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An investigation of indoor thermal environments and thermal comfort in naturally ventilated educational buildings

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ABSTRACT

Indoor thermal conditions are essential in educational buildings. The health and well-being of students can be affected by a poor thermal environment, which also has a clear impact on building energy consumption. In this context, the indoor thermal environment in naturally ventilated university classrooms is explored in this study during a complete academic year. A monitoring campaign and a questionnaire survey were conducted simultaneously in higher education buildings in Spain. A total of 2115 sets of data were collected. Thermal sensation prediction indices (predicted mean vote, extended predicted mean vote and adaptive predicted mean vote) were applied to evaluate student's thermal perception and their prediction accuracy was assessed. Additionally, two machine-learning models, based on Artificial neural network (ANN) and random forest (RF) algorithms, were formulated to predict occupants' thermal sensation. The obtained results evidenced that the proposed ANN and RF models outperform traditional indices. Finally, it is also proposed an adaptive thermal comfort model. The results obtained suggest that students have a greater adaptive capacity to changes in environmental conditions than suggested by the ASHRAE-55 adaptive model and that they preferred an environment with lower temperatures than those suggested by the EN-16798 adaptive model.

List of abbreviations

ANN	Artificial Neural Network
aPMV	Adaptive Predicted Mean Vote
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
ePMV	Extended Predictive Mean Vote
IEQ	Indoor Environmental Quality
N	Number of data
NV	Natural ventilation
MSE	Mean Square Error
MAE	Mean Absolute Error
PMV	Predictive Mean Model

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RF	Random forests
RH	Relative Humidity
RH_{in}	Indoor Relative Humidity
RH_{out}	Outdoor Relative Humidity
T_{comf}	Comfort temperature
$T_{in\text{-}op}$	Indoor Operative Temperature
T_n	Neutral temperature
T_{out}	Outdoor temperature
T_{rm}	*Running mean temperature*
TSaV	Thermal Satisfaction Vote
TSV	Thermal Sensation Vote
V_{in}	Indoor air velocity
V_{out}	Outdoor air velocity
x	Actual parameter value
X	Set of x
Z	Normalised data

1. Introduction

People in modern society spend most of their time, around 80 %, indoors. This fact results in the indoor environmental quality (IEQ) influencing well-being and satisfaction of buildings occupants [1]. In fact, this influence was even higher during the COVID-19 and confinement periods. Different environmental parameters, such as relative humidity (RH), air temperature, radiant temperature and air velocity are related to the indoor thermal environment [2]. Heating, ventilation and air conditioning systems in buildings can be used to influence these parameters and create a more comfortable environment, but they also have a high impact on the buildings' energy demand. In fact, at least 50 % of energy consumption in buildings is used for space heating [3]. In this context, it is necessary to analyse the thermal perception of buildings occupants to improve the sustainability of buildings by reducing their energy demand and achieve suitable indoor environmental conditions. Numerous studies have analysed indoor thermal conditions in different types of buildings, such as offices [4–7], educational buildings [8–15] or residential buildings [16–20].

The thermal comfort is defined by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) as that condition of mind that expresses satisfaction with the thermal environment [1]. Both, the static heat balance model and the thermal adaptive model, are the two approaches used to assess indoor thermal comfort. The Predicted Mean Model (PMV) is among the most widely used static heat models [2]. It is based on the heat balance of the human body in a given environment and was developed by Fanger in 1970, from experimental tests conducted in climatic chambers. This model states that the indoor environmental conditions (air temperature, radiant temperature, air velocity and relative humidity) and personal parameters (clothing insulation and metabolic rate) can be used to evaluate the occupants' thermal sensation [2]. However, the PMV model ignores factors such as social and cultural aspects, and occupant adaptation. Previous studies have pointed out that static models, such as PMV, predict occupants' thermal sensation effectively in uniformly controlled stationary conditions (e.g., air-conditioned (AC) buildings), but the results are not accurate when this model is applied to naturally ventilated (NV) buildings [21,22].

Humphreys [23] found that the discrepancy between the actual mean vote and the PMV increased for higher activity levels and heavier clothing, whereas accurate values were obtained when the PMV model was applied in laboratory studies using light clothing and sedentary activities. Clothing insulation influences occupants' thermal perception and varies significantly between seasons [24]. Cheung et al. [25] analysed the ASHRAE Global Database II and found that the PMV-PPD model accuracy was only 34. Thus, several studies have proposed new indexes to relate these factors to the heat balance model, to improve the accuracy of the PMV model. Fanger and Toftum proposed the extended Predicted Mean Vote (ePMV) using an expectancy factor [26]. The adaptive Predictive Mean Vote (aPMV) was proposed by Yao et al. [27] including an 'adaptive factor', by using the black box method to explore the relationship between field and laboratory results.

In addition, other models were proposed to overcome this limitation in naturally ventilated buildings and to achieve a closer approximation between the predicted thermal sensation vote (TSV) and the actual TSV. In this context, the approach proposed by previous studies was the adaptive thermal comfort model [22], which relates outdoor or indoor air temperature and thermal sensations by a linear regression equation. International and national thermal standards have adopted this model (e.g., ASHRAE-55 [1] and EN 16798–1:2019 [28]). This model is a method of evaluating thermal environments with NV and considers the different occupants' adaptation to NV conditions, including physiological, psychological, and behavioural adaptations [29]. Nevertheless, it is worth mentioning that not all occupants of a building may have the same individual characteristics and these factors influence the thermal perception [30]. The significance of individual differences in the preferred/neutral/comfort temperature was explore by Wang et al. [31] and a strong influence of these differences on thermal comfort was found. Not only individual variables such as age or gender, but also the sensitivity to climate change adaptation (e.g., geographical location, social, psychological, and cultural habit, etc.) influence occupants' thermal perception [32].

The assessment of indoor thermal conditions in educational buildings is especially relevant. Students and teachers spend long periods of time in classrooms, and their health and performance may be impaired by a poor quality of the thermal environment. Studies on indoor environmental conditions in educational buildings are essential to understand the perception and behaviour of students in different environments, as well as to identify gaps to improve building performance and occupants' well-being and productivity [33]. The thermal environment was found to be the most important factor for achieving overall satisfaction with the indoor environment according to the literature survey conducted by Frontczak and Wargocki [34]. In this line, a significant correlation between the subjective perceptions of students and the quality of the indoor environmental conditions was found by Corgnati, Filippi and Viazzo [35] in their field study about thermal, acoustic, visual and air quality parameters in classrooms.

In this context, and given the importance of indoor environmental conditions, new thermal comfort models have been developed based on new approaches and techniques in recent years. The evolution of machine learning algorithms provides potential resources that can be used to predict parameters that depend on multiple variables. The outstanding advantages offered by these algorithms have resulted in them being applied in different research areas. Both Artificial Neural Network (ANN) and the Random Forest (RF) are types of machine learning algorithms widely used to predict non-linear relationships between independent and dependent variables. The use of ANN to develop thermal comfort models was proposed by Chan and Chau [36] for predict thermal sensation in urban parks. A new model based on ANN was proposed by Mahgoub et al. [37] to predict standard effective temperature for outdoor environments. ANN algorithms were also used by Wu et al. [38] to formulate a predictive model of thermal comfort in some regions of China. Li et al. [39] proposed a thermal sensation model for a personalised conditioning system in office buildings using the RF classification algorithm. Wang et al. [40] applied the RF algorithm to predict older people's thermal sensation in aged/care homes. Chaudhuri et al. [41] proposed an RF-based thermal comfort model from gender-specific physiological parameters collected in a typical office room in the Nanyang Technological University (Singapore).

Regarding educational buildings, models developed in other spaces (such as public urban areas, residential buildings, or mechanically ventilated buildings) are not suitable for direct application to NV higher educational buildings because of their characteristics (e.g., high density of individuals, NV protocols and the type of activity performed the occupants have a greater degree of freedom to take adaptive actions compared with other educational stages). To date, few studies have focused on the development of adaptive thermal comfort models in Mediterranean university classrooms [15] and, given that thermal acceptability ranges vary from one climatic region to another, the innovation of this study includes the proposal of an adaptive thermal comfort model.

In addition, Fard et al. [42] conducted a systematic review of the use of machine learning techniques in thermal comfort studies and concluded that future studies need to focus on educational buildings and NV buildings. Nevertheless, since there is a wide variety of building types and climates, comfort temperature assessments from machine learning based models is not yet fully developed [43]. Hence, more research to evaluate the performance of models for occupant thermal sensation assessment is still needed in educational buildings and the present study aims to fill this research gap.

The main objectives of this study are: (i) to analyse the thermal environment of NV classrooms; (ii) to formulate models to predict TSV evaluation in NV educational buildings using ANN and RF machine learning algorithms; (iii) to investigate the prediction accuracy of traditional thermal sensation models (PMV, ePMV and aPMV) when applied to these scenarios, and compare their performance with the proposed machine learning models; and (iv) to develop an adaptive thermal comfort model to evaluate students' thermal sensation. For this purpose, a field measurement campaign was conducted over an academic year, and objective and subjective data were collected from educational buildings in Southern Spain. The proposed models aim to constitute a tool to complement the evaluation of TSV and to manage indoor environments in educational buildings, as well as contribute to the knowledge of thermal conditions in these buildings.

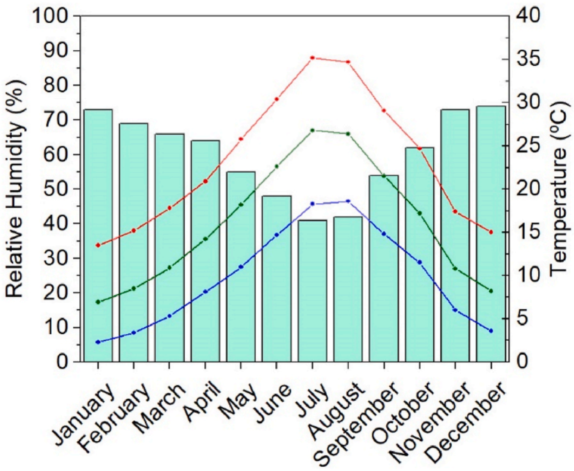

Fig. 1. The average monthly temperatures (green line), the average maximum temperatures (red line), the average minimum temperatures (blue line) and the average relative humidity (blue bars), by month, for the period 2012–2023 [44].

2. Materials and methods

This section describes the design of the experimental setup, the data collection process, the method used to build the machine learning-based models to predict the TSV, and the static and adaptive thermal comfort models used to assess indoor environmental conditions.

2.1. Data collection

A field measurement campaign was defined to gather relevant data in order to develop thermal comfort models and test their performance. This data collection process was conducted in higher education buildings of Campus Fuentenueva, located in Granada (Spain). The climate in this city is classified as 'Csa', according to the Köppen–Geiger climate classification. It is characterized by cold long winters and very hot short summers. The temperature usually ranging between 0 and 34 °C (rarely drops below −4 °C or rises above 38 °C). Extreme temperatures can be reached in summer (44 °C) and in winter (-4 °C). The annual average RH value is 58 %, with lower average values in the summer months (41 %). Fig. 1 shows, by month, the average of RH value, the average temperature values, the average maximum temperature values, and the average minimum temperature values, for the period 2012–2023 [44]. The Csa climate dominates most of Spain, covering the south, the northeast, and the Balearic Islands; it also reaches a small part of the Canary Islands [45].

All of the buildings selected in this study, like the majority of all educational buildings in Europe [46], are NV (through doors and windows). The field study was conducted during the academic year 2021/2022 (September to June). The field measurements and questionnaire survey were conducted in classrooms of the Fuentenueva Campus. The buildings characteristics are shown in Table 1. All the classrooms have similar characteristics: they are all NV and have heating systems (radiators) but do not have cooling systems. The radiators are placed under the windows of the classrooms. The collected data were measured in a total of 30 classrooms. The location of Fuentenueva Campus is shown in Fig. 2.

The measurement campaign consisted of a sensor measurement campaign survey conducted simultaneously with a paper-based questionnaire to collect subjective thermal perceptions from buildings' occupants and indoor thermal parameters. This process followed the recommendations defined in the ISO 28802:2012 [47] standard. The questionnaire included questions about building occupants' demographic data (i.e., age and gender) as well as the clothing that they were wearing during the survey (respondents selected their clothes from a checklist) based on ISO 7730 standard. The clothing insulation values were calculated based on the participants' responses. Additionally, occupants were also asked to indicate their thermal satisfaction vote (TSaV) using a 7-point Likert scale (from −3 for 'very dissatisfied' to 3 for 'very satisfied') and their TSV (from −3 for 'cold' to 3 for 'hot'). The survey respondents were university students who had been seated in classrooms for at least 2 h. The sensors were installed in the classroom 15 min before the lesson started. Fig. 3 shows the layout of sensors' location. Subsequently, the questionnaires were distributed to all students in the classroom 15 min before the end of the lesson. Students ~~They~~ were asked to complete the questionnaire during the last 15 min of the lecture or class. This procedure aims to minimise disruption to the class activity and to eliminate the influences of prior activities on TSVs [13,48]. Fig. 4 shows the survey scheme used in this study.

Table 2 shows the instruments used to collect the indoor environmental variables of the classrooms. These variables included RH, indoor air temperature, radiant temperature, and air velocity. The instruments were located at the front, middle and end positions of the classrooms. Regarding the radiant temperature and air velocity, the sensors were place in the middle of the classrooms. The sensors' locations followed the recommendations stated in ASHRAE 55–2020 [1] and ISO 7726:2002 [49], were located 0.6 m above the floor level, separated by at least 1.0 m from the surrounding surfaces and away from any heating or cooling sources. A 1-min interval was selected to record all the parameters (from the beginning to the end of each lecture or class).

The outdoor environmental parameters were obtained from a meteorological station located close to the buildings under study. The State Meteorological Agency of Spain (AEMET) [44] provided these data. The meteorological weather station was equipped with sensors for measuring air velocity (Anemometer THIES Compact, measurement ranged from 0.5 to 65.0 m/s) and temperature and relative humidity (TH THIES Compact, measurement ranged from −40 to 70 °C and from 0.2 to 100.0 %, respectively).

A total of 2293 responses were collected from the questionnaire survey, together with the indoor/outdoor measurement data. Before processing and analysing these data, the questionnaires were checked for incompleteness or clear inconsistencies and 178 were discarded due to incompleteness, finally resulting in a total of 2115 sets of data.

2.2. Static predictive thermal comfort models

The PMV, ePMV and aPMV were applied in this study. Regarding the PMV model, it was applied according to the ISO 7730 [2]. The PMV model is based in a 7-point Likert scale (from −3 to +3) and is calculated from four factors related to the thermal environment (i.e., air temperature, RH, mean radiant temperature and air velocity) and two factors related to the human body (i.e., metabolic rate and

Table 1
Surveyed building characteristics.

Building	Type of building components			Structure	Ventilation systems	Type of windows
	Wall	Ceiling	Floor			
B1	Ceramic tile	Registrable suspended ceiling	Natural stone	Concrete frame	NV	Aluminium glazed windows
B2	Gypsum plaster	Registrable suspended ceiling	Terrazzo	Concrete frame	NV	Aluminium glazed windows
B3	Gypsum plaster	Registrable suspended ceiling	Terrazzo	Concrete frame	NV	Aluminium glazed windows

Fig. 2. Location of buildings surveyed in the Fuentenueva Campus.

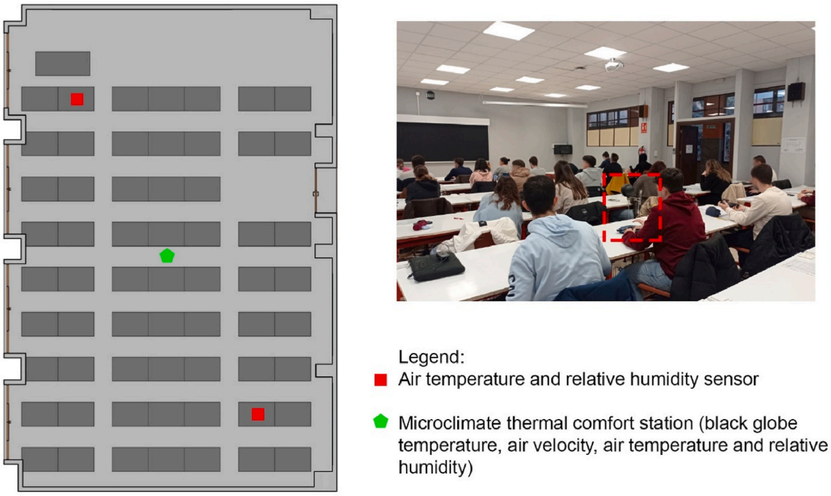

Fig. 3. Example of the layout of the sensors' location in the classrooms.

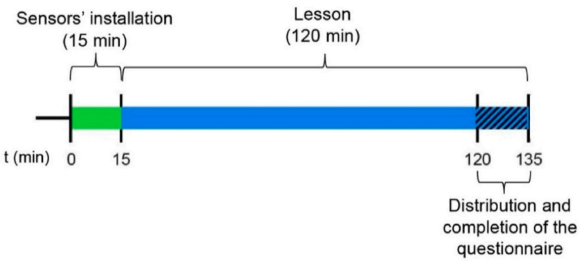

Fig. 4. Survey scheme.

Table 2
Equipment used in the field study.

Parameter	Instrument	Range	Accuracy
Air temperature	FHAD 46-C41A AHLBORN	−20 to +80 °C	Typical ±0.2 K at 5–60 °C Maximum ±0.4 K at 5–60 °C Maximum ±0.7 K at −20 to +80 °C
Radiant temperature	FPA805GTS AHLBORN	−50 to 200 °C	0.1 °C
RH	FHAD 46-C41A AHLBORN	0–98 % RH	±2.0 % RH in range from 10 to 90 % RH
Air velocity	HD403TS2 Delta OHM®	0.1–5.0 m/s	±0.03 m/s + 3 % f.s

clothing insulation). Since students were seated during the lectures when the field measurements were carried out, a metabolic rate of 1.2 met was selected. The data collected during the field measurements and questionnaire surveys were used to predict students' thermal sensation based on PMV.

In addition, the revised PMV methods, ePMV and aPMV, were also applied in this study. The ePMV is derived by multiplying an expectancy factor to the PMV, as calculated using Eq. (1).

$$ePMV = e \bullet PMV \tag{1}$$

where e stands for the expectancy factor. According to Fanger and Toftum [26], the value of e for free-running buildings is assumed to vary according to the length of the warm season, in a year, and the comparison with other AC buildings in the same region. Table 3 shows the expectancy factor for each climate zone, according to Fanger and Toftum [26].

The aPMV was also applied and the adaptive coefficient that reflects the adaptive behaviour of occupants to PMV was calculated [27]. The aPMV is calculated using Eq. (2).

$$aPMV = \frac{PMV}{1 + \lambda \bullet PMV} \tag{2}$$

where λ is the adaptive coefficient, which is calculated using the least square method and following the methods defined by Yao et al. [27], using Eq. (3):

$$\lambda = \frac{\sum_{i=1}^{n} \left(\frac{1}{PMV_i} - \frac{1}{TSV_i} \right)}{n} \tag{3}$$

where n is the total number of data collected.

2.3. Adaptive thermal comfort models

The adaptive comfort models implemented in ASHRAE-55:2020 and EN 16798–1:2019 are alternatives to the heat balance methods for the assessment of indoor thermal conditions in NV buildings. These models are based on the relationship between the thermal sensation and the indoor temperature and the running mean temperature (T_{rm}). The T_{rm} is determined based on Eq. (4):

$$T_{rm} = \frac{(T_{ed-1} + 0.8\, T_{ed-2} + 0.6\, T_{ed-3} + 0.5\, T_{ed-4} + 0.4\, T_{ed-5} + 0.3\, T_{ed-6} + 0.2 T_{ed-7})}{3.8} \tag{4}$$

where T_{ed-j} is the average daily outdoor air temperature of the previous j-th day. As observed in Eq. (4), as time progresses, T_{ed-j} become less significant. In addition, comfort temperature was also estimated based on the Griffiths method, according to Eq. (5):

$$T_{comf} = T_{air} \frac{(0 - TSV)}{G} \tag{5}$$

where T_{comf} is the comfort temperature (°C), T_{air} is the indoor air temperature (°C) and G is the Griffiths constant. In this study, G has been assumed to be 0.50 in the analysis, since this value was widely used in thermal comfort field studies [9,50–52].

The model defined in ASHRAE 55:2020 was used to assess the indoor thermal environment. The acceptance range in the adaptive model is established based on the PMV model. According to this standard, a predicted percentage of dissatisfaction of 20 % corresponds to a PMV range between −0.85 and 0.85. A predicted percentage of dissatisfaction of 10 % corresponds to a range of $-0.5 < PMV < 0.5$. According to ASHRAE 55, the upper and lower limits of 80 % and 90 % acceptance ranges are calculated using the equations shown in Table 4.

EN 16798–1:2020 also implements the adaptive thermal comfort model. However, this standard defines different categories (I, II and III), according to the indoor temperature and the T_{rm}. The upper and lower limits which define each category are shown in Table 5.

Additionally, comfort ranges and an adaptive thermal comfort model were also proposed in this study, based on the data collected.

2.4. Supervised learning algorithms and model development process

Both ANN and RF are machine learning algorithms widely used in different areas. Regarding the ANN algorithm, the basic structural architecture includes the sequence of an input layer, a hidden layer and an output layer. Although the structure of a neural network may comprise more than one hidden layer, ANN theory states that any complex nonlinear function can be approximated by a

Table 3
Expectancy factor according to the climate zone [26].

Climate zone	Expectancy factor
Temperate zone	0.7
Hot summer - warm winter zone	0.7
Hot summer – cold winter zone	0.8
Cold zone	0.8
Severe cold zone	0.9

Table 4
Upper and lower limits defined in the ASHRAE-55 adaptive thermal comfort model.

Category	Limit	Equation
Comfort	Comfort equation	$\Theta_O = 0.31\ t_{rm} + 17.8$
90 %	Upper limit	$\Theta_O = 0.31\ t_{rm} + 20.3$
	Lower limit	$\Theta_O = 0.31\ t_{rm} + 15.3$
80 %	Upper limit	$\Theta_O = 0.31\ t_{rm} + 21.3$
	Lower limit	$\Theta_O = 0.31\ t_{rm} + 14.3$

Table 5
Upper and lower limits defined in EN 16798–1:2020 for each category.

Category	Limit	Equation
Comfort	Comfort equation	$\Theta_O = 0.33\ t_{rm} + 18.8$
I	Upper limit	$\Theta_O = 0.33\ t_{rm} + 18.8 + 2$
	Lower limit	$\Theta_O = 0.33\ t_{rm} + 18.8 - 3$
II	Upper limit	$\Theta_O = 0.33\ t_{rm} + 18.8 + 3$
	Lower limit	$\Theta_O = 0.33\ t_{rm} + 18.8 - 4$
III	Upper limit	$\Theta_O = 0.33\ t_{rm} + 18.8 + 4$
	Lower limit	$\Theta_O = 0.33\ t_{rm} + 18.8 - 5$

three-layer neural network [53] in the first instance. In this study, an ANN model based on a single hidden layer was selected to generate the TSV model. Regarding the ANN hyperparameters, the Levenberg-Marquardt back propagation algorithm and the Sigmoid activation function was used to train the ANN model. Equation (6) was used to determine the optimal number of neurons in the hidden layers [54–56].

$$N_h = 2 \bullet N_i + 1 \tag{6}$$

where N_i is the number of neurons in the input layer and N_h is the number of neurons in the hidden layer. In addition, since previous studies pointed out that ANN with one hidden layer can approximate the most nonlinear function with finite discontinuities at high accuracy when the number of neurons is high enough [57], this structure was selected in this study.

The RF algorithm is also a popular machine learning technique because of its interpretability and ease of use [58]. It is a nonparametric statistical method which was introduced by Breiman [59] and operates by building a multitude of decision trees. It is implemented to solve regression and classification problems and has been widely applied to a wide range of prediction problems. In this study, the RF hyperparameters were tuned to optimise the performance of the proposed model. The number of trees and the maximum depth of trees was 100 and 12, respectively. The bootstrap method was used for random feature selection. The variable importance and error are determined using the out-of-bag data (i.e., the omitted values from each bootstrap sample) [59].

Both algorithms were used to developed TSV models. As mentioned in Section 1, thermal perception is influenced by different factors, so the same factors used as input in the PMV have been used as input to develop the models. These parameters are the indoor air temperature ($T_{\text{in-air}}$), indoor radiant temperature ($T_{\text{in-rad}}$), indoor relative humidity (RH_{in}), indoor air velocity (V_{in}), and the clothing insulation of each participant. The output parameter of the models is the TSV prediction.

The input data were normalised within a uniform range to prevent both, premature saturation of hidden neurons and larger numbers from overriding smaller numbers [60]. Since some variables can be very large numbers (e.g., RH ranged from 14.0 to 94.0 %) compared to others with very small values (e.g., clothing insulation ranged from 0.18 to 1.18 clo), this process guarantees the comparability of the data. If data without normalisation were used to feed the proposed models, they would be wrongly trained because its weights could not represent the input and output relations. The weights changed, based on the 'height' of the derivation of the neuron activation functions and, for the case of very large or very small input values of logistic functions, it behaves in the same way: constantly equal to zero [60,61]. Eq. (7) shows the used normalised method.

$$Z = \frac{x - \min(x)}{\max(X) - \min(x)} \tag{7}$$

where Z is the normalised data (ranging from 0 to 1), x is the actual parameter value, X is the set of x, $\max(X)$ is the maximum value of X and $\min(X)$ is the minimum value of X. Regarding the output variable, the 7-point TSV collected during the survey campaign was used. A continuous TSV output was selected to build the models. Regarding the training and validation of the models, the data set values were segmented (80 % training and 20 % testing) and used to formulate models for predicting the TSV.

2.5. Methods for evaluating the prediction accuracy

For the evaluation of the performance of each model, the actual TSV values from the questionnaire were compared with the predicted TSV values of each model. For this purpose, the mean absolute error (MAE) and the mean square error (MSE) were used. Eq. (8) and Eq. (9) were used to estimate the MSE and MAE, respectively.

$$MSE = \frac{1}{N}\sum_{1}^{n}(O_i - P_i)^2 \tag{8}$$

$$MAE = \frac{1}{N}\sum_{1}^{n}|O_i - P_i| \tag{9}$$

where N is the number of data, O_i is the observed TSV value and P_i is the predicted TSV.

3. Results and discussion

After the initial checking of the surveys, a total of 2115 questionnaire responses (1267 from male students and 848 from female students) were collected from the field measurement campaign and used in this study. A statistical summary of the students' characteristics is shown in Table 6. 86 % of respondents were aged between 18 and 25. This rate is similar to the values published by the University of Granada in the statistics report for the academic year 2021 (85.6 %) [62].

3.1. Analysis of the environmental data obtained from the field campaign

A summary of the obtained values from the measured environmental parameters are shown in Tables 7 and 8. The outdoor variables showed a wider range of values than the indoor variables. The mean value for outdoor temperature (T_{out}), T_{rm}, outdoor temperature measured at 6 a.m. (T_{6am}) were 14.5 °C, 13.8 °C, and 8.4 °C, respectively. While the outdoor relative humidity (RH_{out}) and outdoor air velocity (V_{out}) were 56.7 % and 4.0 m/s. In contrast, the mean value for indoor air temperature ($T_{in\text{-}air}$), indoor radiant temperature ($T_{in\text{-}air}$), operative temperature (T_{op}) was 20.8 °C, 21.1 °C and 21.0 °C, respectively. The indoor relative humidity (RH_{in}) and indoor air velocity (V_{in}) were 38.8 % and 0.013 m/s. Among the measured outdoor parameters, the greatest deviation was found in RH and air temperature, with 19.4 % and 7.5 °C, while among the measured indoor parameters was found in RH and air temperature, with 7.2 % and 4.1 °C, respectively. Table A1 in Appendix A shows a summary of the outdoor and indoor environmental parameters recorded during the field measurement campaign by season. During the coldest season (winter) a mean outdoor temperature value of 9.8 °C (±4.5 °C) was observed, with RH values between 40.8 and 91.0 % (the mean value was 63.9 % ± 17.1 %). While the mean operative temperature was 17.8 °C (±2.1 °C), with an average minimum temperature value of 14.6 °C and the indoor RH ranged between 32.5 and 47.8 % (39.0 ± 4.4 %). In contrast, during the warmest season (summer), a mean outdoor temperature value of 23.1 (±4.8 °C) was observed, with a maximum average value of 33.0 °C, while the RH ranged between 21.3 and 58.0 %. The average operative temperature value was 26.1 °C (±2.1 °C), with an average maximum temperature value of 29.2 °C. The indoor RH ranged from 23.5 to 46.0 %.

3.2. Analysis of the subjective thermal evaluations obtained from the questionnaire survey

Fig. 5a shows the TSV relative frequency for binned data at 2 °C intervals. As shown in this bar graph, 86 % and 85 % of the students voted 'slightly warm', 'neutral' or 'slightly cool' (i.e., $-1 \leq TSV \leq +1$) at the ranges 22–24 °C and 24–26 °C, respectively. This percentage is reduced to less than 75 % at temperatures below 22 °C. In fact, at temperatures below 18 °C, more than 50 % of the students voted that the thermal environment was 'cool' or 'cold' ($TSV < -1$). In contrast, the percentage of students who voted that the indoor environment was 'warm' or 'hot' ($TSV > +1$) when the operative temperature was 26–28 °C was 20 %, increasing to over 50 % when the temperature exceeded 28 °C.

Regarding thermal satisfaction, Fig. 5b shows the TSaVs reported by the students. The lowest percentage of dissatisfaction was obtained when the operative temperature was 24–26 °C, increasing to 28 % in the temperature ranges of 22–24 °C and 26–28 °C. Dissatisfaction percentages above 50 % were found for temperatures outside these ranges (Top <22 °C and Top >28 °C).

The relationship between the outdoor and indoor thermal environment and the subjective responses obtained from the questionnaire survey was also explored. The Spearman test was carried out to identify significant correlations. Table 9 shows the results obtained. Significantly strong correlations (i.e., $\rho < -0.5$ or $\rho > +0.5$) are marked in bold. A strong correlation ($\rho = 0.568$) was found between TSaV and TSV. Regarding the students' clothing insulation, a negative correlation was found between this variable and the TSV (ρ=-0.523), as well as with the indoor temperatures ($T_{in\text{-}air}$, $T_{in\text{-}ra}$ and T_{op}) and outdoor temperatures (T_{out}, T_{6am} and T_{rm}). Significant correlations were also found between TSV and indoor and outdoor temperatures, but they were positive in this case. As for correlations between indoor environmental variables, only positive correlations were found between the temperatures ($T_{in\text{-}air}$, $T_{in\text{-}ra}$ and T_{op}). In addition, negative correlations were found between indoor temperatures and RH_{out} and positive ones with the outdoor temperatures T_{6am} and T_{out}. Among the outdoor environmental variables, significant positive correlations were found between temperatures (T_{out}, T_{rm} and T_{6am}), but only a strong negative correlation between T_{out} and RH_{out} ($\rho = -0.836$).

Table 6
Participants' characteristics.

	Number of respondents, N (%)	
Gender	Male	1267 (59 %)
	Female	848 (41 %)
Age	18–24	1822 (86 %)
	25–30	247 (12 %)
	+30	46 (2 %)

Table 7
Summary of the measured outdoor environmental parameters.

Parameter	T_{out} (°C)	T_{rm} (°C)	T_{6am} (°C)	RH_{out} (%)	V_{out} (m/s)
Mean	14.5	13.8	8.4	56.7	4.0
Standard Deviation	7.5	6.9	6.1	19.4	4.7
Minimum	0.0	5.16	0.0	14.0	0.0
Maximum	36.5	28.2	25.6	94.0	23.0

Table 8
Summary of the measured indoor environmental parameters.

Parameter	$T_{in\text{-}air}$ (°C)	$T_{in\text{-}rad}$ (°C)	T_{op} (°C)	RH_{in} (%)	V_{in} (m/s)
Mean	20.8	21.1	21.0	38.8	0.013
Standard Deviation	4.1	4.0	4,0	7.2	0.04
Minimum	14.1	14.7	14,5	19.6	<0.01
Maximum	29.2	29.6	29.3	54.0	0.22

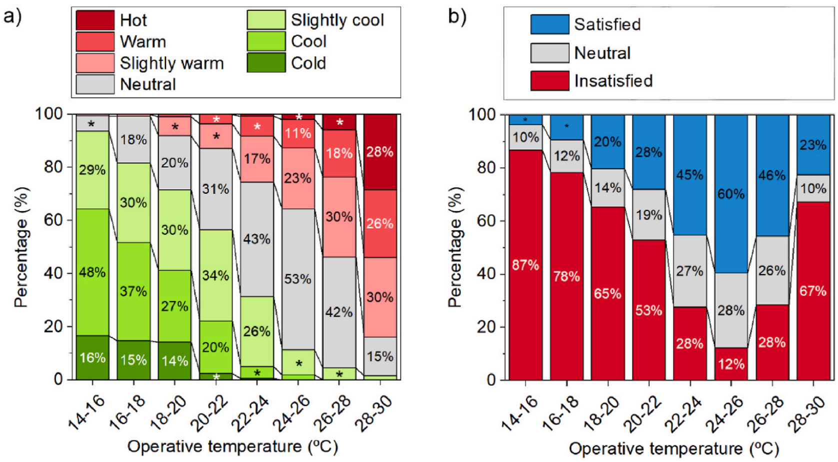

Fig. 5. a) Distribution of TSV at different indoor temperatures. b) Distribution of thermal satisfaction vote at different indoor temperatures. * indicates that the percentage is less than 10 %.

The clothing insulation variations with T_{op} are shown in Fig. 6a. In addition, the relationship between clothing insulation and T_{6am} is shown in Fig. 7b, since ASHRAE 55 proposed a clothing insulation prediction model based on this environmental parameter. To easily discriminate data trends, the average values of clothing insulation are also plotted against each of these environmental variables in Figs. 6b and 7b, respectively. As mentioned before, a negative correlation is confirmed between clothing insulation and both, T_{op} and T_{6am}. Figs. 6 and 7 show that occupants adjusted their clothing patterns: they wear lighter clothing when the thermal conditions become warmer. The adaptive effect of changes of clothing on T_{op} and T_{6am} evidenced the capacity of adaption of the occupants to the thermal environment. The regressions shown in Fig. 6b and 7b provide high R^2 values (0.65 and 0.64, respectively). The relationship between operative temperature and the level of clothing insulation in Mediterranean university classrooms has also been explored in previous studies. The studies conducted by Lamberti et al. [15] and Torriani et al. [63] found similar results to those obtained in this study (both studies reported R^2 values of 0.34 for the regression between the two variables).

3.3. Neutral temperature and comfort range evaluation

The responses obtained were analysed and compared with the indoor operative temperature, to identify when the indoor thermal environment was neutral (i.e., respondents did not feel cold or hot, TSV = 0). Fig. 8a and b shows the linear regression of TSV and mean TSV against indoor operative temperature, respectively. The slope of the linear regression determines the sensitivity of occupants to indoor temperature. In this study, the obtained neutral temperature was 23.0 °C. The comfort temperature (Fig. 9) was also calculated, based on the Griffith method, and a value of 22.1 ± 2.91 °C was obtained. As can be seen, the values of the neutral temperature and the Griffith temperature are close (only with a difference of 0.9 °C).

Previous studies in classrooms in the Mediterranean region have also explored neutral temperature based on questionnaire surveys. Aparicio et al. [64] found that, in primary schools, a neutral temperature was observed at average indoor temperatures of 24–27 °C. Aguilar et al. [65] conducted a field study during the cold season and found that neutral temperature was 23.8 °C. Lamberti et al. [15] conducted a field study in NV university classrooms in Italy (Mediterranean climate) and France (Continental climate) and found the neutral temperature to be 23.6 °C in Italy and 20.5 °C in France. Torriani et al. [63] compared thermal comfort at various school stages

Table 9
Spearman's correlation coefficient between environmental parameters and subjective thermal responses.

	TSaV	TSV	$T_{in\text{-}air}$	$T_{in\text{-}rad}$	T_{op}	RH_{in}	V_{in}	T_{out}	RH_{out}	V_{out}	T_{6am}	T_{rm}
Clothing insulation	−0.312**	**−0.523****	**−0.625****	**−0.629****	**−0.626****	0.207**	−0.212**	**−0.601****	0.452**	−0.171**	**−0.613****	**−0.640****
TSAV		**0.568****	0.382**	0.380**	0.385**	−0.022	0.043	0.295**	−0.184**	0.072**	0.321**	0.328**
TSV			**0.674****	**0.671****	**0.676****	−0.258**	0.139**	**0.568****	−0.434**	0.204**	**0.580****	**0.555****
$T_{in\text{-}air}$				**0.989****	**0.997****	−0.366**	0.190**	**0.787****	**−0.594****	0.338**	**0.792****	**0.837****
$T_{in\text{-}rad}$					**0.995****	−0.378**	0.204**	**0.795****	**−0.614****	0.360**	**0.792****	**0.845****
T_{op}						−0.365**	0.203**	**0.788****	**−0.594****	0.338**	**0.794****	**0.846****
RH_{in}							0.150**	−0.253**	**0.558****	−0.162**	−0.003	−0.111**
V_{in}								0.292**	−0.163**	0.092**	0.350**	0.387**
T_{out}									**−0.836****	0.490**	**0.749****	**0.741****
RH_{out}										−0.483**	−0.430**	−0.467**
V_{out}											0.195**	0.359**
T_{6am}												**0.859****

**Indicates that the correlation is significant at the 0.01 level.

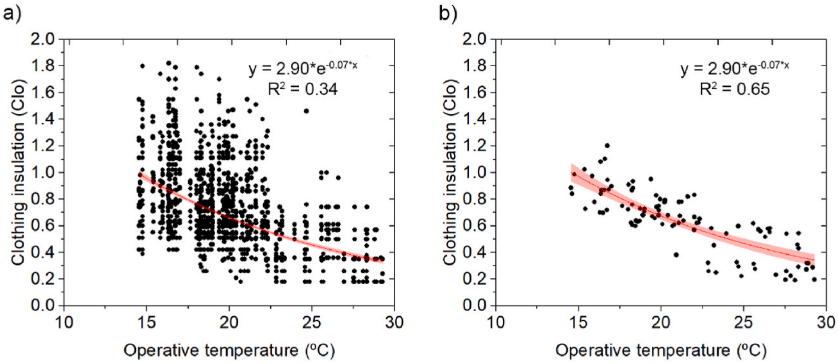

Fig. 6. a) Relationship between clothing insulation and T_{op}. b) Relationship between the average clothing insulation and $T_{op.}$ The red lines indicate the curve fit (95 % confidence interval).

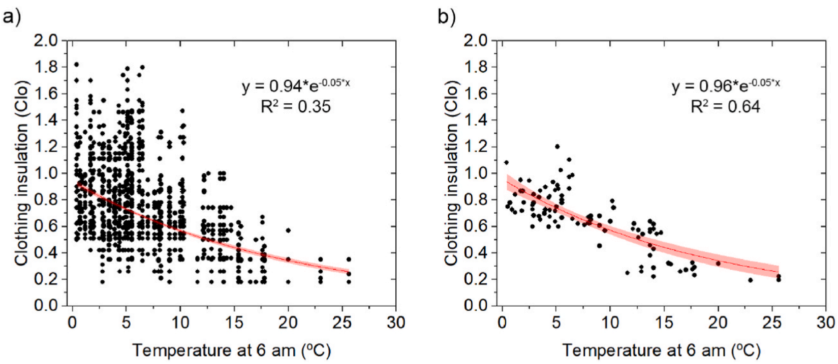

Fig. 7. a) Relationship between clothing insulation and T_{6am}. b) Relationship between the average clothing insulation and T_{6am}. The red lines indicate the curve fit (95 % confidence interval).

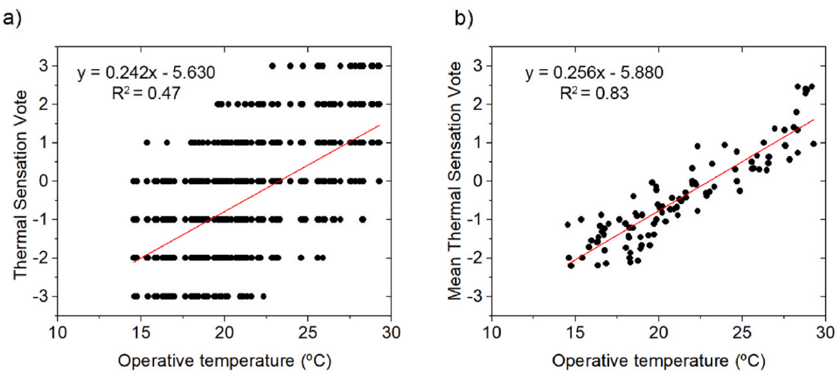

Fig. 8. a) Relationship between clothing insulation and T_{op}. b) Relationship between the average clothing insulation and T_{op}.

in Italy during winter and found the neutral temperature to be 23.6 °C in university classrooms. As can be seen, the neutral temperatures reported in these studies are close to the neutral temperature obtained in this study. Nevertheless, the neutral temperature obtained in this study is slightly lower than that reported by Refs. [15,63,65]. This difference may be due to the fact that the above-mentioned studies were carried out only during the cold season, so the results can be influenced by the warmer thermal preference of the occupants in cold climates or during heating period [15].

In terms of thermal sensitivity, the slope obtained in this study from the linear regression between operative temperature and TSV is steeper than that reported in Mediterranean university classrooms by Lamberti et al. [15] (0.18), Torriani et al. [63] (0.1751) and Aguilar et al. [65] (0.21). Thus, a higher thermal sensitivity of students to changes in indoor operative temperature is observed compared to previous studies mentioned above.

The obtained values of neutral temperature and comfort temperature are close to the temperature ranges established as thermal

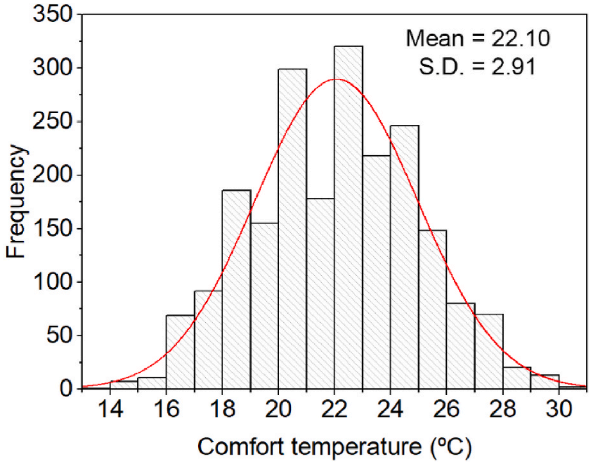

Fig. 9. Histogram of comfort temperature.

quality requirements in the Spanish Regulation on Building Heating Installations (RITE) [66]; according to this regulation, indoor operative temperature should range between 23 and 25 °C in the warm season and between 21 and 23 °C in the cool season.

Linear regression was also used to identify comfort temperature ranges. These ranges correspond with thermal comfort ratings of 90 % and 80 % and were calculated according to the relationship between the group mean TSV. A mean TSV of ±0.50 implies that 10 % of the occupants can be expected to vote 'dissatisfaction', while a TSV of ±0.85 implies 20 % [67]. The 90 % and 80 % comfort ranges obtained in this study were 21.0–24.9 °C and 19.7–26.3 °C, respectively. These thermal comfort range limits are lower than those reported by Lamberti et al. (22.7 °C-27.3 °C and 21.6°C-28.4 °C for the 90 % and 80 % comfort ranges, respectively) and Aguilar et al. (21.8°C-27.8 °C for the 80 % comfort range). Therefore, the values found by these studies [15,65] conducted in the cold season show a preference for warmer temperatures compared to those found in this study.

In addition, it should be noted that one aspect of university students that influence their thermal comfort experiences is their long-term thermal history. Jowkar et al. [13] explored the influence of university students' climatic background compared to the UK (i.e., cooler, similar or warmer climatic background) in university classrooms of Coventry (England) and Edinburgh (Scotland). The upper thermal acceptable limit obtained in our study using the minimum 80 % acceptability criterion (26.3 °C) is higher than those found by Jowkar et al. [13], for both groups of students (25.0 °C). This aspect may be due to the fact that the climate in Granada is warmer than the climate in Coventry and Edinburgh, and therefore the zone of thermal acceptability is slightly shifted to higher temperatures.

3.4. *Machine learning based models to predict thermal sensation*

Two predictive TSV models were generated, one based on an ANN algorithm and the other based on an RF algorithm. The same factors used as the input in the PMV were selected as inputs for the development of both machine learning models. The obtained statistical errors (MSE and MAE) are shown in Table 10. It is worth mentioning that the smaller the statistical error of the model, the better the prediction accuracy. As can be seen, the obtained values from the train and test of the RF model are slightly better than ANN model.

Fig. 10 shows the relationships between the predicted TSVs obtained from the machine learning developed models and the actual TSVs obtained from the questionnaire survey. The red line represents the fit curves of each model. These results allow further evaluation of the performance of each model, since the closer the fit line is to the bisector line (i.e., y = x), the better the performance of the model. If both models are compared, the regression line obtained from the ANN model is slightly closer to the bisector line than the regression line obtained from the RF model. The coefficient of determination of the RF model and the ANN model are very similar (R^2 = 0.58 and R^2 = 0.55, respectively).

In terms of the performance, this aspect was evaluated based on the comparison of all the values predicted by the proposed models and the entire set of actual TSV collected in the questionnaire survey. The MSE and MAE of the models was 0.90 and 0.79 for the ANN model, and 0.75 and 0.69 for the RF model, respectively. The correlation coefficients and R^2 values of both models were also calculated. If both models are compared, the RF model performs slightly better (R^2 = 0.58) than the ANN model (R^2 = 0.55). In terms of

Table 10
Statistical errors, correlation coefficients and R^2 values of each model.

Parameter	ANN model		RF model	
	Train	Test	Train	Test
R^2	0.56	0.55	0.64	0.58
Pearson	0.75	0.74	0.80	0.76
MSE	0.90	0.91	0.73	0.84
MAE	0.76	0.76	0.68	0.74

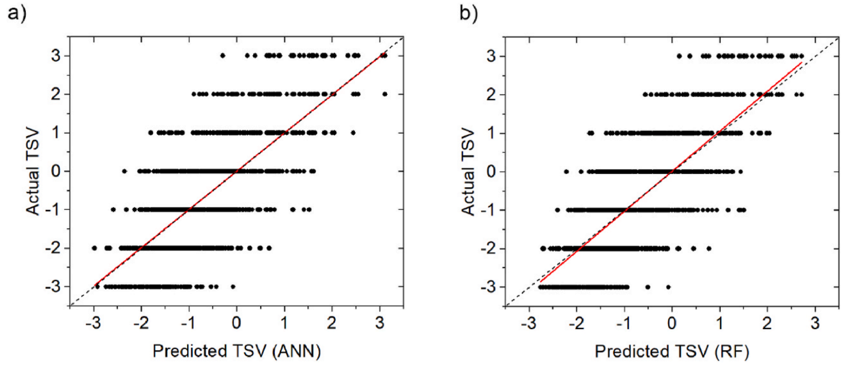

Fig. 10. a) Scatter plot of actual and predicted values of TSV using the ANN model. b) Scatter plot of actual and predicted values of TSV using the RF model.

Pearson coefficient, both models showed similar values (0.74 and 0.79 for the ANN model and RF model, respectively).

It should be highlighted that ANN and RF algorithms provide the potential for including input data from different types and sources (environmental, individual, etc.) and generating models to predict occupants' thermal perception. This approach has been used in previous studies, such as the one conducted by Chan and Chau [36], who developed ANN models for predicting thermal comfort in outdoor urban parks in Hong Kong. In this study, they defined two models of ANNs (winter and summer), using a multilayer perceptron with one hidden layer and the R^2 obtained were 0.357 and 0.281, respectively. Chai et al. [21] used different machine learning algorithm-based models to predict thermal sensation and comfort in NV residential buildings in different cities in China. The model generated using ANN provided the best performance (the reported R^2 and Pearson's correlation coefficient were 0.4872 and 0.6984, respectively).

A second important finding was that the obtained results highlighted the potential usefulness of ANN and RF algorithms to generate models for the assessment of TSV in educational buildings. However, it should be remarked that, since the output of the regression models is continuous and the distribution of the actual TSV is discrete (7-points integer scale), it makes it difficult to achieve a model with high accuracy. In this study, a continuous TSV output was selected to build the model because, although it results in more difficulties in implementing machine learning based TSV, it also makes it possible to analyse the occupants' TSV in more detail.

3.5. Comparison with static heat balance models

In this section, the values predicted by the proposed machine learning models and the actual TSVs are compared with the results obtained after applying traditional models based on the heat balance of the human body. This process pursued a double objective: on the one hand, it investigated the validity of traditional predictive models of thermal comfort in NV classrooms and, on the other hand, it compared their performance with that of the proposed models based on machine learning. For this purpose, the traditional predictive model PMV and the revised PMV methods (ePMV and aPMV) were also used to evaluate the indoor thermal environment.

A summary of the results obtained after applying the Fanger PMV model (ISO 7730) and the ePMV (assuming an expectation factor of 0.8, according to the climate of Granada) is shown in Table 11. In addition, the aPMV model proposed by Yao et al. [27] which reflects cultural, psychological and adaptive behavioural factors in the PMV using the black box method, was applied. The adaptive coefficient (λ) considered these factors and modified the PMV in order to improve prediction accuracy. In this study, the λ coefficient was calculated based on the occupants' TSV. The value of λ was 0.71 under warm conditions and −0.49 under cool conditions. The λ values reported by Yao et al. were 0.293 and −0.125 for warm and cool conditions, respectively. Values similar to those reported in this study were found by Liu et al. [68] (−0.49 and 0.21, based on analysis of a large sample survey with 11,524 subjects) and by Wang et al. [69] (−0.42 and 0.28, based on experimental measurements carried out in classrooms). A summary of the results obtained from the aPMV method is also shown in Table 11. Additionally, to facilitate a comparison, a summary of the results obtained from the actual TSVs and the values predicted by the proposed machine learning models have been included in Table 11. The ANN model, RF model and aPMV provided the closest mean values to the mean actual TSV.

Fig. 11 show the regression analysis between the actual TSVs and the values obtained from PMV, ePMV and aPMV. As the regression lines show, the PMV model predicts a lower thermal sensation compared to TSV (Fig. 11a). A similar conclusion is obtained

Table 11
Statistical summary of the actual TSV and the predicted results obtained from the models based on the human body heat balance and the proposed machine-learning models.

Parameter	Mean	S.D.	Median	Max	Min
Actual TSV	−0.55	1.42	−1.00	3.00	−3.00
ANN model	−0.56	1.06	−0.68	3.10	−2.98
RF model	−0.54	1.08	−0.62	2.72	−2.76
PMV	−0.88	0.93	−0.89	1.15	−3.96
ePMV	−0.71	0.75	−0.71	0.92	−3.17
aPMV	−0.54	0.55	−0.67	0.64	−2.42

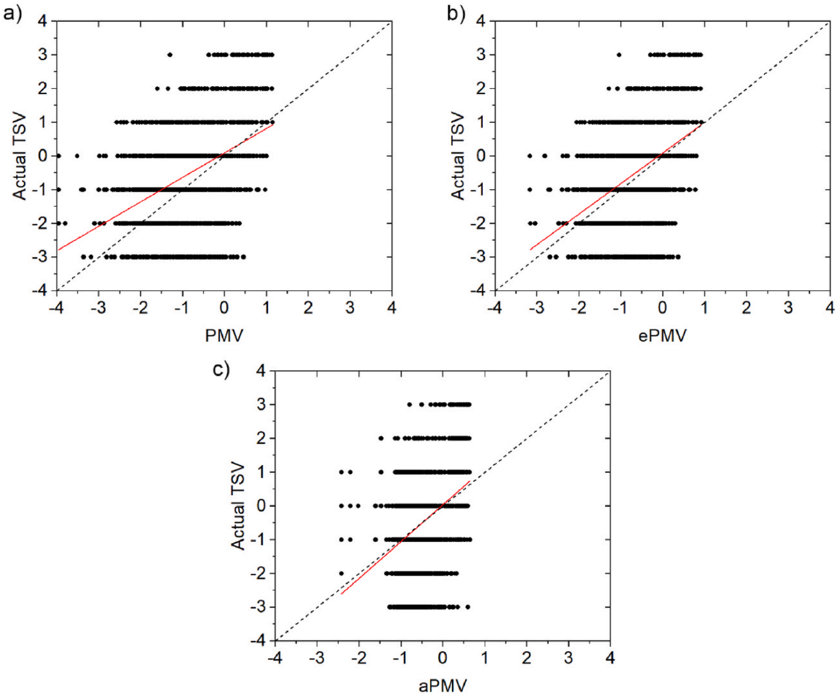

Fig. 11. a) Scatter plot of actual and predicted values of PMV. b) Scatter plot of actual and predicted values of ePMV. c) Scatter plot of actual and predicted values of aPMV.

when comparing the ePMV and TSV regression lines under warm conditions (Fig. 11b); however, the ePMV model predicts higher thermal sensation than the PMV in cool environments. Regarding the aPMV (Fig. 11c), the regression line shows that this model predicted higher thermal sensation votes compared to TSV under cool environments (TSV < -0.5). If the fitting equations shown in Fig. 11 are compared with the fitting equations shown in Fig. 10, it can be concluded that the proposed ANN and RF models outperform PMV, ePMV and aPMV.

In addition, to further compare the performance of the PMV, ePMV and aPMV models with the machine learning generated models, Table 12 shows the R^2, Pearson, MSE and MAE of each model. As derived from the values shown in the table, the ANN and RF models provide more accurate predictions than PMV, ePMV and aPMV. This conclusion is also evidenced in Fig. 12, which shows the error distribution profile obtained from each model. If the error profiles are analysed, a large difference can be seen between the traditional models and the ANN and RF models. The positive error indicates that the predicted value underestimates the actual value, while the negative error indicates that the predicted value overestimates the actual value. It is observed that the distribution of the error profile in the two developed machine learning models is very similar. In the case of the RF model, 44 % of the predicted TSVs deviate less than 0.5 from the actual TSV. For the ANN model, this percentage drops to 40 %. In contrast, the PMV, ePMV and aPMV models have a more distributed error profile, concentrating only 29 %, 29 % and 30 % of the errors in the range -0.5 to 0.5, respectively. Furthermore, PMV and ePMV show a clear and positive deviation, indicating that these models underestimate TSV.

Finally, the results obtained from the evaluation carried out by each model were used to calculate the neutral temperature (Table 13). For this purpose, the relationship between the mean obtained values and the operative temperatures were analysed. The comparison of the deviations of the thermal acceptability ranges, with respect to the acceptable range obtained from the actual TSVs, shows that both the ANN model and RF model provided the most similar acceptability ranges. As for the other methods, the closest limit was provided by aPMV (lower limit for TSV $= -0.5$) and ePMV (lower limit for TSV $= -0.85$). The values obtained show that the PMV, ePMV and aPMV, in general, do not provide close limits of thermal acceptability to those obtained from the actual TSVs.

It should be noted that, although the developed ANN model and RF model outperform the PMV model, they cannot be used as a reliable predictor in other different circumstances (i.e., different activities, cultures, climatic zones, etc.). Cultural aspects and climatic conditions influence individual parameters, such as clothing insulation. The models developed in this study constitute a tool to

Table 12
Comparison of models' performance with respect to the actual TSV.

Parameter	PMV	ePMV	aPMV	ANN model	RF model
R^2	0.23	0.23	0.18	0.55	0.58
Pearson	0.48	0.48	0.42	0.74	0.79
MSE	1.74	1.59	1.67	0.90	0.75
MAE	1.06	1.02	1.04	0.76	0.69

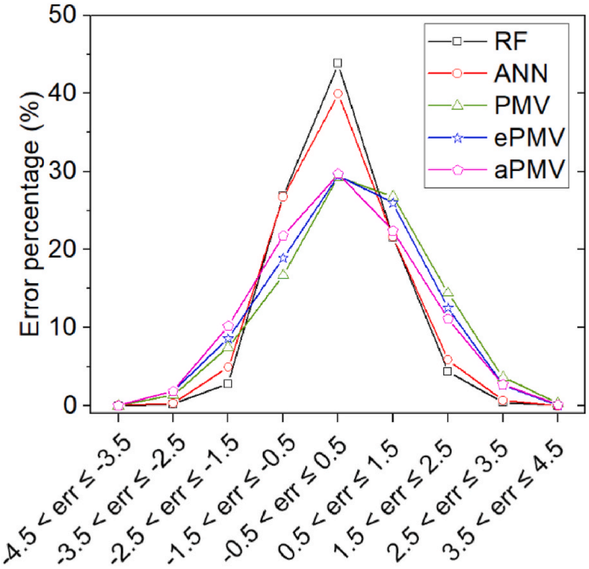

Fig. 12. Error distribution profiles of the PMV, ePMV, aPMV, ANN model and RF model.

Table 13
Regression analysis of operative temperature and each predictive model.

Parameter	Lineal regression equation	R^2	Tn	Acceptable range (±0.5)	Acceptable range (±0.85)
TSV	TSV = 0.256 T_{op} – 5.880	0.83	23.0	21.0–24.9	19.7–26.3
PMV	PMV = 0.181 T_{op} – 4.728	0.81	26.1	23.4–28.9	21.4–30.8
ePMV	ePMV = 0.145 T_{op} – 3.782	0.81	26.1	22.6–29.5	20.2–31.9
aPMV	aPMV = 0.089 T_{op} – 2.443	0.55	27.4	21.8–33.1	17.9–37.0
ANN model	ANN = 0.245 T_{op} – 5.660	0.87	23.1	21.1–25.1	19.6–26.6
RF model	RF = 0.244 T_{op} – 5.641	0.85	23.1	21.1–25.2	19.6–26.6

complement the PMV model and can be implemented in National Standards and contribute to the knowledge of thermal conditions in NV educational buildings.

3.6. Adaptive thermal comfort models

In this study, and adaptive thermal comfort model was calculated based on the TSVs obtained from the questionnaire survey, the indoor comfort temperature and the running mean temperature. The comfort bands were determined using ±0.85 and ± 0.50 TSVs, since these values describe 80 % and 90 % of the acceptability limits, respectively. The obtained thermal comfort regression equation and the upper and lower limits for each band are shown in Table 14. This analysis showed that the comfort temperature changes as outdoor environmental conditions change. The slope in the thermal comfort regression equation reflects the rate of its change as the outdoor conditions vary. A lower rate means that occupants adapt more slowly to the outdoor environmental conditions, while a higher rate means that they adapt more quickly.

Fig. 13 shows the linear regression obtained from comfort temperature versus the running mean temperature. The thermal comfort equation provided by ASHRAE 55 and EN 16798 are also compared with these results. The comfort temperature obtained in this study is lower than that indicated by the model defined in the EN 16798 Standard, showing a similar slope in both comfort temperature equations. In contrast, although the comfort temperature equation found in this study is more similar to the thermal comfort temperature model defined in the ASHRAE 55 Standard, the slope of the obtained equation is steeper, resulting in the comfort temperature obtained in this study being slightly lower for the cooler T_{rm} values and slightly higher for the warmer values. These differences are shown in Fig. 13.

The adaptive model developed from the data collected in this study can be compared with the adaptive comfort models defined in EN 16798 and ASHRAE 55 (Fig. 14). Fig. 14a shows the comparison of the comfort model from the current study with the EN 16798 adaptive model. It can be seen that the 90 % and 80 % comfort bands obtained in this study are lower than the upper limits of categories I and II, and practically lower than category III at almost all of the T_{rm} values. This fact reflects a cooler preference on the part of the students than those indicated by the EN 16798 adaptive model. This finding is in line with previous studies conducted in educational buildings, where it was reported that a lower temperature environment is preferred by students [70–72].

The comparison of the comfort bands obtained in this study, with the 80 % and 90 % acceptability limits of ASHRAE-55 (Fig. 14b), shows that both methods have relatively close limit equations. The 90 % comfort band obtained in this study is narrow compared to the ASHRAE-55 90 % comfort band: under cold outdoor environmental conditions, the 90 % upper limit of our proposed model is more

Table 14
Band limit obtained for the proposed adaptive thermal comfort model.

Category	Limit	Equation
Central	Comfort	$T_c = 0.384\ T_{rm} + 16.252$
90 %	Upper band	$T_c = 0.384\ T_{rm} + 18.212$
	Lower band	$T_c = 0.384\ T_{rm} + 14.292$
80 %	Upper limit	$T_c = 0.384\ T_{rm} + 19.572$
	Lower limit	$T_c = 0.384\ T_{rm} + 12.932$

*T_c stands for comfort temperature and T_{rm} stands for running mean temperature.

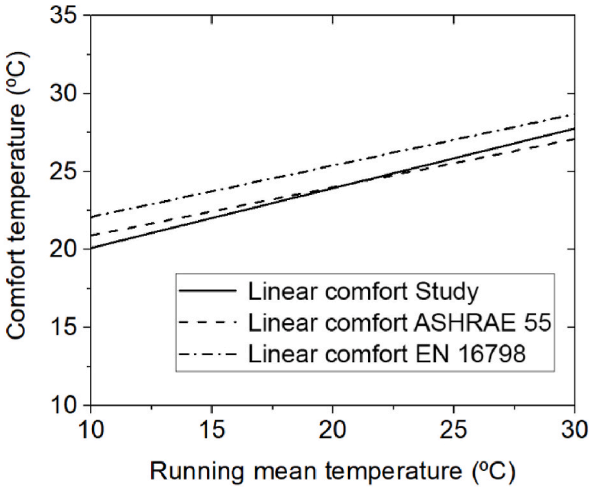

Fig. 13. Linear regression of comfort temperature with running mean temperature.

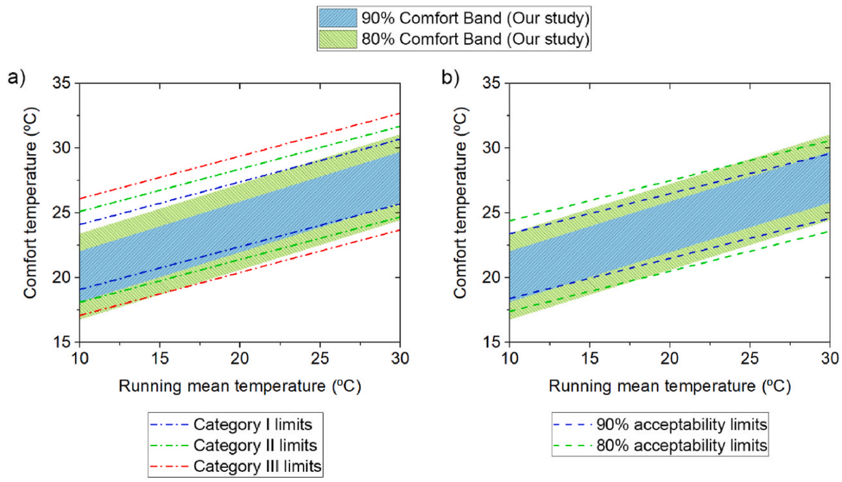

Fig. 14. a) Comparison of comfort bands obtained in this study and EN-16798 thermal acceptability limits. b) Comparison of comfort bands obtained in this study and those defined in ASHRAE-55.

restrictive than the same limit of ASHARE 55. On the contrary, under warm outdoor environmental conditions, the lower limit of the 90 % comfort band is more restrictive than the ASHRAE 55 90 % lower limit comfort band. Consequently, the comfort band obtained in this study is narrower and the obtained limits have a steeper slope, evidencing a quicker adaptation of students to the environmental conditions. In terms of the 80 % comfort band, similar differences can be observed. Under cold environmental conditions, the lower limit of the proposed adaptive model is lower than the lower 80 % limit defined in ASHRAE 55, while the opposite case can be found for the upper 80 % limit when environmental conditions are warmer.

The results obtained from the proposed model indicate that, when outdoor environmental conditions are warm (T_{rm}>23.4 °C), even if the indoor temperature is warmer than that indicated by the ASHRAE-55 adaptive model, the percentage of dissatisfied occupants will not exceed 20 %. Similarly, under cold outdoor environmental conditions (T_{rm}<18.5 °C), the percentage of dissatisfied occupants will not exceed 20 %, even if temperatures are lower than those suggested by the ASHRAE adaptive thermal comfort model.

Moreover, a comparison with existing studies has shown that few studies have focused on the development of adaptive thermal comfort models in Mediterranean university buildings. In this context, Lamberti et al. [15] explored the adaptation of Italian university classroom occupants during winter and the relationship found between neutral temperature and T_{rm} is shown in (Eq. (10)).

$$y = 0.25\,x + 19.63 \tag{10}$$

This relationship (Eq. (10)) shows a lower slope than that found in this study (Table 14). Nevertheless, among the limitations point out by Lamberti et al. [15] is the narrow range of T_{rm} collected in their study because it was only conducted during the winter season. This issue influences their findings. The thermal acceptability ranges of the adaptive thermal comfort models vary from one climate region to another and depend on the type of educational building (primary, secondary and university) [72]. In fact, Singh et al. [72] highlighted that university students have a greater degree of freedom to take adaptive actions. Therefore, the development of studies in different climatic zones is essential to generate reliable adaptive models, especially in the Mediterranean region where very few studies address this issue.

Furthermore, in Spain, the current version of the RITE standard does not consider the adaptive thermal comfort model approach and does not differentiate between operating modes (NV, AC or MM) and types of buildings (residential, educational, etc.) Although the widely used EN 16798 and ASHRAE-55 standards include this approach, the adaptive capacity suggested in the models of both standards is lower than that found in this study.

In this context, these findings are especially relevant for the management and maintenance of educational buildings. As mentioned in Section 1, the cooling/heating energy demand required to ensure a comfortable indoor environment accounts for a high percentage of the building's energy consumption. Adapting the set point temperatures, based on the application of the proposed model, could reduce the heating and cooling energy demand in the cold season and warm season, respectively. More studies are needed where the research approach used in this study is applied to generate models that take into account the particular local conditions of each space.

Finally, it should be noted that the field measurements were conducted during normal operation of the classrooms and students were free to adapt (they could choose their seat and open/close windows and doors). This study aims to analyse to proposed thermal comfort models, based on machine learning algorithms and the adaptative approach, which can be used as a reliable tool to assess indoor thermal conditions and maximize the number of comfortable occupants in higher educational buildings. Nevertheless, since individual factor (such as physical, psychological and behavioural) can influence the thermal experience of the students, future studies are needed to include these factors in the design of individual thermal comfort models based on machine learning.

4. Conclusions

In this study, the indoor environmental conditions of NV classrooms in Southern Spain were investigated. A field measurement campaign, which included environmental measurements conducted simultaneously with a questionnaire survey, was carried out during the academic year 2021/2022 (September to June). The following conclusions can be drawn from the results obtained.

- The field measurements revealed that, when indoor operative temperature was 24–26 °C, more than 80 % of the students rated indoor environment as 'slightly cool', 'neutral' or 'slightly warm' and less than 20 % of students were dissatisfied. The minimum 90 % and 80 % acceptability criterion were used to define the thermally acceptable zones. The neutral temperature obtained in this study was 23.0 °C and the comfort temperature ranges, determined assuming thermal comfort ratings of 90 % and 80 %, were 21.0–24.9 °C and 19.7–26.3 °C, respectively. The 80 % acceptability range obtained in this study is considerably wider than the indoor temperature range required in building design by the Spanish RITE standard. This fact shows the limitations of the Spanish regulation, which does not consider the adaptive behaviour of occupants in NV buildings and does not differentiate between the different mode of operation (NV, AC or MM) and the different uses of buildings (residential, educational, offices, etc.).
- In terms thermal comfort, ML-based models provided higher accuracy than traditional statics methods (PMV, ePMV and aPMV).The comparison of the deviations of the thermal acceptability ranges evidenced that the traditional methods, in general, do not provide thermal acceptability limits close to those obtained from the actual TSVs. Comparison of these results with those obtained by applying the developed ANN model and RF model shows that the latter outperform the PMV, ePMV and aPMV. The proposed ML model can contribute to the knowledge of thermal conditions in NV higher educational buildings.
- The proposed adaptive thermal comfort model and the obtained comfort temperature equation provide lower temperature values than the adaptive comfort model defined in the EN-16798 Standard. These results suggest that students preferred an environment with lower temperatures than those suggested by the EN-16798 adaptive model. In addition, the slope of the thermal comfort equation obtained in this study is steeper than that in the ASHRAE-55 adaptive comfort model. This fact evidences a greater adaptive capacity of students to changes in environmental conditions than what is suggested by the ASHRAE-55 adaptive comfort model. As a result, the proposed adaptive comfort model shows that, under warm thermal conditions, the upper 80 % thermal limit is higher; while under cooler conditions, the lower 80 % thermal comfort limit is lower.

In summary, this research provides new information about the applicability of the static thermal comfort model in NV classrooms and compared their performance with newly proposed models, based on machine learning algorithms. From the obtained results and discussion, it can be concluded that the development of an ANN-model and RF-model to predict the TSV evaluation is a relevant tool to analyse indoor environmental conditions and assess their potential impact on the occupants of higher educational buildings. In addition, the developed adaptive thermal comfort model showed that: under warm environmental conditions (T_{rm}>23.4 °C), 80 % of the occupants would still be thermally comfortable at temperatures above those suggested by the 80 % upper band limit defined in ASHRAE-55; for cold environmental conditions (T_{rm}<18.5 °C) 80 % of occupants would still be thermally comfortable at temperatures below those suggested by the 80 % lower band limit defined in ASHRAE 55. The thermal requirements established in the Spanish regulations for the design of higher education buildings do not consider the adaptive approach and set more restrictive limits than those found in the proposed model. In this context, the application of the developed adaptive thermal comfort model in those temperature ranges would contribute to reduce the heating and cooling energy demand during the cold and warm season and, consequently, its application can contribute to making buildings more resilient, reducing energy consumption at the same time as ensuring suitable indoor environmental conditions.

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CRediT authorship contribution statement

María Luisa de la Hoz-Torres: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Antonio J. Aguilar:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Diego P. Ruiz:** Writing – review & editing, Resources, Project administration, Funding acquisition, Conceptualization. **Mª Dolores Martínez-Aires:** Writing – review & editing, Resources, Project administration, Funding acquisition, Conceptualization.

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 authors do not have permission to share data.

APPENDIX A

Table A1
Summary of the measured outdoor-indoor environmental parameters during measured campaign by season.

Season		Parameter	Mean	SD	Min.	Max.
Autumn	**Outdoor**	**T_{out} (°C)**	11,70	6,30	2,10	30,30
		RH_{out} (%)	59,90	19,30	16,00	94,00
		V_{out} (m/s)	4,61	5,02	0,00	23,00
	Indoor	**T_{op} (°C)**	19,9	3,4	14,5	28,30
		RH_{in} (%)	38,4	6,7	19,6	50,10
		V_{in} (m/s)	0,04	0,04	0,00	0,19
Winter	**Outdoor**	**T_{out} (°C)**	9,80	4,50	0,00	15,00
		RH_{out} (%)	63,90	17,10	40,80	91,00
		V_{out} (m/s)	2,61	4,10	0,00	20,36
	Indoor	**T_{op} (°C)**	17,80	2,10	14,60	22,20
		RH_{in} (%)	39,00	4,40	32,50	47,80
		V_{in} (m/s)	0,01	0,02	0,00	0,08
Spring	**Outdoor**	**T_{out} (°C)**	19,50	6,50	9,00	36,50
		RH_{out} (%)	52,50	19,30	14,00	93,50
		V_{out} (m/s)	2,56	3,07	0,00	15,10
	Indoor	**T_{op} (°C)**	23,10	3,50	18,30	29,30
		RH_{in} (%)	41,40	8,80	21,30	54,00
		V_{in} (m/s)	0,04	0,03	0,01	0,11
Summer	**Outdoor**	**T_{out} (°C)**	23,10	4,80	18,30	33,00
		RH_{out} (%)	41,30	11,90	21,30	58,00
		V_{out} (m/s)	6,35	5,38	1,00	23,00
	Indoor	**T_{op} (°C)**	26,10	2,10	22,90	29,20
		RH_{in} (%)	35,00	7,60	23,50	46,00
		V_{in} (m/s)	0,08	0,07	0,01	0,22

References

[1] ASHRAE 55-2020, Thermal Environmental Conditions for Human Occupancy, 2020.

[2] ISO, ISO 7730:2005, Ergonomics of the Thermal Environment — Analytical Determination and Interpretation of Thermal Comfort Using Calculation of the PMV and PPD Indices and Local Thermal Comfort Criteria, 2005.

[3] R.T. Fleiter, M. Elsland, J. Rehfeldt, U. Steibach, G. Reiter, F. Dittman Catenazzi, Heat Roadmap Europe: EU Profile of Heating and Cooling Demand in 2015, 2017. www.heatroadmap.eu. (Accessed 10 October 2023).

[4] Y. Zhai, A. Honnekeri, M. Pigman, M. Fountain, H. Zhang, X. Zhou, E. Arens, Use of adaptive control and its effects on human comfort in a naturally ventilated office in Alameda, California, Energy Build. 203 (2019) 109435, https://doi.org/10.1016/J.ENBUILD.2019.109435.

[5] Z. Wu, N. Li, P. Wargocki, J. Peng, J. Li, H. Cui, Field study on thermal comfort and energy saving potential in 11 split air-conditioned office buildings in Changsha, China, Energy 182 (2019) 471–482, https://doi.org/10.1016/J.ENERGY.2019.05.204.

[6] M. Khoshbakht, Z. Gou, F. Zhang, A pilot study of thermal comfort in subtropical mixed-mode higher education office buildings with different change-over control strategies, Energy Build. 196 (2019) 194–205, https://doi.org/10.1016/J.ENBUILD.2019.05.030.

[7] S.A. Damiati, S.A. Zaki, H.B. Rijal, S. Wonorahardjo, Field study on adaptive thermal comfort in office buildings in Malaysia, Indonesia, Singapore, and Japan during hot and humid season, Build. Environ. 109 (2016) 208–223, https://doi.org/10.1016/J.BUILDENV.2016.09.024.

[8] A.J. Aguilar, M.L. de la Hoz-Torres, L. Oltra-Nieto, D.P. Ruiz, M.D. Martínez-Aires, Impact of COVID-19 protocols on IEQ and students' perception within educational buildings in Southern Spain, Build. Res. Inf. 50 (2022) 755–770, https://doi.org/10.1080/09613218.2022.2082356.

[9] N. Bhandari, S. Tadepalli, P. Gopalakrishnan, Influence of non-uniform distribution of fan-induced air on thermal comfort conditions in university classrooms in warm and humid climate, India, Build. Environ. 238 (2023) 110373, https://doi.org/10.1016/J.BUILDENV.2023.110373.

[10] C. Heracleous, A. Michael, A. Savvides, C. Hayles, Climate change resilience of school premises in Cyprus: an examination of retrofit approaches and their implications on thermal and energy performance, J. Build. Eng. 44 (2021) 103358, https://doi.org/10.1016/J.JOBE.2021.103358.

[11] X. Wang, L. Yang, S. Gao, S. Zhao, Y. Zhai, Thermal comfort in naturally ventilated university classrooms: a seasonal field study in Xi'an, China, Energy Build. 247 (2021) 111126, https://doi.org/10.1016/J.ENBUILD.2021.111126.

[12] H. Ikeda, T. Nakaya, A. Nakagawa, Y. Maeda, An investigation of indoor thermal environment in semi-cold region in Japan – validity of thermal predictive indices in Nagano during the summer season, J. Build. Eng. 35 (2021) 101897, https://doi.org/10.1016/J.JOBE.2020.101897.

[13] M. Jowkar, R. de Dear, J. Brusey, Influence of long-term thermal history on thermal comfort and preference, Energy Build. 210 (2020) 109685, https://doi.org/10.1016/J.ENBUILD.2019.109685.

[14] M.L. de la Hoz-Torres, A.J. Aguilar, N. Costa, P. Arezes, D.P. Ruiz, M.D. Martínez-Aires, Reopening higher education buildings in post-epidemic COVID-19 scenario: monitoring and assessment of indoor environmental quality after implementing ventilation protocols in Spain and Portugal, Indoor Air 32 (2022) e13040, https://doi.org/10.1111/INA.13040.

[15] G. Lamberti, F. Leccese, G. Salvadori, F. Contrada, A. Kindinis, Investigating the effects of climate on thermal adaptation: a comparative field study in naturally ventilated university classrooms, Energy Build. 294 (2023) 113227, https://doi.org/10.1016/J.ENBUILD.2023.113227.

[16] R. Rawal, Y. Shukla, V. Vardhan, S. Asrani, M. Schweiker, R. de Dear, V. Garg, J. Mathur, S. Prakash, S. Diddi, S.V. Ranjan, A.N. Siddiqui, G. Somani, Adaptive thermal comfort model based on field studies in five climate zones across India, Build. Environ. 219 (2022) 109187, https://doi.org/10.1016/J.BUILDENV.2022.109187.

[17] A. Bassoud, H. Khelafi, A.M. Mokhtari, A. Bada, Evaluation of summer thermal comfort in arid desert areas. Case study: old adobe building in Adrar (South of Algeria), Build. Environ. 205 (2021) 108140, https://doi.org/10.1016/J.BUILDENV.2021.108140.

[18] S. Sharifi, W. Saman, A. Alemu, Identification of overheating in the top floors of energy-efficient multilevel dwellings, Energy Build. 204 (2019) 109452, https://doi.org/10.1016/J.ENBUILD.2019.109452.

[19] Z. Wu, N. Li, P. Wargocki, J. Peng, J. Li, H. Cui, Adaptive thermal comfort in naturally ventilated dormitory buildings in Changsha, China, Energy Build. 186 (2019) 56–70, https://doi.org/10.1016/J.ENBUILD.2019.01.029.

[20] H. Liu, Y. Wu, B. Li, Y. Cheng, R. Yao, Seasonal variation of thermal sensations in residential buildings in the Hot Summer and Cold Winter zone of China, Energy Build. 140 (2017) 9–18, https://doi.org/10.1016/J.ENBUILD.2017.01.066.

[21] Q. Chai, H. Wang, Y. Zhai, L. Yang, Using machine learning algorithms to predict occupants' thermal comfort in naturally ventilated residential buildings, Energy Build. 217 (2020) 109937, https://doi.org/10.1016/J.ENBUILD.2020.109937.

[22] G. Brager, R. de Dear, A Standard for Natural Ventilation, Center for the Built Environment., UC Berkeley, 2000. https://escholarship.org/uc/item/3f73w323. (Accessed 10 October 2023).

[23] M. Humphreys, Field Studies and Climate Chamber Experiments in Thermal Comfort Research, Standard for Thermal Comfort, 1994, https://doi.org/10.18948/SHASETAIKAI.2000.3.0_1189.

[24] M.L. de la Hoz-Torres, A.J. Aguilar, N. Costa, P. Arezes, D.P. Ruiz, M.D. Martínez-Aires, Predictive model of clothing insulation in naturally ventilated educational buildings, Buildings 13 (2023) 1002, https://doi.org/10.3390/BUILDINGS13041002, 13 (2023) 1002.

[25] T. Cheung, S. Schiavon, T. Parkinson, P. Li, G. Brager, Analysis of the accuracy on PMV – PPD model using the ASHRAE global thermal comfort Database II, Build. Environ. 153 (2019) 205–217, https://doi.org/10.1016/J.BUILDENV.2019.01.055.

[26] P. Ole Fanger, J. Toftum, Extension of the PMV model to non-air-conditioned buildings in warm climates, Energy Build. 34 (2002) 533–536, https://doi.org/10.1016/S0378-7788(02)00003-8.

[27] R. Yao, B. Li, J. Liu, A theoretical adaptive model of thermal comfort – adaptive Predicted Mean Vote (aPMV), Build. Environ. 44 (2009) 2089–2096, https://doi.org/10.1016/J.BUILDENV.2009.02.014.

[28] EN 16798-1:2019, Energy Performance of Buildings - Ventilation for Buildings - Part 1: Indoor Environmental Input Parameters for Design and Assessment of Energy Performance of Buildings Addressing Indoor Air Quality, Thermal Environment, Lighting and Acoustics - Module M1-6, 2019. https://www.une.org/encuentra-tu-norma/busca-tu-norma/norma?c=N0063261. (Accessed 10 October 2023).

[29] R.J. de Dear, Gail Schiller Brager, J. Reardon, F. Nicol, Developing an Adaptive Model of Thermal Comfort and Preference/Discussion, 1998. https://www.proquest.com/openview/bd3427db1cb55e6e9ab20d3099a6d8e4/1?casa_token=mTIjis8HTaoAAAAA:vFxjgMTuCMF8gEME3_z0d-aWEZwVbW8ttZzRnOXQuYkSyBUGV-UPP1NN_UHghrElQKgawCRDujk&cbl=34619&pq-origsite=gscholar&parentSessionId=7v9tt3Ub07df94KSGXf1j3vX7DOp3JS8SuoBwzBKCQQ%3D. (Accessed 10 October 2023).

[30] N.M. Abd Rahman, L.C. Haw, A. Fazlizan, A. Hussin, M.S. Imran, Thermal comfort assessment of naturally ventilated public hospital wards in the tropics, Build. Environ. 207 (2022) 108480, https://doi.org/10.1016/J.BUILDENV.2021.108480.

[31] Z. Wang, R. de Dear, M. Luo, B. Lin, Y. He, A. Ghahramani, Y. Zhu, Individual difference in thermal comfort: a literature review, Build. Environ. 138 (2018) 181–193, https://doi.org/10.1016/J.BUILDENV.2018.04.040.

[32] B. Chenari, J. Dias Carrilho, M. Gameiro Da Silva, Towards sustainable, energy-efficient and healthy ventilation strategies in buildings: a review, Renew. Sustain. Energy Rev. 59 (2016) 1426–1447, https://doi.org/10.1016/J.RSER.2016.01.074.

[33] G. Guevara, G. Soriano, I. Mino-Rodriguez, Thermal comfort in university classrooms: an experimental study in the tropics, Build. Environ. 187 (2021) 107430, https://doi.org/10.1016/J.BUILDENV.2020.107430.

[34] M. Frontczak, P. Wargocki, Literature survey on how different factors influence human comfort in indoor environments, Build. Environ. 46 (2011) 922–937, https://doi.org/10.1016/J.BUILDENV.2010.10.021.

[35] S.P. Corgnati, M. Filippi, S. Viazzo, Perception of the thermal environment in high school and university classrooms: subjective preferences and thermal comfort, Build. Environ. 42 (2007) 951–959, https://doi.org/10.1016/J.BUILDENV.2005.10.027.

[36] S.Y. Chan, C.K. Chau, Development of artificial neural network models for predicting thermal comfort evaluation in urban parks in summer and winter, Build. Environ. 164 (2019) 106364, https://doi.org/10.1016/J.BUILDENV.2019.106364.

[37] A.O. Mahgoub, S. Gowid, S. Ghani, Global evaluation of WBGT and SET indices for outdoor environments using thermal imaging and artificial neural networks, Sustain. Cities Soc. 60 (2020) 102182, https://doi.org/10.1016/J.SCS.2020.102182.
[38] Z. Wu, N. Li, J. Peng, H. Cui, P. Liu, H. Li, X. Li, Using an ensemble machine learning methodology-Bagging to predict occupants' thermal comfort in buildings, Energy Build. 173 (2018) 117–127, https://doi.org/10.1016/J.ENBUILD.2018.05.031.
[39] Q.Y. Li, J. Han, L. Lu, A random forest classification algorithm based personal thermal sensation model for personalized conditioning system in office buildings, Comput. J. 64 (2021) 500–508, https://doi.org/10.1093/COMJNL/BXAA165.
[40] Z. Wang, H. Yu, M. Luo, Z. Wang, H. Zhang, Y. Jiao, Predicting older people's thermal sensation in building environment through a machine learning approach: modelling, interpretation, and application, Build. Environ. 161 (2019) 106231, https://doi.org/10.1016/J.BUILDENV.2019.106231.
[41] T. Chaudhuri, D. Zhai, Y.C. Soh, H. Li, L. Xie, Random forest based thermal comfort prediction from gender-specific physiological parameters using wearable sensing technology, Energy Build. 166 (2018) 391–406, https://doi.org/10.1016/J.ENBUILD.2018.02.035.
[42] Z. Qavidel Fard, Z.S. Zomorodian, S.S. Korsavi, Application of machine learning in thermal comfort studies: a review of methods, performance and challenges, Energy Build. 256 (2022) 111771, https://doi.org/10.1016/J.ENBUILD.2021.111771.
[43] L.A. López-Pérez, J.J. Flores-Prieto, C. Ríos-Rojas, Comfort temperature prediction according to an adaptive approach for educational buildings in tropical climate using artificial neural networks, Energy Build. 251 (2021) 111328, https://doi.org/10.1016/J.ENBUILD.2021.111328.
[44] AEMET, State Meteorological Agency. Spanish Goverment (n.d.), www.aemet.es/. (Accessed 21 October 2023).
[45] A. Chazarra, B. Belinda, L. Mariño, R. Romero, F. José, V. Moreno García, Arcimis: evolución de los climas de Köppen en España en el periodo 1951-2020. https://doi.org/10.31978/666-22-011-4, 2022.
[46] W. Health Organization Regional Office for Europe, School Environment: Policies and Current Status, 2015. http://www.euro.who.int/pubrequest. (Accessed 21 October 2023).
[47] ISO 28802:2012, Ergonomics of the Physical Environment — Assessment of Environments by Means of an Environmental Survey Involving Physical Measurements of the Environment and Subjective Responses of People, 2012. https://www.iso.org/standard/44964.html. (Accessed 21 October 2023).
[48] K. Nagano, A. Takaki, M. Hirakawa, Y. Tochihara, Effects of ambient temperature steps on thermal comfort requirements, Int. J. Biometeorol. 50 (2005) 33–39, https://doi.org/10.1007/S00484-005-0265-3/FIGURES/6.
[49] ISO 7726:1998, Ergonomics of the Thermal Environment — Instruments for Measuring Physical Quantities, 1998. https://www.iso.org/standard/14562.html. (Accessed 21 October 2023).
[50] S. Kumar, M.K. Singh, A. Mathur, M. Košir, Occupant's thermal comfort expectations in naturally ventilated engineering workshop building: a case study at high metabolic rates, Energy Build. 217 (2020) 109970, https://doi.org/10.1016/J.ENBUILD.2020.109970.
[51] S. Haddad, A. Synnefa, M. Ángel Padilla Marcos, R. Paolini, S. Delrue, D. Prasad, M. Santamouris, On the potential of demand-controlled ventilation system to enhance indoor air quality and thermal condition in Australian school classrooms, Energy Build. 238 (2021) 110838, https://doi.org/10.1016/J.ENBUILD.2021.110838.
[52] M.S.J. Talukdar, T.H. Talukdar, M.K. Singh, M.A. Baten, M.S. Hossen, Status of thermal comfort in naturally ventilated university classrooms of Bangladesh in hot and humid summer season, J. Build. Eng. 32 (2020) 101700, https://doi.org/10.1016/J.JOBE.2020.101700.
[53] K. l Hsu, H.V. Gupta, S. Sorooshian, Artificial neural network modeling of the rainfall-runoff process, Water Resour. Res. 31 (1995) 2517–2530, https://doi.org/10.1029/95WR01955.
[54] R. Hecht-Nielsen, Kolmogorov's Mapping Neural Network Existence Theorem, 2018.
[55] J.W. Moon, Performance of ANN-based predictive and adaptive thermal-control methods for disturbances in and around residential buildings, Build. Environ. 48 (2012) 15–26, https://doi.org/10.1016/J.BUILDENV.2011.06.005.
[56] J. Yang, H. Rivard, R. Zmeureanu, On-line building energy prediction using adaptive artificial neural networks, Energy Build. 37 (2005) 1250–1259, https://doi.org/10.1016/J.ENBUILD.2005.02.005.
[57] Stuart Russell, Norving Peter, Artificial Intelligence A Modern Approach, third ed., 2010.
[58] R.O. Duda, P.E. Hart, D.G. Stork, Pattern Classiication and Scene Analysis, second ed., Part 1: Pattern Classiication, 1995.
[59] L. Breiman, Random forests, Mach. Learn. 45 (2001) 5–32, https://doi.org/10.1023/A:1010933404324/METRICS.
[60] I.A. Basheer, M. Hajmeer, Artificial neural networks: fundamentals, computing, design, and application, J. Microbiol. Methods 43 (2000) 3–31, https://doi.org/10.1016/S0167-7012(00)00201-3.
[61] D. Lukač, M. Milić, ANN solution for increasing the efficiency of tracking PV systems, (n.d.). http://www.pv-mover.com/tl_files/pv_mover/(accessed October 12, 2023). .
[62] Universidad de Granada (UGR), Annex Statistical Data UGR 2021, 2021. https://secretariageneral.ugr.es/areas-gestion/memorias/academica/2020-2021/. (Accessed 12 October 2023).
[63] G. Torriani, G. Lamberti, G. Salvadori, F. Fantozzi, F. Babich, Thermal comfort and adaptive capacities: differences among students at various school stages, Build. Environ. 237 (2023) 110340, https://doi.org/10.1016/J.BUILDENV.2023.110340.
[64] P. Aparicio-Ruiz, E. Barbadilla-Martín, J. Guadix, J. Muñuzuri, A field study on adaptive thermal comfort in Spanish primary classrooms during summer season, Build. Environ. 203 (2021) 108089, https://doi.org/10.1016/J.BUILDENV.2021.108089.
[65] A.J. Aguilar, M.L. de la Hoz-Torres, M.D. Martínez-Aires, D.P. Ruiz, Thermal perception in naturally ventilated university buildings in Spain during the cold season, Buildings 12 (2022) 890, https://doi.org/10.3390/BUILDINGS12070890, 12 (2022) 890.
[66] Royal Decree 1027/2007, Spanish Regulation on Building Heating Installations, (n.d.). https://energia.gob.es/Eficiencia/RITE/Paginas/InstalacionesTermicas.aspx (accessed October 21, 2023).
[67] R. De Dear, G.S. Brager, The adaptive model of thermal comfort and energy conservation in the built environment, Int. J. Biometeorol. 45 (2001) 100–108, https://doi.org/10.1007/S004840100093/METRICS.
[68] H. Liu, Y. Wu, B. Li, Y. Cheng, R. Yao, Seasonal variation of thermal sensations in residential buildings in the Hot Summer and Cold Winter zone of China, Energy Build. 140 (2017) 9–18, https://doi.org/10.1016/J.ENBUILD.2017.01.066.
[69] D. Wang, J. Jiang, Y. Liu, Y. Wang, Y. Xu, J. Liu, Student responses to classroom thermal environments in rural primary and secondary schools in winter, Build. Environ. 115 (2017) 104–117, https://doi.org/10.1016/J.BUILDENV.2017.01.006.
[70] J. Kim, R. de Dear, Thermal comfort expectations and adaptive behavioural characteristics of primary and secondary school students, Build. Environ. 127 (2018) 13–22, https://doi.org/10.1016/J.BUILDENV.2017.10.031.
[71] A.K. Mishra, M. Ramgopal, Thermal comfort field study in undergraduate laboratories – an analysis of occupant perceptions, Build. Environ. 76 (2014) 62–72, https://doi.org/10.1016/J.BUILDENV.2014.03.005.
[72] M.K. Singh, R. Ooka, H.B. Rijal, S. Kumar, A. Kumar, S. Mahapatra, Progress in thermal comfort studies in classrooms over last 50 years and way forward, Energy Build. 188–189 (2019) 149–174, https://doi.org/10.1016/J.ENBUILD.2019.01.051.