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Dynamic predictive clothing insulation models based on outdoor air and indoor operative temperatures

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Publication Date
2012-09-21

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ABSTRACT

Clothing affects people's perception of the thermal environment. Two dynamic predictive models of clothing insulation were developed based on 6,333 selected observations of the 23,475 available in ASHRAE RP-884 and RP-921 databases. The observations were used to statistically analyze the influence of 20 variables on clothing insulation.

The results show that the median clothing insulation is 0.59 clo (0.50 clo (n=3,384) in summer and 0.69 clo (n=2,949) in winter). The median winter clothing insulation value is significantly smaller than the value suggested in the international standards (1.0 clo). The California data (n= 2,950) shows that occupants dress equally in naturally and mechanically conditioned buildings and all the data has female and male dressing with quite similar clothing insulation levels. Clothing insulation is correlated with outdoor air (r = 0.45) and indoor operative (r=0.3) temperatures, and relative humidity (r=0.26) An index to predict the presence of a dress code is developed.

Two multivariable linear mixed models were developed. In the first one clothing is a function of outdoor air temperature measured at 6 o'clock, and the second one adds the influence of indoor operative temperature. The models were able to predict 19 and 22% of the total variance, respectively. Climate variables explain only a small part of human clothing behavior; nonetheless, the predictive models allow more precise thermal comfort calculation, energy simulation, HVAC sizing and building operation than previous practice of keeping the clothing insulation values equal to 0.5 in the cooling season and 1 in the heating season.

Highlights

- We developed two models to dynamically predict clothing insulation levels, R^2_{adj}=0.19-0.22
- Winter clothing insulation values are significantly lower than 1.0 clo
- In California occupants dress equally in naturally and mechanically conditioned
- Clothing values are correlated with outdoor air and indoor operative temperatures
- Climate variables explain only a small part of human clothing behavior

KEYWORDS

Clothing, behavior modeling, thermal comfort, dress code, occupant behavior, indoor climate

INTRODUCTION

The amount of thermal insulation worn by a person has a substantial impact on thermal comfort [1]. Clothing adjustment is a behaviour that directly affects the heat-balance. The thermal insulation provided by garments and clothing ensembles is expressed in a unit named clo, where 1 clo is equal to 0.155 m^2K/W. For near-sedentary activities where the metabolic rate is approximately 1.2 met, the effect of changing clothing insulation on the optimum operative temperature is approximately 6°C per clo. For example, adding a thin, long-sleeve sweater to a clothing ensemble increases clothing insulation by approximately 0.25 clo. Adding this insulation would lower the optimum operative temperature by approximately 6°C/clo × 0.25 clo = 1.5°C [1]. Clothing adjustment is perhaps the most important of all the thermal comfort adjustments available to occupants in office buildings [2].

Clothing is one of the six variables (others are: Air temperature, mean radiant temperature, air speed, relative humidity and metabolic activity) that affect the calculation of the predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD)[3] and therefore is an input for thermal comfort calculations according to American [1], European [4] and International [5] thermal comfort standards. In the standards thermal comfort ranges are usually calculated for clothing insulation equal to 0.5 clo and 1 clo. If other information is not available, thermal comfort evaluations for the cooling season are performed with a clothing insulation equal to 0.5 clo, and for heating season with a clothing insulation equal to 1 clo. The selection of the clothing insulation for thermal comfort calculations affects the design (sizing and analysis) of HVAC systems, the energy evaluation and the operation of buildings. In annual energy and thermal simulations there are no standardized guidelines on how to set clothing insulation schedules. Often, just two values are used (0.5 and 1 clo) and the change from 0.5 to 1 or vice-versa is done suddenly (from one day to another) and arbitrarily [6].
These simplifications may lead to systems that are incorrectly sized and/or operated. A model that is able to predict how building occupants change their clothing would greatly improve HVAC system operation. Previous attempts to develop a dynamic clothing model demonstrated that the ability to more accurately predict variations in clothing leads to improved thermal comfort [2], smaller HVAC size and lower energy consumption [7].

de Dear and Brager [8] and de Dear [9] analysed the relationship between clothing insulation and mean indoor operative temperature [8] and mean outdoor effective temperature [8] in the publicly available database developed within ASHRAE research project RP-884 [9]. To study the relationships between clothing level and indoor and outdoor temperatures they used the average building value (160 buildings) and not the value for each occupant (22,346 occupants), i.e. the regression analysis was done with 160 statistical units (one value for each building) and not with 22,346 statistical units. They used the building and not the occupant as unit of the statistical analysis to ensure some homogeneity of conditions affecting each subset of data, but there was not an explicit verification of linear regression assumptions. In figure 5b a risk of leverage effect due to four data points (probably outliers) is visible [8]. Using the building as the statistical unit artificially reduces variance and increases the coefficient of determination (R^2). This implies a loss of information. As explained later in the paper, it is possible to take into account the variance caused by the building and use each occupant as the statistical unit by applying regression analysis based on mixed models (fixed plus random effects) instead of linear model (only a fixed effect) [10].
De Carli et al. [7] developed single variable linear regression models to predict the clothing insulation as a function of the outdoor air temperature measured at 6 o'clock in the morning. Independent models were developed for naturally and mechanically air conditioned buildings and for three latitudes ranges. The models were based on the database developed within ASHRAE research project RP-884 [9] and on field measurements performed by Feriadi et al. [11]. Based on energy simulation, De Carli et al. [7] concluded that in mechanically conditioned buildings a variation of 0.1 clo is sufficient to significantly affect the comfort evaluation based on the PMV-PPD model. The developed models have the following limitations: a) the homoscedasticity hypothesis of the developed linear models has not been reported, therefore it is possible that the regression coefficients are not correct [10]; b) the variance introduced by the building was not included in the models; c) all the data from ASHRAE RP-884 was used regardless of the quality of the measurements of the single projects included in the final database and the fact that different standards have been used to quantify the clothing insulation [9]; d) single variable regression models were used, losing the opportunity to check for interaction effect and the combination of several variables at the same time; and e) it is not clear if other relevant variables, such as air velocity and relative humidity were considered.
Morgan and de Dear [12] examined clothing behaviour and its relationship with thermal environments in two indoor settings (shopping mall and call centre) located in Sydney, Australia. They found that day-to-day variation in clothing levels changed significantly in the shopping mall where a dress code was not in place. Clothing varied less in the call centre where a dress code was enforced. For the shopping mall they developed a linear regression equation to relate the daily average clothing value with daily mean outdoor dry bulb temperature.

The aim of this research is to develop dynamic, i.e. changing daily or hourly, predictive models of clothing insulation typically used by office occupants to be applied in thermal comfort calculation, HVAC sizing, building energy analysis and building operation.

METHOD

Database

The data to develop the model were taken from ASHRAE RP-884 [9] and from ASHRAE RP-921 [13] databases. These public-domain databases contain quality-controlled data from thermal comfort field studies conducted in various countries and climate zones around the world. The two research projects are, to the knowledge of the authors, the biggest published and publicly available collection of thermal comfort field measurements. The RP-884 is the basis for the development of the thermal comfort adaptive model used in ASHRAE 55 [1]. The thermal comfort questionnaires were accompanied by simultaneous and local indoor climate measurements (e.g. air temperature, mean radiant temperature, air speed and humidity, etc.). All the data from ASHRAE RP-921 have been used. Data in ASHRAE RP-884 were classified by the authors of the report into three levels of quality (from Class I, the best, to Class III, the lowest quality data). In this research only data of Class I were used because they were collected with 100% compliance with the specification set out in ASHRAE Standard 55-1992 and ISO 7730-1984 (see Paragraph 2.2.2 of [9]). ASHRAE RP-921 complies with the same standards, and therefore it fits with Class I.

Thermal comfort standards (e.g., ISO 7730 and ASHRAE 55) provide techniques to evaluate the clothing insulation. A problem faced in ASHRAE RP-884 [9] was that standards, in their various revisions, have used different techniques, leading to quite different clothing estimates would be calculated for a given set of clothing, depending on which standard and which edition was used. To solve this problem, the researchers converted the different clothing estimation techniques into equivalent ASHRAE Standard 55-92 [14] clothing estimates. In this research only clothing values calculated using ASHRAE Standard 55-81 [15] and ASHRAE Standard 55-92 [14] were used (see Table 1). De Dear et al. [9] estimated, in the conversion from ASHRAE Standard 55-81 to 92, that for male and female the regression equation was able to explain 81% and 61% of the variance (R^2=0.81), respectively. We kept the data collected with the two methods in order to have a bigger sample (6333 observations instead of 3298). The clothing values used here are calculated according to ASHRAE Standard 55-92 [14] and do not include the insulation caused by the chair. De Dear used outdoor climatic information gathered from meteorological stations located close to the building.

Table 1 File identification number, standard used to estimate the clothing insulation, sample size and number of buildings of the data used in this research

File number[1]	City, State and Season	Clothing method	Sample size	Number of buildings
5	Antioch, California (winter)	ASHRAE 55-81	111	1
9,10	Montreal, Canada (summer and winter)	ASHRAE 55-92	869	23
32,33,34,35	Bay Area, California (summer and winter)	ASHRAE 55-81	2330	20
36,37	Townsville, Australia, (dry and wet season)	ASHRAE 55-92	1231	23
43	Grand Rapids, Michigan (winter)	ASHRAE 55-81	85	1
44,45	San Ramon, California (summer and winter)	ASHRAE 55-81	381	3
46	Aubum, California (winter)	ASHRAE 55-81	128	1
47,48	Kalgoorlie, Australia (summer and winter)	ASHRAE 55-92	1198	22

[1] File number: identification of the file according to [9] and [13].

Variables

The ASHRAE RP-884 and 921 reported a large number of variables. In this research, only a subset of variables has been used. We selected the variables that we thought may affect clothing insulation. Twenty variables were identified. We based our selection on the relations found in previously published researches. The variables included in the analysis are summarized in Table 2. Where not otherwise noted, the abbreviation follows the same of [9].

Table 2 Variables included in the analysis

Variable	Abbreviation

Ensemble clothing insulation [clo]	*clo*
subject's gender [M=male, F=female]	*sex*
Metabolic activity [met]	*met*
Indoor operative temperature [°C]	*top*
Relative humidity [%]	*rh*
Air velocity high height (1.1 m) [m/s]	*vel_h*
Air velocity medium height (0.6 m) [m/s]	*vel_m*
Air velocity low height (0.1 m) [m/s]	*vel_l*
Outdoor 15:00 (max) air temp on day of survey [°C]	*day15_ta*
Outdoor 6:00 (min) air temp on day of survey [°C]	*day06_ta*
Outdoor average of min/max air temp on day of survey [°C]	*dayav_ta*
Conditioning system (Mechanical = 1) (Natural=2)*	*bldgtype*
Year	*year*
Month of the year (Jan=1, Feb=2, etc.)	*month*
Day of the month	*day*
Nation	*location*
File identification number referred to RP-884	*file*
Building identification number referred to RP-884 and RP-921	*blcode*
Season (dry season, summer, etc)*	*season*
Building identification number in this research*	*blcodeNew*
Season aggregate (summer, winter)*	*Season1*

*Abbreviation and variable name different from [9]

Statistical analysis

The data distributions are reported as frequency histograms and as box-plots when more than one variable is plotted. A box-plot is a way of graphically summarizing a data distribution. In a box-plot the thick horizontal line in the box shows the median. The bottom and top of the box show the 25th and 75th percentiles, respectively. The horizontal line joined to the box by the dashed line shows either the maximum or 1.5 times the interquartile range of the data, whichever is smaller. Points beyond those lines may be considered as outliers and they are plotted as circles in the boxplot graphs. The interquartile range is the difference between the 25th and 75th percentiles [16]. The normal distribution of the data was tested with the Shapiro-Wilk normality test [17]. Correlation between variables is reported with Spearman’s rank coefficient if the variable does not have a normal distribution and with the Pearson correlation if it has a normal distribution. Multicollinearity was tested with the Variace Inflation Factor (VIF). VIF is a measure that can identify the multicollinearity between one independent variable and other independent variables. There is not a unique threshold value for the determination of collinearity. Pedhazur [18] reported that VIF>3 implies that there is a problem, and Diamantopoulos and Winklhofer [19] reported that VIF>10 implies relevant problems. The description of the methods and tools used for the development of multivariable linear and mixed models is reported in the section "Development of the regression model". To compare means and to test statistical difference t-test and ANOVA were used when appropriate. For all tests the results were considered statistically significant when $p<0.05$. The statistical analysis was performed with R version 2.10.1 [20].

RESULTS AND DISCUSSION

The database includes 6,333 observations. Statistical summaries are reported for categorical variables in Table 3 and for numerical variables in Table 4. From the original database only a couple of dozens data were missing. Those values have been removed.

Table 3 Statistical summary of categorical variables

Name	Level	Observation	Percentage [%]
Conditioning system	Mechanical	5584	88.2

	Natural	749	11.8
sex	Female	3547	56
	Male	2786	44
location	Australia	2429	38.3
	California	2950	46.6
	Canada	869	13.7
	Michigan	85	1.3
season	Dry season	627	9.9
	Summer	2153	34
	Wet season	604	9.5
	winter	2949	46.6
Season2	Summer	3384	53.5
	Winter	2949	46.5

Table 4 Statistical summary of numerical variables

Name	Factor	Measuring unit	Max	Min	Mean	Stand. Dev.	Median
clo	No	[clo]	1.94	0.13	0.6239	0.22	0.59
met	No	[met]	2.58	0.990	1.21	0.20	1.2
top	No	[°C]	31.67	16.64	23.11	1.24	23.10
rh	No	[%]	77.95	10.00	45.22	13	45.30
vel_h	No	[m/s]	1.71	0	0.1161	0.088	0.1
vel_m	No	[m/s]	1.97	0	0.1063	0.085	0.09
vel_l	No	[m/s]	1.55	0	0.0968	0.084	0.08
day15_ta	No	[°C]	41.2	-22.6	20.5	9.7	20.9
day06_ta	No	[°C]	26.2	-27.2	10.8	8.7	11.7
dayav_ta	No	[°C]	31.7	-24.9	15.6	8.9	15.9
year	No		From 1986 to 1997				
month	No	1…12	From January to December				
day	No	1..31	From 1 to 31				

Analysis of the categorical variables

In Figure 1 the frequency distribution of the clothing insulation and box-plots for the clothing insulation (without chair) versus the conditioning system (mechanical or natural), the gender of the occupant, the location of the building, the season divided in summer and winter or in four categories (wet season, summer, dry season and winter) are reported. The clothing insulation does not have a normal distribution but a visual analysis of the Q-Q plots showed that the deviation from normality is not large. One-way ANOVA tests showed that type of *conditioning system* (NV, HVAC), *sex*, *location*, and *season* are all significant ($p<0.001$, except for the ventilation system where $p<0.005$).

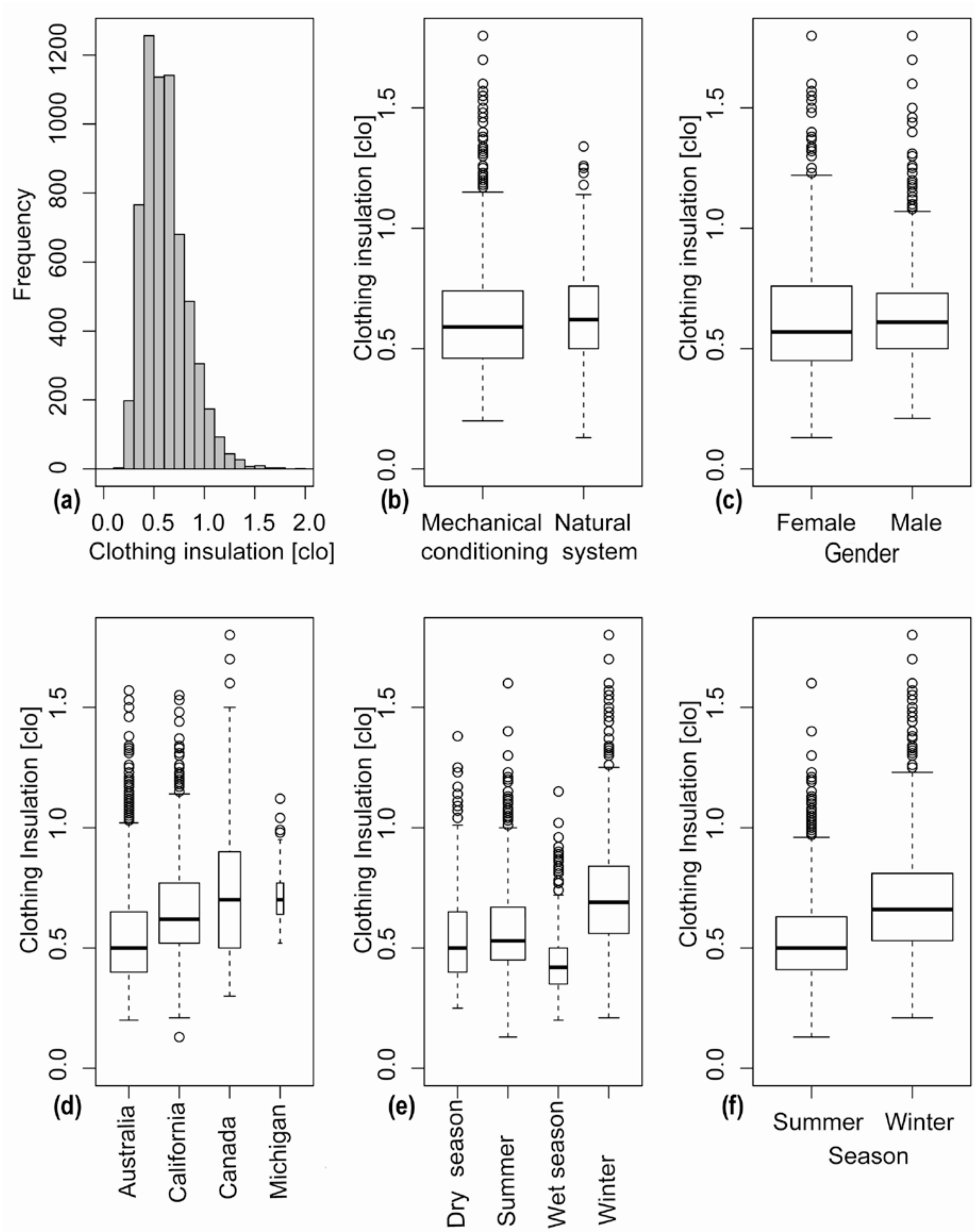

Figure 1 (a) Frequency distribution of the clothing insulation and box-plots for the clothing insulation versus (b) air-conditioning systems (mechanical or natural), (c) gender of the occupant, (d) location of the

building, and season divided into (e) four categories (wet season, summer, dry season and winter) and (f) two categories (summer and winter).

Conditioning system

Even if statistically significant the effects of ventilation system are negligible from engineering point of view because the median *clo* difference is very small (less than 0.03 clo, i.e. equivalent to the insulation of woman's underwear according to ISO 7730-2005). The significance was obtained thanks to the big sample size. The median clothing insulation is 0.59 clo (n=5584) for the mechanically conditioned building and 0.62 clo (n=749) for the naturally cooled building. All the naturally ventilated buildings are located in California and for all California buildings (n=2950) the clothing insulation has been evaluated with the ASHRAE 55-81 method. Therefore, to exclude the influence of the location and wet and dry seasons, a comparison between California buildings has been done. For this subset of the data, there is no engineering relevant difference in the median even if the difference is statistically significant (p=0.02) (HVAC=0.62 clo and NV=0.62 clo). In Figure 2 and Figure 3 the boxplot of the clothing insulation for mechanically conditioned buildings and naturally ventilated buildings as a function of the gender (for male HVAC=0.62 clo and NV=0.62 and for female HVAC=0.63 and NV=0.61) and season (for summer HVAC=0.58 clo and NV=0.55 and for winter HVAC=0.66 and NV=0.69) are shown. Not only are the medians equal, but also the interquartile ranges are very similar. From these figures and the consideration reported above it can be deduced that for the data analyzed, occupants dress equally in naturally and mechanically conditioned buildings in California regardless of gender and season.

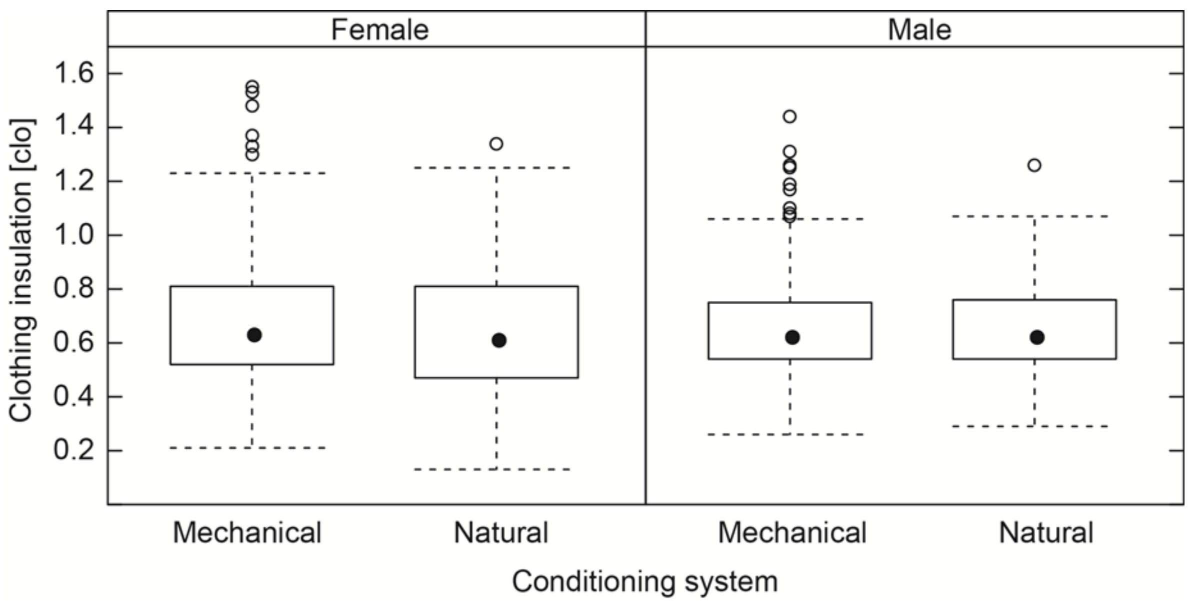

Figure 2 Clothing insulation versus conditioning system as a function of the gender. Only buildings from California have been used because in the analyzed dataset all the naturally conditioned buildings are in California (n=2950).

Schiavon S, Lee KH. 2012. Dynamic predictive clothing insulation models based on outdoor air and indoor operative temperatures. Building and Environment. http://dx.doi.org/10.1016/j.buildenv.2012.08.024

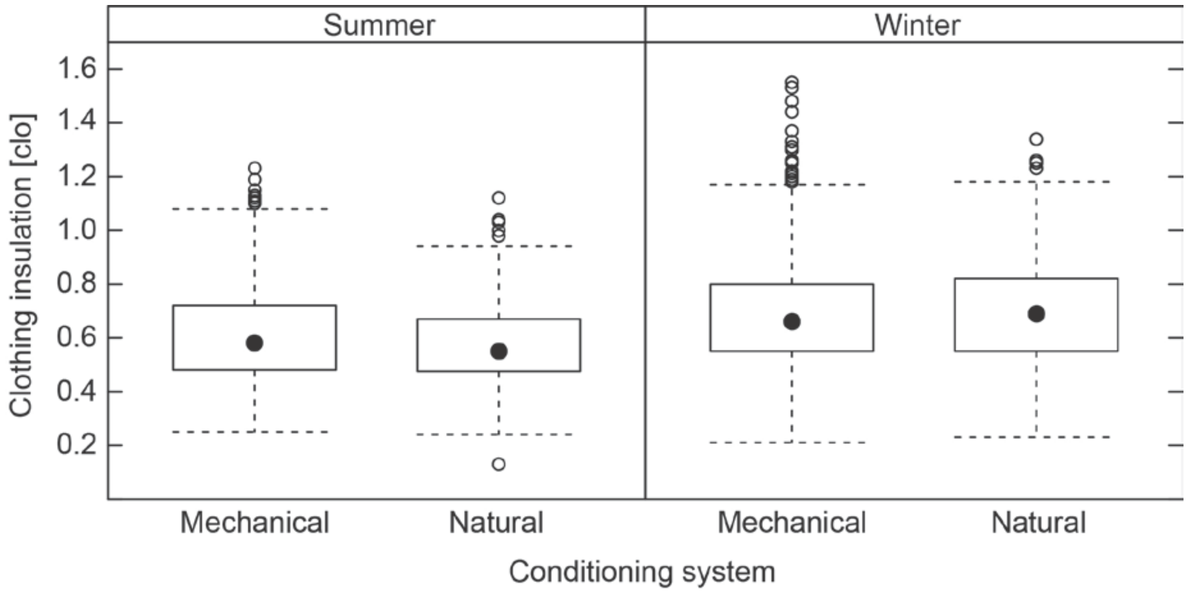

Figure 3 Clothing insulation versus conditioning system as a function of the season. Only buildings from California have been used because in the analyzed dataset all the naturally conditioned buildings are in California (n=2950).

Gender

Even if statistically significant, the effect of gender on clothing insulation is negligible from a engineering point of view because the median *clo* difference is small (less than 0.05 clo). The significance was obtained thanks to the big sample size. The median clothing insulation is 0.57 clo (n=2786) for female and is 0.61 clo (n=3547) for male. The difference between the medians is 0.04 clo, this is equivalent to the clothing insulation generated by a man's brief [1]. By analyzing the data relative to season it was noticed that in winter the two median values are very close and statistically equal (p=0.001, M=0.63 clo and F=0.67 clo), but in summer female dress slightly less than male (M=0.54 clo and F=0.48 clo). This last difference is statistically significant ($p<0.001$). In Figure 4 the boxplots for clothing insulation versus gender clustered as a function of the four seasons are reported. Except for summer the difference between male and female is negligible. From the results reported above it is possible to conclude that female and male dress with quite similar clothing levels. Morgan and de Dear [12] found that for 1172 observations (this value was obtained from the degree of freedom of a statistical test) during six months in a shopping mall in Sydney the mean clothing insulation was 0.51 clo for female and 0.47 clo for male. If the difference was statistically significant, it was not reported.

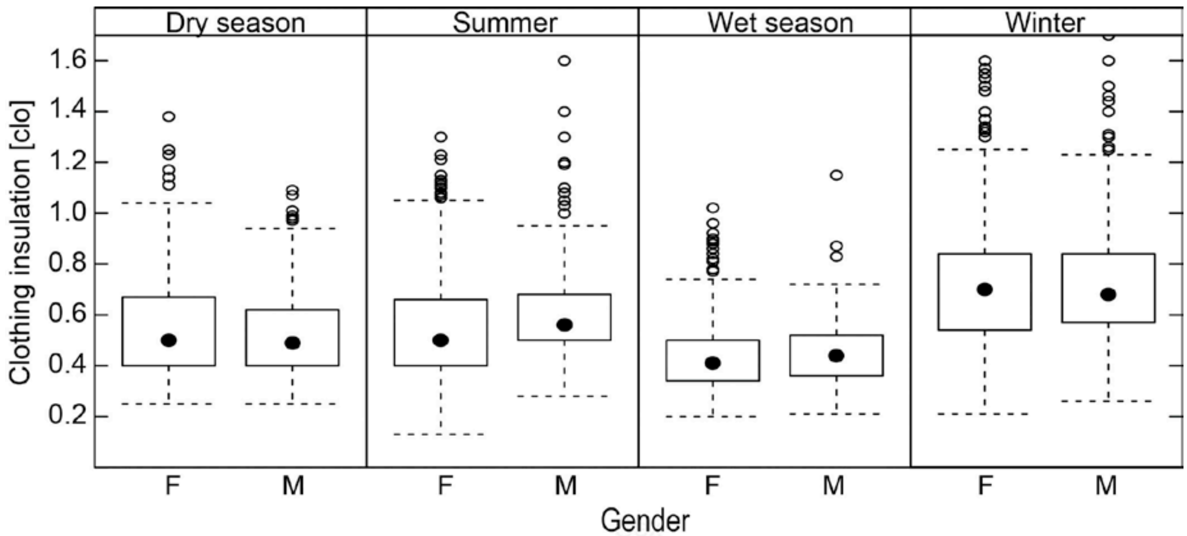

Figure 4 Clothing insulation versus gender for the four analyzed season (n=6333).

Season

Season has a strong effect on clothing. For wet season the median is equal to 0.42 clo (n=604), for summer 0.53 clo (n=2156), for dry season 0.5 clo (n=627) and for winter 0.69 clo (n=2953). In Figure 1f wet season and summer are merged together and the same is done for dry season and winter. The wet and dry seasons are from files 36 and 37 (see Table 1). The measurements were performed in Townsville, Australia where both the wet and dry seasons are classified as summer [9]. In this case the median clothing insulation is 0.50 clo (n=3384) in summer and is 0.69 clo (n=2949) in winter. The winter value (0.69) is significantly smaller than the value suggested in the international standards [1,4,5] for the heating season, which is 1 clo. Winter is relatively mild in California and Australia (median *day06_ta* during the winter is 10.4 and 7.2°C, respectively), therefore it could be that the low winter clothing value is due to the non rigid definition of what is winter. To assess the clothing insulation in a colder climate, the winter data from Michigan and Canada were independently analyzed. The median outdoor air temperature in Michigan is -0.6°C (first quartile=-1.1°C; third quartile=1.1°C). Only 85 data points are available and the data are not widely distributed. The median clothing insulation is 0.7 clo. In Canada colder temperatures were recorded (first quartile=-12.8°C; median=-7.5°C and third quartile=-3.0°C). The winter median clothing insulation in Canada is 0.8 clo that is still significantly lower than 1.0 clo.

For a standard office activity of 1.2 met, a relative humidity of 50%, an air velocity less than 0.1 m/s, and the air temperature equal to the mean radiant temperature, if *clo* is 0.69 the operative temperature that minimizes the Predict Mean Vote (PMV=0 and Predicted Percentage of Dissatisfied - PPD=5%) is 23.6°C. If *clo* is 1, then the temperature is 21.5°C.

Analysis of the numerical variables

Reduction of the number of independent variables

The outdoor air temperature is described by three variables: the minimum outdoor air temperature measured at 6:00 o'clock, the maximum outdoor air temperature measured at 15:00 and the average daily temperature.

In Figure 5 the correlation matrix of the minimum, maximum and average outdoor temperatures is shown. Besides the bivariate scatter plots and the fitted lines (lower-left part) the correlation (Spearman's rank) values (upper-right) and their significance level ($p<0.001$ for the three stars) are also shown. The correlation values are extremely high (0.88-0.97), and therefore there is a high risk of collinearity. Collinearity was tested with VIF. For all the three analyzed variables VIF was higher than 100. Collinearity is a serious problem for the estimation of the regression coefficients as well as the interpretations [21]. To reduce the collinearity two of these variables can be taken out from the model. It is not necessary to keep all three variables in the model because one variable is sufficient to describe the other two. It is not important which one is kept. We arbitrarily preserved the minimum air temperature (6:00 o'clock) to maintain consistency with previous work [7,12] where it was hypothesized that morning temperatures are the most important because in the morning people usually select their clothing. The air velocities are strongly correlated, too (Spearman's rank between 0.46 and 0.67). In particular, the air velocity at medium height, *vel_m*, is strongly correlated with air velocity at high height and low height (0.65 and 0.67, respectively). For the same reasons explained above the air velocity at medium height, *vel_m*, was selected as being representative of other velocities.

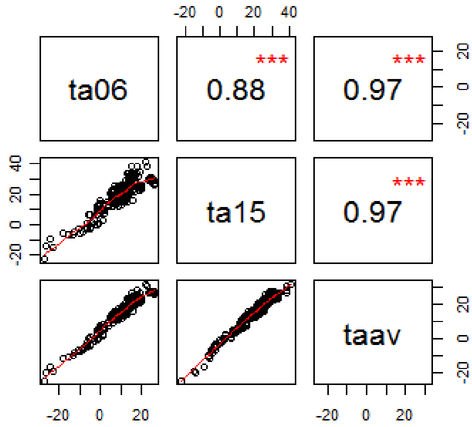

Figure 5 Correlation matrix of the minimum (*day06_ta*), maximum (*day15_ta*) and average (*dayav_ta*) outdoor temperatures. Bivariate scatter plots and the fitted lines (lower-left part); Spearman's rank correlation values (upper-right) and their significance level (p<0.001 for the three stars).

Correlation matrix

In Figure 6 the correlation matrix of the following variables is shown: metabolic activity, relative humidity, indoor operative temperature, air velocity at medium height, minimum outdoor air temperature (outdoor air temperature measured at 6 o'clock), and clothing. Bivariate scatter plots and the fitted lines are shown in the lower-left part of the figure; Spearman's rank correlation values and their significance level (p<0.001 for three stars and p<0.01 for two stars) are shown in the upper-right part. Clothing insulation is correlated with outdoor air temperature measured at 6:00 o'clock (r=0.45), operative temperature (r=0.3), relative humidity (r=0.26) and is slightly correlated with air velocity (r=0.14) and metabolic activity (r=0.12). In this graph it is possible to study the correlation between the dependent variables. This will be helpful to avoid the problem of multicollinearity. Outdoor air temperature is strongly correlated with relative humidity (r=0.64) and operative temperature (r=0.3).

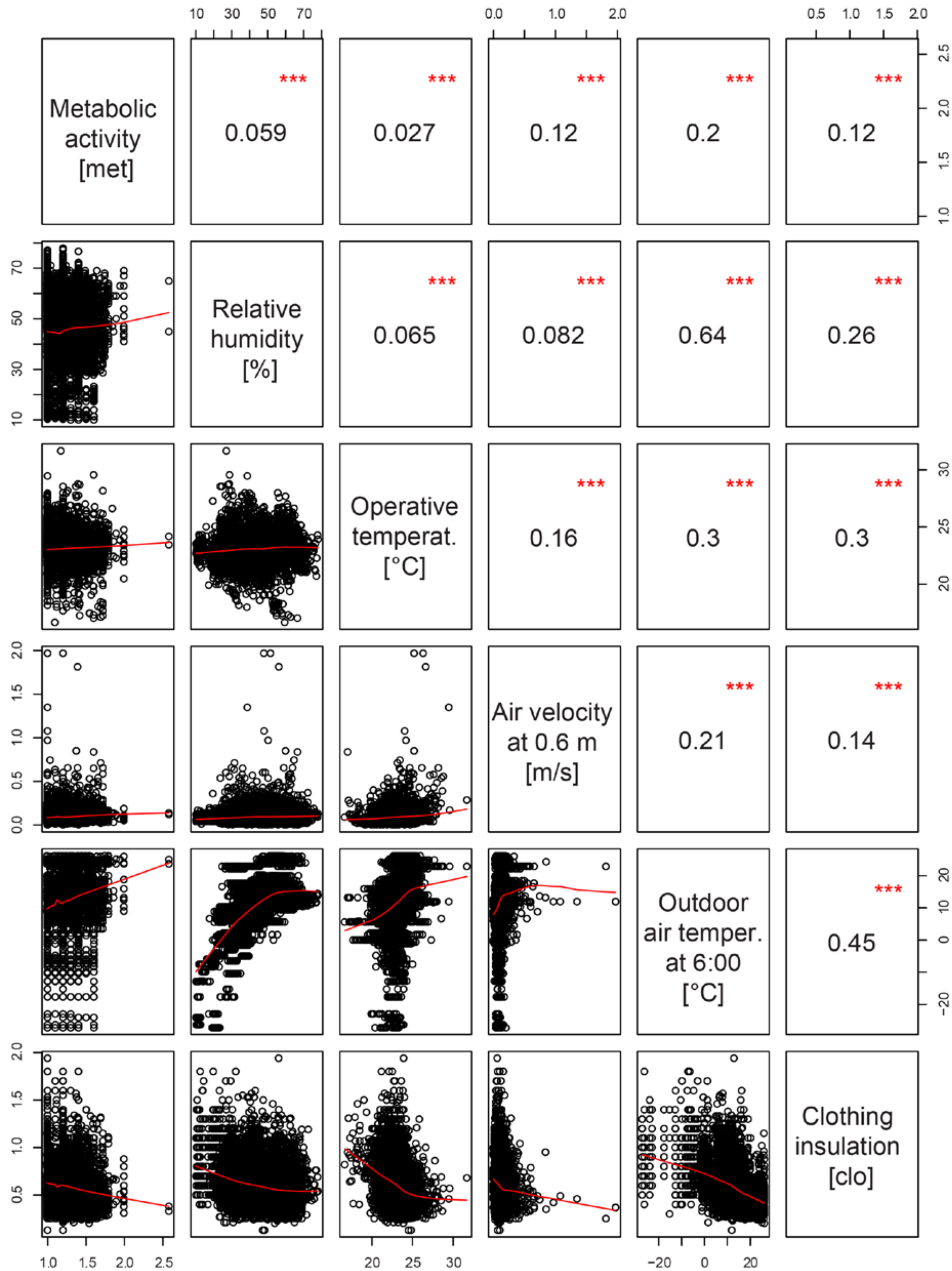

Figure 6 Correlation matrix of the following variables: metabolic activity, relative humidity, indoor operative temperature, air velocity at medium height (0.6 m), minimum outdoor air temperature

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(measured at 6 o'clock) and clothing insulation. Bivariate scatter plots and the fitted lines are shown in the lower-left part of the figure; Spearman's rank correlation values and their significance level ($p<0.001$ for three stars and $p<0.01$ for two stars) are shown in the upper-right part.

Dress code

In office building the dress code may affect the ability of occupants to adapt their clothing insulation to indoor and outdoor weather conditions. In the ASHRAE thermal comfort database the enforcement or lack of a dress code was not recorded, therefore, a the presence of a dress code should be deduced from the available data. This process could generate not very accurate results. If a dress code is present in a building, it is expected that the difference in clothing insulation among occupants would be small. The interquartile range (IQR) of the clothing distribution was used to verify the presence of a dress code inside each surveyed building. IQR is a commonly used measure of statistical dispersion and it is equal to the difference between the third and first quartiles. A single IQR has been calculated for each building. This new variable, named *DressIQR*, has a median value equal to 0.22 clo, with the first percentile equal to 0.16 clo and the third equal to 0.27. In Figure 7 the cumulative distribution of the new variable is shown. At *DressIQR* = 0.31 clo there is a steep change. It has been decide to use this point to classify the building with a dress code (*DressIQR*<0.31 clo; n=5690) and building without a dress code (*DressIQR*>0.31 clo; n=643).

In Figure 8 is shown the relationship between clothing insulation and dress code (*DressIQR*), from the figure it could be deduced that the possibility of adjusting the clothing insulation decreases with the decrease of the clothing insulation (Spearman's rank - r = 0.37). A similar relation has be found with the increase of outdoor air temperature (r=0.57). These results show that the possibility of clothing adjustment diminishes in warmer climate. Comparable results have been reported by [9] and [12].

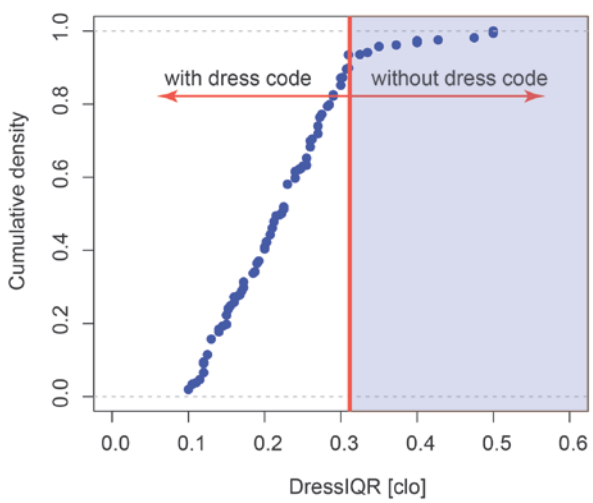


Figure 7 Cumulative distribution of the variable *dressIQR* (interquartile range of the clothing insulation calculated for each building).

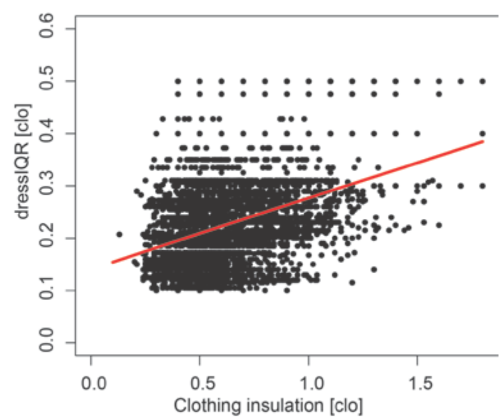


Figure 8 Clothing insulation versus dress code [*dressIQR*] (black dot) and linear regression between the two (red line).

Development of the regression models

Multivariable linear model

Multi-variable linear models have been developed. The best models were selected based on the R-squared adjusted method (R^2_{adj}) the minimum number of explanatory variables has been used. If all the available variables are used, the obtained model has an R-squared adjusted value equal to 0.28. That is the maximum value achievable with a linear multivariable model. The regression linear hypotheses have been tested for all the studied models. The plot of residuals vs. fitted values was used to check the validity of the hypothesis of constant variance required for linear models. This showed that this hypothesis (aka heteroscedastic) was violated if a transformation of the dependent variable was not applied. The same problem was revealed in the plot of the square root of the standardized residuals versus the fitted values. Ignoring non-constant variance when it exists invalidates all inferential tools like p-value, confidence intervals and prediction intervals [21]. Therefore the models with this problem were transformed. To overcome non-constant variance a power transformation of the response variable was applied for each model. The Box-Cox method [22] was used to find the exponent of the transformation. The results showed that applying a logarithm transformation of the dependent variable would remove the problem. In Table 5 the most relevant models are summarized. The selected models are reported in equations (1), (2) and (3). Equation (1) has a R^2_{adj} of 0.21 and the clothing insulation is a function of the minimum outdoor temperature. Equation (2) has a R^2_{adj} of 0.24 and the clothing insulation is a function of the minimum outdoor temperature and indoor operative temperature. Equation (3) has a R^2_{adj} of 0.25 and the clothing insulation is a function of the minimum outdoor temperature, indoor operative temperature and dress code. There is not a strong advantage of having the dress code as independent variable. Therefore it is suggested to use equations (2) or (1) depending on whether or not the operative temperature is known.

Table 5 Model structure, validity and R-squared adjusted for the investigated models

Variables	Validity	R^2_{adj}
Day06_ta	No	0.207
Log10(clo)~day06_ta	Yes	0.214
Day06_ta+top	No	0.236
day06_ta+top+season	No	0.248
Day06_ta+top+DressCode	No	0.2481
log10(clo)~day06_ta+top+ DressCode	Yes	0.2516
log10(clo)~day06_ta+top	Yes	0.2436
day06_ta + I((day06_ta-meanday06_ta)^2)+top+I((top-meantop)^2)	No	0.2412
log10(clo)~day06_ta + I((day06_ta-meanday06_ta)^2)+top+I((top-meantop)^2)	Yes	0.2436

$$log_{10}\,clo = -0.1449\; - 0.0080\text{ day06\_ta} \quad (1)$$

$$log_{10}\,clo = 0.3540 - 0.02203top - 0.0070\text{day06\_ta} \quad (2)$$

$$\begin{aligned} log_{10}\,clo = 0.3506 - 0.02208top - 0.0068\text{day06\_ta} \\ + 0.0208DressCode\;(without\ dress\ code) \end{aligned} \quad (3)$$

Multivariable mixed model

In general data may include both fixed effects and random effects. Fixed effects have informative variables whereas random effects are generally uninformative or not useful for predicting the dependent variable. In this case the building itself may have an influence on the clothing insulation but in the regression model it would be useless to have the specific building as an independent variable. For this reason a multivariable mixed model was used in order to take this effect into account. The R package "lme4" has been used [23]. It is not possible to use R-squared adjusted to compare mixed models. Here the Akaike Information Criterion (AIC) has been used [24]. The AIC is not a test of the model in the sense of hypothesis testing; rather, it provides a means for comparison among models. Given a data set, several candidate models may be ranked according to their AIC, with the model having the minimum AIC being the best. From the AIC values one may also infer that e.g. the top two models are roughly in a tie and the rest are far worse [25]. Two valid mixed models are reported in equations (4) and (5). The relevance of the random effect is measured in term of interclass correlation coefficient. For the developed models the interclass correlation coefficient was equal to 0.17 and 0.13 respectively, meaning that the random effect explain 17% and 13% of the total variance. Therefore the mixed models have to be used instead of the linear models.

(SI) $$log_{10}\, clo = -0.1635 - 0.0066\text{day06\_ta} \quad (4)$$

(SI) $$log_{10}\, clo = 0.2134 - 0.0165top - 0.0063\text{day06\_ta} \quad (5)$$

(IP) $$log_{10}\, clo = -0.0460 - 0.00367\text{day06\_ta} \quad (6)$$

(IP) $$log_{10}\, clo = 0.6189 - 0.00916top - 0.0035\text{day06\_ta} \quad (7)$$

In these equations, *day06_ta* is the outdoor air temperature measured at 6:00 and *top* is the operative temperature. These models are valid within the following boundary: *day06_ta* should be between -27.2°C and 26°C [-17 and 78.8°F] and *top* should be between 16.6°C and 31.7°C [61.9 and 89°F]. These models have been developed with a mixed model approach that does not allow calculating R^2_{adj}. In order to assess the ability of the models they have been tested in the database. The results of this process are plotted in Figure 9. For equation (4) R^2_{adj} is equal to 0.19 and for equation (5) is 0.22. The implications of these two models on energy use, HVAC sizing and thermal comfort evaluation is described in [26]. Indoor and outdoor climate variables explain only a small part of human clothing behavior, nonetheless, the predictive models allow more precise thermal comfort calculation, energy simulation, HVAC sizing and building operation than previous practice of keeping the clothing insulation values equal to 0.5 in the cooling season and 1 in the heating season [26].

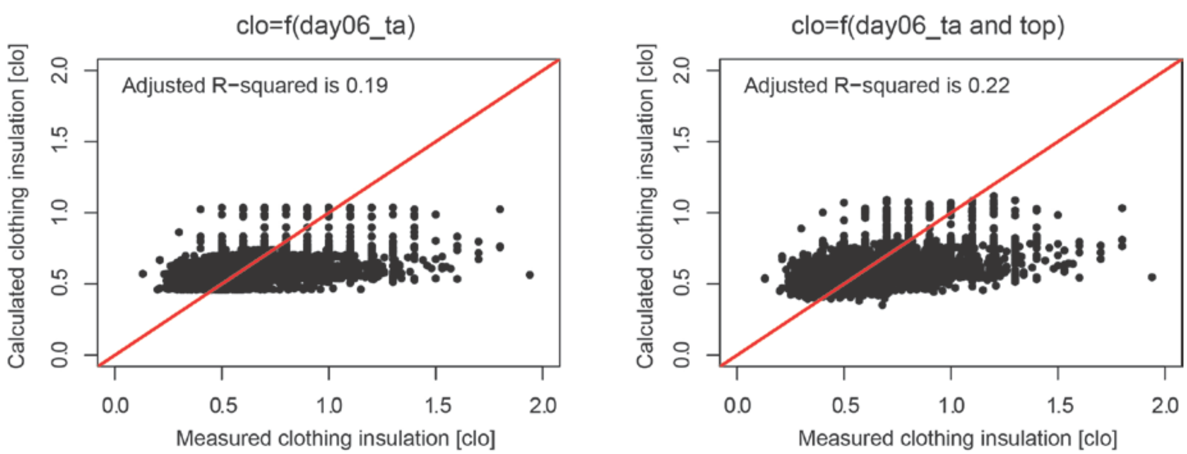


Figure 9 Measured versus fitted clothing insulation values calculated with the two models.

To assess the predictive ability of the two models, the entire dataset has been randomly divided into two parts: a training dataset and a test dataset. Two multivariable mixed models with the same structure of equations (4) and (5) have been fitted for the training dataset. An ANOVA showed that the two models are statistically different ($p<0.001$). The models were tested in the test dataset. The model with only *day06_ta* had a R-squared adjusted (R^2_{adj}) of 0.18 and the model with *day06_ta* and *top* had a $R^2_{adj}$of 0.21. The models developed in the training dataset are reported in equations (8) and (9). The developed models have regression coefficients very similar to the model developed in the whole database and the calculated *clo* values have a difference that is negligible (less than 0.025 clo between the models (4) and (8) and less than 0.02 clo between the models (5) and (9)) therefore it is acceptable to use models obtained in the whole database.

(SI) $$log_{10}\, clo = -0.1554 - 0.0074\text{day06\_ta} \quad (8)$$

(SI) $$log_{10}\, clo = 0.2000 - 0.0156top - 0.0070\text{day06\_ta} \quad (9)$$

Figure 10 reports the graphical representation of the regression model (equation (4)) developed to predict the clothing insulation when only the outside dry bulb air temperature is known. Figure 11 reports the graphical representation of the regression model (equation (5)) when both the outside air and indoor operative temperatures are used. In all the models reported here, the chair is not present and should be added to the calculated value if it is present. Figure 12a reports a yearly example of the application of equation (4). Figure 12b shows a ten-day example of the application of equation (4) and (**5**). The outside dry bulb air temperatures measured at 6 o'clock have been extrapolated by the EnergyPlus EPW weather file of Chicago O'Hare International Airport. From the analysis of Figure 10 it can be seen that only with outdoor temperatures below -10°C, are clothing insulation levels above 0.8 clo. It should be noticed that the outside air temperature used in this equation is measured once a day at 6 o'clock in the morning. Figure 11 shows that only if indoor temperatures are lower than 24°C and outdoor temperature measured at 6 o'clock is lower than -8°C the clothing insulation is higher than 1.

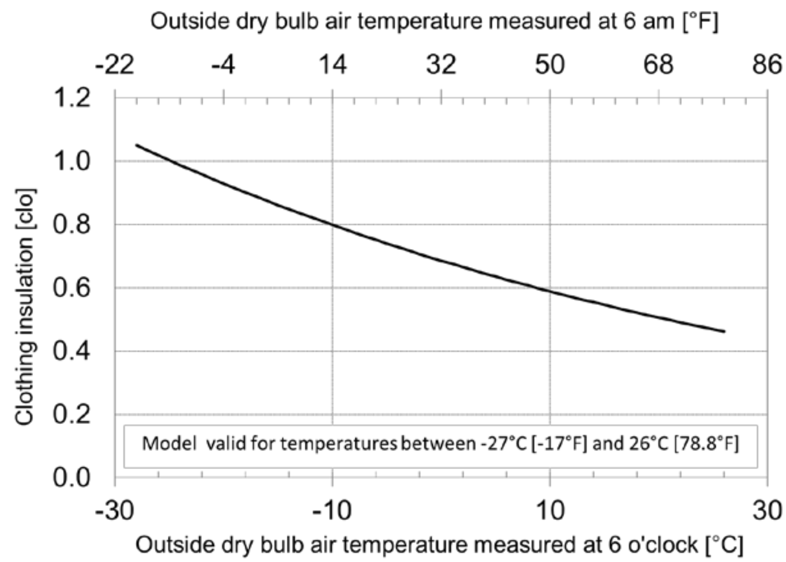


Figure 10 Graphical representation of the regression model developed to predict the clothing insulation when only the outside dry bulb air temperature measured at 6 o'clock is known.

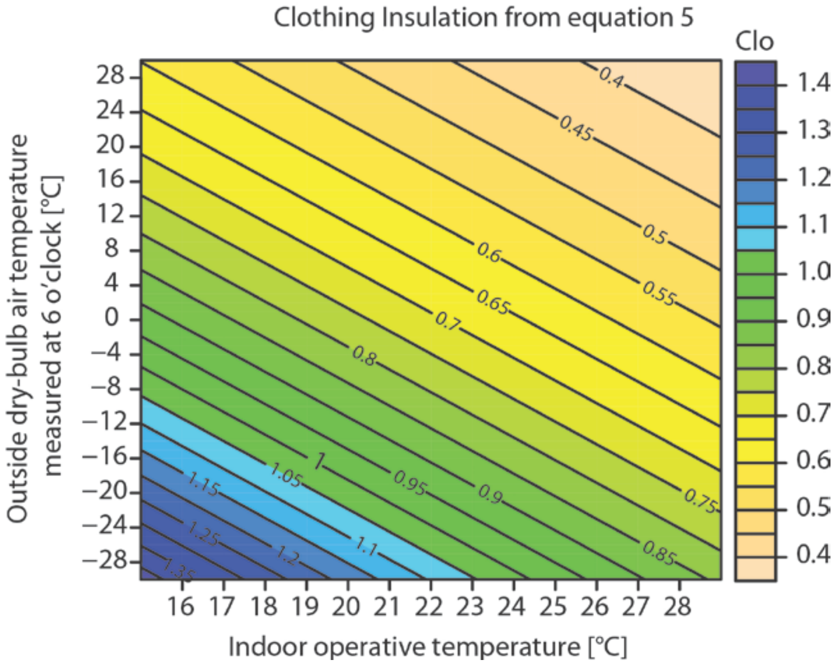
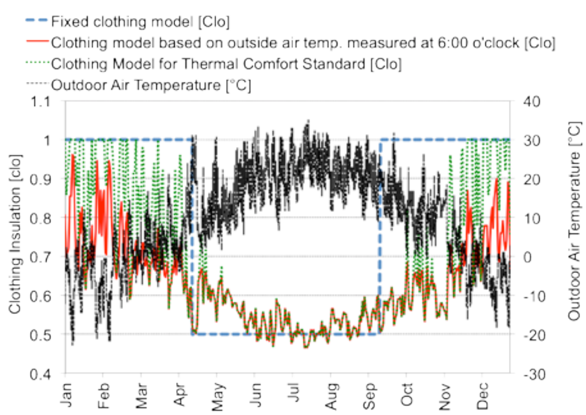


Figure 11 Graphical representation of the regression model developed to predict the clothing insulation when the outside dry bulb air temperature measured at 6 o'clock and the indoor operative temperature are known



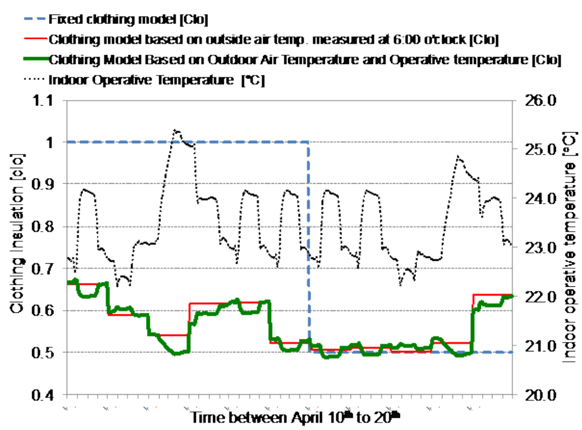


Figure 12 (a) Clothing insulation schedule for a fixed model (blue), for the clothing model based on outdoor air temperature measured at 6 o'clock and for the suggested model for Thermal Comfort Standards for one year. (b) Clothing insulation schedule for a fixed model (blue), for the two clothing models: equation (4) **(red) and equation** (5) **(green) for ten days. Climate data for Chicago O'Hare International Airport has been used.**

Discussion of the influence of indoor and outdoor temperatures on clothing insulation

Morgan and de Dear found that indoor operative temperatures are not statistically associated with clothing insulation levels [12] but they affirmed that the extremely limited variance in both the predictor (indoor temperatures) and the dependent (indoor clo) variables precluded any other finding being made with their data. Moreover, a significant part of the data comes from a cross-sectional study in a shopping mall where visitors stayed indoors for only a short time. It is possible that most of the time the visitors had been exposed to outdoor conditions. In the study reported here, it was found that indoor operative temperature is the second most important variable affecting clothing insulation among the 20 observed variables. This result is based on a higher number of observations and it is supported by a larger variation of indoor temperatures and clothing insulations. This study supports the idea that people, if allowed, change their clothing as a function of the indoor conditions that they are exposed to.

Morgan and de Dear [12] showed why outdoor temperature affects clothing insulation. They stated: "it is not difficult to understand how the temperature of the indoor microclimate surrounding the human body exerts an influence on clothing levels. Indoor temperature directly impacts the body's heat balance, skin temperatures and skin wettedness, which are, in turn, the main thermophysiological drivers for thermal discomfort. In conventional thermal comfort theory we regard the motivation for clothing selection and indeed, any other thermoregulatory behavior, as being proportional to the intensity of conscious sensations of thermal discomfort. Therefore if this is the causal chain linking indoor temperature to indoor clothing insulation levels, how can outdoor temperature exert an effect as well…?". Morgan and de Dear suggested that the timing (usually in the morning) of exactly when clothing decision are made is relevant for explaining the relationship between clothing and outdoor air temperature. They found that both previous day thermal experience and forecast of thermal experience are relevant factors [12].

The results reported here showed that people do not strongly adapt their clothing to the outdoor weather conditions and that indoor air temperature does not significantly change (50% of the data are between 22.4 and 23.7°C, with a median value of 23.1°C). Allowing and supporting a greater clothing adaptation and a wider range of indoor climatic conditions could save a relevant amount of energy without sacrificing thermal comfort [27,28].

A clothing insulation model for thermal comfort standards

In thermal comfort standards is suggested to use 1 clo for winter conditions and 0.5 clo for summer conditions. A dynamic model to predict clothing insulation is needed but the models proposed before are not suited to be implemented directly in thermal comfort standards because:

- The models are valid only for outdoor air temperatures measured at 6 o'clock between -27 and 26°C.
- The database used for the development of the predicting clothing insulation models has only 15.5% and 4.5% of the data that are less than 5°C and -5°C, respectively. Therefore not much data are available for winter conditions.
- When the outdoor air temperature measured at 6 o'clock is less than 5°C, still the median indoor operative temperature is 22.6°C (first quartile = 21.9°C and the third = 23.2°C). This is a clear indication that even if it is cold outside the indoor operative temperature is kept relatively high. Having high indoor operative temperatures allows occupants to dress lighter and regardless to outdoor conditions. This practice has negative energy impact.

Supporting a winter clothing insulation equals to 1 clo would have energy benefits without having thermal comfort drawbacks. Based on these considerations the following adapted model is proposed for being implemented in thermal comfort standards (equation (10)):

$$\begin{array}{rl} \text{For } day06\_ta < -5°\text{C} & clo = 1.00 \\ \text{For } -5°\text{C} \leq day06\_ta < 5°\text{C} & clo = 0.818 - 0.0364 * day06\_ta \\ \text{For } 5°\text{C} \leq day06\_ta < 26°\text{C} & clo = 10^{(-0.1635 - 0.0066 * day06\_ta)} \\ \text{or } day06\_ta \geq 26°\text{C} & clo = 0.46 \end{array} \tag{10}$$

For *day06_ta* lower then to -5°C the clothing insulation has been arbitrarily fixed to 1 clo. For *day06_ta* between -5 and 5°C a linear interpolation between 1 clo and the clothing insulation value calculated with equation (4) for 5°C (0.636 clo) has been implemented. Between 5 and 26°C the model reported in equation (4) has been used. For *day06_ta* equal and higher then 26°C the clothing insulation has been arbitrarily fixed to the value calculated with Equation 1 for 26°C (0.46 clo). The proposed model is graphed in Figure 13 and an example of its application is reported in Figure 12a.

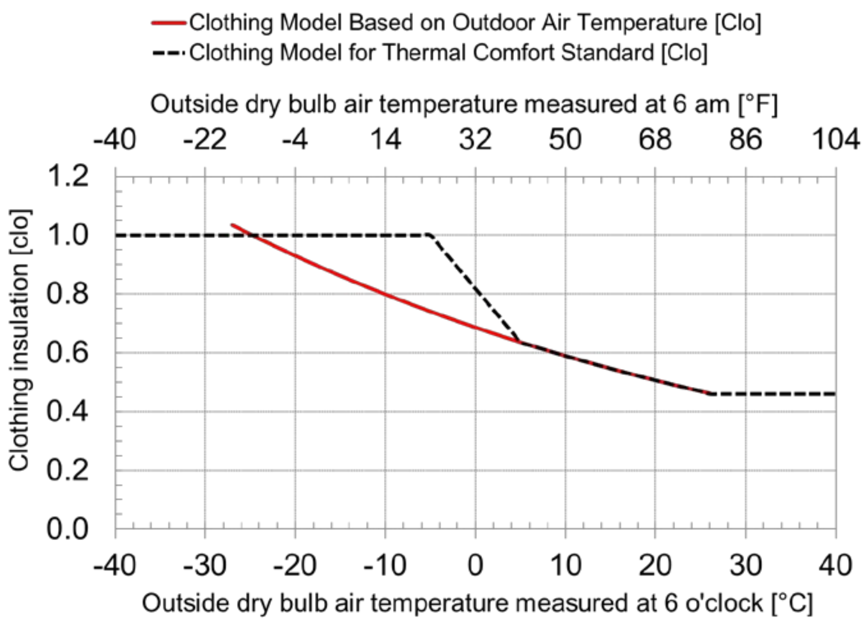


Figure 13 Graphical representation of the proposed model for thermal comfort standard compared to the model to predict the clothing insulation when only the outside dry bulb air temperature measured at 6 o'clock is known.

Study limitations

The main limitations of this study are related to the following: (a) it was not possible to conduct a systematic randomized approach for building selection; (b) when all measured variables are taken into account, the maximum explainable variance was 28%, meaning that many important variables that affect clothing selection have not been measured and considered in this analysis; (c) the two developed predictive models have the ability to predict 19 and 22% of the total variance, a fairly modest predictive ability; and (d) the developed models have a limited range of applicability. Beside the limits of indoor operative temperature and outdoor air temperature, the data are representative of buildings in Australia, California, Canada and Michigan where clothing tends to be more informal, particularly in Australia and California. It is reasonable to assume that cultural and economic forces may create either a stronger connection of the clothing level to the outdoor and indoor climate when heating or cooling is not available, or a weaker connection when dress codes or religious traditions do not allow the adaptation of clothing to climate.

CONCLUSIONS

The main conclusions of the analysis of the clothing insulation behavior are summarized below.

1. The median clothing insulation value is 0.59 clo (0.50 clo (n=3,384) in summer and 0.69 clo (n=2,949) in winter). The winter median clothing insulation in Canada was 0.8 clo (n=426) when the median winter outdoor air temperature measured a six o'clock was -7.5°C. The median winter clothing insulation value is significantly smaller than the value suggested in the international standards (1.0 clo).
2. The data shows that occupants dress equally in naturally and mechanically conditioned buildings (valid only in California) and females and males dress with quite similar clothing insulation levels.
3. Clothing insulation is correlated with outdoor air temperature measured at 6 o'clock in the morning (Spearman's rank correlation coefficient r = 0.45), operative temperature (r=0.3), relative humidity (r=0.26) and only slightly correlated with air velocity (r=0.14) and metabolic activity (r=0.12).
4. An index to predict the presence of a dress code has been developed and it was found that the possibility of clothing adjustment diminished in warmer weather.
5. Multivariable linear and mixed regression models have been developed. Two mixed regression models were finally selected. In the first model, clothing insulation is a function of outdoor air temperature

measured at 6 o’clock in the morning, and in the second model, the influence of indoor operative temperature is also taken into account. The models were able to predict only 19 and 22% of the total variance, respectively. Indoor and outdoor climate variables explain only a small part of human clothing behavior.

ACKNOWLEDGMENTS
For the discussions about the database and suggestions on the statistical analysis, the authors would like to thank Alessandro Calzolato, Richard de Dear, Kasper Jensen, Bjarne Olesen, and Angelo Zarella.

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