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Predictive Model of Clothing Insulation in Naturally Ventilated Educational Buildings

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Abstract: Providing suitable indoor thermal conditions in educational buildings is crucial to ensuring the performance and well-being of students. International standards and building codes state that thermal conditions should be considered during the indoor design process and sizing of heating, ventilation and air conditioning systems. Clothing insulation is one of the main factors influencing the occupants' thermal perception. In this context, a field survey was conducted in higher education buildings to analyse and evaluate the clothing insulation of university students. The results showed that the mean clothing insulation values were 0.60 clo and 0.72 clo for male and female students, respectively. Significant differences were found between seasons. Correlations were found between indoor and outdoor air temperature, radiant temperature, the temperature measured at 6 a.m., and running mean temperature. Based on the collected data, a predictive clothing insulation model, based on an artificial neural network (ANN) algorithm, was developed using indoor and outdoor air temperature, radiant temperature, the temperature measured at 6 a.m. and running mean temperature, gender, and season as input parameters. The ANN model showed a performance of R^2 = 0.60 and r = 0.80. Fifty percent of the predicted values differed by less than 0.1 clo from the actual value, whereas this percentage only amounted to 32% if the model defined in the ASHRAE-55 Standard was applied.

Keywords: built environment; educational buildings; thermal environment; clothing insulation; occupant behaviour; natural ventilation

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1. Introduction

The events of the last few years, including the COVID-19 pandemic and changing climate patterns [1], have increased concern for ensuring that the indoor environment meets the needs of the building's occupants. Indoor thermal conditions are considered a critical variable due to their impact on the occupants' health and work performance [2]. The importance of thermal conditions in buildings has prompted International Standards to define specific requirements for indoor thermal environmental parameters [3,4]. However, maintaining indoor environmental conditions in accordance with the occupant's thermal preferences may also lead to a large amount of energy consumption due to the use of heating, ventilation and air conditioning (HVAC) systems [5]. Indeed, using HVAC systems is the main type of building energy consumption [6,7]. Therefore, the parameters that influence the thermal perception of building users deserve special consideration because they influence indoor environmental conditions and the energy consumption of the building.

This situation is particularly relevant in educational buildings, which represent a large part of the building stock and account for a high share of the non-industrial energy consumption of a country [8]. Thewes et al. [9] analysed the energy benchmarks of schools in European countries. They concluded that the deviations between countries are mostly not significant and that the electricity consumption values of schools vary from 10 to 30 kWh/(m^2a). Part of this energy consumed by educational buildings is used to maintain adequate indoor environmental conditions in classrooms, which is essential due to the significant amount of time that students and teachers spend in these buildings [10,11]. Previous research has shown that poor indoor environmental quality triggers sick buildings syndrome, which leads to poor health conditions, resulting in absenteeism and low productivity in educational institutes [12,13]. Consequently, since the satisfaction and well-being of the occupants of educational buildings may be compromised [11,14,15], indoor thermal conditions are critical factors in these buildings' design and operational process.

Building codes have defined different thermal comfort ranges in this context according to the different climatic zones. International Standards [3,4] state that the criteria for the thermal environment should be based on the PMV-PPD thermal comfort indices [16]. These parameters are calculated based on environmental parameters (relative humidity, air temperature, mean radiant temperature and air speed) and individuals' characteristics (metabolic rate and clothing insulation). The clothing insulation parameter, which substantially impacts thermal perception, quantifies the amount of thermal insulation a person wears [3,16]. Therefore, it is necessary to know the evaluation of the thermal characteristics of a clothing ensemble (i.e., the thermal insulation) when evaluating the degree of comfort or thermal stress provided by the physical environment according to the standardised method [17]. According to Standard ISO 7730 [16], clothing insulation could range between 0 and 2 clo. Nevertheless, if more information is unavailable, clothing insulation should be assumed to be 0.5 clo (e.g., trousers and short sleeves) or 1.0 clo (e.g., trousers, long sleeve shirt and sweater) for the warm and cold seasons, respectively.

However, individual occupants' clothing behaviour influences clothing insulation and, therefore, significantly impacts their thermal comfort. In fact, Newsham [18] investigated the clothing insulation effect on thermal comfort and energy consumption and concluded that realistic clothing adjustment is an important variable for assessing thermal comfort in non-optimal indoor environments. Gauthier and Shipworth [19] concluded that clothing insulation, along with the metabolic rate, were the parameters that most influenced PMV-PPD calculations. During typical sedentary activities in educational buildings (e.g., attending a lecture or a class) where 1.2 met can be assumed as a metabolic rate, variations in the level of clothing insulation affects the optimum operative temperature of approximately 6 °C per clo [3,20].

Therefore, the selection of thermal clothing insulation requires special attention because it influences the calculation of the occupants' thermal sensation and, consequently, the design and sizing of HVAC systems. The two clothing insulation values suggested by the ISO 7730 Standard for warm and cold seasons tend to oversimplify occupant clothing behaviour. The clothing behaviour of building occupants is not constant throughout the seasons but varies according to climatic conditions and is not identical for all individuals [21]. This underscores the need to investigate the clothing behaviour of building occupants and to develop more accurate models. In this context, previous research has analysed the factors influencing clothing behaviour due to their impact on thermal comfort and proposed models for more accurate clothing insulation estimation.

De Carli et al. [22] analysed people's clothing behaviour by investigating the external parameters (outside temperature, mean weekly outside temperature and latitude) and indoor parameters (space temperature). They proposed single variable linear regression models to predict clothing insulation based on the outdoor air temperature measured at 6:00 a.m. Schiavon and Lee [20] developed models to predict clothing insulation based on observations from the RP-921 and ASHRAE RP-884 databases. The first proposed model calculated clothing insulation based on the outdoor air temperature measured at 6:00 a.m., while the second model used the outdoor air temperature measured at 6:00 a.m. and the indoor operating temperature. Zhao et al. [23] analysed the clothing adaptation of rural residents in the cold region of China. They developed predictive clothing insulation models based on the operating temperature and a 7-day running mean temperature as predictors. Rupp et al. [24] analysed the clothing insulation in ASHRAE Global Thermal Comfort Database I and II. They derived predictive models of ensemble insulation based on indoor air temperature, the season and the building ventilation type. They also concluded that PMV predictions were improved by accounting for chair insulation. Wang et al. [25] proposed that a neutral clothing insulation model can be used to determine whether clothing adjustment can sufficiently offset indoor temperatures in naturally ventilated building contexts. They found significant differences between the clothing behaviour of male and female occupants, with female occupants more actively adjusting their clothing. Their findings also showed that climate, season, building type and indoor/outdoor temperature variations were the key contextual variables to be considered for understanding occupant clothing behaviour. The influence of this variable was also pointed out by ASHRAE 55, which stated that its adapted predictive clothing insulation model might not be appropriate for all cultures and occupancy types.

In this context, this study aimed to develop a predictive clothing insulation model for occupants of educational buildings. For this purpose, an artificial neural network (ANN)-based model was developed based on data collected from field measurement campaigns conducted in higher education buildings in southern Spain. In addition, the analysis developed in this study also aims to understand the environmental and individual factors affecting the clothing behaviour of the occupants of higher educational buildings.

2. Materials and Methods

2.1. Location and Characteristics of the Participants

The data used in this study were collected in educational buildings located in the Campus Fuentenueva of the University of Granada, Granada, Spain. There were 6593 students on this campus during the 201/2022 academic year. The climate in Granada is characterised by low rainfall over the year, a very hot and dry summer and the coldest month averaging above 0 °C. Therefore, this climate is classified as Hot-summer Mediterranean (Csa), according to Köppen and Geiger [26].

A questionnaire survey and field measurements were conducted simultaneously in classrooms during university lectures. The buildings on the Campus Fuentenueva are characterised by a concrete frame structure, ceramic façades and aluminium windows. Regarding the finishing material, the floors are finished with terrazzo or natural stone, the ceilings with registrable suspended ceiling systems and the walls with gypsum plaster. The Fuentenueva Campus buildings do not have a mechanical ventilation system, and air circulation relies on windows and doors opening and closing.

The field measurements were carried out from September 2021 to July 2022 on different days; each participant only experienced a single condition. The field measurements were carried out in all months between September and July, except the holiday period in December and January when the educational buildings were closed. A total of 2022 university students participated in this study. Table 1 shows the participant's characteristics and their distribution by season.

2.2. Data Collection: Questionnaire Survey and Monitoring Equipment

The questionnaire survey and the IEQ monitoring campaign were conducted simultaneously during university lectures (1.5–2 h). The students' characteristics and state of clothing were collected using paper-based occupant survey questionnaires. The questionnaire was prepared in Spanish and included questions on personal characteristics (age and gender) and clothing insulation state. For this purpose, the students were asked to indicate what clothes they were wearing from a list defined by the ASHRAE [3]. The questionnaire survey was conducted during the last 15 min of a lecture, and the students remained seated during the class (this protocol ensures that students had been seated for at least 1 h and eliminates the influence of short-term thermal history in transitional spaces before attending the lecture class). The questionnaires were filled out during mid-morning or mid-afternoon, not just after arrival or after a lunch break, following the recommendations stated in UNE EN 16798-2:2019 Annex F [27].

Table 1. Participants' characteristics.

Variable	Number of Respondents (N, %)	
Gender	Male Female	1200 (59%) 822 (41%)
Age	18–24 25–30 >30	1741 (86%) 236 (12%) 45 (2%)
Season	Autumn Winter Spring Summer	707 (35%) 445 (22%) 472 (23%) 398 (20%)

Indoor environmental parameters were measured from the beginning to the end of the university lectures, where the questionnaire surveys were carried out. These parameters included the air temperature ($T_{air,i}$), indoor relative humidity (RH_i), mean radiant temperature ($T_{r,i}$) and air velocity (v_i). The characteristics of the sensors used to collect this data are detailed in Table 2. The sensors were placed at a height of 0.6 m and separated >1 m from the surrounding surfaces in the middle of the classrooms. The sensor location follows the recommendations stated in ASHRAE-55-2020 Standard [3] and UNE EN-ISO 7726:2002 [28]. The logging interval selected to measure all the parameters was 1 min.

Table 2. Sensor characteristics.

Parameter	Sensor	Range	Accuracy
Air temperature	FHAD 46-C41A AHLBORN	−20 to +80 °C	Typical ±0.2 K at 5 to 60 °C Maximum ±0.4 K at 5 to 60 °C Maximum ±0.7 K at −20 to +80 °C
Relative humidity	FHAD 46-C41A AHLBORN	0 to 98% RH	±2.0% RH in range from 10 to 90% RH ±4.0% RH in range from 5 to 98% RH
Mean radiant temperature	FPA805GTS AHLBORN	–50 to 200 °C	0.1 °C
Air velocity	HD403TS2 Delta OHM®	0.05 to 5.00 m/s	±(0.03 m/s + 2% f.s.)

Outdoor weather parameters (air temperature and relative humidity) were also collected from a meteorological station close to the Fuentenueva Campus, owned by AEMET (the State Meteorological Agency). These outdoor parameters were continuously measured during the study period. The running mean outdoor temperature (T_{rm}) was calculated using (1):

$$T_{rm} = (1-\alpha)\left\{T_{t-1} + \alpha\, T_{t-2} + \alpha^2 T_{t-3}\, \ldots + \alpha^{n-1} T_{t-n}\right\} \tag{1}$$

where T_{rm} is the running mean outdoor temperature at time t, n is the previous time interval, and α is the time constant which reflects the rate at which the effect of any past temperature decays ($0 \le \alpha < 1$). In this study, the α value selected was 0.8. A greater effect of outdoor temperatures measured in the previous days is indicated by a higher value of α.

2.3. Data Pre-Processing and ANN-Based Model

The recorded indoor/outdoor environmental values, together with the responses collected from the questionnaire, were processed and analysed. The clothing insulation was estimated using the typical clothing insulation values provided by the ASHRAE

55 Standard [3]. The results were analysed to investigate the relationship between season, gender, and clothing behaviour.

Subsequently, artificial neural network (ANN) algorithms were used to develop a model to predict the clothing insulation level. ANN is a machine learning method widely used in many fields, such as science, engineering, education and other industries [29]. The performance of an ANN model in determining non-standard non-linear relationships between independent and dependent variables is much higher than that of a regression model. For this reason, this mathematical model has been selected. The multilayer perceptron is the structure most used. This ANN structure usually comprises an input, hidden and output layers and many interconnected nodes (or neurons). Previous research has shown that a single hidden layer structure with a sufficient number of neurons can approximate any function with the desired accuracy—including two hidden layers may introduce a higher risk of convergence to a local minimum and rarely improves the model [30,31]. Therefore, the model's input vector is connected to the input layer. Sigmoid and Levenberg–Marquardt was the selected activation function and back-propagation algorithm, respectively. The dataset was segmented: 60% training, 20% validation and 20% testing. Previous studies have used this procedure to develop ANN-based prediction models [32–35]. The training set serves the purpose of optimising the ANN model. The validation set, on the other hand, is utilised to halt the optimisation process. This is achieved by ceasing the training process when there is no further improvement in the model's accuracy on the validation set. Lastly, the test set is employed to evaluate the accuracy of the trained model [36]. The input and output data were normalised to prevent premature saturation and prevent larger numbers from overriding smaller ones. Equation (2) shows the normalised method in this study.

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{2}$$

x_{norm} is the normalised value, x is the actual value, x_{min} is the minimum value of the set x and x_{max} is the minimum value of the set x. The performance of the generated models were evaluated using the mean square error (MSE) and the mean absolute error (MAE) (3) and (4).

$$\text{MSE} = \frac{1}{N} \sum_{i}^{n} (y_j - z_j)^2 \tag{3}$$

$$\text{MAE} = \frac{1}{N} \sum_{i}^{n} |y_j - z_j| \tag{4}$$

Both parameters provide a direct quantification of the predictive error and have been widely used to evaluate the performance of ANN models. Additionally, the coefficient of determination (R^2) was also calculated.

2.4. Predictive Clothing Insulation Models

The UNE 7730 and ASHRAE 55 standards suggest that clothing insulation can be assumed as 1.0 clo and 0.5 clo for winter and summer conditions, respectively. However, as mentioned in Section 1, this method is very inaccurate for estimating clothing insulation. In addition, another method defined in ASHRAE 55 is the adapted model shown in (5).

$$\begin{pmatrix} T_{air(out,6)} < -5°\text{C} & \rightarrow & I_C = 1.00 \\ -5°\text{C} \leq T_{air(out,6)} < 5°\text{C} & \rightarrow & I_C = 0.818 - 0.0364 \cdot T_{air(out,6)} \\ 5°\text{C} \leq T_{air(out,6)} < 26°\text{C} & \rightarrow & I_C = 10^{(-0.1635 - 0.0066 \cdot T_{air(out,6)})} \\ 26°\text{C} \leq T_{air(out,6)} & \rightarrow & I_C = 0.46 \end{pmatrix} \tag{5}$$

where $T_{air(out,6)}$ stands for the outdoor air temperature measured at 6:00 a.m.

3. Results

3.1. Environmental Conditions

As stated in Section 2.1, the climate of Granada is characterised by short, hot and dry summers and long, cold and partly cloudy winters, while the intermediate seasons (i.e., spring and autumn) are periods of more moderate temperatures. Table 3 shows the characteristics of the environmental parameters measured during the data collection campaign in each season. During the entire study, the outdoor temperature ranged between 0.00 °C and 36.5 °C, while RH_{out} and v_{out} ranged between 14% and 94% and 0–23 m/s, respectively. Regarding the outdoor temperature measured at 6:00 a.m., the collected minimum and maximum values were 0.0 °C and 25.6 °C, while T_{rm} ranged between 1.8 °C and 14.8 °C.

Table 3. Outdoor and indoor environmental parameters.

		Outdoor Parameters					**Indoor Parameters**			
		$T_{air,out}$	RH_{out}	v_{out}	$T_{air\ (out,6)}$	T_{rm}	$T_{air,in}$	T_{rad}	RH_{in}	v_{in}
Summer	Mean	23.4	39.9	6.18	14.6	11.0	25.9	26.4	35.4	0.08
	SD	5.1	12.9	5.02	2.2	1.2	2.1	1.9	7.5	0.06
	Min	18.3	14.0	1.00	11.6	9.5	22.3	23.6	19.6	0.01
	Max	33.7	58.0	23.00	20.0	13.1	29.2	29.2	46.0	0.22
Autumn	Mean	11.3	61.1	4.40	6.0	5.3	19.5	19.9	38.6	0.04
	SD	6.0	19.1	4.89	4.0	2.4	3.3	3.3	6.7	0.04
	Min	2.1	16.0	0.00	0.4	2.6	14.1	14.9	19.6	0.00
	Max	30.3	94.0	23.00	14.7	10.4	28.0	28.5	50.1	0.19
Winter	Mean	9.8	63.9	2.61	3.2	3.6	17.7	17.9	38.9	0.01
	SD	4.5	17.1	4.10	2.3	1.3	2.3	1.9	4.4	0.02
	Min	0.0	40.8	0.00	0.0	1.8	14.5	14.7	32.5	0.00
	Max	15.0	91.0	20.36	9.5	6.4	22.2	22.0	47.8	0.08
Spring	Mean	19.6	52.4	2.56	14.1	9.2	23.1	23.1	41.4	0.04
	SD	6.5	19.3	3.06	6.1	3.2	3.5	3.5	8.8	0.03
	Min	9.0	14.0	0.00	7.6	5.0	18.1	18.5	21.3	0.01
	Max	36.5	93.5	15.10	25.6	14.8	28.9	29.6	54.0	0.11

Regarding the indoor environmental parameters, the mean $T_{air,in}$ ranged between 14.1–29.2 °C, similar to the minimum and maximum values of T_{rad} (14.8 °C and 29.6 °C, respectively). RH_{in} ranged between 19.6% and 54.0%, and V_i ranged between 0.00 m/s and 0.22 m/s. It should be noted that since the ventilation strategy during this period stated that classrooms had to be naturally ventilated through windows and doors, no window adjustments were observed during the field measurement campaign.

Figure 1 shows each season's outdoor and indoor air conditions during the study period. As expected, the seasons with the warmer indoor air temperatures were summer (mean = 25.92 °C, SD = 2.10 °C) and spring (mean = 23.08 °C, SD = 3.57 °C), while the lowest values were recorded during the winter (mean = 17.68 °C, SD = 2.25 °C). The recorded outdoor air temperature values were slightly lower than the indoor air temperature values during the summer. During the other seasons (winter and intermediate spring, and autumn), a larger variation was observed between indoor and outdoor air temperature values.

Regarding RH, the outdoor values were higher than those measured indoors, with the lowest values collected during the summer season (mean RH_{out} = 39.94%; SD RH_{out} = 12.85%; mean RH_{in} = 35.43%; SD RH_{in} = 7.48%), and the highest values during the winter season (mean RH_{out} = 63.92%; SD RH_{out} = 17.06%; mean RH_{in} = 38.98%; SD RH_{in} = 4.40%). Similar trends were also observed for air velocity, with higher values measured outdoors during all seasons. It is worth noting that there were large variations between the mean values of outdoor air temperature measured at 6:00 a.m. during the different seasons: the mean values of $T_{air\ (out,6)}$ were 3.20 °C and 14.62 °C in the winter and summer seasons, respectively.

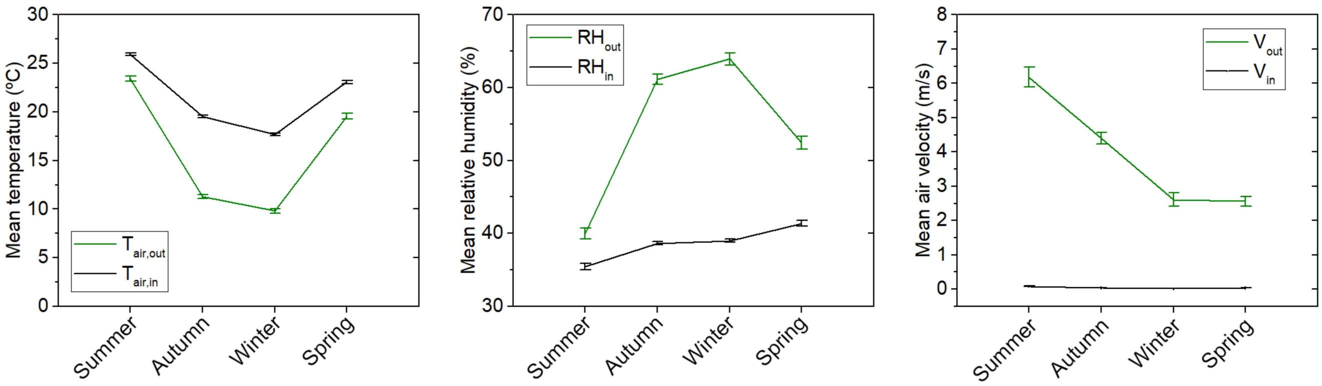

Figure 1. Variation of the indoor and outdoor environmental parameters by season.

3.2. Clothing Insulation and Gender

Figure 2 shows the collected values of clothing insulation reported by male and female students. As can be seen, the mean value of clothing insulation reported by male students (mean = 0.60 clo; SD = 0.29 clo) is lower than that reported by female students (mean = 0.72 clo; SD = 0.33 clo). In fact, these values have been analysed, and the results obtained after performing a Kruskal–Wallis test showed that there are statistically significant differences between the two populations (of male and female students) (χ^2 = 60.21; p-value < 0.001). Similar results were already reported by previous studies conducted in educational buildings [21,37–39].

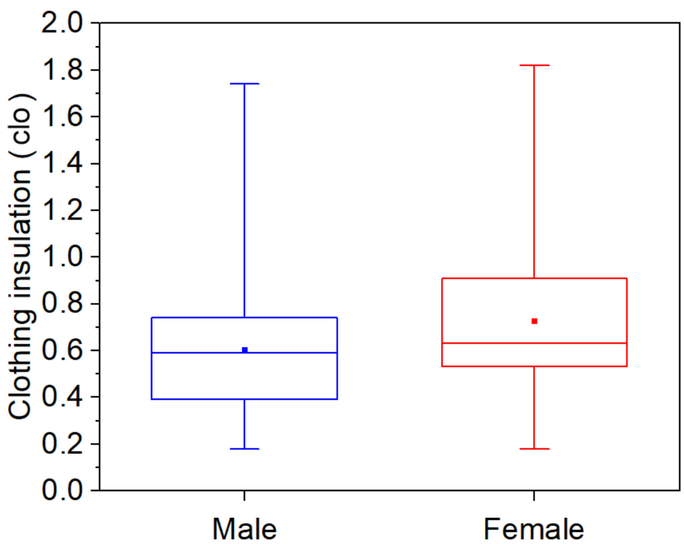

Figure 2. Clothing insulation level by gender. Whiskers stand for minimum and maximum values.

3.3. Clothing Insulation and Seasons

The relationship between clothing insulation and the seasons was assessed in this study. Different mean clothing insulation values were obtained for the summer (mean = 0.35 clo, SD = 0.15 clo), autumn (mean = 0.83 clo; SD = 0.29 clo), winter (mean = 0.73 clo; SD = 0.20 clo), and spring season (mean = 0.46 clo; SD = 0.26 clo). The results revealed statistically significant differences between seasons (χ^2 = 799.76; p-value < 0.001). Figure 3 shows the clothing insulation level by season and gender.

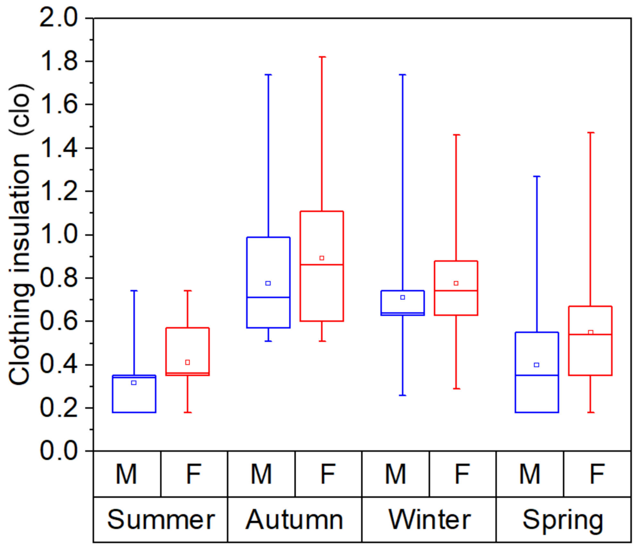

Figure 3. Clothing insulation level by season and gender. M indicates male; F indicates female. Whiskers stand for minimum and maximum values.

In addition, this study assessed whether there are differences between the level of clothing insulation of male and female students by season. The obtained values showed evidence of statistically significant differences for all seasons (Table 4).

Table 4. Results obtained between the clothing insulation level of male and female students for each season.

	χ^2	*p*-Value
Summer	33.554	<0.001
Autumn	27.667	<0.001
Winter	17.646	<0.001
Spring	38.837	<0.001

3.4. Clothing and Environmental Parameters

The results in the previous sections revealed significant differences in the levels of students' clothing insulation in the different seasons and by gender. Subsequently, the relationship between indoor and outdoor environmental parameters and the level of clothing insulation was examined (Table 5). A strong inverse correlation ($\rho < -0.5$) was found between clothing insulation and $T_{air,out}$, $T_{air\ (out,6)}$, T_{rm}, $T_{air,in}$ and T_{rad}. Additionally, the parameters that showed the least correlation were v_{out} ($\rho = -0.157$), RH_{in} ($\rho = -0.187$) and v_{in} ($\rho = -0.216$). Figures 4 and 5 show the relationship between clothing insulation and the indoor and outdoor environmental parameters, respectively.

Table 5. Correlation between clothing insulation and environmental parameters.

		Outdoor Parameters					Indoor Parameters			
		$T_{air,out}$	RH_{out}	V_{out}	$T_{air\ (out,6)}$	T_{rm}	$T_{air,in}$	T_{rad}	RH_{in}	V_{in}
Clothing insulation	ρ *	**−0.625**	−0.458	−0.157	**−0.634**	**−0.655**	**−0.640**	**−0.640**	−0.187	−0.216
	p-value	**	**	**	**	**	**	**	**	**

* ρ indicates Spearman coefficient; ** $p < 0.01$.

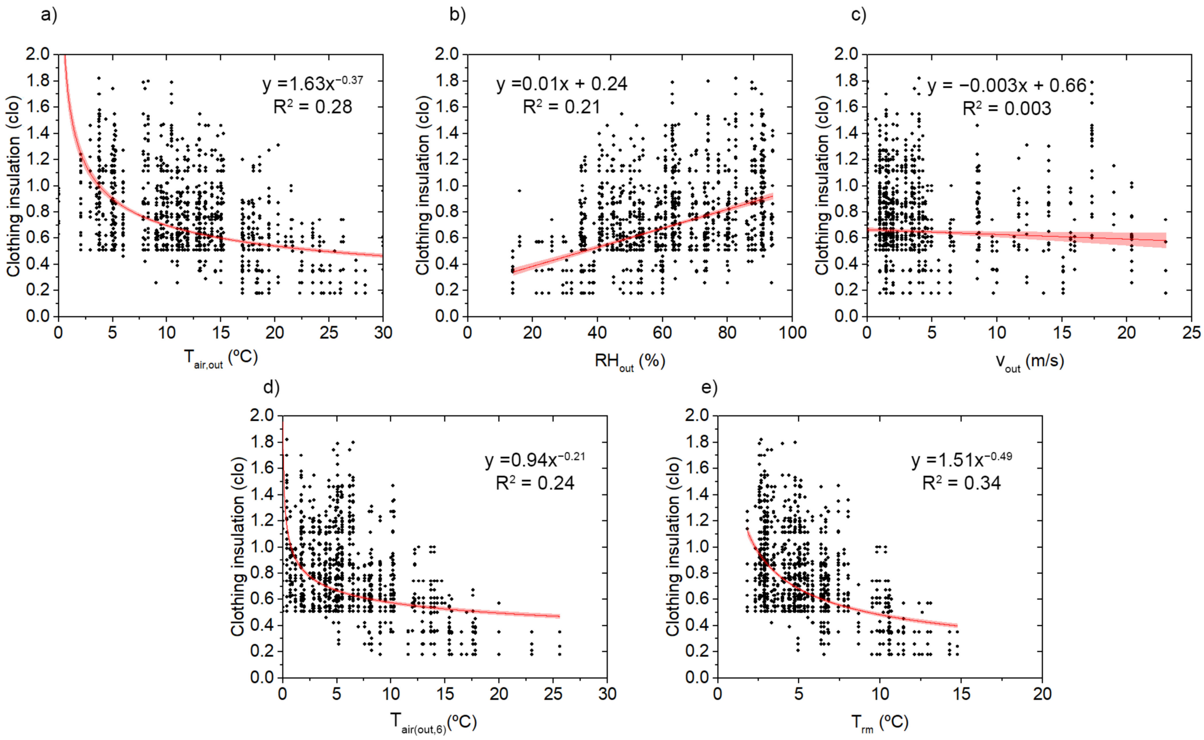

Figure 4. Relationship between outdoor environmental factors and clothing insulation: (**a**) outdoor air temperature; (**b**) outdoor air RH; (**c**) outdoor air velocity; (**d**) outdoor air temperature measured at 6:00 a.m.; (**e**) outdoor running mean temperature. The red line indicates the curve fit (95% confidence interval).

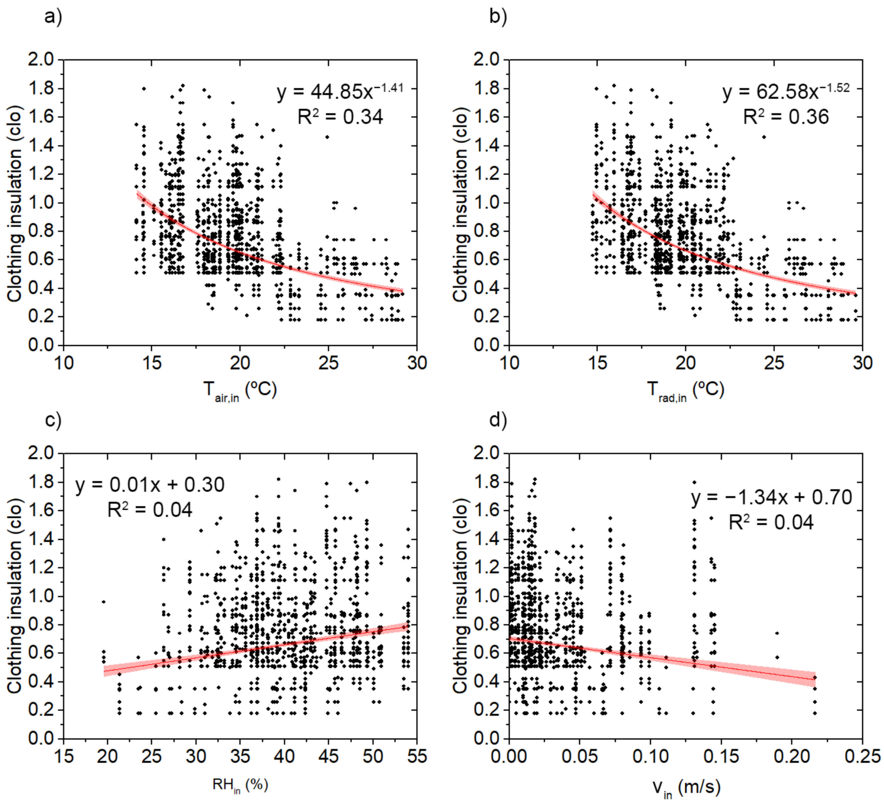

Figure 5. Relationship between indoor environmental factors and clothing insulation: (**a**) indoor air temperature; (**b**) indoor radiant temperature; (**c**) indoor RH; (**d**) indoor air velocity. The red line indicates the curve fit (95% confidence interval).

Additionally, to analyse the influence of the variability of indoor and outdoor environmental factors on the variability of the results, univariate feature ranking for regression using F-tests was used. The method employs an F-test to individually examine the importance of each predictor. The F-test assesses the hypothesis that the response values, grouped by predictor variable values, are derived from populations with identical means. The alternative hypothesis posits that the population means are not all equal. A small *p*-value for the test statistic indicates that the corresponding predictor is significant. Consequently, a large score value indicates that the corresponding predictor is important.

The score rank (Figure 6) shows the parameters of $T_{air\ (out,6)}$, T_{rm}, T_{rad}, $T_{air,in}$ and $T_{air,out}$ as features with the highest importance.

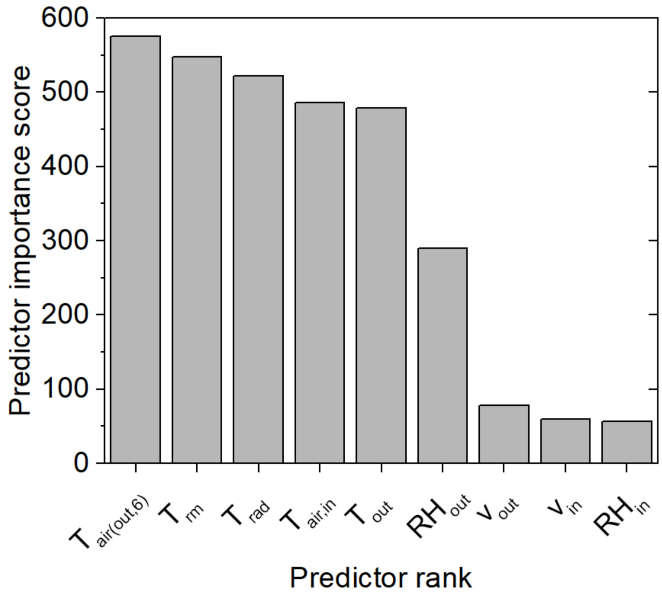

Figure 6. Univariate feature ranking for regression using F-tests.

3.5. ANN-Based Predictive Clothing Insulation Model

The results obtained in the above analysis were used to identify the variables that influence the level of clothing insulation. This section shows the ANN-based model developed using individual observations. The selected model's input variables were $T_{air,out}$, $T_{air\ (out,6)}$, T_{rm}, $T_{air,in}$, T_{rad}, gender and season. The environmental parameters selected as input variables were chosen because the previous statistical analyses showed a correlation with the level of clothing insulation. In addition, the other non-environmental variables (i.e., gender and season) were selected due to their influence on the level of clothing insulation and because of the statistically significant differences found.

The performance of the developed model was evaluated, and the obtained results are shown in Table 6. The model performance is similar to the training and validation data (R^2 = 0.624 and R^2 = 0.630, respectively), with MAE and MSE also being very similar between both datasets (MAE = 0.083 and MSE = 0.013 for training data and MAE = 0.082, MSE = 0.013 for validation data). Figure 7 shows the predicted clothing insulation values obtained from the proposed ANN-based model versus the actual clothing insulation values. The linear regression shows an R^2 of 0.62 between both variables.

Table 6. Performance characteristics of the developed ANN-based predictive clothing insulation model.

	Training			Validation		
	MAE	**MSE**	**R^2**	**MAE**	**MSE**	**R^2**
Proposed model	0.083	0.013	0.624	0.082	0.013	0.630

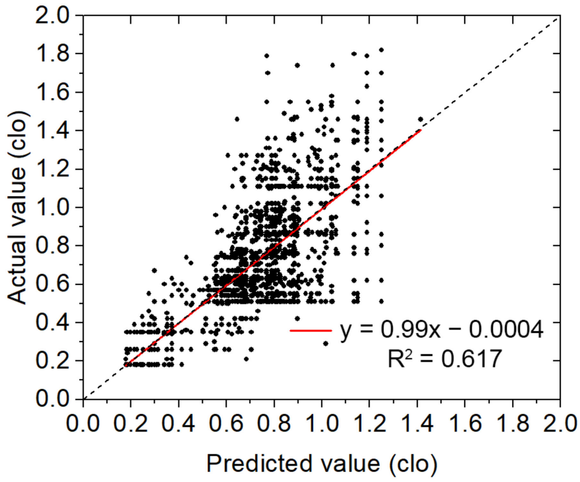

Figure 7. Relationship between predicted values and actual values of the entire dataset.

The error distribution profile of the developed model is shown in Figure 8. The accuracy of the predictive model can be assessed by comparing the difference between the predicted and actual values. Figure 8 shows that 50% of the predictive values differ by less than 0.1 clo from the actual values. This percentage increases to 76% if the range is extended from −0.2 clo to +0.2 clo. In contrast, only 11.5% and 12.5% of the predicted values overestimate or underestimate the clothing insulation by more than ±0.2 clo, respectively.

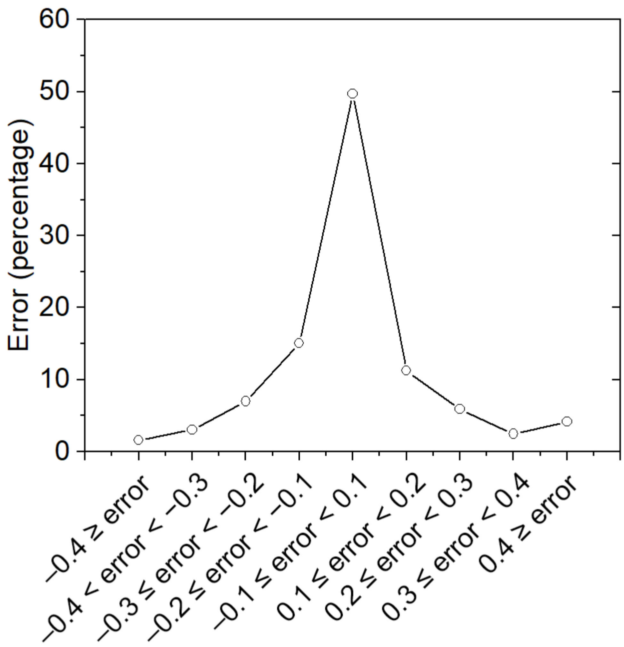

Figure 8. Error distribution profile of the developed ANN-based model.

4. Discussion

As briefly discussed in the introduction section, the selection of clothing insulation is a crucial parameter for evaluating the indoor thermal conditions and thermal perception of buildings' occupants. In fact, clothing insulation is an input parameter used to calculate different methods of predicting the general thermal sensation and degree of discomfort, such as PMV-PPD [16]. International, European, or national regulations establish methods for their calculation or recommendations, depending on the season. For example, UNE-EN ISO 7730:2006 provided operative temperature (T_{op}) ranges that should be calculated based on a clothing insulation value of 0.5 clo during the summer (cooling season) and 1.0 clo during the winter (heating season). The Spanish standard (RITE) also defined T_{op} values (assuming a metabolic activity rate of 1.2 met and the same values of clothing insulation) that should be applied during the design process of indoor spaces. Other standards, such as ASHRAE 55-2020 [3], define models for predicting the clothing insulation level as a function of outdoor air temperature measured at 6 a.m. However, this model was developed based on a field study and may not be appropriate for different cultures or climate zones.

In this context, the results obtained from our study showed that there are significant differences in the clothing insulation level between seasons. The mean clothing insulation was 0.35 and 0.73 clo for the summer and winter, respectively, while, for the intermediate seasons, the observed mean value was 0.83 and 0.46 for the autumn and spring. The lowest mean value was obtained in the summer, while the highest mean value was observed in the autumn. Although the insulation value of clothing was expected to be higher in winter, the average outdoor air temperatures during autumn and winter were very similar (11.28 °C and 9.80 °C).

Similar clothing insulation values were reported in previous studies; Aguilar [38] found that the mean values were 0.72 and 0.84 clo during the winter for male and female students, respectively. Alghamdi et al. [40] assessed the clothing insulation level of higher university students in Australia and reported a range of values from 0.20 to 0.58 clo for summer and from 0.40 to 0.85 clo for winter. Hu et al. [41] found values of 1.11 and 1.20 clo in naturally ventilated university classrooms and 1.11 and 1.16 clo for air-conditioned classrooms in China (for males and females, respectively). Talukdar et al. [42] conducted a field study in naturally ventilated university classrooms in Bangladesh. They found that the mean clothing insulation value was 0.6 clo for male students and 0.65 clo for female students. Finally, Jowkar et al. [43] conducted a measurement campaign during the academic year 2017/2018 (October–March). They found that the mean clothing insulation value was 0.86 clo and 0.92 clo for men and women in England, while slightly lower values (0.82 clo for men and 0.91 for women) were found in Scotland.

Consequently, it can be observed that the mean clothing insulation values reported by studies carried out in different locations are not the same. Therefore, the indoor and outdoor environmental characteristics of each location must be considered for the development of predictive clothing insulation models. In addition, while the studies mentioned previously have analysed the thermal perception of university students and reported the observed clothing insulation values, none of them proposed a model to predict the level of clothing insulation.

In this sense, the results obtained from the model developed in this study have been compared with those obtained from the model defined in the ASHRAE 55 standard to assess its performance. Figure 9 shows the relationship between the predicted values obtained from the ASHRAE 55 model and the actual values. The linear regression between both variables shows $R^2 = 0.39$ and a Pearson coefficient $r = 0.63$. These values are lower than those obtained from the developed model ($R^2 = 0.62$ and Pearson coefficient $r = 0.79$). These values show that the performance of the developed model is better than that obtained by the ASHRAE 55 model.

Figure 10 shows the error distribution profile of the developed ANN-based model and the ASHRAE 55 model. In general, the results shown in Figure 9 are evidence that the accuracy of the developed model is higher than that of the ASHRAE 55 model. In fact, only 32% of the predicted values obtained from the ASHRAE 55 model differ from the actual values by less than 0.1 clo, while this percentage rises to 50% with the developed model. On the other hand, the ASHRAE model tends to underestimate the clothing insulation value, as seen in Figure 10, where the positive error distribution is higher.

Nevertheless, it should be noted that ASHRAE 55 pointed out that cultural and climate conditions influence the clothing insulation level, resulting in the need to generate models that can predict clothing insulation by considering specific climatic and cultural conditions. Therefore, the model developed in this study constitutes a tool that can respond to the needs identified in the standards. It is also worth mentioning that although the developed model outperforms the adaptive model defined in the ASHRAE-55 standard, it cannot be applied as a reliable predictor in other scenarios (i.e., other different activities, climatic zone, culture conditions, etc.)

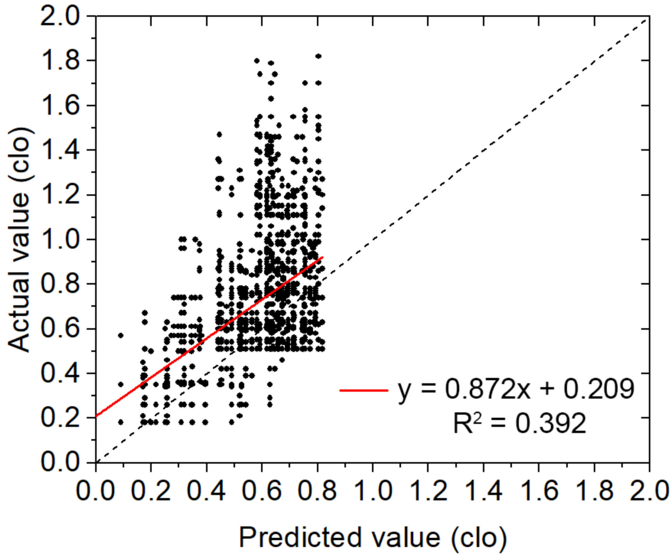

Figure 9. Relationship between the predicted values obtained from the ASHRAE 55 model and actual values.

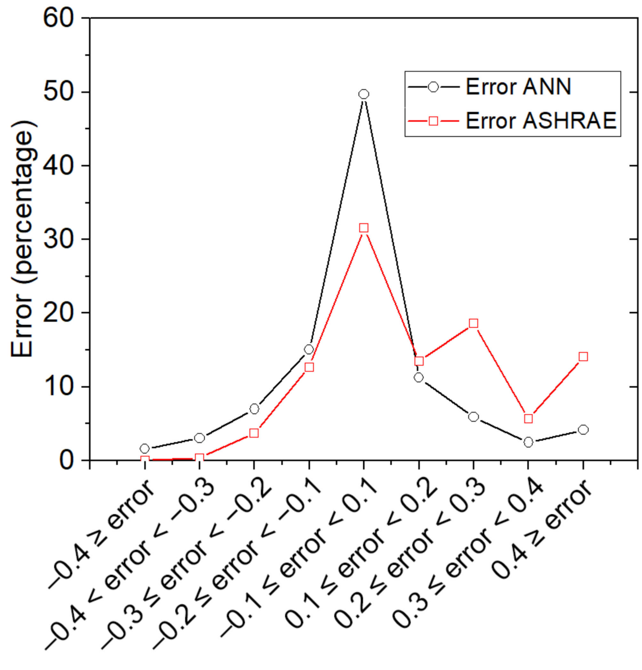

Figure 10. Comparison of the error distribution profile of the developed ANN-based model and the ASHRAE model.

5. Research Limitations

In this study, an ANN-based model has been developed to predict the clothing insulation of educational buildings' occupants. This model is based on data obtained from a field measurement campaign, including a questionnaire survey and monitoring environmental variables simultaneously. As a result, the model has a limited range of applicability due to the measured range of indoor and outdoor environmental variables. Additionally, the surveyed participants were young university students, and the data collected are representative of educational buildings where the clothing tends to be informal. As such, the model should not be applied to buildings or activities other than lecture classes without further analysis and verification.

In addition, it is noteworthy that this study did not analyse non-environmental variables such as building characteristics. Future research is needed to analyse the influence of these variables on the clothing behaviour of occupants of educational buildings. It is also reasonable to assume that the clothing insulation level may also be strongly connected with the cultural and economic characteristics of the population under study or that buildings' occupants may be unable to adapt their clothing insulation when dress codes are implemented.

6. Conclusions

The influence of environmental and non-environmental variables on the level of clothing insulation of students in higher education has been evaluated in this study. The obtained results evidenced a correlation between clothing insulation and $T_{air,out}$ ($\rho = -0.625$), $T_{air\ (out,6)}$ ($\rho = -0.634$), T_{rm} ($\rho = -0.665$), $T_{air,in}$ ($\rho = -0.640$) and T_{rad} ($\rho = -0.640$). In addition, statistically significant differences were found between male and female students and between the seasons. In fact, gender differences in clothing insulation were also found in all seasons. Female students reported higher clothing insulation than male students, with the highest values observed in winter.

These results revealed the significance of these factors in determining the level of clothing insulation, leading to their selection as input variables for developing a clothing insulation prediction model using ANN. Therefore, the following conclusions have been drawn based on the obtained results:

- The generated ANN-based model predicts clothing insulation with considerably high accuracy ($R^2 = 0.60$). The performance of the proposed model is similar to or better than the individual predictive clothing insulation models generated in previous research.
- The error distribution profile of the proposed model concentrates 50% in the range −0.1 to 0.1 clo, in contrast to the method suggested in the ASHRAE 55, which has only provided 32% of the predictions in the same range.
- The developed model can be used to more accurately predict the individual clothing insulation and, subsequently, to assess the indoor thermal conditions of educational buildings based on these results. This information is crucial to the design and size of HVAC systems and to the definition of management strategies that ensure suitable indoor thermal environmental conditions for the occupants while minimising the energy consumption of the building.

Finally, it should be noted that the ASHRAE 55 and ISO 7730 standards concluded that specific models are needed since factors such as geographic location, climate and cultural conditions influence the clothing insulation level and the thermal perception of building occupants. In this sense, this study responds to this need by providing a novel ANN-based method, which can be used by building managers to obtain more accurate predictions of the clothing insulation level of students in education in southern Spain.

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