Assessing occupants’ personal attributes in relation to human perception of environmental comfort: measurement procedure and data analysis

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Abstract

The assessment of occupants' behavior impact on building energy performance is becoming a key topic in recent years due to increasing performance of the building stock still threaten by occupants' variable. The paper aims to deeply investigate human perception in indoors which drives occupants' behavior. A novel measurement procedure is developed aiming at producing a multipurpose comfort perception scheme, i.e. considering thermal, visual, acoustic, and air quality comfort spheres. Data belonging to different domains of human perception are simultaneously measured: physical environmental parameters, physiological signals, and psychological response of the subject. A first series of measurement tests is here presented specifically focused on human response to thermal stimuli, i.e. subject exposed to increasing/decreasing temperature. Obtained data and signals are thus analyzed coupling (i) physiological and psychological response through machine learning techniques, and (ii) personal attributes to actual sensation votes and environmental data variations. Results show potentials of the proposed measurement procedure which allows a comprehensive collection of physical attributes and subjects' psychological characterization. In conclusion, this work demonstrates the strictly connection, with a prediction accuracy up to 84%, between physiological parameters (Heart Rate Variability and its indices) and human thermal comfort, opening the perspective of real-time measuring comfort for control purposes, taking into account human-centric parameters.

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1. Introduction

Reduction in building energy consumption is a key goal within the sustainable development framework since building sector globally consumes more than one-third of the total primary energy [1]. Great results have already been achieved by the scientific community during the last decades mainly focusing on the development of (i) passive strategies for the building envelope [2]–[4] and (ii) advanced technologies for the building energy system [5], [6]. Nevertheless, the optimization of resources and the energy efficiency enhancement of buildings facilities seems not to produce the expected results in terms of energy consumption reduction and wellbeing improvement of the building sector. In particular, many studies highlighted the existence of the so-called "performance gap" between designed and real energy use in buildings [7], [8] also due to boundaries wrong estimation in the specific built environment [9]. The magnitude of the outlined discrepancy could be significant with measured consumption reaching up to 2.5 times their predicted values [10]. Bridging this gap is therefore of primary importance to achieve the designed target in terms of building efficiency which can be better managed by implementing innovative technologies for the control of the indoor environment [11]–[13].

In this perspective, a better understanding of occupants' behavior has a key role since many studies identify in this term the main cause of the performance gap [10], [14]–[17]. Occupants are generally oversimplified in modeling and analysis due to its stochastic, complex and interdisciplinary nature [18]. To overcome this issue, researchers investigate how people interact with the building through its control system, its components, and appliance usage [19]–[23] and what are the main drivers of certain habits.

Among them, human comfort perception plays an important role as it is highlighted by Ortiz and al. [24] in their comprehensive review on comfort, health, and energy use. Particularly, the review provides building energy usage influencing factors from a psychological and behavioral perspective of the occupants in their environment. Moreover, occupants' actual comfort perception is strictly related to specifics of each individual and the assessment of these "drivers of diversity" is extremely important as highlighted by Schweiker et al. in [25] specifically focusing on thermal perception. Actual standards [26]–[29] already consider occupants' perception in indoors by defining limits and goals that must be achieved during the design phase of a building in terms of indoor environmental quality parameters, i.e. IEQ. These factors are all related to measurable physical characteristics of the indoor environment including visual, thermal, acoustic, and air quality parameters [30]. Physiological characteristics of the occupants are also taken into account, but these are generally oversimplified [31] while their correct evaluation require the implementation of novel measurement devices and methods [32], [33]. Furthermore, standards still do not consider other aspects of the human comfort whose holistic definition is given by Slater as a pleasant state of physiological, psychological and physical harmony between a human being and its environment [34]. Subjective and objective techniques [35] should be implemented to correctly determine the three domain of human perception, i.e. psychological, physiological and physical. Occupants' perception of the IEQ leans on a cognition process which leads to a physiological and behavioral response. Novel approaches in comfort investigation are therefore necessary to improve actual regulations. These approaches should aim to link (i) environmental stimuli to (ii) physiological signals alteration considering (iii) personal characteristics of the investigated subject [36], [37].

In this perspective, investigation by means of wearable devices for physiological variables monitoring of subjects shows an increasing trend in research. Electrocardiogram, electrodermal and electroencephalogram signals, i.e. ECG, EDA, and EEG respectively, are the main investigated physiological signals in relation to human comfort perception [38]. EDA signal allows to quantify changes in the sympathetic nervous system and it is mainly tested to assess Arousal level in patients. Therefore, it is useful to get information about emotional state of the subject [39], [40]. Choi and Yeom [41] investigate thermal perception of occupants in office environment by means of their physiological responses finding out a priority order in skin temperature data collection on thermal satisfaction information. Nevertheless, EDA standardized features still do not exist, and that leads researchers to look for algorithms' identification and software solutions [42]. Concerning ECG signals, literature shows that the Heart Rate Variability (HRV) parameter and the indices extracted from HRV could be used as a predictor of the comfort status of the subject [43]. The HRV is defined as the variation over time of the distance between two consecutive heartbeats (R-R intervals) and it is an important indicator for evaluating the correct functioning of the autonomic nervous system, i.e. ANS. ANS manages thermoregulation of the body in response to an external stimulus, i.e. environment temperature changes. HRV can be deeply investigated using the time-domain and frequency-domain analysis to obtain HRV indices. Time-domain indices allow to describe the beat-to-beat variability using a statistical approach while frequency-domain decompose HRV into its fundamental frequency components providing an overall insight in the fluctuations of heartbeat [44]. A review of the literature revealed that there is an increasing interest in discovering HRV measurements as indices of the thermal comfort of the occupant. Nkurikiyeyezu et al. [45] propose to adopt HRV indices extracted from the ECG signal to determine occupants' thermal comfort and therefore design real-time thermal comfort controllers.

Zhu et al [46] correlated features extracted from ECG signal recording to estimate thermal comfort.. Their analysis points out that the ratio between low (LF) and high frequency (HF) components of the HRV, i.e. LF/HF ratio, is strictly connected to changes in thermal sensation. Higher LF/HF ratio is expected in cold and hot environments, while lower LF/HF ratio ranges in more neutral conditions, giving to the LF/HF ratio-temperature waveform a trend with its minimum representing the thermal comfort. Kim et al. [47] get a personal comfort model with a tested mean accuracy of 75% training a Random Forest algorithm with physiological, i.e. skin temperature and HRV, and environmental parameters. Other studies associate EEG signal to IEQ perception and its relation to human performance [48], [49]. Tiago-Costa et al. [50] focus on specific spectral frequencies of the EEG, i.e. Alpha and Beta waves, and observe their amplitude variation varying external thermal stimuli. Local thermal discomfort and cerebral response is the focus of the work from Lv et al. [51]. In Shan et al. [52] the EEG analysis is adopted to enhance human-building interaction which is a really promising field in the main framework of smart buildings and IoT systems development [53].

On the other hand, the psychological dimension and how subjective characteristics influence occupants' perception and thus their interaction with building facilities needs to be further investigated in the framework of an interdisciplinary approach between engineering and social sciences [54]. Such investigation field is of particular interest since behavior changes are demonstrated to have significant potentials in reducing, for example, energy-related costs for social housing residents which are particularly vulnerable categories [55]. Cottafava et al. [56] demonstrate how behavioral changes induced through feedbacks directly provided to occupants could simultaneously provide energy reduction and comfort improvement. Socio-economical and personal attitude impact on occupants' behavior are commonly invested through surveys submission mainly focused on pro-environmental behavior awareness of the interviewed [57]–[59]. Moreover, a variety of studies already point out gender influence on IEQ perception in indoors [60]–[62], and even the adaptive thermal comfort theory, in general, takes into account thermal history of people to assess their actual thermal sensation [63]–[65].

Based on the outlined background, this work presents a novel measurement campaign and monitoring setup aiming to get an overview of IEQ occupants' perception and proposes a new holistic and multi-domain indoor comfort analysis protocol. To this aim, in section 2, authors get through the implemented methodology focusing on:

- The measurement procedure, where the sensors network is presented as composed by (i) an environmental monitoring system collecting physical parameters associated to visual, both global and local thermal comfort, and indoor air quality and (ii) wearable sensing devices for the contemporary acquisition of ECG, EDA, and EEG signals;

- The measurement test procedure, where all the timing of the performed tests and information about subjective response collection through survey submission are given;
- Data processing, including (i) preliminary elaboration of raw physiological signals and validation procedure through combined analysis of HRV features and environmental parameters of the acquired dataset with current literature; (ii) the adoption of machine learning classification algorithms to predict thermal sensation vote basing on computed HRV indices to explore the relationship between the physiological data and human perception [66]; (iii) the evaluation of physical stimuli affection on expressed sensation vote and psychological aspects affecting comfort perception.

Achieved results are thus presented in section 3 and main outcomes summarized in section 4 in which also future developments of the work are presented.

The described measurement campaign specifically focuses on thermal comfort which has been recognized as a main driver domain for the IEQ perception [67]. Moreover, comparable outcomes in terms of the adopted biometrics, i.e. HRV and in particular LF/HF ratio, are at disposal in literature to allow a first validation phase of the experimental setup proposed [45], [46]. As future development, the same approach will be adopted to deepen the investigation of others field of comfort, i.e. visual, acoustic and air quality, through the subjects' exposure to specific environmental stimuli.

2. Methodology

The implemented methodology aims to comprehensively assess comfort perception of occupants to produce a multidimensional occupancy-related comfort perception scheme. The measurement activity includes the simultaneous collection of (i) physical environmental parameters, (ii) human physiological metrics, and (iii) subjective responses of the occupants. The measurement set-up includes different monitoring tools whose outputs are therefore synchronized and analyzed. More details about the measurement test procedure, implied tools and data analysis are given in the following sections.

2.1. Measurement setup

All the tests take place in the same mechanically controlled environment. It is a house-like cubicle located within the Engineering campus of the Perugia University (Italy). The cubicle inner dimensions are 3 m x 3 m and the reduced volume allows to easily control the indoor environment by means of the installed air-conditioning system which is a heat pump with an inverter. The system provides also three different levels of ventilation, i.e. low, medium, and high-speed mode, while no air change is provided. The Southern wall has a rectangular window which is shaded during all the tests to let the lighting level within the space as constant as possible, only depending by the lighting system of the test-room [68].

The space is continuously monitored by means of a fixed microclimatic station located in the middle of the room recording data every minute. The monitored parameters are: air temperature at both 1.1 and 0.1 m [°C], relative humidity [%], superficial temperatures of floor, roof, North- and South-facing walls [°C], black globe temperature [°C], net-radiation between glazed and opaque surfaces [W/m^2], air velocity [m/s], concentration of CO_2 [ppm], and illuminance level [lux]. The accuracies of all involved sensors are reported in Table 1.

Table 1. Technical information of the sensors for monitoring environmental parameters.

Sensor	**Environmental parameter**	**Accuracy**
Thermal-hygrometer	Air Temperature [°C]	± 0.1°C
	Relative humidity [%]	± 1.5%
Surface and air temperature sensor	Floor temperature [°C]	± 0.15°C
	Roof temperature [°C]	± 0.15°C
	Walls temperature [°C]	± 0.15°C
Black globe radiant temperature sensor	Mean radiant Temperature [°C]	± 0.15°C
Hot wire anemometer	Air velocity [m/s]	± 0.5-1.5 m/s
CO_2 sensor	CO_2 concentration [ppm]	± 50 ppm (+2%)
Luxmeter	Illuminance [lx]	± 5%

These parameters are therefore adopted to assess (i) global and (ii) local thermal comfort, by computing vertical temperature gradient, radiant asymmetry of the environment, and draught rate, and (iii) indoor air quality, in terms of CO_2 concentration. Moreover, visual comfort is measured through illuminance data collection taking into account that the subject has no relevant visual tasks to solve. All the implied sensors are compliant with ISO 7726 [69].

The physiological parameters of the tested subject are measured by means of three wearable systems. The subject wears a multi-parametric belt, BioHarness 3.0. from Zephyr, with an attached electronic module at the thorax level for the ECG signal acquisition (sampling rate 250 Hz, Heart Rate accuracy ±1 bpm, operating range 25-240 bpm) [66], [70]. Measured data are stored within the device and downloaded at the end of the test. A wireless neural headset with 14 electrodes gives the EEG signal with a sampling rate of 128 Hz per channel (operating bandwidth 0.16-43 Hz) [71]. Finally, the EDA signal is measured through a BITalino acquisition board developed by the authors (sampling rate 100 Hz, operating range 0-1 MOhm) [72]. The subject wears two EDA electrodes on his/her left index and middle finger while the acquisition board and the sensors modules are fixed in the left arm. Open-Source software allows waveforms acquisition through Bluetooth communication protocol.

Finally, personal information of subjects are collected through survey submission. The submitted survey comprehends three parts. The first one aims to collect general personal information which are divided into objective and subjective as shown in Table 2. The outlined distinction points out personal characteristics which are (i) independent from personal attitude of the subject, i.e. objective, and (ii) general information which already express subject lifestyle, i.e. subjective.

Table 2. Personal information gathered in the first part of the survey divided into objective and subjective categories

Objective	**Subjective**
Gender	Body-Mass-Index*
Age	Education
Birthplace (origin)	Smoking habits
	Worn garments**

*expressed as body mass on the square of body height [kg/m^2]

**selected from a list of garments of known thermal insulation, expressed in [clo]

Figure 1. Measurement procedure setup: (a) microclimatic station, (b) neural headset EPOC+, (c) Bioharness, (d) BITalino, (e) on-going test.

The second section of the survey focuses on health state and psychological description of the subject. This is an adaptation of the Physiological General Well-Being Index questionnaire, i.e. PGWBI [73]. The last part concerns the environmental perception of the subject and it is fulfilled directly in the test-room during different parts of the test, as it is described in detail in the following section. In this part of the survey, questions are developed according to ISO 10551 [74] which is focused on the thermal perception assessment. The same typologies of questions, i.e. concerning perceived sensation, comfort level, preferences, acceptability, and tolerability, and the same rating scale are therefore applied to the whole comfort domain, i.e. thermal, visual, acoustic, and air quality. In particular, the sensation vote for each domain is given through a 7-points scale going from -3 to +3 where 0 corresponds to neutrality. Figure 1 shows the above described experimental set-up.

2.2. Measurement test procedure

The current work includes outcomes of two different series of measurement tests done in winter and summer seasons. The winter series comprehends 34 participants, while 28 are the participants considered in summer tests, for a total amount of 62 performed measurement tests. The involved subjects are all volunteers and the general personal information of the winter and summer samples are resumed by the graphs in Figure 2**Errore. L'origine riferimento non è stata trovata.**.

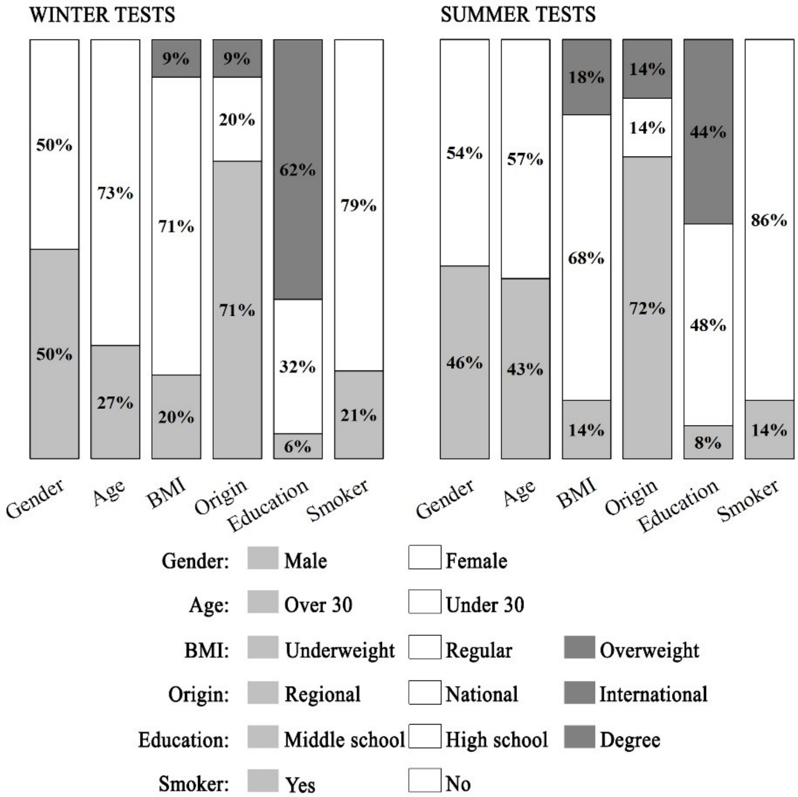

Figure 2. Personal information of the sample composition during winter and summer tests.

The two series have the same measurement setup, i.e. same test-room and same adopted monitoring systems, but slightly differ in terms of followed measurement procedure as express in Figure 3 which schematically shows the adopted procedure for both the seasons.

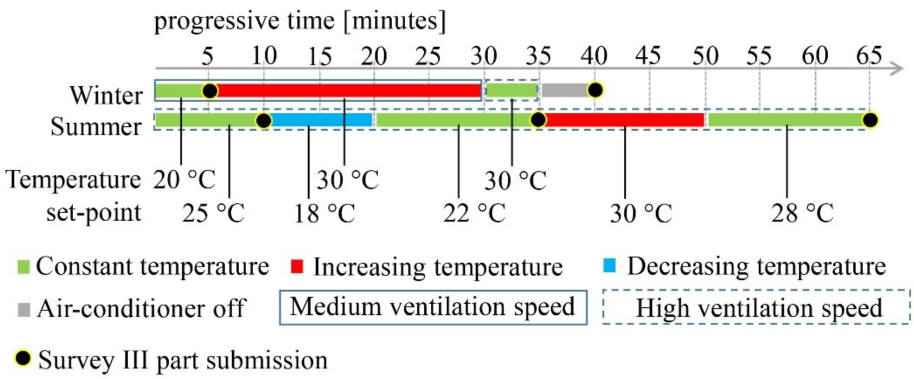

Figure 3. Timelines of the experimental test procedure in winter and summer.

During both the campaigns, the subject is firstly exposed to a stabilization period of 20 minutes outside the test-room, in the conditioned spaces of the closest building. The space is conditioned at the same temperature settled in the test-room for the first part of the test which corresponds to the neutral state according to standards [26], [29], i.e. 20 °C and 25 °C in winter and summer respectively. In particular, the initial values of air temperature are selected considering a normal level of expectations, i.e. environment belonging to II category, for subjects wearing typical clothes for the considered season, i.e. clothing insulation of 1.0 clo and 0.5 clo in winter and summer respectively. The initial temperature set point in summer is 1 °C lower than the value suggested by standards, i.e. 25 °C instead of 26 °C, to guarantee reasonable time for the test considering the double temperature ramp realized as specified later. Such initial temperature assumptions are necessaire since no specific constraints are given to the tested subjects considering the personal attitude of everyone in wearing comfortable suites according to weather and his/her own personal preferences. Nevertheless, clothing information are collected in the first part of the survey, as specified in the above section, in order to check the validity of such assumptions during the data analysis process.

During the stabilization period, the subject fulfills the first two sections of the survey and wears the chest strip for the ECG recording. Once in the test-room, the subject seats in between of the microclimatic station and the window and the monitoring set-up is completed connecting the headset and the electrode for the EEG and EDA signals record respectively. These actions are made by an operator that will stay with the subject in the test-room for the whole test. When the set-up is completed the test starts.

During the winter, the measurement test last 40 minutes in total, progressively: 5 minutes of acclimatization at 20 °C, 30 minutes of warming up with an air-conditioning set-point at 30 °C, 5 minutes at the same temperature, but increasing the ventilation speed, i.e. from medium to high speed, and 5 minutes with the conditioning system switched off. The operator asks the subject to answer the third part of the survey at the end of the first period of acclimatization, i.e. at 20 °C, and at the end of the whole test. During the summer, the test last 65 minutes in total, progressively: 10 minutes of acclimatization at 25 °C, 10 minutes of cooling down with an air-conditioning set-point at 18 °C, 15 minutes at constant temperature, i.e. 22 °C, 15 minutes of warming up with an air-conditioning set-point at 30 °C, 15 minutes at constant temperature, i.e. 28 °C. The ventilation speed is settled at the high mode for the whole test in summer. The operator asks the subject to answer at third part of the survey at the end of each period characterized by stable temperature, i.e. at 25 °C, 22 °C, and 28 °C. During the whole test and for both the seasons, the subject expresses any kind of changes in his/her environmental perception which are noted by the operator.

The authors want to specify that since the measurement test is not done in a climatic chamber a perfect control of the thermal environment is not guaranteed, but air temperature is continuously monitored by the operator in the test-room who checks the environmental data in real time. The continuous control allows to have the two above mentioned 15 minutes-periods of constant temperature during the summer test.

2.3. Analysis of measured data

Due to the variety of monitoring systems adopted in the current experimental work, a first process of measured data synchronization is needed to provide exact correspondence among all the data time-series at disposal for the analysis, i.e. environmental data, EDA, ECG, and EEG signals.

Physiological raw data are therefore processed to reduce signal noise, get a smooth waveform, and extract useful features to be correlated to the measured environmental data and subjective responses. These features are extracted every minute which corresponds to the environmental data sampling rate. In particular, this paper focuses the physiological investigation on ECG signal processing since it is commonly related to thermal comfort evaluation in literature. On this purpose, authors conducted a first analysis that examines the correlation of the trend of LF/HF extracted from the ECG with the trend of some environmental parameters (air temperature, CO_2 concentration, relative humidity, mean radiant temperature, PMV) and thus to check effectively the influence of environmental changes on physiological quantities i.e. LF/HF. After this analysis, that proofs how environmental parameters can affect the trend of LF/HF, ML classification is introducted excluding environmental parameters and using only physiological quantities. The reason of this approach is to determine with a certain degree of accuracy whether user experiences comfort or discomfort without taking into account environmental quantities thus allowing to add this parameter for a more precise subjective evaluation of comfort.

Processed signals are thus analyzed through supervised machine learning algorithms to predict occupants' thermal comfort as expressed by subjects during the performed tests. Finally, expressed sensations are correlated to measured environmental parameters and personal characteristics of the subjects in order to point out how IEQ perception is subjective and its dependency on personal aspects, i.e. subjective and objective information. All the above-mentioned data analysis steps are given in details in the following subsections.

2.4. **ECG signal processing and validation procedure**

The goodness of the proposed methodology is evaluated analyzing the ECG signal in relation with the thermal comfort expressed by the subject, i.e. HRV and LF/HF ratio. Before extracting HRV, the raw signal is processed according the procedure shown in Figure 4: initially a mean removal is performed, and the resulting signal is filtered with a bandpass filter [0.8-40 Hz]. The signal passes through a 3rd order high-pass Butterworth filter with cut-off frequency of 0.8 Hz and the a 3rd low-pass Butterworth filter with 40 Hz of cut-off frequency in cascade. The following step consists on dividing the ECG signal in 5 minutes consecutive windows for extracting the R-R intervals (also named normal-to-normal intervals) through the deployment of the Pan-Tompkins algorithm [75]. The algorithm is used to denoise the signal and detect QRS complexes in the ECG signal. A QRS complex indicates the presence of a beat and therefore its detection is useful to compute RR intervals. A bandpass filter is firstly applied to reduce noise, to eliminate movement artifacts, 60 Hz powerline interference and baseline wandering. Then a derivative filter is applied to obtain information about the slope of the QRS complex, followed by the squaring of the signal which highlights better QRS complexes. Finally, signal passes through a moving integrator.

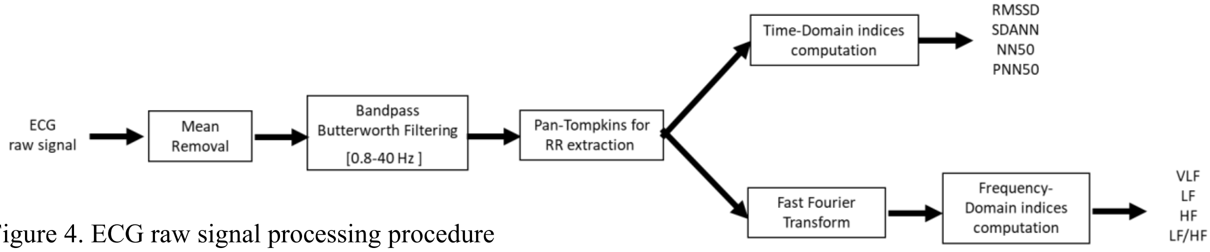

Figure 4. ECG raw signal processing procedure

After detecting RR intervals from Pan-Tompkins algorithm it is possible to compute HRV measurements. In particular, time-domain measurements include: RMSSD defined as the square root of the mean squared difference of successive R-R intervals; SDANN which is the standard deviation of the R-R intervals; NN50 that represents the number of interval differences of successive R-R intervals greater than 50 milliseconds; and pNN50 which is the ratio between NN50 and the total number of R-R intervals. Fast Fourier Transform (FFT) is implemented to obtain frequency-domain measurements by computing the power spectral density (PSD) of HRV. Three frequency-domain indices are extracted from PSD: the very low frequency (VLF) in the range [0.01 - 0.04] Hz, the low frequency (LF), and the high frequency (HF) in the range [0.04 - 0.15] Hz and [0.15 - 0.40] Hz, respectively. Finally, the computed ratio between LF and HF spectral density provides LF/HF [76].

Therefore, indices computed from data processing are compared to the ones existing literature mentioned in the Introduction section to evaluate the goodness of the experimental setup. In particular, the relationship between LF/HF and environmental quantities is explored: LF/HF is correlated with environmental quantities, i.e. air temperature (T_a), mean radiant temperature ($\overline{t_r}$), and CO_2 concentration (CO_2), acquired during the test by computing Pearson's correlation coefficient, i.e. R. The provided analysis computes R-T_a , R-$\overline{t_r}$, and R-CO_2 , for consecutive 5-minutes-long time windows. This kind of approach seems to be more suitable, respect to a correlation made throughout the entire test, because highlights every minute of the testif any change in the external environment have an impact on LF/HF ratio and though, the thermoregulatory system. The analysis is considered preliminary to the following section: the relationship between LF/HF and environmental parameters allow to shift the focus from environmental quantities measured in the room by paying attention to the occupant thermal perception and the physiological quantities acquired.

2.5. Analysis of environmental and physiological quantities

This section describes the procedure adopted to investigate how LF/HF is influenced by environmental parameters. After the synchronization of the signals, Pearson's linear correlation is applied between LF/HF and each environmental quantity, e.g. mean radiant temperature, air temperature, relative humidity, PMV, CO_2 concentration.

On this assumption, the correlation analysis conducted in this work first individuates windows of 5 minutes that slide of 1 minutes for the environmental and LF/HF signals. For each window, the Pearson's coefficient between the environmental parameters and LF/HF is computed. At this point, a vector of Pearson's coefficient is provided for each participant's test and for each environmental quantities. The second step considered the percentage of Pearson's coefficient that are greater and equal of 75 % to evaluate which are the most influenced environmental parameters on the LF/HF signals.

2.6. Supervised Machine Learning Analysis

To predict the thermal comfort of occupants from the knowledge of HRV and its indices, supervised machine learning (ML) algorithms are implemented. In this study, authors select six classification algorithms: Linear Discriminant Analysis (LDA), K-nearest neighbors (KNN), Decision Tree (DT), Naïve Bayes (NB), Support Vector Machine (SVM), and Random Forest (RF) classifiers. ML classifiers are applied to four datasets to point out what are the HRV indices that classify with higher accuracy human's thermal sensation vote. The first dataset consists on LF/HF; the second dataset comprises time-frequency indices, the third dataset is made up by frequency-domain indices while the last one includes the entire set of estimated HRV indices. The HRV indices are used to train the ML algorithms to foresee the thermal sensation surveys used as label in the analysis. The datasets are built using the surveys and the related HRV indices of subjects which have provided a realistic survey and excluding all the thermal perception assessment that never changed during the test.

The classification accuracy (A) of each algorithm is computed using a 5-fold cross-validation, in which the dataset is partitioned into 5 randomly chosen subsets (or folds) of equal size. One subset is used by the classifier to validate the trained model using the residual subsets. The procedure is replicated 5 times, so every subset is adopted only once for the validation. The accuracy of the model is the average accuracy of each fold.

2.7. Subjective attributes affecting IEQ perception

The analysis of the psychological affection on IEQ perception moves from a preliminary analysis of expressed sensation and corresponding measurement environmental data. In particular, thermal and air quality perception expressed by tested subjects in both the seasons, i.e. winter and summer tests, are analyzed with respect to measured air temperature and drought rate.

Thereafter, the analysis of the psychological affection on IEQ perception leans on the assessment of existing correlation between the characteristics of the participants, assumed as dependent variables, and the perceived sensations expressed through the third part of the survey, i.e. the independent variable. Strength of tested hypothesis is expressed by the probability value, i.e. p-value. Furthermore, the outlined hypothesis is tested considering both single personal characteristics and group of objective and subjective descriptors, i.e. not-depending or depending from the will of the subject (Table 2).

3. Results and Discussion

The current section deals with an analysis of the complex dataset measured during tests performed following the proposed innovative measurement procedure. Section 3.1 presents preliminary analyses on recorded ECG signals and extracted features which are correlated to monitored environmental parameters. The obtained results are thus compared to literature achievements in the field in a view of measuring procedure validation. Section 3.2 shows obtained results in predicting thermal comfort from ECG features through supervised machine learning algorithms, while section 3.3 summarizes achieved outcomes psychological investigation of the perceived comfort in relation to measured environmental data.

3.1. Preliminary analysis results

Results related to the analysis of the environmental and physiological quantities are here presented.. LF/HF ratio is correlated with air temperature (T), mean radiant temperature (MRT), CO2 concentration (CO2), relative humidity (RH) and PMV. Figure 5 shows an example of the output provided by the analysis for two subjects: Subject 1 which performs the test in winter and Subject 2 which performed the test in summer. Pearson coefficient is computed for time intervals of 5 minutes; therefore, every coefficient expresses the linear correlation between LF/HF and one environmental parameter taken in the same time interval.

Figure 5 shows the results of the analysis conducted for two participants. Participants 1 was tested in winter. In the upper panel there is the LF/HF computed from the ECG while the middle panel represents the trend of the air temperature for the whole duration of the test. The lower panel contains the data referred to the Pearson coefficient computed for every time interval and for every environmental parameter considered. The color of every pixel in the image is associated with the value of the Pearson coefficient computed between LF/HF and the respective time interval of the environmental parameter. Lighter region is associated with a low Pearson coefficient while darker region of the image results in a high correlation coefficient. Every row of the image represents in the lower panel represents the Pearson correlation coefficients between LF/HF and air temperature (R-T), mean radiant temperature (R-MRT), CO_2 concentration (R-CO_2), PMV (R-PMV) and relative humidity (R-RH). Participant 1 and participant 2 were chosen to show how a variation in

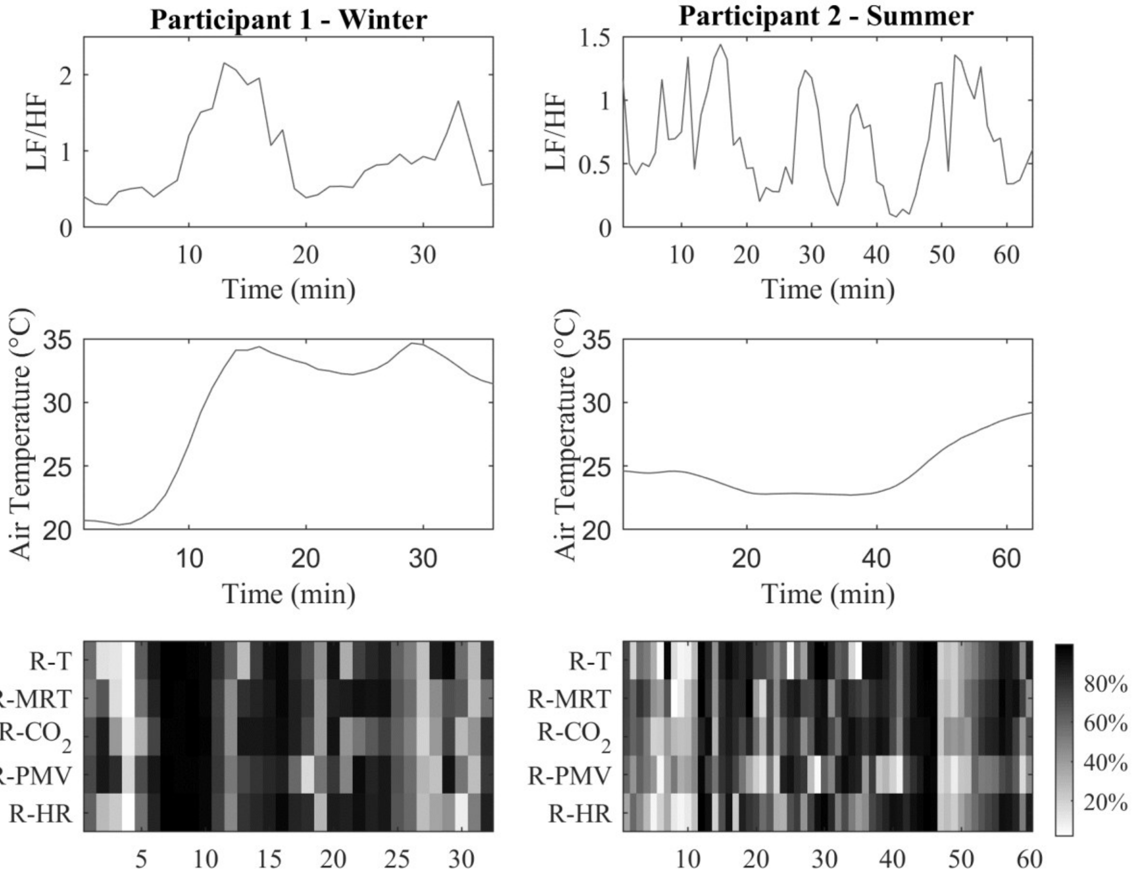

Figure 5. (Upper Panel)Waveform of LF/HF ratio, (Middle panel) air temperature, across time during the test for participant 1 (left) and participant 2(right). (Lower panel) Pearson correlation coefficient computed between 5 minutes time interval of LF/HF and the respective time interval in the environmental parameter.

the trend of the LF/HF does not correlate only with one environmental parameters but, on the contrary, the trend is also strictly connected with other environmental parameters.

For example, participant 1 exhibits an LF/HF ratio increase between 10 and 15 minutes during the test that is strongly correlated with all the four environmental parameters of interest, i.e. T, MRT, CO_2, PMV and RH. In fact, increasing the LF/HF ratio derives from the simultaneous increasing of the correlated parameters. In the same way, it is possible to interpret results of Participant 2: T and MRT do not exhibit significant correlation with LF/HF especially considering the first LF/HF ratio observed peaks, i.e. around minute 5 and 10. This can be probably explained due to the small variation of the environmental parameters in the first part of the test, while a higher variation is presented at the end. These results put in evidence that LF/HF trend during a variation in the environmental parameters is not only strictly related on one parameters but can be also influenced by CO_2 concentration in the room, mean radiant temperature and relative humidity.

The observed correlations are quantitatively given in Figure 5 where each color map in the lower panel refers to a specific Pearson value showing the degree of correlation between LF/HF ratio and one time interval of the five parameters. Computed Pearson coefficient between LF/HF ratio and both *CO2* and MRT, is generally above the 80% for the entire duration of the subject 1 test. Moreover, R-CO_2 is higher in correspondence of the peaks in LF/HF ratio at minute 10, 29 and 40 of the subject 2 test. This is an important result showing that subject's comfort is not only related to T_a which is relevant for the second peak together with CO_2 and $\overline{t_r}$ but not for the first one where the LF/HF ratio waveform increase for a R- CO_2 raising.

The analysis has been repeated for every participant in which the Pearson's coefficient has been computed. Then, just the Pearson's coefficient values that are greater and equal to 75 % are taken into account for the final evaluation. Table 3 presents the percentage of LF/HF time interval that, correlated with environmental parameter, showed a Pearson's coefficient greater and equal thanto75%. For example, 66.4 % of the air temperature time intervals correlated with LF/HF scored a Pearson's coefficient higher than 75 % in winter, suggesting that there is a relationship between LF/HF and air temperature. Same considerations can be done for CO_2 concentration, since 65.3% of the time interval has correlated more that 75 %.

Table 3. Percentage of LF/HF signal correlated with environmental signal time interval that has a Pearson coefficient greater than 75%, in summer and winter.

	Winter				
	MRT-LF/HF	**T – LF/HF**	**CO2 – LF/HF**	**RH – LF/HF**	**PMV – LF/HF**
Average (%)	56.8	66.4	65.3	60.0	37.0
Standard Deviation (%)	8.1	0.5	5.0	0.6	13.9

	Summer				
	MRT-LF/HF	**T – LF/HF**	**CO2 – LF/HF**	**RH – LF/HF**	**PMV – LF/HF**

Average (%)	59.1	62.5	56.7	65.8	40.8
Standard Deviation (%)	10.4	8.0	10.7	9.3	8.5

3.2. Machine Learning results

Tables 3 expresses the average prediction accuracy of the classification algorithms used to predict the thermal sensation vote expressed from subjects that participated to the study in relation with HRV indices. In particular, in the first row the six classification algorithms are trained only using the LF/HF as input data and the thermal survey as label. The average accuracy of DT, KNN, LDA and RF are close to 50% while NB and SVM increases up to 76 %.

Table 4. ML classification accuracy computed as the average accuracies for each of the 29 subjects.

Mean ML classification accuracy (%)						
Indices	**DT**	**KNN**	**LDA**	**NB**	**SVM**	**RF**
LF/HF	52	52	55	75	76	51
Time	69	73	74	81	82	73
Frequency	63	68	64	79	80	69
All	72	68	77	82	84	79

The second and third row show the average accuracy of the algorithms trained with a dataset obtained from the aggregation of time-domain and frequency-domain HRV measurements respectively. Accuracy has increased in both cases in all the classifiers but also in this case NB and SVM have provided higher accuracy, up to 82%. Moreover, it has to be pointed out that all algorithms classify the thermal vote with lower accuracy in the frequency domain with respect to time-domain indices. Finally, the accuracy of the algorithm trained with a dataset obtained from the aggregation of all the computed HRV indices is shown in the last row. The higher accuracy is reached by SVM algorithm (84%) while KNN provides the lowest performance (68%).

Figure 7 shows the trend of the predicted thermal sensation vote from the model against the real vote obtained for one subject analyzed.

As final consideration, ML classification approach, and in particular NB and SVM allow to use LF/HF to predict the thermal comfort vote of a user in an indoor environment even if better results are shown for the accuracy of time, frequency and aggregated indices.

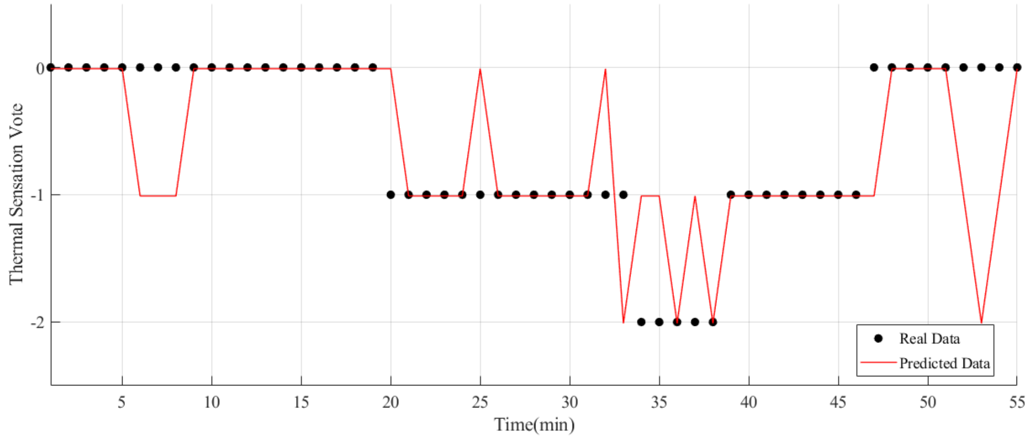

Figure 7. Thermal sensation vote predicted from SVM classification model (red line) against the real thermal sensation vote (blue line) for one subject as example.

3.3. Subjective attributes affecting IEQ perception

This section focuses on subjectivity of the perceived IEQ moving from a preliminary combined analysis of environmental data measured by the indoor microclimate station end expressed actual sensation votes. These are continuously noted by the operator throughout the whole test being translated into a 7-points comfort scale ranging between -3 and +3 where 0 expresses neutral conditions. Presented data are thus referring to a collection rate of 1 minute which is the settled rate for the microclimate monitoring. More specifically, the analysis focuses on comfort domains mainly affected by given environmental stimuli which are related to the activation of an HVAC system causing air temperature and velocity variation.

Graphs of Figure 8 show thermal (Figure8a, c) and air quality (Figure 8b, d) perception given by the subjects during both winter (Figure 8a, b) and summer (Figure 8c, d) tests with respect to corresponding monitored operative temperature and CO_2 concentration respectively, i.e. left y-axes, which are the physical environmental parameters mainly related to such spheres of comfort. Same expressed sensations are also correlated to draught rate, i.e. percentage of people predicted to be bothered by draught according to ISO 7730 (right y-axes), which reaches up to 100% during summer tests. The observed high values of air velocity and local turbulence intensity are due to the small dimensions of the test-room, i.e. 27 m^3, and thus to the proximity between the split of

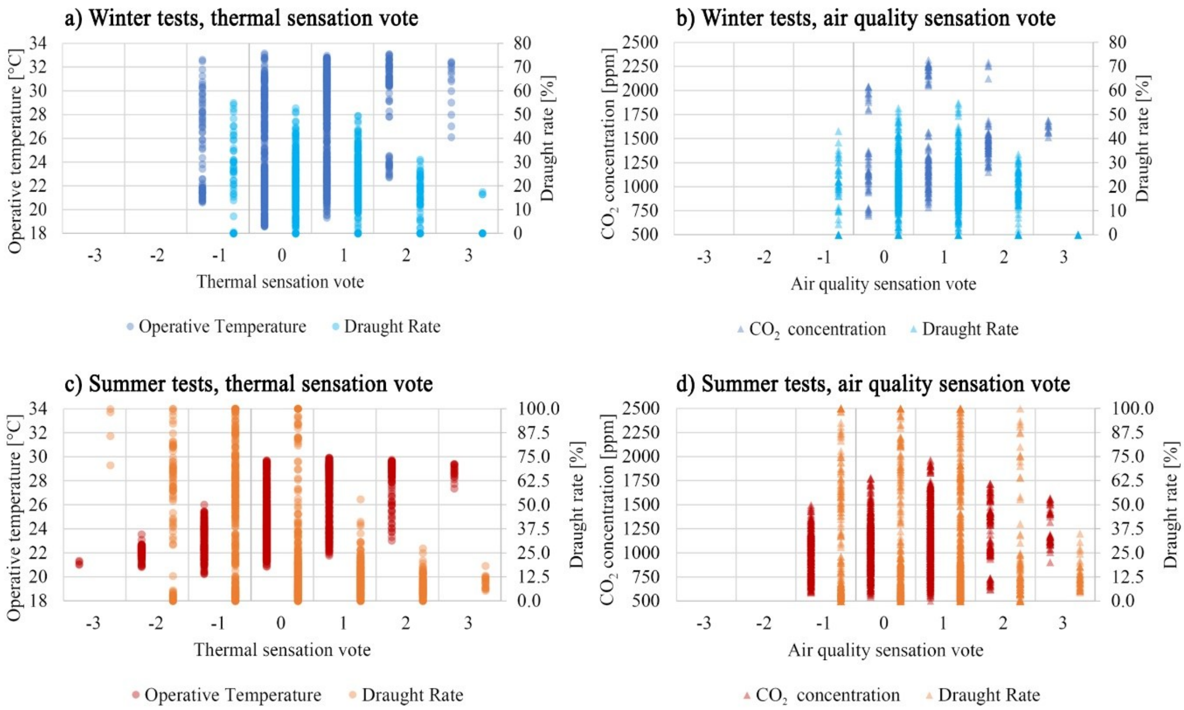

Figure 8. Actual Thermal and Air Quality sensation votes given with respect to most influencing physical parameters, i.e. measured operative temperature, draught rate, and CO_2 concentration.

the HVAC system and the subject.

In Figure 8, plots dispersion expresses the extent of the physical variable range corresponding to specific sensation vote while plots transparency gives an idea of the statistical strength of the pointed-out correlation. Presented outcomes highlight how much IEQ perception varies among different subjects and thus occupants in general. Physical variables ranges corresponding to specific sensations are wide, e.g. up to 14.6 °C and 8.9 °C of operative temperature interval expressing thermal neutrality in winter and summer respectively, and almost overlapped. Nevertheless, correlations among thermal sensation votes and both operative temperature and draught rate are found out to be weak but consistent throughout the seasons. In particular, operative temperature seems to positively influences actual thermal votes with an R^2 equal to 0.18 and 0.48 during winter and summer tests respectively. On the other hand, percentage of people predicted to be bothered by draught is negatively correlated to expressed thermal sensation with an R^2 of 0.15 during summer tests.

No significant relationships are highlighted between air quality perception and detected CO_2 concentration within the room even if during almost all the performed tests this value overcomes the suggested limit of 1000 ppm, i.e. up to 2319 ppm observed in winter, due to missing ventilation rate during the experiment. Clear correlation is also missing between air quality perception and draught rate in summer when this value reaches up to 100% while a weak positive correlation is shown in winter meaning that not particularly strong draught may improve the perception of air quality towards “fresh air”.

In order to understand reasons underneath the presented differences among expressed sensations combined to monitored environmental parameters, possible influences due to personal attributes of the subject are here investigated. In particular, the hypothesis here statistically tested assumes expressed IEQ satisfaction, i.e. fill-up survey part III, as dependent from personal characteristics of the subject gathered in survey part I. This hypothesis is tested considering both single personal characteristics and group of objective and subjective descriptors, i.e. not-depending or depending from the will of the subject (Table 2).

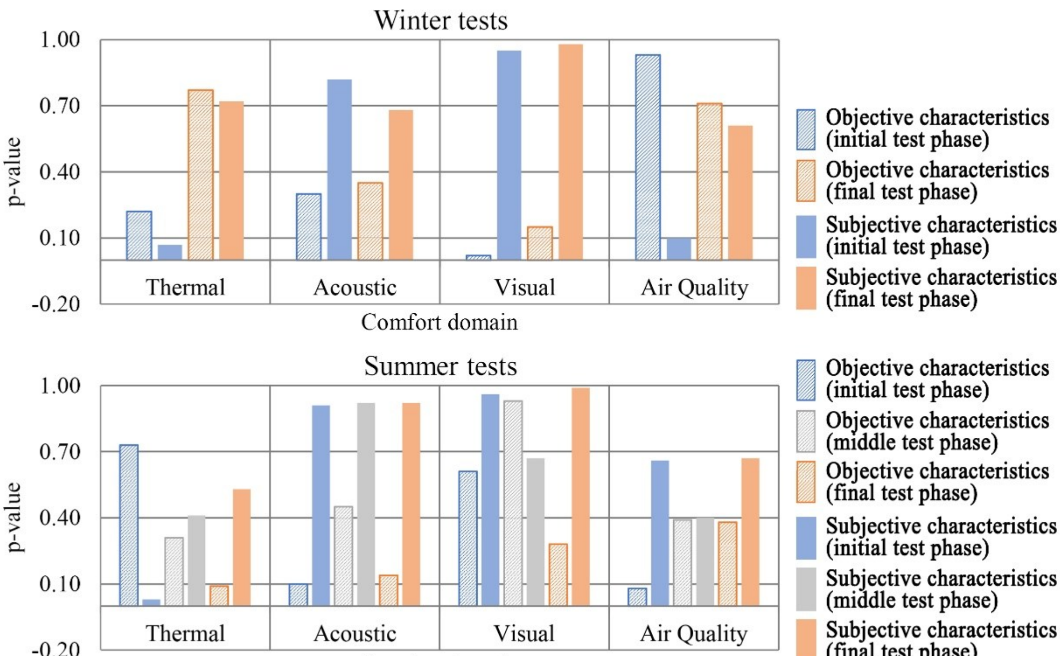

Figure 9. Statistical investigation of objective and subjective groups of personal characteristics impact on expressed IEQ during both winter and summer tests.

The *p*-value quantifies the goodness of the proposed assumption as shown in Figure 9 for perception dependency from groups of personal variables. The lower the p-value, the higher the significance of the tested hypothesis. Only few of the proposed correlations show up to be significant assuming a level of significance equal to 0.07 but such relations are not consistent throughout different tested seasons. The lowest *p*-value is 0.02 obtained for the hypothesis of objective personal parameters influencing the visual perception in winter at the beginning of the test. The other significant relation found out in the coldest season still refers to the initial phase of the test, it has a *p*-value of 0.07, and concerns thermal comfort perception as depending on personal subjective attributes, i.e. Body-Mass-Index, education, smoking habits, and worn garments. This is the only relation confirmed by the summer test with a *p*-value of 0.03.

Table 5. The three most significant single personal characteristics influencing expressed IEQ perception in winter and related p-value

	Initial test phase Personal characteristic	*p*-value	Final test phase Personal characteristic	*p*-value
Thermal comfort	Smoking habits	**0.01**	Education	0.30
	Gender	**0.05**	BMI	0.43
	BMI	0.36	Age	0.47
Acoustic comfort	Age	**0.06**	Birthplace	0.20
	Gender	0.26	Smoking habits	0.24
	BMI	0.36	Age	0.27
Visual comfort	Birthplace	**0.05**	Birthplace	0.14
	Age	0.10	Age	0.17
	Gender	0.47	Gender	0.65
Air quality	Education	**0.03**	Gender	0.44
	Smoking habits	0.20	Worn garments	0.45
	Worn garments	0.28	Smoking habits	0.46

Table 6. The three most significant single personal characteristics influencing expressed IEQ perception in summer and related p-value

	Initial test phase Personal characteristic	*p*-value	Middle test phase Personal characteristic	*p*-value	Final test phase Personal characteristic	*p*-value
Thermal comfort	Worn garments	**0.03**	Gender	**0.07**	Gender	**0.02**
	Education	0.12	Smoking habits	0.11	Age	0.11
	Age	0.26	BMI	0.18	BMI	0.30
Acoustic comfort	Gender	**0.02**	Gender	0.15	Gender	**0.04**
	BMI	0.40	Birthplace	0.45	Age	0.53
	Age	0.55	Age	0.58	Birthplace	0.53
Visual comfort	Age	0.25	Smoking habits	0.34	Birthplace	0.12
	Smoking habits	0.57	Worn garments	0.55	BMI	0.22

	Gender	0.65	Gender	0.58	Age	0.31
Air quality	Age	**0.01**	Age	0.13	Age	0.08
	Gender	0.20	Gender	0.37	Education	0.35
	Worn garments	0.20	Worn garments	0.37	BMI	0.39

Table 5 and Table 6 report the obtained results testing each single personal characteristic as driver of the perceived level of comfort in all the comfort-domains, i.e. thermal, acoustic, visual, and air quality. Significant relations are highlighted in bold. Some of the obtained p-values identify stronger relations, but these are never consistent throughout seasons or different phases of the test.

The outlined findings suggest that the tested hypothesis are generally not convincing. Nevertheless, the influence on IEQ perception due to complex life-styles seems more reasonable than single-parameter affection. The investigation of such groups of personal characteristics on indoor comfort perception could be promising in deepening psychological aspects.

4. Conclusions and future developments

Building energy consumption is driven by occupants' energy-needy behaviors which are driven, again, by human comfort perception in indoors, among other personal variables. Nowadays, scientific community is approaching the theme of human comfort assessment in indoors trying to overcome the strictly environmental-driven procedure proposed by actual regulations. Comfort should be indeed investigated in all its components including physiological and psychological parameters.

Within this framework, the current work aims to present a novel measurement procedure designed to get a complete overview of occupants' IEQ perception. From a technical point of view, the challenge of the study is to involve at the same time different typologies of measurement systems since a unique platform is not available so far. Proper synchronization of all the measured signals is therefore fundamental for the goodness of the pretended outcomes and it represents one of the key original efforts performed in this research. In fact, environmental data, as well as physiological and psychological ones are simultaneously monitored during specific tests conducted in winter and summer. These are mainly focused on the variation of the thermal environment, but the study is not only restricted to thermal perception in order to investigate even the existing interaction among different domains of comfort, i.e. thermal, visual, acoustic, and air quality. In particular, the current work presents preliminary results in terms of both (i) combined physical and physiological analysis and (ii) psychological interpretation of the expressed perception even combined to environmental data.

ECG signal processes of 29 out of the 62 performed tests are presented in this study. Extracted features are the ones most related to thermal comfort variation according to the literature, i.e. HRV and LF/HF ratio. ML algorithms allow to confirm that HRV and its indices are strictly connected with human thermal comfort with prediction accuracy up to 82%.

The combined analysis of expressed sensation votes with both (i) physical environmental variables and (ii) personal characteristics does not lead to statistically significant results. Nevertheless, the obtained outcomes highlight that subjective responses are most probably driven by the identification of complex life-style while relations among physical stimuli and univocal response from occupants is not so strict as it is proposed by actual regulations.

As further development, similar experimental tests will be performed with varying typology of environmental stimuli given to the subjects and a complete database is going to be collected to finally get to the definition of a new comfort model. This complex and complete model could enhance building energy consumption prediction reducing performance gaps and could be associated to real-time environmental control system for a better management of the building during its operative life and without compromise occupants' comfort perception. Additionally, the evaluation of the whole personal perception, together with collection of physical measurements within the indoors may be of key help for improving indoor environmental quality and for elaborating more tailored human-centered building design strategies.

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