Calibrating a Clothing Insulation Model for Thermal Comfort Assessment in Educational Buildings

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Abstract

Thermal comfort assessment in buildings usually relies on the calculation of Predicted Mean Vote (PMV) which is determined by four environmental variables, such as air temperature, air humidity, air velocity and mean radiant temperature, and by two personal factors, namely the metabolic rate and the clothing level. The latter factor is fundamental in determining the thermal sensation since it can be changed and adapted in response to the indoor conditions, thus allowing an extension of the neutral temperature range. Moreover, the uncertainty of clothing level in simulated models can affect the reliability of results in terms of thermal comfort and overall IEQ assessment. This study aims to calibrate existing models on an extensive set of data collected in an Italian high school located near Rome and to build a new clothing model. The outdoor and indoor environmental conditions in 22 natural ventilated classrooms were monitored during the school years 2020-2022. Students' thermal sensation votes and the corresponding clothing levels were surveyed during regular lessons. First, the physical variables used in the literature to predict clothing insulation were at first analyzed to highlight the significant ones based on the collected data. Second, the significant physical variable (i.e., operative temperature) was used as input to feed existing models and to predict clothing insulation; the predicted values were then compared with the observed mean clothing insulation of the students in each classroom. Third, a calibration of a clothing linear model based on operative temperature was carried out and a new linear model based on the indoor running mean temperature was set. Finally, to explore to which extent the linear clothing model based on T_{op} can affect the thermal comfort simulation, the Predicted Mean Vote (PMV) was calculated.

1. Introduction

In building energy simulation (BES) the possibility of predicting people behavior is fundamental when the objective is the accurate calculation of the energy demand during the operating phase. It is acknowledged that people usually behave in such a way to maintain comfort conditions. Regarding thermal comfort, people usually adopt personal strategies, such as adapting their clothing (i) or making interventions on the system control (ii) or operating the windows (iii). Regardless of the adopted strategy, the more accurate the thermal comfort prevision, the more reliable is also the estimated energy demand. However, there are some indoor environments, such as classrooms in educational buildings, where the system regulation is not possible, and the operation of windows is not effective in guaranteeing the thermal comfort of all the students. In this kind of building, clothing adaptation can play an important role in providing students' thermal comfort. According to Fanger's model, thermal comfort clothing insulation is one of the personal factors which determines thermal comfort, together with the metabolic rate, and the four environmental variables (i.e., air temperature, air humidity, air velocity and mean radiant temperature (Fanger, 1970). Predicted Mean Vote (PMV) can be calculated using (i) standard clothing based on the reference season (i.e., 1 clo for winter and 0.5 for summer), (ii) observed clothing insulation collected through questionnaires or (iii) predicted clothing values derived from environmental physical parameters.

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As highlighted in the literature, clothing adjustment according to the variation of environmental parameters is evidence of the behavioral adaptation (Torriani et al., 2023). The relationship between clothing insulation and environmental parameters has been investigated in different studies to identify simulation models able to predict occupants' clothing insulation levels, avoiding data collection through questionnaires that could be time-consuming.

Several research studies have focused on adult workers in office buildings, highlighting that occupants seem to choose their daily clothing according to the outdoor conditions, such as the daily mean outdoor temperature (Morgan & de Dear, 2003; Haldi & Robinson, 2011) and the outdoor temperature at 6 am (De Carli et al., 2007; Schiavon & Lee, 2013). A few authors present clothing models based on field campaigns in educational buildings, reporting different clothing adaptation behaviors adopted by students according to outdoor and indoor conditions. Table 1 reports a summary of the most recent studies presenting clothing insulation models based on dataset collected in educational buildings. The study conducted by Mors et al. (2011) in primary school reported Linear Regressions (LR) between the mean clothing insulation and external temperatures, namely the daily minimum ($T_{ext,min}$), the mean ($T_{ext,mean}$) and running mean outdoor temperature (Θ_{mr}). The study by Carvalho et al. (2013) based on university students revealed that clothing insulation levels are linked to a recent thermal memory of the external conditions. Particularly, clothing is predicted from the mean outdoor temperature of the previous day ($T_{ext,\ dayx-1}$) and the maximum value of the current day ($T_{ext,max\ dayx}$), through Multi Linear Regression model (MLR). Studies focusing on secondary and high school students highlighted the relationship between clothing and indoor conditions (i.e., operative temperature, T_{op}). Torriani et al. (2023) and Wu & Wagner (2024) implemented a linear regression (LR) model using binned operative at 0.5 °C and obtaining a similar slope but a different intercept term. In addition to LR model, Nakagawa et al. (2020) also developed a logistic model with 1 °C intervals of T_{op}.

When models rely on data collected in real buildings, it is useful to validate them in different buildings and locations. Therefore, the present work aims to (i) train and test new linear model on sets of real data in an Italian high school during the two-year period 2020-2022 in order to predict clothing insulation, (ii) compare the model with existing linear models, and finally to (iii) evaluate the effect of a detailed clothing model on the thermal comfort evaluation.

Table 1 –List of studies on clothing insulation models in educational buildings based indoor and outdoor temperatures

Ref.	Method	Model(s)	R^2
Mors et al. 2011	LR	I_{cl}=0.816-0.029*$T_{ext,min}$ I_{cl}=0.93-0.024*$T_{ext,mean}$ I_{cl}=0.934-0.028*Θ_{mr}	0.85 0.91 0.91
Carvhalo et al. 2013	MLR	I_{cl}=1.48-0.04272*$T_{ext,\ dayx-1}$ - 0.009827*$T_{ext,max\ dayx}$	0.90
Nakagawa et al. 2020	LR Logit	I_{cl}=1.204-0.027*T_{op} I_{cl}=0.339+(0.781-0.339)/ (1+exp((T_{op}-23.42)/2.54))	0.20 0.91
Torriani et al. 2023	LR	I_{cl}=1.0718-0.0136*T_{op}	0.88
Wu and Wagner 2024	LR	I_{cl}=1.44 -0.0252*T_{op}	0.86

2. Methodology

2.1 Data Collection

Data were collected in five field campaigns conducted in 22 naturally ventilated classrooms of a high school located near Rome (Italy) during the school years 2020-2022. Onsite measurements and subjective surveys were carried out simultaneously, while students were attending regular classes. During the campaigns, students could adjust their clothing insulation. For the short-term monitoring during questionnaire administration, globe temperature, air temperature, relative humidity and air velocity were recorded with a 1-minute timestep in the middle of the room at a height of 1.1 m by means of a DeltaOhm HD32.1 multilogger, in agreement with the Standard EN ISO 7726 (CEN 2001), so that it could be possible to calculate the operative temperature. However, the long-term measurements were carried out using one Hobo MX1102A sensor installed inside each selected reference room. Sensors' specifications are reported in Table 2. The planimetry with sensors' location and the internal view of one of the monitored classrooms are shown in Figure 1 and 2, respectively.

Table 2 – List of instruments used in indoor thermal monitoring: monitored parameters and measurement accuracy

Sensor	Parameters	Accuracy [Range]
DeltaOhm HD32.1	Globe Temperature	±0.01 °C [±199.99°C]
	Ambient Temperature	± 0.1 °C [> 199.99°C]
	Relative Humidity	±0.1% [< 80%]
		±3% [> 80%]
	Air Velocity	±0.2 m/s [0 -0.99 m/s]
		±0.4 m/s [1-9.99 m/s]
Hobo MX1102A	Ambient Temperature	± 0.2 °C [0-50°C]
	Relative Humidity	± 2% [1-90%]

With the help of a questionnaire, students were asked to report their actual clothing insulation using a checklist with a selection of garments. Clothing insulation I_{cl} was attributed to each garment according to the ISO 7730 (CEN 2005) standard. Questionnaires were filled out by students, after being exposed for a suitable period (i.e., min 1 h) to the indoor environmental conditions.

2.2 Data Analysis

2.2.1 Significance of independent variables

Physical parameters used in existing clothing models (Table 1) were tested through regression analysis to identify possible independent variables

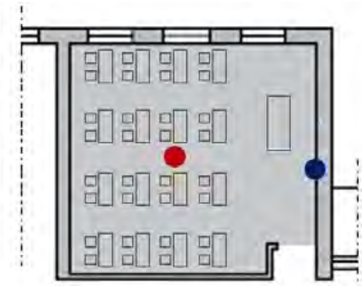

Fig. 1 – Planimetry of a classroom involved in the project with instruments location: red and blue dots indicate the sensor used for short-term and long-term monitoring, respectively

Fig. 2 – Internal view of one of the monitored classrooms

to build new clothing models based on the collected dataset. The physical parameters tested were the minimum, maximum and mean outdoor temperatures, namely, $T_{ext,min}$, T_{max}, Θ_{mr}, $T_{ext,mean}$, the running mean temperature Θ_{mr} of the 7 previous days, the average value of outdoor temperature of the day before, $T_{ext,\ dayx-1}$ and the indoor operative temperature. Moreover, the indoor running mean temperature, $T_{rm,in}$, of the 5 previous days was included in the analysis. Regressions with p-value below 0.05 were considered significant.

2.2.2 Clothing model calibration and validation based on operative temperature

Before testing the linear clothing model based on operative temperature, the collected data were processed (i.e., data binning) and sampled into two groups (i.e., training and testing sets). Specifically, in order to consider subjects exposed to similar conditions, data were binned into 0.6 °C intervals as suggested by EN ISO 7726 (CEN 2001) and then randomized. Linear regression was implemented using a portion of data as a training set to predict the clothing insulation based on the operative temperature, T_{op}, calculated with the equation suggested by EN ISO 7726 (CEN 2001). The model has been validated using the rest of the data as a set and compared with existing models. The metrics used to assess calibration and validation accuracy are the Mean Absolute Error (MAE) and the Rooted Mean Squared Error (RMSE).

2.2.3 New clothing linear model based on indoor running mean temperature

Linear regression was also carried out to forecast the clothing insulation based on the running mean indoor temperature, $T_{rm\ in}$, considering the 5 previous school days. $T_{rm\ in}$ was calculated for a limited dataset (i.e., Dataset II) according to the EN 16798-1:2019 (CEN 2019) standard as follows:

$$\Theta_{mr,in} = (1-\alpha)*(Tday_{x-1}+\alpha Tday_{x-2}+\alpha^2 Tday_{x-2}+\alpha^3 Tday_{x-3}+\alpha^4 Tday_{x-4}) \quad (1)$$

with α = 0.8. As for the model based on T_{op}, the metrics used to assess the calibration accuracy are MAE and RMSE.

2.2.4 Thermal comfort simulation

Predicted clothing insulation, I_{cl}, derived from the linear model based on operative temperature was used to calculate the Predicted Mean Vote (PMV) and evaluate thermal comfort inside the monitored classrooms. PMV calculated with predicted I_{cl} and PMV calculated using the standard values (i.e., 1 clo for the heating season and 0.5 for the cooling season), were compared with the one calculated using the mean observed I_{cl}, and the discrepancy were evaluated in terms of MAE and RMSE.

3. Results

A number of 825 questionnaires were collected during 50 regular classes. The analysis focuses on two different subsets: Dataset I includes all the interviewed subjects (i.e., 825), while Dataset II refers to those who attended lessons in the classrooms equipped for a long-term monitoring (i.e., 511 subjects), and it was used to calculate the indoor running mean temperature (section 3.3). Students were aged from 13 to 20 years old, and the female-to-male ratio was 55%-45%. Table 3 summarizes the mean value of the parameters monitored during short-term monitoring. The daily mean outdoor measured during the 50 campaigns ranged between 6.0 and 22.4±3.6 °C. The average indoor air temperature (Ta) varied from 19.5 to 24.5±1.2 °C. The mean clothing insulation level worn by students varied from 0.34 to 1.65 clo ± 0.23.

Table 3 – Statistical summary of measurements collected during the short-term monitoring and clothing insulation (Dataset I)

	T_{ext} [°C]	**RH_{ext} [%]**	**Ta [°C]**	**Tmr [°C]**	**RH [%]**	**Va [m/s]**	**Icl [clo]**
Min	6.0	28	19.5	19.5	16	0.00	0.34
Max	22.4	88	24.4	24.6	68	0.06	1.65
Mean	14.4	69	**22.3**	**21.8**	**47**	**0.01**	**0.85**
SD	3.6	16	1.2	1.3	14	0.01	0.23

3.1 Statistical Analysis

Table 4 reports the results of the linear regression analysis carried out using the mean observed clothing insulation as dependent variable and (i) the outdoor temperatures, i.e., the outdoor temperatures of the current day, namely, $T_{ext,min}$, T_{max}, $T_{ext,mean}$, and of previous days, namely running mean temperature Θ_{mr}, and the average value of the outdoor temperature of the day before, and (ii) the mean indoor temperature of the current day, i.e., operative temperature and indoor running mean temperature. All the variables, except the outdoor minimum temperature, are significantly related to the clothing insulation (p-value < 0.05) but the coefficient of determination referred to external temperatures is very low. As a consequence, models were trained considering only the indoor operative temperature and running mean temperature.

Table 4 – Statistical analysis of the effect of outdoor and indoor parameters on clothing insulation

Independent variable	**p-value**	**R^2 adj.**
$T_{ext,min}$	0.524	0.00
$T_{ext,mean}$	0.000*	0.03
Θ_{mr}	0.000*	0.08
$T_{ext,(day\ x-1)}$	0.000*	0.04
$T_{ext,max}$	0.000*	0.14
T_{op}	0.000*	0.30
$T_{mr,in}$	0.000*	0.46

**p-value < 0.05*

3.2 Clothing Model Calibration and Validation Based on Operative Temperature

First, in order to consider the clothing insulation worn by groups of students exposed to similar indoor thermal conditions, the operative temperatures were binned into 0.6 °C intervals as suggested by EN ISO 7726 (CEN 2001). Second, data were randomized and divided into training (i.e., 414 samplings) and testing (i.e., 411 samplings) sets to calibrate and validate the linear model. Results of model calibration and validation are reported in Figure 3 and Table 5-6.

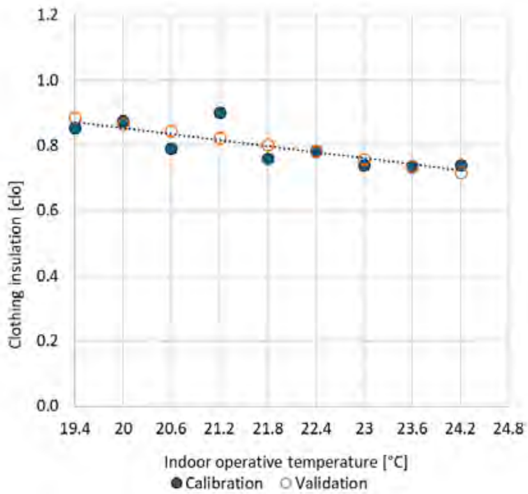

Fig. 3 – Relationship between clothing insulation (I_{cl}) and operative temperature (T_{op}): full blue markers refer to model calibration while empty orange markers to model validation

Table 5 – Statistical analysis of the effect of operative temperature on clothing insulation

	Regression	p-value	R^2 adj.
Bins 0.6° C	$I_{cl} = 1.573 - 0.0354 * T_{op}$	**0.000***	**0.58**

**p-value < 0.05*

Based on the dataset, there is a significant correlation (p-value < 0.05) between clothing level of students and operative temperature, with a decrease of clothing insulation when T_{op} rises. This result is consistent with previous studies conducted in high school (Torriani et al., 2023; Wu and Wagner, 2024). The model validation on the testing set and using existing models is reported in Table 6 through RMSE and MAE. The lower the errors, the better the model performs.

Considering these two metrics, the validated model led to RMSE and MAE equal to 0.03 clo.

Testing the dataset with existing models, the worst performance is given by the model proposed by Nakagawa et al. (2020) with RMSE and MAE equal to 0.20 clo. Conversely, the models that better fit with the data collected during the present field campaign are those proposed by Torriani et al. (2023), i.e., RMSE = 0.06 clo, MAE = 0.05 clo, and Wu and Wagner (2024), i.e., RMSE = 0.08 clo, MAE = 0.07 clo.

Validation performance is reported also in the scatterplot between observed and predicted clothing insulation (Figure 4) which show that the clothing insulations forecasted by the model proposed by Torriani et al. (2023) and Wu and Wagner (2024) remain within the ± 20% tolerance intervals from the bisector.

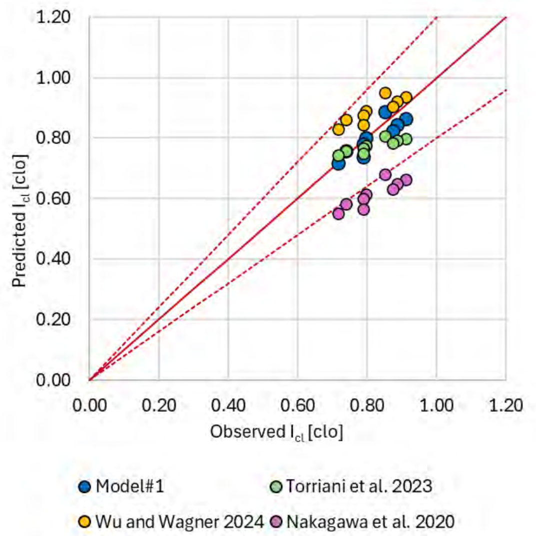

Fig. 4 – Relationship between predicted and observed clothing insulation (Icl). Solid red line and dashed gray lines represent the bisector, ±20% tolerance intervals, respectively

Table 6 – Summary of metrics for measuring the distance between the predicted and the observed clothing insulation

	Model #1	Nakagawa et al. 2020	Torriani et al. 2023	Wu and Wagner 2024
RMSE [clo]	0.03	0.20	0.06	0.08
MAE [clo]	0.03	0.20	0.05	0.07

3.3 New Clothing Model Based on Indoor Running Mean Temperature

Since the statistical analysis highlights an effective relationship between the clothing insulation worn by students and indoor conditions, rather than the outdoor temperatures, a focus analysis was carried out to explore possible thermal memory based on indoor conditions monitored through the long-term onsite measurements. This analysis considers Dataset II, namely students attending lessons in the classrooms equipped for a long-term monitoring. Only school hours and only school days were considered to calculate the mean indoor temperature and the running mean temperature. For this analysis the same procedure adopted for the operative temperature model was carried out, namely data binning (i.e., 0.6 °C step intervals), randomization and sampling into training (i.e., 248 subjects) and testing (i.e., 243 subjects) sets.

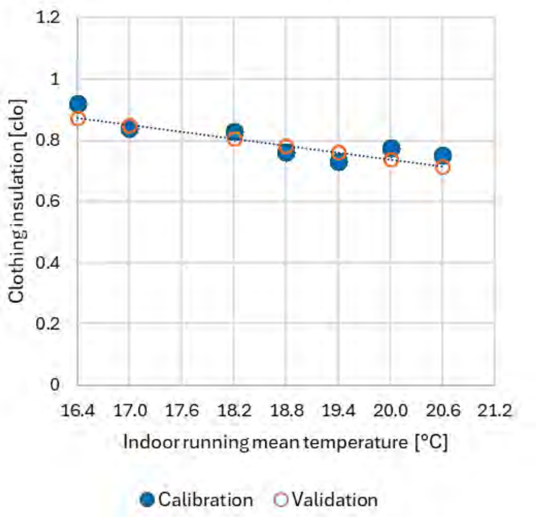

Fig. 5 – Relationship between clothing insulation (I_{cl}) and mean indoor running temperature ($T_{rm\ in}$): full blue markers refer to model calibration while empty orange markers to model validation

Table 7 – Statistical analysis of the effect of indoor running mean temperature on clothing insulation

	Regression	p-value	R² adj.
Bins 0.6° C	**I_{cl} = 1.482 - 0.037*T_{rm}**	**0.000***	**0.74**

**p-value < 0.05*

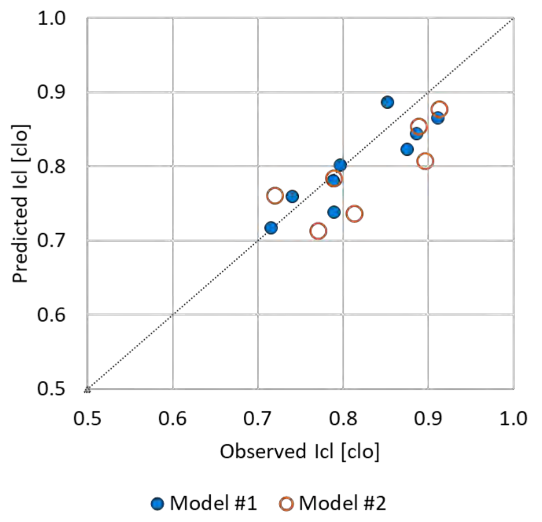

Fig. 6 – Relationship between predicted and observed clothing insulation (I_{cl}): full blue markers refer to model calibration while empty orange markers to model validation

Table 8 – Summary of different metrics for measuring the distance between observed and predicted clothing insulation

Metrics	Model#1	Model#2
RMSE [clo]	0.03	0.06
MAE [clo]	0.03	0.05

The linear regression model between clothing insulation and indoor running mean temperature, i.e., Model#2, is shown in Figure 5 and Table 7. The intercept term and the slope are similar to those found with the model based on operative temperature (i.e., Model#1), while the coefficient of determination is higher (i.e., R^2=0.74).

Validation performance of Model#2 is reported in Figure 6 and Table 8 in comparison with the results obtained for Model#1. It can be seen that the RMSE and MAE calculated for Model#2 are similar to those calculated for Model#1, meaning that indoor running mean temperature can be used to predict students' clothing insulation.

3.4 Thermal Comfort Simulation

Figure 7 and Table 9 report the results of the thermal comfort simulation in terms of Predicted Mean Vote (PMV). The scatter plot shows the relationship between PMV calculated with the observed clothing insulation (x axis) and PMV obtained using Icl derived from the linear model based on operative temperature and PMV calculated using standard clothing. It can be seen that PMV that consider the predicted Icl is quite a good proxy of PMV calculated with observed clothing insulation (RMSE=0.13, MAE= 0.10), while there is an overestimation or underestimation if the PMV which uses standard seasonal clothing (RMSE=0.32, MAE= 0.29).

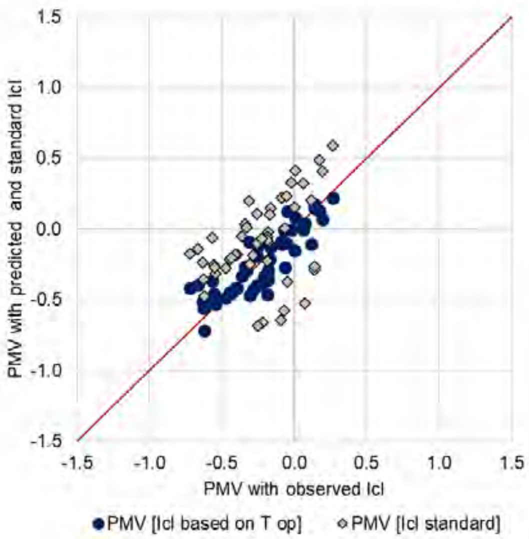

Fig. 7 – Relationship between PMV calculated with predicted and standard clothing insulation (I_{cl}) and PMV based on observed I_{cl}

Table 9 – Summary of different metrics for measuring the distance between PMV calculated with observed I_{cl} and PMV obtained with Top and using standard clothing

Metrics	PMV Model#1	PMV standard
RMSE	0.13	0.32
MAE	0.10	0.29

4. Conclusion and Further Development

This study focused on the calibration and validation of linear models for predicting the clothing insulation of students in real classrooms based on an extensive set of data collected in an Italian high school located near Rome. Linear regression models have tested using operative temperature and indoor running mean temperature of the previous 5 school days.

Based on the collected data and the presented analysis, this study shows that:

1. Linear models in the literature based on indoor operative temperature can predict clothing insulation of students with a Mean Absolute Error lower than 0.07 even when applied to different datasets/conditions
2. When developed or tuned on monitoring data are available, this error can be decreased (0.03 for Model#1)
3. Based on collected data, indoor running mean temperature (Model#2) can be used instead of operative temperature to predict clothing insulation (MAE = 0.05).
4. PMV with detailed clothing (Model#1) reduces the over/underestimation of thermal comfort, which could be beneficial in BES IEQ evaluation

As a future development, it could be interesting to extend the research including other educational stages (i.e., primary school or university). This could also allow for the further validation of the models, improving their reliability. Moreover, multi linear regressions considering different independent variables and different type of regressions will be explored.

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