, Fig. 8 shows the differences between hot and cold thermal conditions; in particular, when TS < 0 PSDs values generally increase in HF band and this is attributable to the higher attention level [33].

The application of the features selection procedure based on correlation feature selection method, applied on features extracted from physiological signals and integrated with previous findings, gave the results reported in Table 3. It can be noticed that different types of physiological signals are involved, namely:

- Skin temperature, in particular the mean value (mean_temp); it seems the most relevant feature according to ranking.
- EDA signal: tonic_quartdev and tonic_std; the tonic component, as said in literature, results to be relevant in terms of TS.
- EEG signal: temporal_asym_alpha and gamma_af7. Previous works demonstrated that gamma waves are correlated with the anxiousness level [70], which surely impacts on the perceived thermal sensation. Alpha waves are considered as indicative of attention level and also correlated to discomfort due to cool environment [71].
- Cardiac signal: the values of heart rate and the features extracted from HRV analysis (both in time and frequency domain) turned to be significant. In particular, the selected features are the following ones: cvsd, pnni20, RMSSD, std_HR, and LF/HF.

The obtained subset is composed by 149 instances as the original dataset, but the number of features is reduced (10 physiological features) according to the results from the feature selection approach. In particular, it is possible to distinguish among thermal conditions (i.e., neutral, hot, and cold) and lightning conditions (i.e., reddish, bluish, and whitish). Some characteristics of the dataset can be summarized as follows:

- Neutral thermal condition: a total of 24 instances are present. The mean TS from questionnaires is equal to 0.10 ± 1.20, −0.5 ± 1.31, 0.83 ± 0.98 in case of whitish, reddish, and bluish lights. The illuminance mean value is equal to 129, 137, and 79 lx in case of whitish, reddish, and bluish lights;
- Hot thermal condition: a total of 65 instances are present. The mean TS from questionnaires is equal to 2.38 ± 0.74, 1.73 ± 1.03, 2.27 ± 0.70 in case of whitish, reddish, and bluish lights. The illuminance mean value is equal to 126, 127, and 126 lx in case of whitish, reddish, and bluish lights;
- Cold thermal condition: a total of 60 instances are present. The TS from questionnaires is equal to −1.85 ± 0.88, −1.70 ± 1.02, −1.71 ± 0.60 in case of whitish, reddish, and bluish lights. The illuminance mean value is equal to 128, 127, and 127 lx in case of whitish, reddish, and bluish lights.

Hence, this optimal subset was used as input to different ML models for classification purposes, together with a limited number of environmental features (i.e., air temperature and velocity) and other test conditions (i.e., gender, light colour, and order of exposition).

The results obtained from classification procedures are reported in Tables 4 and 5 for the identification of hot (TS > 0) and cold (TS < 0) thermal sensations, respectively; the average performance metrics are reported in Table 6. The best results were globally achieved by the Random Forest classifier, which shows an average accuracy of 89.93% when fed with the identified subset of physiological features together with environmental variables and test conditions. It is followed by the SL classifier, which reports an accuracy of 88.59%. On the contrary, J48 reports the worst (even if still very good) results, providing an average accuracy of 81.21% with the same feature subset as input. Looking at the detailed information on accuracy, it is possible to observe how the classifiers performance differentiates between the two classes (i.e., hot thermal sensations, TS > 0 – Table 4 – and cold one, TS < 0, Table 5 –). Nevertheless, the RF classifier confirms the best one also in the detection of both hot thermal sensation (with a Recall of 0.896, a Precision of 0.908, a F-measure of 0.902, and an AUC of 0.938 – only in terms if Recall it is outperformed by the GNB model, with a Recall of 0.909) and cold one (with a Recall of 0.903, a Precision of 0.890, a F-measure of 0.897, and an AUC of 0.938).

It is worth to mention that the performance results did not improve if

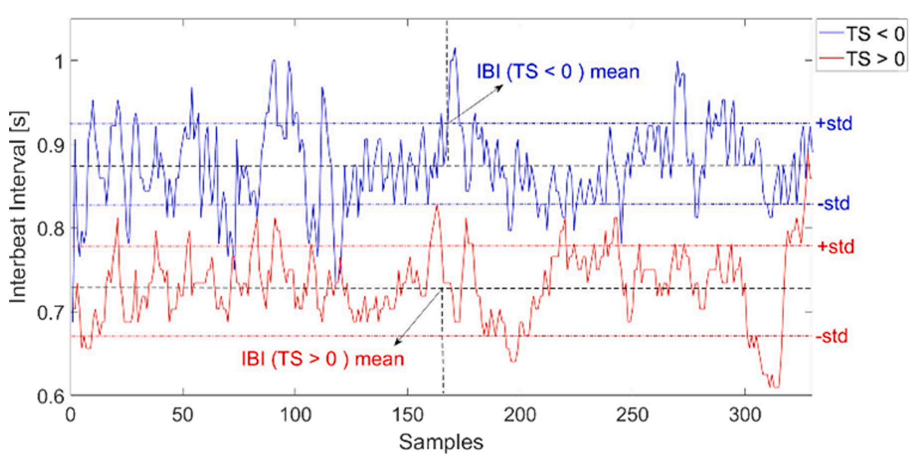

Fig. 5. Example of IBIs signal in correspondence of hot (TS > 0, red line) and cold (TS < 0, blue line) – sampling frequency: 64 Hz. Mean and standard deviation values are reported in the two thermal conditions.

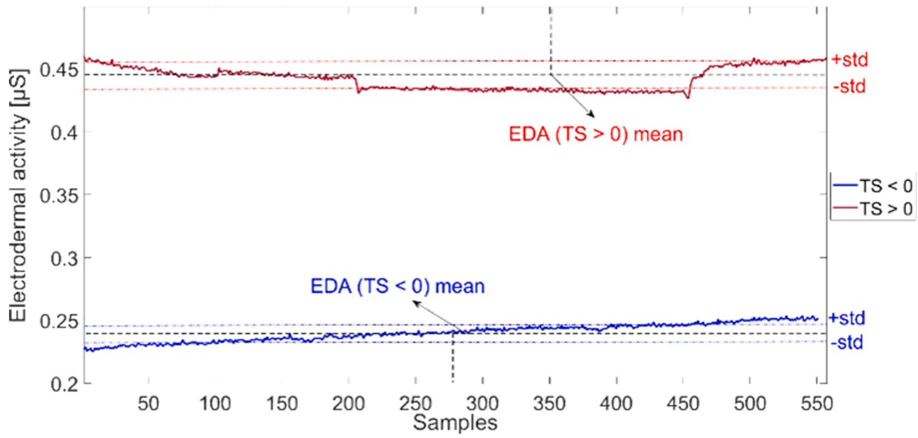

Fig. 6. Example of EDA signal in correspondence of hot (TS > 0, red line) and cold (TS < 0, blue line) – sampling frequency: 4 Hz. Mean and standard deviation values are reported (dash-dot and dashed lines, respectively) in the two thermal conditions.

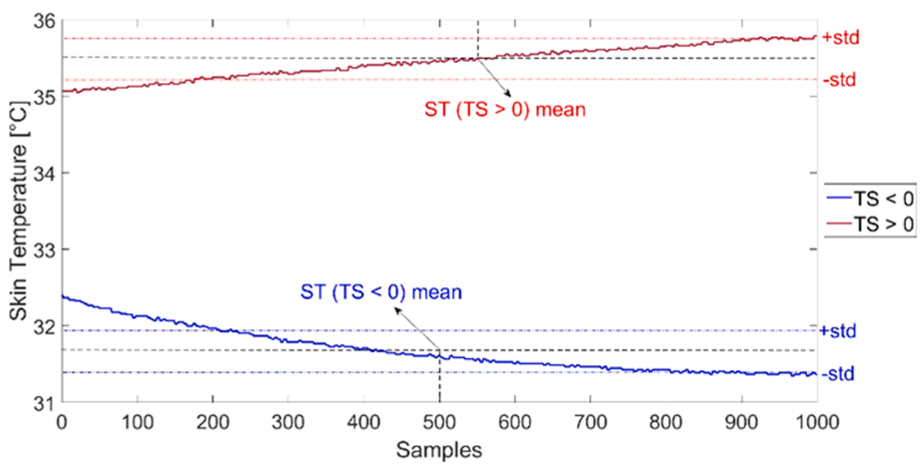

Fig. 7. Example of ST signal in correspondence of hot (TS > 0, red line) and cold (TS < 0, blue line) – sampling frequency: 4 Hz. Mean and standard deviation values are reported (dash-dot and dashed lines, respectively) in the two thermal conditions.

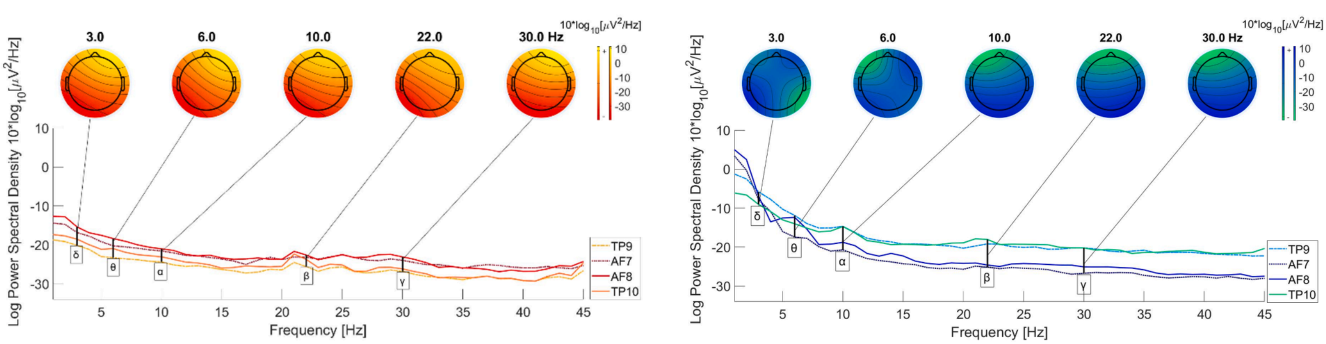

Fig. 8. Example of EEG signal in correspondence of (a) hot (TS > 0) and cold (TS < 0) environment. PSD values are reported for the different electrodes.

further environmental parameters (e.g., air CO_2 concentration or illuminance) were added as input. This means that in a real application environment a well-performing model could be obtained limiting the measurement to physiological signals, air temperature/velocity, and CCT. Also gender seems to have a relevant weight on the outcome. However, these results are probably linked to the fact that air temperature and air velocity were the quantities most changed in order to achieve the desired TS in the tests.

4. Conclusions

In this paper, the authors evaluated the relationship between physiological parameters measured through wearable sensors (namely a smartband, Empatica E4, and a headband, Interaxon MUSE) and the subject's thermal sensation (TS). In this framework, while TS is commonly assessed through survey-based investigations, some objective parameters should be added to better depict the effective status of a subject and obtain more robust results, going beyond possible perceptual bias. Given that the literature highlights the influence of

Table 3
Results from features selection process (CfsSubsetEval) performed on physiological features, after comparison with previous results [33]. Note: results are reported according to decreasing rank.

Feature	Type of signal	Description	Average merit	Average rank
mean_temp	ST	Mean skin temperature	0.500	1
tonic_quartdev	EDA	Quartile deviation of tonic component	0.522	2.2
tonic_STD	EDA	Standard deviation of tonic component	0.536	4.5
cvsd	PPG	Coefficient of variation of successive differences between RR intervals	0.536	8.1
pnni_20	PPG	Percentage of successive RR intervals exceeding 20 ms	0.534	8.6
RMSSD	PPG	Beat-to-beat variance	0.526	11.1
std_HR	PPG	Standard deviation of heart rate	0.528	12.4
LF/HF	PPG	Ratio between low and high frequency components	0.500	12.5
temporal_asym_alpha	EEG	Alpha band power difference between left and right hemispheres	0.492	14
gamma_af7	EEG	Gamma waves of left frontal electrode	0.460	22.6

Table 4
Average Recall, Precision, F-measure, and ROC area achieved by each combination of physiological signals and ML classifier (TS > 0).

ML classifier	Recall	Precision	F-Measure	ROC area
GNB	0.909	0.833	0.870	0.927
LR	0.896	0.852	0.873	0.919
SL	0.896	0.885	0.890	0.931
SVM	0.870	0.882	0.786	0.873
BAG	0.896	0.863	0.879	0.902
DT	0.805	0.838	0.821	0.876
J48	0.831	0.810	0.821	0.813
RF	0.896	0.908	0.902	0.938

Table 5
Average Recall, Precision, F-measure, and ROC area achieved by each combination of physiological signals and ML classifier (TS < 0).

ML classifier	Recall	Precision	F-Measure	ROC area
GNB	0.806	0.892	0.847	0.927
LR	0.833	0.882	0.857	0.919
SL	0.875	0.887	0.881	0.931
SVM	0.875	0.863	0.869	0.873
BAG	0.847	0.884	0.865	0.902
DT	0.833	0.800	0.816	0.876
J48	0.792	0.814	0.803	0.813
RF	0.903	0.890	0.897	0.938

physiological parameters on the subject's thermal sensation, since thermal comfort conditions mirror in the subject's physiological conditions, the authors have investigated the strength of the correlation between physiological variables and the TS itself. Identifying an optimal subset of features, the authors fed a few ML-based classifiers (i.e., Gaussian Naïve Bayes, Logistic Regression, Simple Logistic, Support Vector Machine, Bagging, Decision table, J48, and Random Forest) with those features plus environmental quantities and test boundary conditions, to have a wider depiction of the thermal conditions perceived by the subject under test. As ground truth, the authors considered the TS value declared by the subjects in a dedicated survey filled in the experimental campaign.

Table 6
Average Accuracy, Recall, Precision, F-measure, and ROC area achieved by each combination of physiological signals and ML classifier (all).

ML classifier	Accuracy	Recall	Precision	F-Measure	ROC area
GNB	0.859	0.859	0.862	0.859	0.927
LR	0.866	0.866	0.867	0.866	0.919
SL	0.886	0.886	0.886	0.886	0.931
SVM	0.872	0.872	0.873	0.873	0.873
BAG	0.872	0.872	0.873	0.872	0.902
DT	0.819	0.819	0.820	0.819	0.876
J48	0.812	0.812	0.812	0.812	0.813
RF	0.899	0.899	0.899	0.899	0.938

Results from the features selection process (performed according to the Correlation-based Feature Selection algorithm, coupled with the Greedy Stepwise search method) show that all the considered physiological signals from the different domains (i.e., ST, EEG, PPG, and EDA signals) provide relevant features in the classification between hot and cold thermal sensation. Concerning ML-based models, the best accuracy in classification between hot and cold TS was achieved by the RF classifier (89.93%), followed by SL (88.59%). The same model maintained the best performance also considering separately the two conditions (i.e., hot and cold TS). These results are in line with literature (e.g., Fayyaz et al. reported an accuracy of 86.08% [72]).

The findings of this study emphasize the importance of integrating subjective surveys on thermal sensation with objective measurements of physiological parameters (e.g., ECG, PPG, EDA, EEG, and ST) to reduce the subjectivity of questionnaires and mitigate perceptual bias. Physiological features offer a more accurate and objective assessment of the subject's response to their living environment, while subjective surveys can be influenced by personal factors and mental state. Hence, the measurement of physiological signals is an objective tool that can contribute to assess thermal sensation in living environments in a more accurate way, going beyond the perception bias that could affect survey-based evaluations. The results from this study can inform the development of personalized comfort systems that optimize both occupants' well-being and building energy consumption. In Fig. 9 a potential application of the proposed strategy is illustrated. Both physiological and environmental quantities are measured (from subjects and living environment, respectively) and the gathered data are fed to a controller based on dedicated ML algorithms (i.e., personal comfort models). In this way, information relevant in terms of personal thermal sensation is provided, hence being exploitable by Heating, Ventilation and Air Conditioning (HVAC) systems for automated control purposes.

Future research should explore the effect of non-thermal parameters on thermal comfort models to evaluate potential cross-modal effects that could further enhance the dwellers' comfort and the energy efficiency of the living environment. This approach aligns with the multi-domain comfort theory [73], which seeks to maximize comfort across different domains while minimizing energy consumption. Additionally, the proposed methodology can be adapted to assess outdoor comfort using portable and wearable sensing techniques. As wearable technology advances and measurement procedures become optimized, this approach holds great potential for improving our understanding of multi-domain physiological responses and enhancing occupant comfort. Moreover, the features selection performed in this study can route future studies on specific parameters, also analysing them in terms of measurement uncertainty, in order to always meet the specific requirements for a certain target application. In this context, the metrological performance of the employed sensors undoubtedly plays a pivotal role.

Finally, predictive models could be developed for TS, hence going beyond classification purposes.

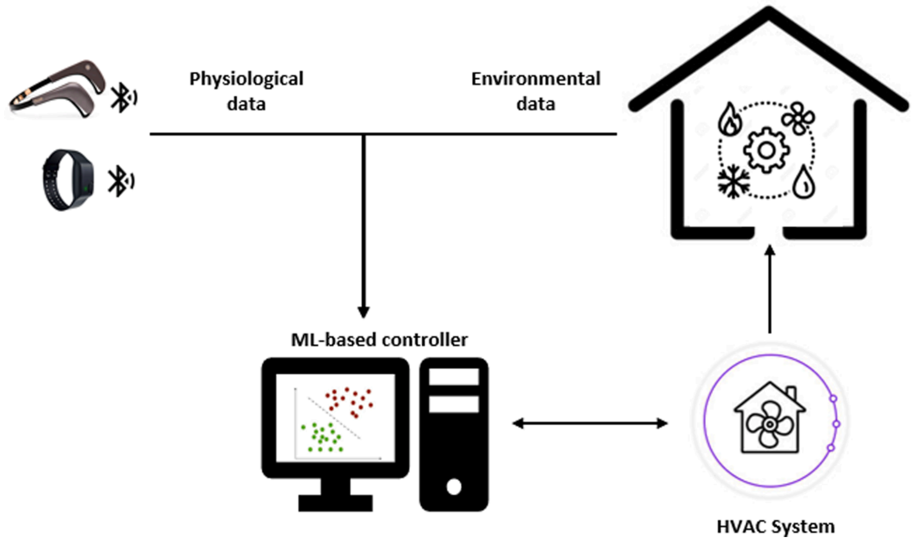

Fig. 9. Potential application of the proposed methodology for the assessment of thermal sensation in indoor living environments.

CRediT authorship contribution statement

Gloria Cosoli: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – review & editing. **Silvia Angela Mansi:** Conceptualization. **Ilaria Pigliautile:** Conceptualization, Methodology, Investigation, Writing – review & editing. **Anna Laura Pisello:** Conceptualization, Resources, Writing – review & editing, Supervision, Funding acquisition. **Gian Marco Revel:** Conceptualization, Resources, Writing – review & editing, Supervision, Funding acquisition. **Marco Arnesano:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Resources, Writing – review & editing, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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