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Published in:
Energy and Buildings

Link to article, DOI:
10.1016/j.enbuild.2021.111431

Publication date:
2021

Document Version
Publisher's PDF, also known as Version of record

Energy & Buildings 252 (2021) 111431

Contents lists available at ScienceDirect

Energy & Buildings

journal homepage: www.elsevier.com/locate/enb

Investigating current trends in clothing insulation using a global thermal comfort database

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ARTICLE INFO

Article history:
Received 2 July 2021
Revised 23 August 2021
Accepted 31 August 2021
Available online 3 September 2021

Keywords:
Field studies
Chair insulation
Logistic regression
Sensitivity analysis
PMV

ABSTRACT

Clothing insulation is a key parameter to assess thermal comfort and is one of the most difficult parameters to estimate in field studies. The recent ASHRAE Global Thermal Comfort Database II contains a large sample of clothing insulation in addition to a wide range of other thermal and contextual parameters. However, the database does not provide details on whether the clothing insulation included the additional insulation that is provided by chairs for seated occupants. This may affect thermal comfort predictions. The objective of this study was to analyse the clothing insulation in ASHRAE Global Thermal Comfort Database I and II. First, additional information on ensemble and chair insulation was collected to complement database II. Then, predictive models of ensemble insulation were derived for office buildings, and the combined ensemble and chair insulation was used to analyse the sensitivity of the Predicted Mean Vote (PMV) to the clothing insulation. The developed model can predict the ensemble insulation as a function of the indoor air temperature, the season and the building ventilation type (air-conditioning, natural ventilation or mixed-mode). The PMV predictions improved by accounting for the chair insulation, which may further impact the indoor environment classification according to the European standard EN 16798-1.

1. Introduction

The large potential of using easily accessible archival data to develop new or analyse existing thermal comfort models became clear after the publication of the first global database of thermal comfort experiments [1]. Most prominently, this database was the backbone of the adaptive model of thermal comfort and preference that is now setting the standard for a wide range of models of similar nature [2]. A greatly expanded and updated repository of thermal comfort field data is now available, including the original data from the first version of the database [3]. Data in the database is comprised of surveys carried out in a wide range of buildings and climate zones in 23 countries during a 20-year period. The database covers a fairly extended time span and may thus enable studies of how personal factors such as clothing insulation or metabolic rate or parameters characterizing the indoor environment have changed over time.

ASHRAE database II has been openly accessible since 2018 and a large and increasing number of studies have used the database in different analytical, experimental and validation contexts. To some degree, observations and measurements in the database depend on the researcher studying a building and thus on experience, available instrumentation and a range of other factors, including the conditions in the particular building (e.g. access to a representative or only limited part of the building, orientation and interior of rooms, internal and external heat gains). The large number of records in the database may in itself moderate unwanted bias, but outcomes of analyses using the data may be affected when non-sampling errors dominate or when data is not entirely in agreement with standardised requirements for inclusion. This is particularly a risk when analyses rely on smaller subsets of data. Also, some studies are more vulnerable than others depending on how they select data and use the information retrieved from the database.

The objective of the current study was to evaluate the clothing insulation recorded in the database, as clothing insulation, together with the estimation of metabolic rate, is one of the most difficult, but also critical parameters for the assessment of thermal comfort. Clothing insulation may differ between contexts such as building typology or building ventilation type or change over time. Specific objectives of the study were therefore to explore associations between clothing insulation and different thermal and contextual parameters; to evaluate the variability of the clothing insulation in the database by clarifying if the chair insulation

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https://doi.org/10.1016/j.enbuild.2021.111431
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was accounted for; and to evaluate the sensitivity of the predicted mean vote (PMV) to the variability of the clothing insulation level.

2. Initial analyses

To understand the types of analysis relying on the database, a systematic examination of studies citing the database reference publication [3] was first carried out. The outcome of this is described shortly in the following.

2.1. Studies citing the database

Web of Science was queried for studies citing the database reference publication [3] by the end of April 2021. This resulted in 66 hits that after initial screening were classified according to the strength of the study's dependency on the database data (references in supplementary material). Six categories from strong (1) to no obvious dependency (6) were defined. The categories and their corresponding description are shown in Table 1, which also shows the number of hits in each category.

The 20 studies classified in category 1 that explicitly used the database in their analyses were further examined for their approach and in particular if the study outcome could be assumed to directly or indirectly depend on the estimated clothing insulation (I_{cl}) values. We considered six of these studies to rely on the recorded I_{cl}, e.g. to calculate PMV and compare with observed thermal sensation, to include in machine learning algorithms to predict thermal sensation, or when acceptable temperature ranges were inferred from sets of parameters in the database [4–9]. None of the studies reported sensitivity analyses of how inaccuracy in clothing insulation (or other included parameters) affected the study outcome and conclusions. One study made an assumption regarding marginal chair insulation [5], while most did not mention if their analysis in- or excluded insulation provided by chairs for seated occupants. This prompted us to carry out a survey of how clothing insulation was estimated in the studies that supplied data to the database and if and how chair insulation was accounted for.

2.2. Collecting clothing insulation data from ASHRAE databases I and II

Different standards and different revisions of the same standards suggest a range of tabulated values and equations to estimate clothing insulation. This complicated the estimation of clothing insulation values when the ASHRAE database I was developed [1,2]. Also, clothing insulation is defined differently depending on the in- or exclusion of the insulation of the air layer surrounding the body. This study focuses on the intrinsic or basic ensemble insulation, defined as the thermal resistance from the skin to the outer clothing surface, i.e. excluding the surrounding air layer [10]. The incremental insulation caused by chairs was generally considered for subjects who were seated when they filled in the questionnaire by adding 0.15 clo to the ensemble insulation.

The information on clothing and chair insulation in ASHRAE database II is not presented equally clearly, since it was not entirely clear if researchers supplying data to the database included the chair insulation. Especially for offices, where chair insulation can normally range between 0.10 and 0.30 clo [11], it is important to differentiate between clothing insulation values with and without the chair insulation. The ensemble and chair insulation may be used to estimate the PMV [12], whereas only the ensemble insulation value is more suitable to be used when developing predictive models of clothing insulation.

In order to conduct our analysis of the clothing insulation properties of Database II, we first tried to collect information from the publications describing studies included in the ASHRAE Global Thermal Comfort Database II [3]. Then we, for sub-datasets from the studies where we could not extract detailed information on clothing insulation, proceeded by contacting the researchers to ask them how they estimated the clothing insulation. After that, if we were unable to differentiate the ensemble insulation people wore at the moment of the survey from the chair insulation in a particular sub-dataset, we excluded that sub-dataset from our analyses.

Table 1
Classification and number of studies citing Ličina et al. [3].

Category	Description	Number of hits
1	Uses the database or a subset of the database in the analysis.	20
2	Uses the database to verify/compare with laboratory or field measurements, or with modeling results.	3
3	References the database to substantiate associations between thermal perception and environmental/personal parameters or used the database for this purpose, but does not use the data.	16
4	References the database as a potential source of data for analysis or validation, but does not use the data.	4
5	References the database as an existing archive of thermal comfort data, but does not use the data.	13
6	Unclear exactly how the database supports the study methodology or findings, or the reference seems incorrect.	10

3. Methodology

3.1. Predictive models of clothing insulation for offices

Clothing insulation has been mainly associated with the outdoor climate and with the indoor thermal environment. Predictive models of clothing insulation have been proposed using different outdoor climate parameters, e.g. daily mean outdoor air temperature, outdoor air temperature at 6 am, running mean outdoor air temperature, season, climate classification, indoor thermal parameters such as indoor air/globe/operative temperature, amongst others [13–15].

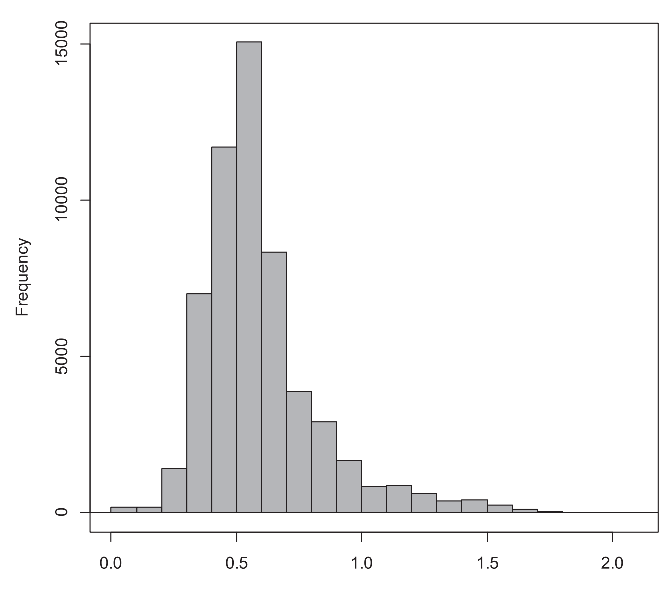

Fig. 1. Histogram of ensemble insulation considering office data from ASHRAE database I and II.

Table 2
Summary statistics of clothing/chair insulation in ASHRAE databases I and II.

Source	Insulation (clo)	N	Mean	S.D.
Database I	Ensemble	25,298	0.62	0.29
	Ensemble + Chair	25,293	0.75	0.30
Database II	Original*	74,379	0.69	0.28
	Ensemble	58,954	0.60	0.26
	Ensemble + Chair	58,954	0.69	0.27

* The clothing insulation values from database II do not discriminate whether the chair insulation was considered or not.

Table 3
Summary statistics of ensemble and chair insulation according to building type in ASHRAE databases I and II.

Source	Building type	Insulation (clo)	N	Mean	S.D.
Database I	Office	Ensemble	15,773	0.58	0.21
		Ensemble + Chair	15,768	0.72	0.22
	Classroom	Ensemble	4421	0.45	0.18
		Ensemble + Chair	4421	0.56	0.19
	Other	Ensemble	905	0.71	0.29
		Ensemble + Chair	905	0.87	0.35
Database II	Office	Original*	47,190	0.74	0.26
		Ensemble	41,131	0.62	0.24
		Ensemble + Chair	41,131	0.74	0.25
	Classroom	Original*	13,050	0.59	0.27
		Ensemble	12,241	0.58	0.27
		Ensemble + Chair	12,241	0.58	0.27
	Residential	Original*	7672	0.58	0.34
		Ensemble	3600	0.56	0.31
		Ensemble + Chair	3600	0.60	0.33
	Other	Original*	6467	0.69	0.30
		Ensemble	1982	0.52	0.26
		Ensemble + Chair	1982	0.52	0.26

* The clothing insulation values from database II do not discriminate whether the chair insulation was considered or not.

Table 4
Summary statistics of ensemble and chair insulation for office buildings according to building ventilation type (disregarding mechanically ventilated spaces) in ASHRAE databases I and II.

Source, Building type	Building ventilation type	Insulation (clo)	N	Mean	S.D.
Database I, Office	Air-conditioned	Ensemble	10,574	0.62	0.20
		Ensemble + Chair	10,571	0.77	0.21
	Naturally ventilated	Ensemble	4,733	0.46	0.17
		Ensemble + Chair	4,731	0.59	0.19
	Mixed-mode	Ensemble	466	0.68	0.24
		Ensemble + Chair	466	0.80	0.25
Database II, Office	Air-conditioned	Original*	15,355	0.75	0.24
		Ensemble	14,668	0.62	0.24
		Ensemble + Chair	14,668	0.75	0.24
	Naturally ventilated	Original*	17,147	0.77	0.30
		Ensemble	14,710	0.65	0.27
		Ensemble + Chair	14,710	0.77	0.27
	Mixed-mode	Original*	14,546	0.69	0.22
		Ensemble	11,753	0.57	0.21
		Ensemble + Chair	11,753	0.70	0.22

* The clothing insulation values from database II do not discriminate whether the chair insulation was considered or not.

Surprisingly, to date, only one study proposed a predictive model of clothing insulation for naturally ventilated buildings using ASHRAE database II [5]. A concept of neutral clothing was proposed, i.e. the clothing insulation that would keep a neutral thermal sensation without requiring cooling or heating. The concept was inspired by the calculation of the Required Clothing Insulation index (IREQ) that is used in cool and cold environments to determine clothing insulation to prevent overall cooling of the body [16,17]. Different predictors and regression functions were explored, which resulted in a predictive model of neutral clothing as a function of the indoor air temperature, season and building type, including office, classroom and residential. The model employed a logarithmically transformed linear function. For their analyses, only data linked to a neutral thermal sensation was used (n = 11,717) – ASHRAE database II has around 82,000 records. This vast source of information provides an excellent basis for reaching a deeper understanding of the clothing insulation worn by building occupants and the factors that affect clothing insulation.

In the present work, we propose a predictive model of clothing insulation for office buildings (Equation 1). Records from the database were right-skewed and therefore log-transformed prior to analysis to promote a normal distribution of residuals. Multiple regression analysis was performed between the predictors indoor temperature, season and building ventilation type and ensemble

Table 5
Percentage frequency distribution of ensemble insulation according to season for naturally ventilated offices.

Season	Database I	Database II
Autumn	26%	3%
Spring	7%	2%
Summer	62%	46%
Winter	5%	50%

Table 6
Percentage frequency distribution of ensemble insulation according to climate for naturally ventilated offices.

Climate	Database I	Database II
Cold semi-arid	0%	0%
Cool-summer Mediterranean	11%	10%
Hot desert	0%	0%
Hot semi-arid	0%	4%
Hot-summer Mediterranean	34%	60%
Humid subtropical	13%	0%
Oceanic	12%	0%
Subtropical highland	0%	5%
Temperate oceanic	8%	2%
Tropical monsoon	2%	0%
Tropical rainforest	12%	0%
Tropical wet savanna	8%	5%
Warm-summer Mediterranean	0%	14%

insulation as outcome. Ventilation type was categorized as natural ventilation, air-conditioning and mixed-mode. We did not consider records from mechanically ventilated buildings, which are buildings with mechanical ventilation, but no mechanical cooling, since these were very few ($N_{mech\ vent}$ = 180). We limited the ensemble insulation values to the range 0.4 to 1.5, since only more extreme and somewhat unrealistic observations for indoor settings were outside this range (Fig. 1). The database even included some zero (0) clo values.

A common parameter to describe the outdoor climate is the outdoor air temperature. However, ASHRAE databases I and II present different information on the outdoor temperature. Database I shows the daily mean outdoor air temperature while database II uses the monthly mean outdoor air temperature. In order to overcome this mismatch, we instead adopted the season, which

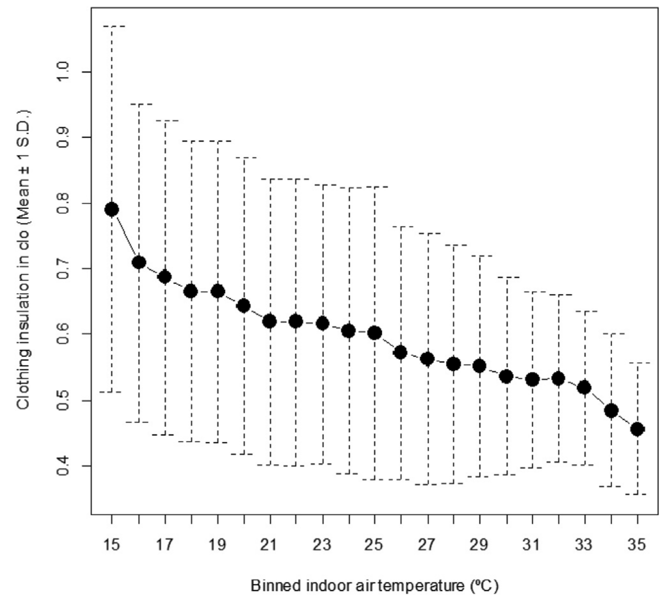

Fig. 2. Mean ensemble insulation in office buildings at different indoor air temperatures. Error bars indicate standard deviation.

appears in both databases. Appendix A presents a contextualization of the outdoor climate for the different seasons.

$$\ln(ensembleinsulation) = b_0 + b_1.T_a + b_2[Season] + b_3[BuildVentType] \quad (1)$$

where ln*(ensemble insulation)* is the natural logarithm of the predicted ensemble insulation (clo); b_0 is the intercept; b_1 is the regression coefficient of the indoor air temperature (T_a);b_2 is the factor level related with Season (Winter, Spring, Summer or Autumn); b_3 is the factor level related with Building Ventilation Type (natural ventilation, air-conditioning or mixed-mode).

Furthermore, we also expanded the idea of neutral clothing [5] to comfortable clothing, i.e. instead of considering only neutral thermal sensation votes, we predicted ensemble insulation for a range of thermal sensation between −1 and +1 where people also indicated a "no change" thermal preference, suggesting they would be in thermal comfort. Therefore, comfortable clothing can be

Table 7
Mean ensemble insulation for naturally ventilated offices according to outdoor conditions.

Climate / Season	Database I		Database II		Dif. mean?	Country
	N	Mean	N	Mean		
Cool-summer Mediterranean	502	0.63	1399	0.63		USA vs. USA
Hot semi-arid	–	–	560	0.59		India
Hot-summer Mediterranean	1626	0.39	8868	0.67	Yes*	Greece and UK
Autumn	839	0.39	–	–		Greece
Summer	787	0.39	3787	0.51	Yes*	Greece vs. UK
Winter	–	–	5081	0.79		UK
Humid subtropical	611	0.51	–	–		Australia
Oceanic	555	0.65	–	–		Australia
Subtropical highland	–	–	774	0.83		India
Temperate oceanic	376	0.50	228	0.35	Yes*	UK and Germany
Autumn	246	0.51	–	–		UK
Spring	19	0.55	–	–		UK
Summer	8	0.37	228	0.35		UK vs. Germany
Winter	103	0.47	–	–		UK
Tropical monsoon	89	0.56	–	–		Indonesia
Tropical rainforest	583	0.23	–	–		Singapore
Tropical wet savanna	391	0.50	806	0.50		Thailand vs India
Warm-summer Mediterranean	–	–	2075	0.60		USA

* Based on independent *t*-test (p < 0.05).

Table 8
Summary of the effects of chair insulation on PMV.

Operative temperature (°C)	Icl (clo)	PMV, ensemble only	PMV, ensemble + standard office chair	ΔPMV, standard office chair	PMV, ensemble + executive chair	ΔPMV, executive chair
20	0.75	−0.80	−0.61	0.19	−0.52	0.28
	1.00	−0.36	−0.21	0.15	−0.14	0.22
23	0.5	−0.54	−0.32	0.22	−0.23	0.31
	0.75	−0.05	0.10	0.15	0.17	0.22
26	0.4	0.18	0.36	0.18	0.44	0.26
	0.5	0.36	0.52	0.16	0.59	0.23

defined as the clothing insulation that would keep occupants thermally comfortable without requiring cooling or heating. Using this subset of the data for naturally ventilated buildings, we derived another predictive model of ensemble insulation following the abovementioned description and Equation 1 (here disregarding the B_3 factor level since we included only records from naturally ventilated buildings in the analysis).

3.2. Sensitivity analysis

The personal factors used to predict PMV are metabolic rate and clothing insulation, which are hard to estimate correctly in practice. Both factors influence noticeably the predicted and actual mean votes. Since the focus of the present study is on clothing, the sensitivity of the PMV prediction to estimated clothing insulation was first quantified.

In the sensitivity analysis, air speed was assumed to be 0.1 m/s, relative humidity was assumed to be 50% and metabolic rate was assumed to be 1.2 met (sedentary activity, offices and spaces with similar activity). It was assumed that the air and mean radiant temperatures were identical. The thermal insulation values selected corresponded to typical values for summer (0.5 clo) and winter clothing (1.0 clo); 0.4 clo was selected to represent the lowest feasible thermal insulation used at workplaces and 0.75 clo corresponded to the typical thermal insulation value during transition periods [18,19]. These values correspond to the ensemble only, excluding the effect of a chair for seated persons. PMV was also calculated by adding the thermal insulation of a standard office chair (0.1 clo) and an executive chair (0.15 clo) [20]. The effects of chair thermal insulation on PMV for different operative temperatures were quantified.

Comparisons between predicted (PMV) and actual mean vote (AMV) were performed using data from office buildings. Since PMV predicts the average thermal sensation of a large group of people exposed to the same thermal environment, the best way to compare PMV and AMV would be to group the data by field study, i.e. a spot measurement of environmental parameters in a day in a space, where a group of people replied to a thermal comfort questionnaire a single time. However, the ASHRAE database II does not show such information. Instead, we used a metadata combination (publication, year, season, city, cooling strategy and outdoor temperature) to create an ID, which approximates a field study identifier. We then calculated the mean air/radiant temperature, air speed, relative humidity, metabolic rate and clothing insulation with and without the chair for each field study ID, in order to estimate the PMV by building ventilation type (natural ventilation and air-conditioning). PMV was calculated using the CBE Thermal Comfort tool [21]. We also calculated the mean of occupants' thermal sensation votes (AMV) for each field study ID. Only field study IDs with more than 30 observations were considered.

Table 9
Comparison between the AMV and the PMV with and without the chair insulation for air-conditioned and naturally ventilated offices.

Parameter	Air-conditioning	Natural ventilation
Unique database field study IDs	175	86
Mean indoor temperature (°C)	23.5	26.0
Mean air speed (m/s)	0.11	0.20
Mean relative humidity (%)	48	47
Mean metabolic rate (met)	1.20	1.20
Mean ensemble insulation (clo)	0.60	0.57
Mean ensemble and chair insulation (clo)	0.74	0.71
Mean AMV	0.04	0.55
Mean PMV (ensemble and chair)	−0.08	0.42
Mean PMV (ensemble)	−0.34	0.20

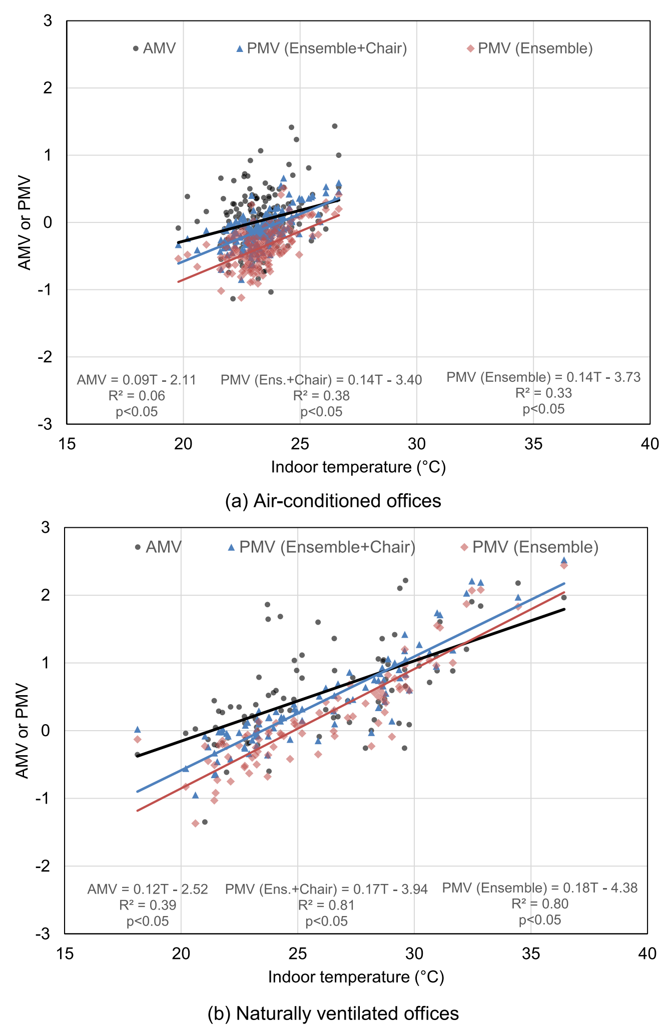

Fig. 3. Comparing AMV with the PMV (with and without the chair) as a function of the indoor temperature.

Table 10
Multiple linear regression model of ensemble insulation as a function of indoor air temperature, season and building ventilation type for office buildings.

Outcome = ln(ensemble insulation)	Coefficients (*b*)			95% CI		
Predictors	*b*	S.E.	*t*-value	Sig.	Lower	Upper
Indoor air temperature (°C)	−0.02	0.000	−47.12	p < 0.001	−0.02	−0.02
Season [Autumn]	−0.13	0.004	−32.19	p < 0.001	−0.14	−0.12
Season [Spring]	−0.14	0.004	−33.80	p < 0.001	−0.15	−0.13
Season [Summer]	−0.20	0.003	−77.78	p < 0.001	−0.20	−0.19
Building ventilation type [AC]	0.04	0.003	13.83	p < 0.001	0.04	0.05
Building ventilation type [NV]	0.04	0.003	12.56	p < 0.001	0.03	0.05

Note: N = 44,650. Model intercept = 0.10, p < 0.001. Model F (6, 44,644) = 2143, p < 0.001. R^2 = 0.22, Adjusted R^2 = 0.22. Reference category: Season = Winter, Building ventilation type = Mixed-mode.

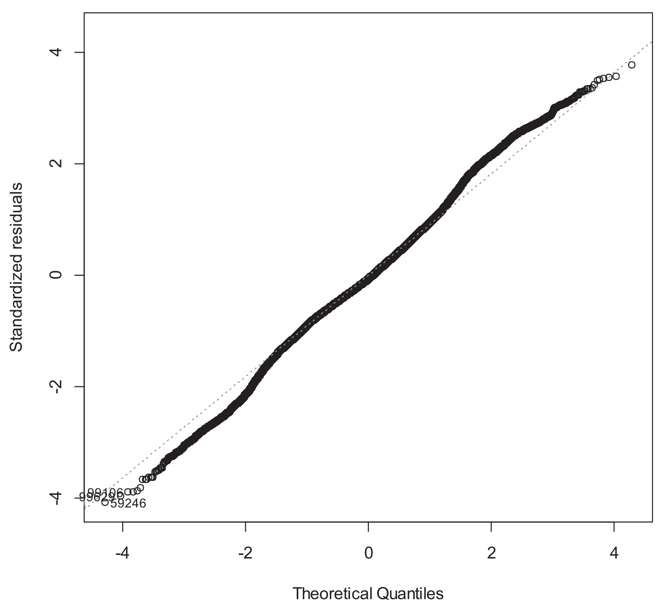

Fig. 4. Normal QQ-plot of the standardized residuals.

4. Results and discussion

4.1. Clothing data from ASHRAE database I and II

From the 81,967 records in database II, 7,588 do not have information on clothing insulation and were excluded from our analysis. From the remaining 74,379 records, by reading the publications included in database II, we could not differentiate the ensemble from the chair insulation in 27,309 records, which represent 24 contributions to the database II. This way, we wrote to the 24 contributors and 13 of them answered us providing detailed information on ensemble and chair insulation. Five of those studies included the chair insulation and eight did not. The remaining 11 contributors did not reply, and therefore we omitted their corresponding 15,425 records from our analysis. This way we ended up with 58,954 datasets (81,967–7,588–15,425) where we could differentiate the ensemble insulation from the chair insulation, and this data was analysed in this work. Statistical summaries of the ensemble and chair insulation in ASHRAE databases I and II are shown in: a) Table 2 for the whole databases; b) Table 3 for each building type; c) Table 4 for office buildings stratified on ventilation type. Overall, the combined ensemble and chair insulation was about 0.13 clo higher in database I and 0.09 clo higher in database II as compared with only the ensemble insulation (Table 2). Table 2 also shows that most of the data provided by the contributors to database II included the chair insulation. Lower chair insulation was considered for the residential datasets in database II (Table 3). Chair insulation (e.g. wooden chair) was not accounted for in classrooms and other building types in our sample of database II.

The mean ensemble insulation in office buildings (Table 3) was rather similar in database I (0.58 clo) and II (0.62 clo), which is interesting since the databases vary in climate distribution and time as there is a 20-year difference between the publication of the databases. The similarity is even greater for air-conditioned office buildings (Table 4); for naturally ventilated offices (Table 4), a lower mean ensemble insulation was observed in database I (N = 4773, mean = 0.46) than in database II (N = 14,710, mean = 0.65), and the differences are statistically significant (independent t-test, p < 0.05). Tables 5 and 6 show the percentage frequency distribution of the ensemble insulation according to the season and climate, respectively. A comparison between the mean ensemble insulation according to outdoor conditions is presented in Table 7. Most data from database I is from summer (62%) followed by autumn (26%), while the data from database II is more evenly distributed between summer (46%) and winter (50%). This may tend to bias the mean ensemble insulation from database I to lower clo-values. Most data in both databases are from the hot-summer Mediterranean climate (Table 6). However, the ensemble insulation from database II is from occupants of naturally ventilated offices in the UK mostly during winter, while for database I the data is from buildings in Greece (a warmer climate than in the UK) – Table 7. This is why the mean ensemble insulation for the hot-summer Mediterranean climate is lower for database I.

Fig. 1 shows a histogram of ensemble insulation for occupants in office buildings considering both databases I and II. The distribu-

Table 11
Multiple linear regression model of comfortable clothing insulation as a function of indoor air temperature and season for occupants of naturally ventilated office buildings.

Outcome = ln(comfortable insulation)	Coefficients (*b*)			95% CI		
Predictors	*b*	S.E.	*t*-value	Sig.	Lower	Upper
Indoor air temperature (°C)	−0.02	0.001	−16.429	p < 0.001	−0.02	−0.02
Season [Autumn]	−0.15	0.014	−10.360	p < 0.001	−0.17	−0.12
Season [Spring]	−0.16	0.015	−10.586	p < 0.001	−0.19	−0.13
Season [Summer]	−0.18	0.007	−26.865	p < 0.001	−0.19	−0.17

Note: N = 6,810. Model intercept = 0.11, p < 0.001. Model F (4, 6,806) = 378, p < 0.001. R^2 = 0.31, Adjusted R^2 = 0.31. Reference category: Season = Winter.

tion of the data indicates a clear right-tailed skewness. Fig. 2 shows that the mean ensemble insulation clearly decreased with increasing (binned) indoor air temperature. Fig. 2 also shows the standard deviation of the clo-values for each temperature bin. The standard deviation decreased with increasing indoor temperature, indicating that occupants may have worn the lowest acceptable clo-value for office standards at higher temperatures - in other words, occupants have more freedom to adapt (i.e. adjust clothes) in lower indoor air temperatures.

4.2. Sensitivity of PMV to clothing insulation

Table 8 summarizes the effects of the chair insulation on PMV for different operative temperatures. For the studied conditions in Table 8, a standard office chair adding 0.1 clo increased PMV by 0.15 to 0.22, and an executive chair adding 0.15 clo increased PMV by 0.22 to 0.31.

EN 16798-1 [18] allows defining indoor environmental categories based on the PMV; Category I requires a PMV between −0.2 and 0.2, Category II requires a PMV between −0.5 and 0.5, Category III requires a PMV between −0.7 and 0.7, and Category IV requires a PMV between −1.0 and 1.0. The differences in PMV caused by the inclusion of chair insulation (ΔPMV columns in Table 8) are large enough to make a difference of one Category according to the standard (e.g. from Category III to Category II) and under certain conditions, close to making a difference of two Categories, indicating that the inclusion of chair insulation is critical for making accurate estimations of comfort. This can also be shown by the comparison of the PMV values indicated in Table 9 and the actual mean vote (AMV) for office data. Overall, including the chair insulation in the estimation of the PMV reduced the difference between the PMV predictions and the actual thermal sensation votes.

Fig. 3 presents a comparison between the AMV and the PMV (with and without the chair insulation) as a function of the indoor temperature for air-conditioned and naturally ventilated offices. The PMV overestimated the cold sensation of occupants for air-conditioned spaces and in lower indoor temperature for naturally ventilated spaces, which was also reported by other field studies [23–26]. The inclusion of the chair insulation in the estimation of

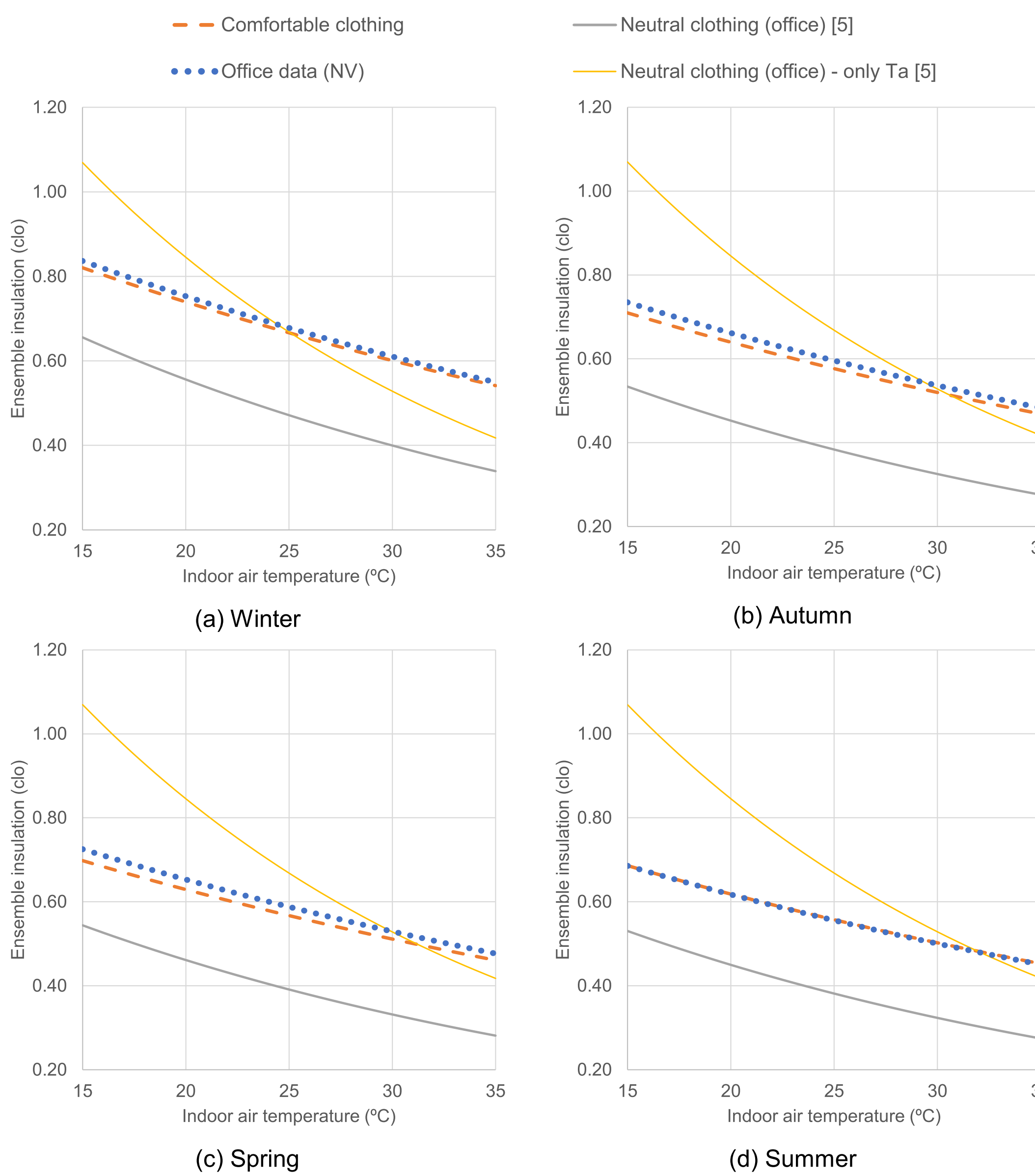

Fig. 5. Comparison of predictive models of ensemble insulation for occupants of naturally ventilated (NV) office buildings in this study and in [5].

the PMV improved significantly the PMV predictions for both building types. For naturally ventilated spaces, the PMV slightly overestimated the hot sensation of occupants at higher indoor temperatures (similar to the findings of [24–26]). In this case, with indoor temperatures above 32 °C and AMV or PMV close to or higher than +2, accounting for the chair insulation did not improve the PMV predictions.

4.3. Predicting clothing insulation

4.3.1. Predicting ensemble insulation based on all office data

Table 10 presents the result of multiple linear regression analysis to predict the ensemble insulation from the indoor air temperature, the season and type of building ventilation. As expected, higher indoor temperatures led to lower ensemble insulation. Lower ensemble insulation was also observed in summer, spring and autumn as compared with winter. A slightly, but significant, higher ensemble insulation was observed in air-conditioned and naturally ventilated spaces than in mixed-mode buildings. The model R-squared indicates that 22% of the variance in ensemble insulation is explained by the indoor temperature, season and building ventilation type. The relatively low R^2 may reflect the large number of observations used in the analysis. The number of observations resulted in well-established regression coefficients as indicated by the narrow confidence intervals around the equation coefficients. With the exception of some observations at the lower tail, the regression residuals followed a normal distribution, as can be seen in the Q-Q plot (Fig. 4). As an example, the predicted ensemble insulation in an air-conditioned office running at 24 °C of indoor air temperature in summer would be 0.57 clo:

$\ln(\text{ens. insulation}) = 0.10 + (-0.02\text{x}24) + (-0.20) + 0.04 = -0.56$; $\exp(-0.56) = 0.57$ clo.

4.3.2. Predicting ensemble insulation based on comfort data in naturally ventilated buildings

Table 11 shows the result of multiple linear regression analysis using a subset of the database containing only responses associated with thermal comfort (i.e. thermal sensation vote ±1 and thermal preference vote = "no change") for naturally ventilated buildings. Overall, the ensemble insulation followed a similar trend regarding the indoor temperature and season as did our previous analysis (Table 10) on all naturally ventilated office data (Office data-NV). However, the slight changes in the regression coefficients had a minor impact on the clo-values (Fig. 5). People wore slightly less clothes when comparing the comfortable clothing curves against the general model (Office data-NV), with the exception of summer, where both clothing curves were virtually identical – people were wearing the lowest possible clo-value during summer. It is evident from Fig. 5 that people were wearing higher ensemble insulation in cooler outdoor conditions (winter and autumn) and lower ensemble insulation in warmer seasons (summer and spring). Overall, people were also wearing less clothes with increasing indoor temperature. This suggests that people were adjusting their clothes in an adaptive manner, i.e. restoring their thermal comfort by adapting the clothing [2,22]. We adopted season as a parameter in the analysis to quantify the effect of the outdoor climate on ensemble insulation, since databases I and II do not share a common outdoor temperature parameter. Overall, seasons may have different contexts depending on the climate (e.g. outdoor temperature range and variability).

The neutral clothing insulation models from [5] are also shown in Fig. 5 for comparison with our models. Overall, their model considering the indoor air temperature and the season always predicted lower clo-values than both our models, even in winter. This seems counterintuitive since the insulation value should be higher or at least similar to our clothing levels. One reason could be that the model presented in [5] was biased to an oceanic climate or that clothing insulation values below 0.4 clo were included in their analysis. The indoor temperature explained about 17% of the variance in the neutral clothing insulation in their model based solely on indoor air temperature (Fig. 5, Neutral clothing (office) - only Ta); this model does not account for outdoor climate. In our comparable model, the indoor air temperature and the season explained 31% of the variance in the comfortable clothing insulation (Table 11). Our predictive models of clothing insulation considered clo-values between 0.4 and 1.5 clo and indoor air temperatures from 13.4 °C to 39.5 °C.

5. Conclusions

In this work, we investigated clothing insulation using the ASHRAE Global Thermal Comfort Database I and II. We complemented database II by differentiating the ensemble and the chair insulation for 58,954 datasets. We found that most of the clothing data provided by the contributors to database II included the chair insulation. The mean chair insulation for office buildings was in the range 0.10–0.13 clo, representing standard and executive office chairs. An interesting finding of our work was that the overall mean ensemble insulation in office buildings ($\approx$ 0.6 clo) did not change significantly over the 20-year difference between database I and II. When considering only naturally ventilated office buildings, a lower mean ensemble insulation was observed in database I (0.46 clo) than in database II (0.65 clo) because the first contains a larger sample of data from warmer outdoor conditions. We also found that occupants had more freedom to adjust their clothes at lower indoor air temperatures since they were already wearing the lowest possible clo-value for workplaces at higher indoor temperatures.

The data on office buildings was used to explore associations between ensemble insulation and different thermal and contextual parameters, resulting in a predictive model of ensemble insulation. The developed model can predict the clothing insulation as a function of the indoor air temperature, the season and the building ventilation type (air-conditioning, natural ventilation or mixed-mode). In addition, a predictive model of ensemble insulation was developed for naturally ventilated office buildings considering data from comfortable occupants only. The models are based on ensemble insulations between 0.4 and 1.5 clo and indoor air temperatures from 13.4 °C to 39.5 °C.

Clothing insulation is one of the most important thermal comfort parameters, influencing its predictions e.g. the Predicted Mean Vote (PMV). The sensitivity of the PMV prediction to the clothing insulation was quantified. The agreement between PMV predictions and the actual thermal sensation vote improved noticeably by accounting for the chair insulation. Including the chair insulation when calculating the PMV may impact the classification of the indoor environment according to EN 16798-1 [18]. This underlines the importance of quantifying properly the ensemble and chair insulation in order to improve thermal comfort predictions.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The research leading to these results has received funding from the European Union's Horizon 2020 research and innovation pro-

Table A1
Description of outdoor climate for each database according to season and ventilation type of office buildings.

Season/ building ventilation type	Database I		Database II	
	Outdoor daily air temperature (°C)		Outdoor monthly air temperature (°C)	
	Mean	S.D.	Mean	S.D.
Autumn	14.6	7.4	20.2	8.1
Air Conditioned	10.2	5.2	19.3	5.5
Mixed Mode	12.9	4.5	21.3	9.1
Naturally Ventilated	20.8	5.8	15.3	2.8
Spring	22.3	8.3	25.3	9.0
Air Conditioned	20.9	8.7	22.2	8.6
Mixed Mode	22.9	4.7	27.9	8.3
Naturally Ventilated	27.7	4.3	15.9	5.0
Summer	24.4	4.5	18.3	9.8
Air Conditioned	24.6	4.4	14.6	11.5
Mixed Mode	19.1	3.1	23.9	7.0
Naturally Ventilated	24.3	4.6	16.9	7.9
Winter	8.7	8.9	12.4	8.0
Air Conditioned	8.1	9.3	12.1	7.9
Mixed Mode	14.9	4.6	18.1	7.5
Naturally Ventilated	10.4	4.2	9.7	6.4

gram under the Marie Sklodowska-Curie grant agreement no. 713683 (COFUNDfellowsDTU).

Appendix A

Table A1

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enbuild.2021.111431.

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