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Measuring thermal comfort using wearable technology in transient conditions during office activities

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ABSTRACT

This paper presents an experiment for assessing thermal comfort of occupants in the built environment, from a subjective perspective, focusing on office environment; a dedicated measurement campaign using sensors for acquisition of physiological and environmental parameters was conducted. Skin temperature was measured with two sensors: a minimally invasive sensor for measuring wrist temperature, and a thermal camera to retrieve forehead temperature; simultaneously, heart rate variability was measured using a wearable device. 15 participants were exposed to dynamic changes of air temperature. Data was collected to measure the participants' thermal sensation vote, with machine learning algorithms. Decision Tree provided higher performances, using a dataset made of wrist temperature, heart rate variability features and air temperature, with mean average error and mean absolute percentage error of 0.86 and 20.9%. The research contributes to thermal comfort personalization in the built environment, to improve well-being and productivity of occupants using minimally invasive sensor network.

1. Introduction

1.1. Background

The measurement and evaluation of thermal comfort (TC) in the context of the indoor environments is of particular interest because of its impact on occupants' wellbeing and on the energy consumption of buildings. TC is strictly related to environmental and personal factors and to handle it, buildings are equipped with HVAC systems that act on one or more environmental parameters [1]. As a consequence, the impact for maintaining TC in the built environment reflects negatively on buildings' energy performance: in fact, buildings are responsible for 40 % of global consumption and approximately half of it is due to activate the HVAC systems, contributing largely to most of the CO_2 gas emissions [1–3]. Nonetheless, TC assessment is a necessary requirement in the built environment, since it has a great impact on occupants' health, workers' productivity, and satisfaction with the environment [3]. It is reported that 38 % of occupants in office buildings are not satisfied with indoor thermal environment, and given the strict relationship that exists between comfort, wellbeing, and workers' productivity, it is necessary to develop new strategies and sensor network that can guarantee TC and at the same time reduce energy costs of the built environment [4]. In fact, 89 % of buildings are not capable of guaranteeing indoor TC demands, in which the rule of thumb is that at least the 80 % of occupants should express satisfaction with the thermal environment. It is therefore necessary to renovate the way of measuring TC and the way in which building energy is supplied: the upcoming trend is to apply a human-centered design approach, which is based on the demands of the single occupant, rather than using a building centered approach [5,6]. In particular, the context of office environment is of particular interest since occupants tend to spend one third of their daily routine in this kind of environment [7]; for this reason, improving TC in office buildings may lead to a substantial increase in occupant productivity but also an increase of their wellbeing [8]; possible solutions to monitor workers in office buildings involves the use of a sensor network that measures in real-time their comfort, with the aim of avoiding thermal stress.

Within this framework, human-centred design is moving to the assessment of personal and physiological quantities of the occupant for TC evaluation in office buildings, to have a comprehensive overview of all the aspects of the human being that are TC-related, while participants are performing typical office tasks. With this approach, it is possible to have customized thermal environment that are based on the single

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Nomenclature

TC	Thermal comfort
HVAC	Heating Ventilation and air conditioning
PMV	Predicted Mean Vote
ECG	Electrocardiographic signal
HRV	Heart Rate Variability
ST	Skin Temperature
EEG	Electroencephalography
EDA	Electrodermal Activity
ASHRAE	American society of Heating, Refrigerating and Air-conditioning Engineers
ML	Machine Learning
DL	Deep Learning
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
PPG	Photopletismographic
tL	Air temperature at 0.1 m
tM	Air temperature at 0.6 m
tH	Air temperature at 1.1 m
RH	Relative Humidity
va	Air velocity
t_a	Air Temperature
t_r	Mean radiant Temperature
t_w	Wrist Temperature
t_f	Forehead Temperature
BMI	Body Mass Index
TSV	Thermal sensation vote
ROIs	Region of Interest
MEAN	Mean Value
MEDIAN	Median
RMSSD	Root Mean Square of Successive Differences
SDNN	Standard Deviation of NN Intervals
PNN50	Percentage of 50 NN intervals
NN50	Numbers of NN intervals
PNN20	Percentage of NN20 intervals
NN20	Numbers of NN intervals
VLF	Very Low Frequency
LF	Low Frequency
HF	High Frequency
TP	Total Power
SD1	Standard Deviation – Short Term Variability
SD2	Standard Deviation – Long Term Variability
R	Pearson's correlation coefficient
ETR	Extra Tree Regressor
LOSO	Leave-One-Subject-Out
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
KNN	K-Nearest Neighbors
ADA	Adaboost
RF	Random Forest
DT	Decision Tree
SVM	Support Vector Machine
MLP	Multi Layer Perceptron

differences of occupants, driving to the personalization of TC. Personalized TC aims therefore at increasing the accuracy of the measurement of human TC with the consequent effect of minimizing the interference of occupants on TC management; however, the current state of the art reports that there are some challenges in the establishment of the most appropriate set of parameters for building personalized TC. For this reason, TC assessment should be done basing on sensor network that measure real-time physiological and environmental parameters, through reliable but also minimally invasive equipment that does not interfere with occupants' daily activities [9].

1.2. Literature review and research gap

Currently in buildings the standard approach for TC evaluation is based on the predicted mean vote (PMV) index, developed by Fanger; the PMV is an index which is dependent on 6 parameters, according to ISO 7730 [10]. Four of these are environmental parameters (air velocity, air temperature, mean radiant temperature and relative humidity), while two parameters are personal factors (clothing insulation according to ISO 9920 and metabolic rate according to ISO 8896). Being the PMV an index that represents the average behaviour of a group of people, it occurs that its value does not consider the peculiarities of each occupant in terms of physiological and personal differences, impacting in deviations in TC perception of the occupant [11,12].

Personalized TC measurement are intended to capture personal characteristics by monitoring the thermal response of every occupant, and developing models using AI algorithms [3]. A great amount of AI algorithms were developed to obtain personalized comfort models, and research demonstrated that the accuracy of these models is higher respect with the traditional PMV model [13–15]. In this context, AI algorithms are suitable since occupants' thermal preferences, and the related thermal sensation, change actively through time, since the thermal environment is not uniform and also that the outdoor conditions are changing [16]. For these reasons, TC measurement through personalized approach is still a challenge to address. All the studies suggest that this approach as good potential, but this field still needs to be further explored.

Personalized TC measurement can be obtained by employing different sensor network and varying environmental conditions of the experiment and measurement set-up. An extensive bunch of literature has already demonstrated that the measurement of physiological parameters can lead to the development of the next generation of TC models: with the recent advancements in the sector of non-invasive wearable technology, it is possible to monitor occupants during their daily activities in the built environment. Thermal environment assessment through physiological parameters comes from several research conducted with human subjects, in a highly controlled, and consequently unreal environments [16]. Typically, the most relevant physiological signals related to TC perception are the electrocardiographic signal (ECG), through the estimation of heart rate and heart rate variability (HRV), skin temperature (ST), electroencephalography (EEG) and electrodermal activity (EDA)[17].

Specifically, personalized TC quantification methods based on HRV features and ST are the most spread techniques that can be found in this scientific field, given their correlation with the human thermoregulatory system, which in turn is triggered when thermal discomfort situation may occur. Indeed, HRV is linked to the activity of the sympathetic and parasympathetic neural systems, which rule on the human body responses to environmental changes in the surroundings [17]. In particular, the LF/HF ratio derived from HRV serves as an indicator of how the nervous system responds to thermal conditions in accordance with the human thermoregulatory system. Hence, the scientific community has provided several measurement techniques based on innovative procedures based on machine learning (ML) algorithms, that measure TC using datasets created through the acquisition of physiological parameters such as HRV or ST. However, it is still missing a thermal comfort assessment technique that includes and exploits both of these two physiological aspects [18–20].

In this research it is explored the usage of ST in the measurement of TC, since much research analyzed the relationship among TC and skin temperature: literature pointed out that these two quantities are correlated and that makes skin temperature an indicator for estimating human TC [21] and typically the TC assessment is done by applying ML and DL algorithms on the collected dataset. The current state of the art has highlighted many studies that involve ST measurement to derive TC. There are two main methodologies to measure ST that can be adaptable to the built environment and can reduce the degree of invasiveness to the occupant: non-invasive methods, that uses thermal images collected from thermal cameras and contact measurements, such as sensors positioned in different locations of the skin.

Non-contact measurement methods typically are represented by thermal cameras that collect thermal images from which it is possible to retrieve skin temperature at various locations: FLIR One Pro thermal camera is used, as an example, to predict the 7-point scale from ASHRAE [22]; their measurement set-up is able to provide a real-time assessment of comfort using facial skin temperature features. The research also pointed out that it is possible to decrease by 64 % the measurement of TC, outperforming conventional approach. FLIR Lepton thermal camera is also used for an automated assessment of TC, using ML techniques: skin temperature was measured from multiple locations of the body to retrieve the thermal preference of participants. The resulting models were applied to the data measured from experiments conducted in office environments where indoor air temperature was varying from 21.1 °C to 27.8 °C: in this case, the accuracy of the prediction of TC was 80 %[23]. Contact measurements to measure ST encompass sensors that are positioned on the skin or wearable devices. Recent studies typically adopt thermocouples that measure skin temperature at different locations of the body, and the collected data are used to train ML and DL model to predict thermal comfort. Thermocouples can be used to acquire temperature at different sites of the human body: as an example, thermocouples can be used to retrieve facial skin temperatures, to estimate human thermal sensation using artificial neural networks (ANN), with an average accuracy of the 80.4 % [24]; thermocouples typically present promising results, but they cannot be then applied in daily and real-life context. Example of literature works showed that thermal state of occupants can be measured using a contact sensor for skin temperature: for example, deep CNN that employs ST measured on the hand, predicts the thermal state with an accuracy of 93.3 % [18 25]. Fuzzy logic can be used to control indoor air temperature, predicting the thermal sensation of occupants measuring ST and heart rate: this study in fact demonstrates that by adjusting the indoor temperature set-point, using physiological quantities, may prevent occupants from interfering with their regular work [26].

Among the other physiological quantities related to TC (EDA, EEG, ECG), although all these signals demonstrated to have correlations with human thermal comfort, the devices for measuring EDA and EEG result often in invasive set-up that cannot be adequately used in daily life-contexts, such as the office environment; thermal stress due to thermal discomfort could be experienced in daily life situations, therefore is expected that the devices are placed on the measurement site 24/7 [27]. HRV and its related features were demonstrated to be related to thermal comfort and thermoregulatory activities; however, HRV is retrieved using photopletismographic signal (PPG), which is typically affected by movement artefacts that occur while the occupant is placed in in-the-wild applications; HRV in fact is subjected to different measurement uncertainties, according to the activity conducted by the occupant (e.g., walking, writing at the laptop, handwriting [28,24]). HRV and ST, therefore, can be measured through minimally invasive or non-invasive devices; given the different methodology available for measuring human ST and HRV, they could be measured in real conditions, as the office environment.

1.3. Objectives

Within this framework, the proposed research aims at providing contributions to literature, by proposing an experimental set-up, made by the combination of 2 sensors for the measurement of ST, and a wearable for HRV collection. The experiment aims at exploring the response of ST, combined with HRV features in a semi-controlled environment, trying to recreate real-life conditions in the office environment. The study aims to investigate the role of skin temperature and heart rate variability (HRV) features in a semi-controlled environment, simulating real-life office conditions. Participants engage in light office activities to explore the feasibility of quantifying thermal comfort during such tasks. Although literature has already extensively presented the relationship that exists among HRV and human response to a thermal stimulus, it is preferable to combine it with ST measurement to improve thermal comfort assessment. This kind of approach is trying to overcome the current state of the art, which is often characterized by unrealistic experimental design that do not accurately reflect the real-world scenarios. A commercial smartwatch is used to retrieve HRV, while two different sensors are used to measure ST: a non-obtrusive sensor that collects the skin temperature of the occupant's wrist and a non-invasive thermal camera that is placed in the test room to measure forehead skin temperature. These two techniques for measuring skin temperature are then compared in this research, in order to evaluate their impact in the measurement of skin temperature, for assessing thermal comfort.

The paper is structured as follows also by considering the research methodology represented in the flowchart in Fig. 1: Section 2 describes the measurement setup, the experimental campaign, and the techniques applied for the data analysis, including machine learning algorithms selected for the prediction of thermal comfort and the dataset used. Section 3 reports the results, including the dataset used for training ML algorithms, highlighting the physiological parameter that provides better performance in measuring TC. Section 4 contains a detailed discussion of the differences and similarities with literature, also including the limitation of the study, while Section 5 presents the conclusions of the research.

2. Material and methods

The proposed experimental protocol aimed at measuring human thermal comfort through an in-the wild approach, using a minimally invasive sensor network for collecting physiological quantities, with the final aim of exploring and measuring the dynamics of human TC of occupants in an office environment. The focus is twofold: first, to evaluate the correlation between human thermal comfort and physiological parameters, and second, to use these quantities to apply machine learning algorithms (ML) and evaluate the set of physiological features that provides higher performance in the measurement of TC.

The experiment took place in one test-room (5.0 m x 3.0 m x 3.0 m) at Università Politecnica delle Marche (Ancona, Italy), shown in Fig. 2. This experiment aimed at monitoring voluntarily recruited participants, as they could execute office tasks.

During the experiment, the following environmental quantities were measured (Fig. 3): air temperature at different heights: at 0.1 m, 0.6 m and 1.1 m (t_L, t_M and t_H, respectively), relative humidity (RH), air velocity (v_a), black globe temperature. Table 1 reports the accuracies of the sensors, consistent with ISO 7726.

Physiological quantities were collected by using two sensors for measuring skin temperature and a wearable smartwatch. The wearable device is a smartwatch, and the measurement uncertainty of the HRV was evaluated in past research [16,17]; the smartwatch collected the HRV (sampling frequency of 1 Hz). Two devices were used to measure ST: the first one is a minimally invasive sensor, named iButton DS1922, which was placed on the wrist of the participants, directly in contact with the skin, through a dedicated support; the iButton measures skin temperature at the level of the wrist (t_w); the other sensor for measuring skin temperature at forehead level (t_f) is the thermal infrared camera Flir ThermoCAM S40, with an emissivity value of 0.99 and a temperature range from 22.0 to 40.0 °C. The thermal camera was located at a distance of 1.5 m from the participant.

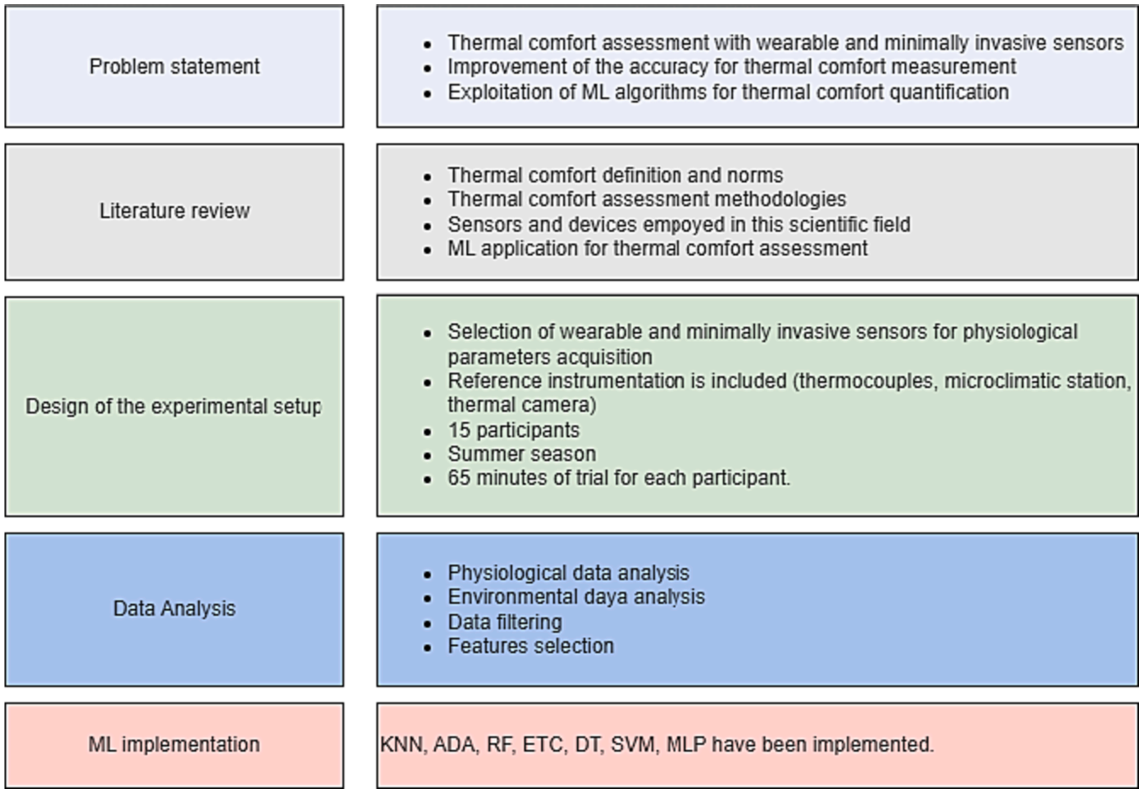


Fig. 1. Flowchart of the research methodology.

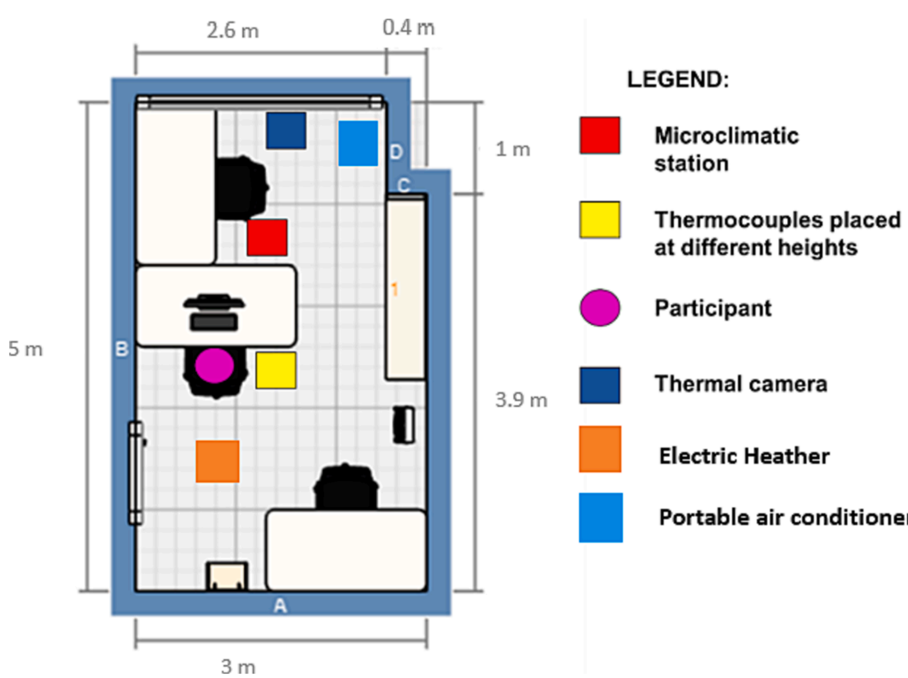


Fig. 2. Layout of the test-room where experiments took place.

2.1. *Experimental procedure*

The presented research includes the results from the experiments conducted in July 2021 in summer season, in center Italy, characterized by a Mediterranean climate. Summer season is considered in this study since literature has reported that there is lack of studies based in summer, that exploit the personal thermal comfort models [29]. The proposed experiment was performed on 15 voluntarily recruited participants, whose personal information is reported in Table 2. The choice regarding the number of participants has been validated through the application of a statistical power analysis performed with the dedicated software G*Power in alignment with literature [30]. Specifically, the software requires specific parameters to be inserted and they are reported in Table 3. The authors have selected these parameters based on

Fig. 3. (a) Microclimatic station, (b) iButton D1922 for skin temperature, (c) Wearable device for HRV measurement, (d-e)) Thermocouples for air temperature and board for acquisition, (f) Example of a test, (g) Thermal camera Flir ThermaCAM S40.

Table 1
Sensors used for measuring environmental quantities and related accuracies.

Measured parameter	Sensor type	Accuracy
Relative humidity (RH) [%]		± 1.5 %
Air temperature at 0.1 m (tL)	Thermocouples	± 0.1 °C
Air temperature at 0.6 m (tM)		± 0.1 °C
Air temperature at 1.1 m (tH)		± 0.1 °C
Air temperature (ta)	Thermal-hygrometer	± 0.1 °C
Mean radiant temperature (tr) [°C]	Black globe radiant temperature sensor	± 0.15 °C
Air velocity (va) [m/s]	Hot wire anemometer	±0.05 m/s
Heart rate variability (HRV)	Samsung Galaxy Watch	± 4 ms (at rest)
Wrist temperature (tw)	iButton	± 0.5 °C
Forehead temperature (tf)	Flir ThermaCAM S40	± 2 °C

Table 2
Personal information of the participants recruited for the experiment.

ID	Age (yrs)	Gender	I_{cl}	Height (m)	Weight (kg)	BMI (kg/m^2)
1	24	F	0.41	1.61	54	20.8
2	32	M	0.42	1.85	84	24.5
3	28	F	0.31	1.75	63	20.6
4	28	M	0.42	1.8	73	22.5
5	27	M	0.44	1.9	90	24.9
6	31	M	0.44	1.87	74	21.2
7	34	F	0.25	1.79	67	20.9
8	31	F	0.4	1.68	55	19.5
9	22	F	0.41	1.7	75	26.0
10	21	F	0.26	1.63	51	19.2
11	31	M	0.33	1.94	98	26.0
12	24	F	0.35	1.67	53	19.0
13	30	M	0.44	1.73	64	21.4
14	23	F	0.35	1.66	60	21.8
15	25	F	0.28	1.78	64	20.2
μ	27		0.4	2	67	22
σ	4		0.1	0.1	13	2

Table 3
The options that have been inserted in G*Power.

G*Power Options	
Type of power analysis	Post Hoc
Test	T-test
Effect size	0.66
probability of ***α error*** occurrence	0.05
Total Sample size	15

literature findings [31]. G*Power tool has demonstrated that by choosing a sample size of 15 subjects, the current work could reach a power of 0.88 which represent the 88 % of probability of obtaining statistically significant results. For the whole duration of the test, a user from the operating personnel was inside the test-room to certify the correct functioning of all sensors and the indoor parameters of the test-room, which were maintained at the desired set-point using a portable heater and air-conditioning system.

The participant must enter the test-room, as the experiment begins. At this stage, the set-point of temperature is 25 °C, which reflects to the condition of thermal neutrality during summer, as reported in actual standards [32]. This aspect reflects the pivotal role that seasonal effect has on human thermal sensation [33]. The experimental protocol considers precise temperature configurations in alignment with established regulations, as well as the potential impact of outdoor temperatures on human thermal perception [34].

To defend the subjectivity of the experiment, they were not required to follow a specific dress code. Subsequently, participant is required should complete a questionnaire to communicate its personal information (Table 2); moreover to evaluate the individual clothing insulation (I_cl), ISO 9920 was employed. In addition, the participant positions himself on the workstation and starts wearing the wearable device and the sensor for measuring skin wrist temperature. During the entirety of the experiment, each participant was required to complete a questionnaire to record their Thermal Sensation Vote (TSV). This vote is expressed using the ASHRAE 7-point scale, which assesses perceived thermal sensation on a discrete scale from −3 (cold) to + 3 (hot) with incremental steps of one. Additional descriptors include −2 (cool), −1 (slightly cool), +1 (slightly warm), +2 (warm), and 0 (neutral) for thermal neutrality [35]; in this way, thermal discomfort is therefore identified whenever the participant provides a TSV different from zero.

Before entering in test room, one operator explained to the recruited participant the aim of the experiment, i.e., to personalize thermal comfort measurement using physiological quantities, so that each participant provided written informed consent and thus filled up a general survey on personal information including age, gender, height, and weight. To ensure the correct execution of the test, these steps are monitored by the external personnel whose aim is to check that data are correctly acquired and to note participant's movement that could invalidate the data.

The experiment was conceived to let the participant perform low-intensity and daily office activities that comprises reading papers or activities on the laptop. Another requirement of the experiment is that participants is not subjected to any constraints in the hand movement constraints to reduce as much as possible the stressful conditions that can arise from the test. This aspect serves to ensure that the only perturbation applied to the physiological parameters is due to the change in room temperature. When all these actions are completed, the experiment can start, according to the following procedure (Fig. 4):

- 5 min where the room temperature is maintained at 25 °C (**Comfort session**), [19].
- 30 min where the test-room is cooled down from 25 °C to 22 °C (**Discomfort session 1**).
- 30 min in which the test-room is heated up from 22 °C to 28 °C (**Discomfort session 2**).

Specifically the variation of temperature chosen in this research ranges from 25 °C to 22 °C and from 22 °C to 28 °C and refers to previous literature works (e.g., from 15 °C to 26 °C in 60 min, from 20 °C to 30 °C in 30 min [19,36].To achieve the desired temperatures, an electrical heater (220 V PTC resistance, net power of 1870 W) was used to heat and a local air conditioner (Olimpia Splendid, 220–240 V, 865 W) to lower the room temperature to the desired setpoints, both of them by convection. The location of the two systems is reported in the planimetry in Fig. 1. Participants are not aware of the procedure of cooling and heating to prevent the TSV from being biased. During the experiment, the participant is required to communicate its Thermal Sensation Vote (TSV) by completing the TSV questionnaire according to the ASHRAE guidelines. The participant is asked to report the TSV each time its thermal sensation differs from the previous one, hence there is no fixed sampling frequency for TSV collection. This procedure minimizes the influence of stress related to the participant's inclusion in the experiment, which could otherwise result in interfering input in the measurement of Heart Rate Variability (HRV), known in the literature to be influenced by external factors such as stress [37]. Subsequently, the measured TSV is resampled at a frequency of 1 sample per minute, resulting in a total of 60 data points for each participant. Fig. 5 presents the profile the air temperature and relative humidity recorded during the test. Air temperature was varying according to the nature of the experiment, while relative humidity experienced small fluctuations during the experiment.

2.2. Data processing

The proposed measurement system is used to acquire a dataset made of physiological parameters (skin temperature and heart rate variability), personal parameter which is the TSV of the participants recorded during the experiment, and the environmental quantities. Therefore, in the following sections, it is described the procedure for analysing and filtering the data, which will be used for the thermal comfort assessment.

2.2.1. Measurement of skin temperature

2.2.1.1. Skin temperature measured through thermal camera. Every frame acquired from the thermal camera are analyzed to retrieve the forehead temperature of the participants. Forehead temperature was extracted for each participant from the videos recorded with the thermal camera during the experimental procedure. Specifically, these videos have been split into frames with a frequency of one frame every 30 s. After that, t_f has been computed by selecting the regions of interest (ROIs) in the thermal image, at the participants' forehead level. This operation was performed automatically, for every recorded frame, through a dedicated algorithm named Template Matching Method, selected from literature [38]. In the current work, it has been used to automatically detect human faces in all the thermal images by applying the following steps:

1) The raw infrared image is firstly segmented by using Otsu's method [38]. It is an image thresholding technique used to transform images into binary ones based on pixel [39]. This type of segmentation method is based on the principle of maximum between-class variance, and it has become one of the most used techniques given its solid performance and adaptability [40]. The core idea is extracting a histogram for each image and separating it into two clusters accordingly to a threshold [41]. This last one is denoted by $\sigma_w^2(t)$, i.e., the result of the minimization of the weighted variance between the just mentioned clusters. This operation is exploited in the current work to obtain a binary image that detects faces in the recorded infrared frames, by separating participants' faces from the image background [Fig. 6d].
2) The segmented and binary image is then filtered by using morphological operators' such as dilation, erosion, opening and closing (Fig. 6c) [38]. These operators are mainly used in binary image processing to remove noise, detect contours, adjust irregular shapes and obtain a filtered image [42].
3) The Normalized Cross-Correlation is then applied to the filtered image: this is a matching procedure used between the resulting filtered image and a chosen template. The template (Fig. 6b) was previously created by selecting one frame of the recorded videos, in which the participant was clearly displayed and then it was modified by applying step 1 and step 2 [43]. The template (shown in Fig. 6b) is therefore an image which is used as matching items for all the frames of the experiment [44].

The outcome of the matching procedure between the template and the processed frames is the ensemble of the coordinates of a rectangle centered on the participant's face, recognized by the algorithm (Fig. 6d). To obtain t_f, the rectangle is manually adjusted to get a ROI that enclose the participant's forehead in the image. t_f is then computed as average of all the temperatures included in the selected ROI, for each frame. To remove noisy fluctuations in the trend of the t_f collected during the experiment, Hampel filter was employed to remove the most prominent outliers (window size = 30, polynomial order = 3). Then, the signal was further smothered using the Savitzky-Golay filter (window size = 30, polynomial order = 3); this filter was chosen according to literature, since it can maintain the required profiles and information from the original without causing any time gap, despite the severity of the filter [45]. Finally, t_f is included into the dataset. An example of the processed data can be seen in Fig. 6 (a-d).

2.2.1.2. Skin temperature measured through wearable sensor. Wrist temperature using the iButton was collected with a sampling frequency of 1 Hz. To remove outliers and abnormal peaks caused by movement artefacts, the raw skin temperature signal was subjected to a filtering procedure, using the Savitzky-Golay filter (window size = 30, polynomial order = 3)[6]. Fig. 7 shows the result of this process, comparing wrist temperature and forehead temperature measured through the thermal

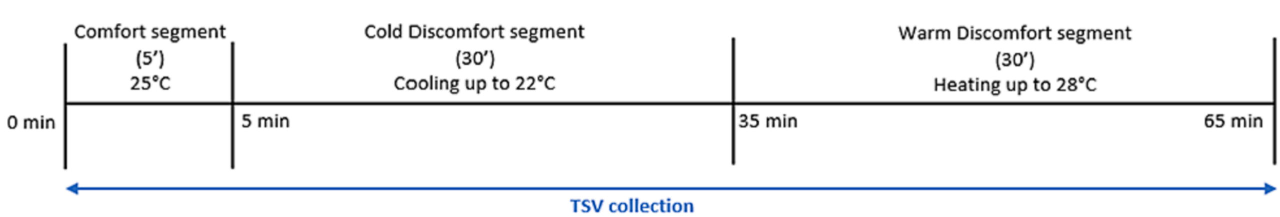


Fig. 4. Graphical representation of the experimental procedure applied during the experiment to expose the participant to discomfort conditions.

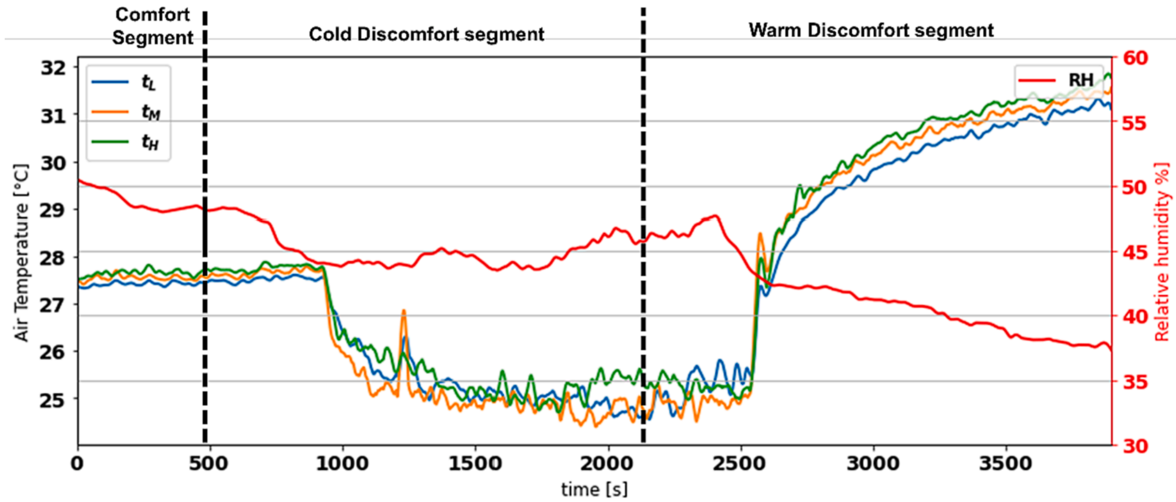


Fig. 5. Raw air temperatures and relative humidity measured from the thermocouples and the hygrometer from the microclimatic station during one of the experiments.

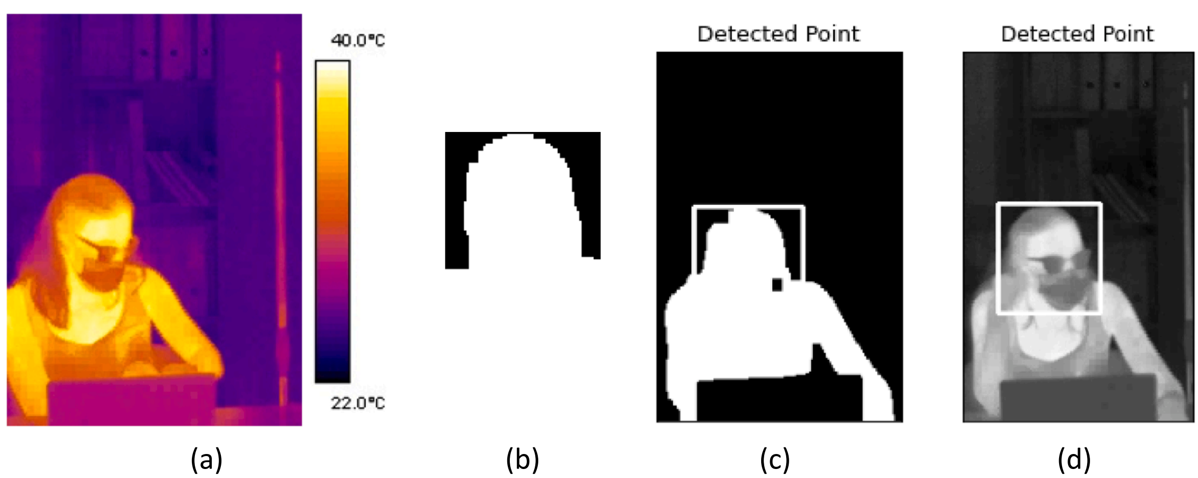


Fig. 6. (a) An example of frame recorded with the thermal camera during the experimental campaign; (b) template image used for the matching procedure; (c) the output image after the filtering step; (d) face detection output performed with the template matching.

camera, and shows the related trend of TSV. After the data processing, the TSV and the skin temperature have the same trend, which is in line with literature findings that reports a positive correlation between the skin temperature and the TSV [46].

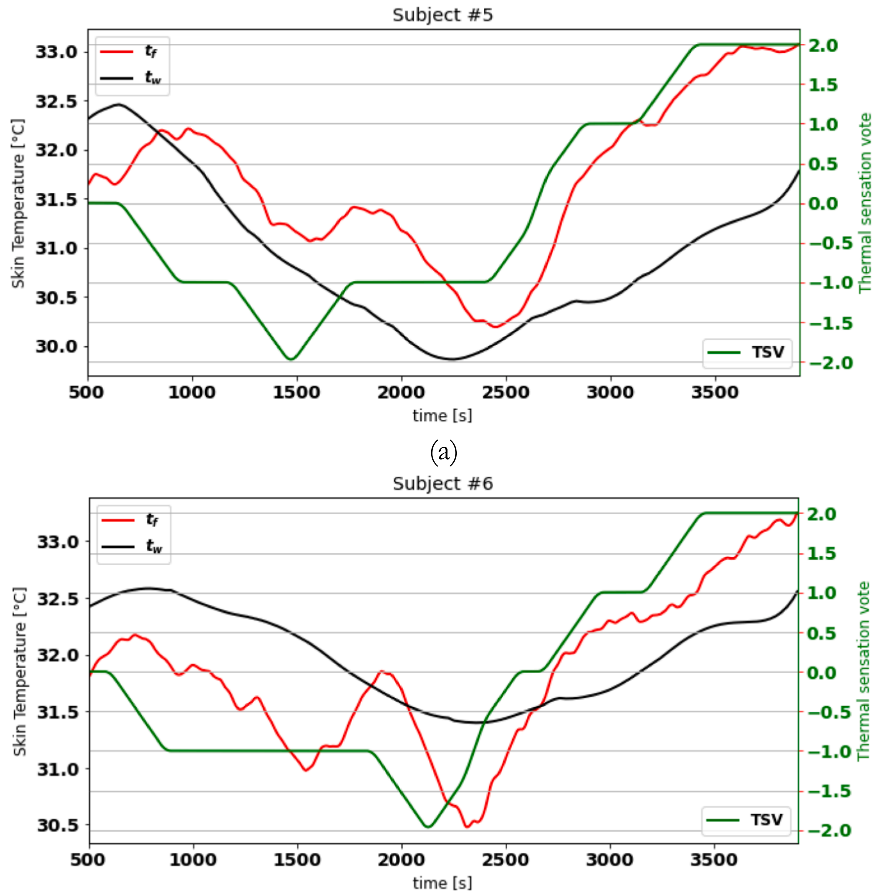
2.2.2. Heart Rate Variability features extraction

HRV signal was used to compute HRV features, from the timeline of RR intervals. The sequence of RR intervals was filtered in order to detect and remove outliers [19,36]. A thresholding method was employed to identify outliers by comparing each HRV sample with the preceding one; in this way, an outlier was defined as a value deviating by more than 50 % from the average value of a one-minute time window. Identified outliers were substituted with the preceding unaltered interval. Subsequently, the HRV signal, post-outlier detection, was segmented into time frames. The initial time frame spanned 5 min, adhering to the recommended minimum duration for short-term HRV series required for spectral analysis [36]. Following the extraction of the first window, a new window was generated by appending a fresh HRV sample interval to the signal, while the oldest sample was removed from the window's beginning. This process iterated until the conclusion of the signal.

The next step consists in the creation of the dataset to be used to measure TSV: all the extracted parameters that can possibly be included in the dataset are environmental and physiological data (Table 4).

2.3. Features selection

The feature selection process aims to detect a potential correlation between collected features and the label of the ML algorithms, which is the TSV. Additionally, it seeks to partition the initial dataset for optimal training of machine learning (ML) algorithms, ensuring superior performance in Thermal Sensation Vote (TSV) prediction. The authors employed a methodology drawn from the literature, integrating Correlation-Based Feature Selection (CFS). CFS identifies a small subset of features characterized by individual high correlation with the class (TSV), yet low inter-correlation. The relevance of feature subsets increases with correlation to the class and decreases with growing inter-correlation. To this aim, Pearson's correlation coefficient (R) e Spearman's rank correlation (S) were exploited to evaluate relationship between the TSV and the feature of the dataset [47]. In this way features that are less correlated with the TSV are excluded from the dataset. If these variables are correlated with each other, then we need to keep only one of them and drop the rest. This process excludes features less correlated with TSV, and in case of inter-correlation, retains only one variable, discarding others. This technique is complemented by feature importance computation using the Extra Tree Regressor (ETR) [19]. The methodology relies on the fact that features that have a high linear correlation with the TSV and that have greater importance as predictors



(a)

(b)

Fig. 7. Trend of t_w measured using the iButton and the forehead temperature measured with the thermal camera, against the TSV collected during the experiment, for two participants.

Table 4
Parameters computed for each participant.

Physiological Parameters		Environmental parameters	Personal parameters
Skin temperature	t_w, t_f	t_a [°C], RH [%], t_r [°C], t_L, t_M, t_H	TSV
HRV (Time-domain features)	MEAN, MEDIAN, RMSSD, SDNN, PNN50, NN50, PNN20, NN20		
HRV (Frequency-domain features)	VLF, LF, HF, LF/HF, HF/LF, TP		
HRV (Non linear-domain features)	SD1, SD2, SD1*SD2		

are included in the dataset, while all the others are excluded. Feature importance is obtained by means of the ETR, which relies on the Gini Importance computed for each feature of the dataset. The dataset used for performing the feature selection is made of data obtained from all the participants. Finally, to check on multicollinearity on the chosen dataset, authors decided to eliminate the predictors from the dataset that exhibits collinearity, exploiting the correlation matrix, using Pearson coefficient [48].

2.4. Model training and validation

Once the proper set of features is identified, AI regression models are employed to estimate participants' TSV. The features selected are used to predict the TSV of the participants, which is the ground truth of the algorithms. Algorithms were trained and then tested through the application of the Leave-One-Subject-Out (LOSO) approach, already proposed in literature to create generalized models [36]; the LOSO approach consists of training the algorithm with data collected from all the participants but one, which is then used for the testing phase. This process iteratively repeated for the data from each participant. The overall dataset is made of a total of 62,356 datapoints. The metrics for evaluation regression algorithms' performance are the mean absolute error (MAE) and the mean absolute percentage error (MAPE), Equation (1) and Equation (2), respectively [49]. The algorithms were chosen from literature and included ML algorithms such as K-Nearest Neighbors (KNN), Adaboost (ADA), Random Forest (RF), Extra Tree Regressor (ET), Decision Tree (DT), Support Vector Machine (SVM); DL algorithms included Multi-layer Perceptron (MLP). The related hyperparameters are reported in Table 5 and the evaluation of the metrics was computed both for the training and validation dataset.

$$MAE = \frac{1}{N}\sum\nolimits_{n=1}^{N} |x_i - y_i| \tag{1}$$

$$MAPE = \frac{1}{N}\left(\frac{\sum\nolimits_{n=1}^{N} |x_i - y_i|}{x_i}\right. \tag{2}$$

Where x_i is the TSV recorded by the participant during the experiment, y_i is the TSV measured by algorithms and N is the number of TSV samples for each participant.

Table 5
Hyperparameters of the ML algorithms developed in the current work.

Algorithm	Hyperparameters
KNN	· N_neighbors: 1,3,5 · Metric: euclidian, manhattan · Weights: uniform, distance
RF	· n_estimators: 100 · random_state: None (default)
ET	· n_estimators: 100 · random_state: 0
ADA	· Base Estimator (base_estimator) · n_estimators: 100 · Regressor: DecisionTreeRegressor(max_depth = 3) · random_state: None (default)
MLP	· hidden_layer_sizes: 6 · activation: identity · solver: adam · alpha: 0.1 · random_state: 1
DT	· criterion: absolute_error · max_depth: 3 · min_samples_leaf: 5 · random_state: 42
SVM	· Kernel: RBF · Gamma: [1e-3, 1e-4] · C: 1, 10

3. Results

This chapter presents the results obtained: firstly, features selection were conducted to train the algorithms, according to the Correlation-Based Feature Selection and the predictor importance among each feature and the label (TSV).

3.1. Feature selection results

Fig. 8 shows all the Pearson's correlation coefficient and Spearman's rank correlation computed between the label of the ML algorithms, which is the TSV recorded by the participant during the experiment, and each feature of the dataset. As expected also from the state of the art, environmental parameters (t_L, t_M, t_H, t_r, t_a) have a medium-to-high Pearson coefficient, indicating a correlation with the TSV; nonetheless, most of the HRV features exhibit low correlation with the TSV, except with LF/HF which exhibits medium correlation with TSV. The experiment is built to expose the participant to transient conditions of the indoor temperature, and therefore, relationships with physiological features cannot be easily retrieved. Skin temperatures (both t_w and t_f) also have medium correlation with the TSV. Moreover, according to Fig. 8, Spearman's rank correlation between the features and the TSV, there are low and medium coefficients, that suggests that non-linear correlation are slightly present between the initial dataset and the TSV. As a result, features such as t_L, t_M, t_H, t_r, t_a can be included in the dataset.

Regarding feature selection using the predictor importance, results are showed in Fig. 9 (a-b). The higher the Gini index, the higher importance of the contribution of the feature in the estimation of the TSV; environmental quantities that presents highest Gini index are t_L, t_M, t_H, t_r, t_a (Fig. 9a), while physiological parameters that have more importance are t_w, t_f, MEDIAN and MEAN. The limit of Gini index were set of 0.03.

The combined evaluation of the results displayed in Fig. 8 and Fig. 9, is used to select features that will be included in the final dataset, which are t_w, t_f, MEDIAN, LF/HF, MEAN and t_M. To check multicollinearity, correlation matrix (Table 6) was computed, and the results indicated that MEAN and MEDIAN are characterized by a high correlation (R = 99.8 %), therefore the variable MEDIAN is kept out of the dataset.

The identified features were then used to build three different groups of datasets, which differentiate based on the measured skin temperature, in order assess whether skin temperature can improve TC measurement, and also to compare different methodologies to measure skin temperature. The first dataset (D_1) consists of environmental parameters, HRV features and forehead temperature. The second dataset (D_2) is made up environmental parameter, the selected HRV features and wrist temperature; the third dataset (D_3) is made of wrist temperature, forehead temperature, environmental quantity and HRV features. These 4 datasets will be then used to predict the label, which is the TSV. The characteristics of which each dataset is composed are shown in Table 7.

3.2. Machine learning results

In Table 8, there are the results of the algorithms, in terms of MAE and MAPE, applied to the training dataset. It is possible to appreciate that the algorithm that provides better results, that do not involve overfitting, are the ETC, MLP and DT. Table 9 shows the performance of each algorithm in the measurement of the TSV for each participant, computed by applying the LOSO validation method. The table shows that, considering all the dataset and algorithms, the one that has higher performance is the DT, which provides an average MAE of 0.90 and an

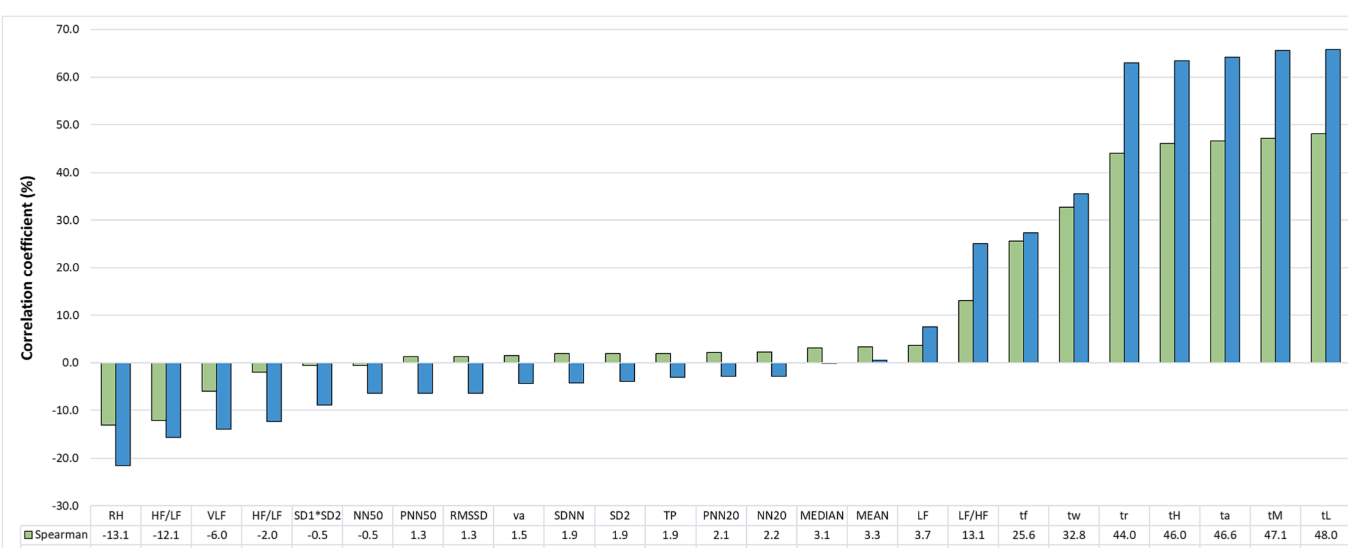


Fig. 8. Pearson and Spearman coefficients between the TSV and every parameter of the dataset, among all subjects.

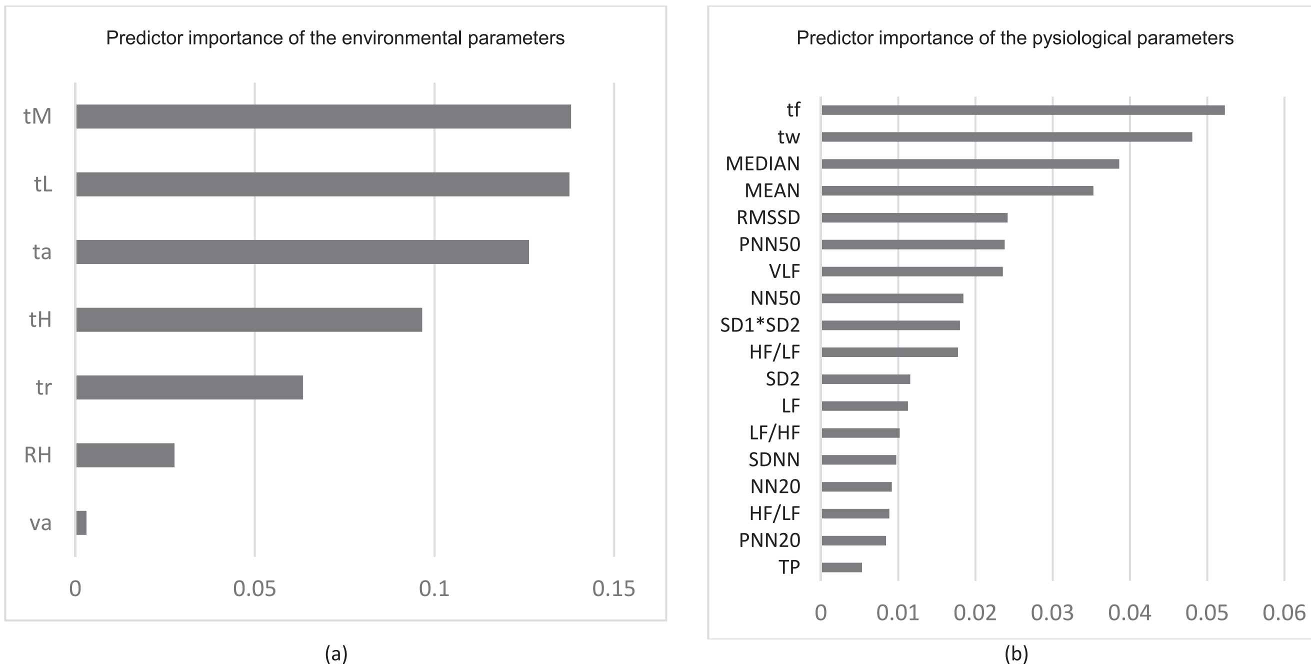


Fig. 9. Importance of the features among environmental parameters (a) and physiological parameters (b).

Table 6
Correlation matrix, performed by computing Pearson coefficient, between the chosen feature of the dataset.

	t_w	t_f	t_M	MEAN	MEDIAN	LF/HF
t_w	100					
t_f	41.9	100				
t_M	59.3	52.6	100			
MEAN	6.0	−4.7	6.3	100		
MEDIAN	6.1	−4.4	6.5	**99.8**	100	
LF/HF	20.5	−4.4	13.0	14.3	13.9	100

Table 7
Final dataset selection and composition.

Dataset name	Description	Selected features				Label
D_1	Forehead temperature, HRV, Environmental	t_f	t_M	MEAN	LF/HF	TSV
D_2	Wrist temperature, Environmental, HRV	t_w	t_M	MEAN	LF/HF	
D_3	Forehead temperature, Wrist temperature, Environmental, HRV	t_f, t_w	t_M	MEAN	LF/HF	

average MAPE of 23.3 %, among the different tested dataset.

When comparing performances among different dataset, which are characterized by a different set of physiological features but same environmental parameters, the one that exhibits best performance is D_1 which is made up by ST measured through the minimally invasive sensor, the air temperature measured at 0.6 m (t_M) and HRV features (MAE: 1.03 and MAPE: 28.5 %). Generally, considering the comparison among the different datasets and algorithms, it is possible to have a best measure using the DT applied to D_2 (MAE of 0.86 and MAPE 20.9 %), which slightly outperforms previous literature studies [19,36]. The comparison chart of the collected TSV against the measured TSV of the algorithm for the dataset D_2 is displayed in Fig. 10.

Table 8
Performance metrics of each algorithm on the training dataset, expressed through MAE and MAPE.

	Training dataset - MAE (TSV unit)						
	KNN	RF	ET	ADA	MLP	DT	Average
D_1	4.60E-03	2.53E-03	0.34	9.30E-13	0.68	0.76	0.30
D_2	5.59E-03	2.11E-03	0.36	9.81E-14	0.70	0.76	0.30
D_3	2.75E-03	1.19E-03	0.22	3.72E-13	0.61	0.74	0.26
Average	4.31E-03	1.94E-03	0.31	4.67E-13	0.66	0.75	
Training dataset -MAPE (%)							
	KNN	RF	ET	ADA	MLP	DT	Average
D_1	0.11	0.07	9.19	2.21E-11	17.38	18.87	7.61
D_2	0.14	0.06	9.40	4.89E-12	17.52	18.73	7.64
D_3	0.07	0.03	5.99	1.86E-11	15.74	18.68	6.75
Average	0.11	0.05	8.20	1.52E-11	16.88	18.76	

Table 9
Performance metrics of each algorithm on the validation dataset, expressed through MAE and MAPE.

	Validation dataset - MAE (TSV unit)						
	KNN	RF	ET	ADA	MLP	DT	Average
D_1	1.07	1.08	1.21	0.97	0.96	0.91	1.03
D_2	1.22	1.17	1.41	1.01	0.96	0.86	1.10
D_3	1.21	1.21	1.55	0.98	0.99	0.94	1.15
Average	1.17	1.15	1.39	0.98	0.97	0.90	
	Validation dataset -MAPE (%)						
	KNN	RF	ET	ADA	MLP	DT	Average
D_1	29.3	28.2	43.1	23.9	24.0	22.3	28.5
D_2	33.9	32.0	114.5	25.6	22.8	20.9	41.6
D_3	36.3	31.9	60.1	24.1	24.6	23.6	33.4
Average	33.2	30.7	72.6	24.5	23.8	22.3	

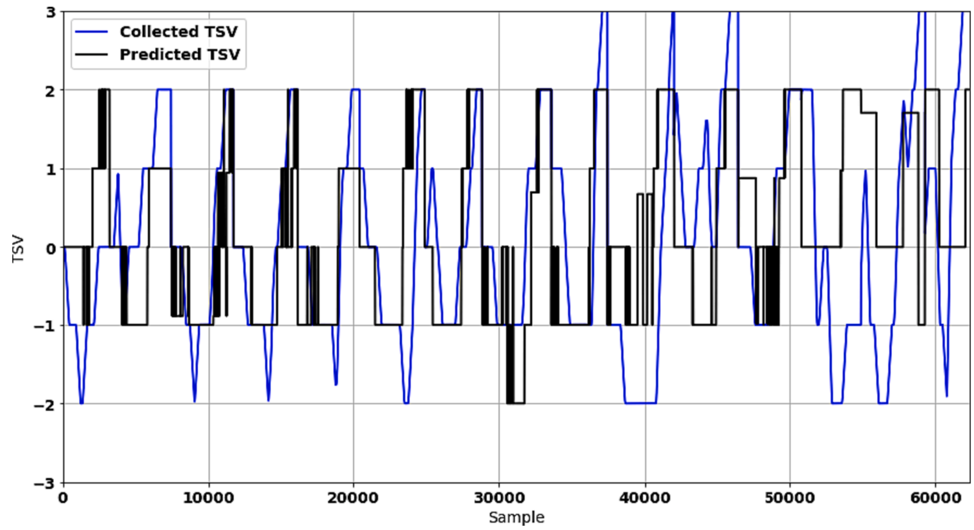


Fig. 10. Example of the collected TSV from the participants during the experiment against the predicted TSV, obtained from the DT algorithm, applied to the dataset D2.

4. Discussion

The goal of this work is based on the necessity of measuring human TC through an innovative approach that comprises the measurement of physiological parameters (skin temperature, HRV) and environmental parameters, in the office settings, in order to find strategies and real-time sensor network that can help improving thermal stress in buildings. The experiment applies a transient change of the environmental condition of the indoor environment, trying to overcome the current status of literature that present thermal comfort experiments in laboratory environments, that are not always reproducible in a real-life context. The proposed measurement setup is composed of two sensors for measuring skin temperature (a minimally invasive sensor and a thermal camera), with the aim of introducing the skin temperature in the measurement of TC; these two devices are adaptable to different occupants (in terms of age, state of health, physical condition) but also to different types of environments, in addition to the office environment. Similarly, the wearable for measuring HRV can be used in different daily contexts. This aspect makes the measurement set-up adaptable for other studies for the measurement of TC, but also of other physiological quantities related to human well-being. Furthermore, this advantage detaches the current work from the state of the art where the proposed experimental procedures are not compliant with real-life contexts [17]. Skin temperature (measured on the wrist and the forehead) acquired with the two sensors has a medium Pearson coefficient with the TSV, which is the index used to express thermal comfort and the label of the ML algorithms. Therefore, this research contributed to analyzing the physiological response to thermal stimuli, under uncontrolled conditions, of both skin temperature and HRV features. This aspect separates the current paper from the scientific production that can be found in literature since it is known that thermal comfort can be quantified with the collection of physiological signals such as skin temperature and HRV. However, none of the literature findings has provided a comfort measurement process based on ML and on datasets that included both of these physiological features in office context [17,18,20].

Moreover, the features extracted from HRV (MEAN, MEDIAN and LF/HF) proved to be good predictors for TSV, despite their medium–low linear correlation with TSV. This justifies the type of approach that implies the usage of ML, for quantifying TC starting from a heterogeneous dataset, where the relationships between the input and output variables are not always easily deducible. In fact, by computing the Pearson coefficient it is possible to deduce the type of relationship between the input data, and it is a methodology that suits if input parameters are continuous variables; on the other hand, predictor importance method is widely employed in regression problems, which is a quite tangled task, especially when features that build up the dataset are not linearly correlated.

The proposed methodology aims at developing personalized TC model, using the LOSO validation as a training methodology: although the algorithms demonstrate a MAE of 0.8 and a MAPE of 21.3 % (for MLP), the LOSO approach excludes the possibility of overfitting of the algorithms, which could eventually occur in the case of models trained and tested on data collected from the same participant. These findings align with numerous instances in literature where MAE and MAPE have been utilized as validation metrics [50]. For instance, in reference [36], the authors devised multiple ML algorithms that achieved MAE and MAPE values of 1.2 and 20 %, respectively. In another study [51], a regression problem was addressed, resulting in a MAE of 0.71. These instances from the literature emphasize the efficacy of the methodology and techniques employed in the present study. The study also pointed out that, under uncontrolled conditions, skin temperature measured from both the forehead and the wrist has a medium correlation with thermal sensation; furthermore, another indicator suggesting a strong link between skin temperature and TC is expressed through the calculation of predictor importance, which has the aim of finding which features in the dataset contribute best to the prediction of the label. This aspect also is reflected in the results of the ML algorithms trained on different datasets: D2 is the one that provides the greatest performance; in this case, the dataset is made up of the environmental parameters and the wrist temperature [33].

5. Conclusions

The presented research was developed to measure occupants' TC in the office environment, including skin temperature and HRV in the process, considering that literature reported the association of these parameters with the perceived TC. Recruited participants were subjected to a transient environment, by varying the air temperature of the test room in summer, as they were allowed to perform office activities, with the possibility of moving the arm where sensors were located. The data collected during the experiment are used to measure the TSV, using ML regression algorithms: the algorithm that has better performance is the DT, which provides an average MAE of 0.86 and an average MAPE of 20.9 %. These results outperform the state-of-the-art findings as mentioned in the previous section [36,50,51]. As regards the comparison among different datasets, characterized by a different set of physiological features, the dataset that provides best performance is made of a combination of ST measured through a non-obtrusive sensor and air temperature. This measurement procedure demonstrates that the TSV of occupants can be measured in a real-life condition, using a sensor network that measures both physiological and environmental parameters. The current scientific investigation has set the stage for future advancements that could offer a personalized and reliable methodology for quantifying thermal comfort.

CRediT authorship contribution statement

Nicole Morresi: Conceptualization, Methodology, Software, Data curation, Writing – review & editing. **Vittoria Cipollone:** Conceptualization, Methodology, Software, Data curation, Writing – review & editing. **Sara Casaccia:** Conceptualization, Methodology, Visualization, Investigation, Supervision, Validation, Writing – review & editing. **Gian Marco Revel:** Conceptualization, Methodology, Visualization, Investigation, Supervision, Validation, Writing – review & editing.

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

The data that has been used is confidential.

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