The importance of sample grouping; Exploring thermal sensitivity of occupants within one building type and ventilation mode

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Abstract: Occupants' thermal response is influenced by their sensitivity to temperature variations, i.e. the rate of change in occupants' thermal sensation per unit change in indoor temperature. Thermal sensitivity is commonly taken as constant (Griffiths constant) in the calculation of occupants' comfort temperature. This constant is based on small differences found between buildings' ventilation modes [naturally ventilated (NV) vs. air conditioned (AC)]. However, recent research found significant differences depending on building type, ventilation mode, age, gender and climate. This paper reviews thermal sensitivity within the same building type and main ventilation mode using longitudinal surveys and monitoring data from school buildings, two in the UK (U1 and U2) and one in Sweden (S1). Results show that in two of the schools (U1 and S1) children were half as sensitive as in school U2 and the difference is statistically significant. A similar result with slightly different thermal sensitivities was derived from comparison by clusters derived from the classrooms' indoor temperatures. This outcome suggests that building ventilation mode (AC/NV), which is typically considered the main determinant of occupants' thermal experience and often the only building information recorded in field surveys, is inadequate to explain this important occupant response factor.

Keywords: thermal sensitivity, indoor temperature, thermal comfort, ventilation mode, buildings.

1. Introduction

People's thermal sensation changes with temperature and the rate of this change signifies their ability to adapt to varying thermal conditions, i.e. it is an indicator of people's thermal sensitivity. People's sensitivity to temperature change determines how quickly their thermal state departs from the comfort zone and how quickly it reaches discomfort levels or even unacceptable thresholds. It is therefore an important thermal response factor for thermal comfort but also for people's ability to adapt to rapid temperature changes, in light of the increasing warm temperature extremes and the likelihood of more frequent and longer heat waves (IPCC, 2014).

Regression analysis on thermal comfort survey data, with thermal sensation as the dependent variable and temperature as the predictor variable, gives an estimate of people's sensitivity to temperature changes (regression coefficient) and their neutral (or "comfort") temperature (temperature at which thermal sensation= neutral). When the surveys span over days or longer periods people have adapted to day-to-day changes and therefore the regression coefficient is shallower compared to short survey periods where there is little adaptive opportunity. The regression coefficient for the case where no adaptation is assumed to take place is the maximum rate of change of thermal sensation with temperature and is considered to be a standard value, the so-called 'Griffiths slope' or 'Griffiths constant'.

Initial analysis by Humphreys et al. (2007) on the ASHRAE (de Dear and Brager, 1998) and the SCATs (McCartney and Nicol, 2002) thermal comfort databases found the regression gradient to reach a maximum value of 0.4 when the standard deviation of the operative temperature during the survey period is around 1K, a value typical for short survey periods where people would have limited adaptive opportunities. The regression gradient dropped below and above 1K standard deviation of temperature, probably due to the effects of error in the predictor variable in the former case and the effect of increased adaptation in the latter (Humphreys et al., 2007). Considering that error in the predictor variable and some adaptation error will always be present, it was concluded that an appropriate value for the sensitivity to temperature changes would be higher than 0.40/K and a value of 0.50/K was chosen (Nicol and Humphreys, 2010).

Further analysis (Humphreys et al., 2010, Humphreys et al., 2013), led to the day-pooling method, where data collected in a single day (limited adaptation) were used to derive a value for the Griffiths constant from the SCATs and ASHRAE databases. This value was 0.50/K, the same as previously estimated. The difference between centrally conditioned (AC) and naturally conditioned (NV) buildings was small and not statistically significant and therefore this value was proposed for the Griffiths constant when estimating the neutral temperature from survey data.

The value of 0.5K for the Griffiths constant has been widely used in thermal comfort research. There are also studies which explored the sensitivity of the estimated neutral temperature with different values for the Griffiths constant and found its role to be important (Nguyen et al., 2012, Haddad et al., 2019) and studies that explored the applicability of the value 0.5K in other building types, i.e. schools (Teli et al., 2015) and homes (Ryu et al., 2019). A recent study investigated the validity of Griffiths constant for different contexts and found that it varies depending on building type (office, school, residential) and ventilation mode (AC/NV), recommending that different values should be used according to these categories (Rupp et al., 2019). In the previous studies, for the investigation of differences in thermal sensitivity, samples were grouped according to building type (office, school, etc.) and ventilation mode (AC/NV). To explore further these differences and the above recommendation, this paper reviews thermal sensitivity within the same building type and main ventilation mode. The analysis aims to explore the impact of sample grouping (by building type or AC/NV mode) on determining people's thermal sensitivity.

2. Study design

2.1. **Case study buildings**

The data used in the analysis are from thermal comfort field surveys conducted in three schools; two in Southampton (UK) and one in Gothenburg (Sweden). Both cities have marine west-coast temperate climate, with Köppen Climate Classification Cfb (Kottek et al., 2006). The surveys in the UK were conducted in 2011 and 2012 while the surveys in Sweden in 2016. Table 1 summarises the characteristics of the three schools.

Table 1. Characteristics of the sample of schools

Country	School	Year surveyed	Building weight	Classroom Ventilation strategy	Class-rooms	No of questionnaires	Survey days
UK	U1	2011	LW	All NV	1-8	1,314	12
	U2	2012	MW	All NV	9-19	1,676	14
Sweden	S1	2016	LW	3 EV, 1 NV, 2 MVHR	20-25	2,177	26

Notes:
Building weight - LW: lightweight, MW: mediumweight, HW: heavyweight.
Ventilation - NV: naturally ventilated (free-running/ no cooling in summer], EV: fan-assisted exhaust-only ventilation (no cooling in summer), MVHR: mechanical ventilation with heat recovery (no cooling in summer)

School U1 is a lightweight building constructed in 1978 while school U2 is a Victorian medium-weight building built in 1884 (Figure 1). Both UK schools are naturally ventilated through window opening. School S1 is housed in 9 buildings, seven of which were built in the turn of the 18th to the 19th century and two in the end of the 20th century. The buildings where the surveys took place have a lightweight construction. Three of the classrooms have exhaust-only ventilation (supply through wall inlets), one is naturally ventilated through window opening and two are equipped with mechanical ventilation with heat recovery. Since none of the cases involve summer cooling, it was decided to include all classrooms in the study and see whether the analysis will separate the different systems. All classrooms in all schools are heated in winter with wet central heating systems.

Figure 1. School buildings were the surveys took place. School S1 is housed in several buildings, two of which are shown here.

2.2. **Data collection**

A total of 5,167 pupils' questionnaires are used in the analysis, collected from approximately 650 children during 207 surveys in 25 classrooms. The questions addressed thermal sensation, thermal preference, overall comfort, tiredness, perceived air quality and clothing level at the time of the survey. The English version of the questionnaire can be found in (Teli et al., 2012). During the surveys, measurements of thermal comfort parameters were also taken, i.e. air temperature (T_a, °C), globe temperature (T_g, °C), relative humidity (RH, %), indoor relative air velocity (V_a, m/s). In this paper, children's thermal sensation votes (TSV) and the globe (operative) temperature T_{op} at the time of the survey are used, in order to estimate children's thermal sensitivity (relationship between TSV and T_{op}).

In all surveyed classrooms data loggers were installed which recorded the air temperature and relative humidity at 5-minute intervals. These measurements are used in the cluster analysis and in the calculation of the measurement error in the predictor variable.

2.3. **Analysis method**

In order to investigate the impact of sample grouping on the estimated thermal sensitivity, two groupings were made: the first is by school and the second by cluster. Cluster analysis was conducted on the air temperature measurements from the data loggers in order to group the classrooms according to the temperatures that the children typically experienced. The groups of classrooms with similar indoor temperature profiles are used in order to investigate if thermal experience influences occupants' thermal sensitivity.

Children's thermal sensitivity was then estimated by school and by cluster using children's thermal sensation votes and the operative temperature at the time of the survey for single day survey runs, following Humphreys' day-pooling method. More details on the methods used are provided below.

2.4. **Sample grouping: cluster analysis**

From the classroom datasets with the 5-minute air temperature measurements, one month was selected and used in order to avoid prolonged periods of school holidays, term breaks etc. and have as consistent as possible outdoor weather conditions between school surveys. The most appropriate month was May. A cluster analysis of the occupied hours of the school days (08:30-15:00 weekdays) was conducted to identify groups of classrooms with similar profiles of mean daily temperature. Applying an inductive approach through unsupervised machine learning, cluster analysis is a tool to identify groups in the units of a data frame. In this analysis, each classroom is a unit and each 5-minute monthly mean temperature is a variable. As grouping is based on the distance between temperature profiles of each classroom, data was first standardised to ensure that each feature contributed proportionally to the distance between data points (i.e. 5-minute monthly mean temperature). Classrooms' temperature data were standardised by first subtracting the mean and then dividing the values by the standard deviation. The analysis was twofold. First, the number of clusters was determined using a scree plot of the within groups sum of squares by the number of clusters. Then, both K-means clustering, and Ward's minimum variance methods were applied to determine which classrooms belong to which group.

2.5. **Estimation of thermal sensitivity: day-pooling method**

The day-pooling method for the estimation of the regression coefficient (constant G) was formulated by Humphreys et al. (2013). The estimation process gives a weighted average of the regression coefficient for all day-surveys, which provides a more reliable statistic compared to the analysis of small day-survey samples.

There are two important parts in the procedure: the estimation of the regression coefficient and its adjustment for the presence of error in the predictor variable (measurement error of room temperature).

The estimation of the regression coefficient includes the following:

- Calculation of the variables dTSV and dT_o for each response on a single day (day-survey). dTSV is the difference of the subjective TSV and the mean thermal sensation vote for the day-survey ($TSV_{(day\ mean)}$) and dT_o is the difference of the operative temperature during the survey (T_o) and the mean operative temperature on that day ($T_{o(day\ mean)}$).
- Regression analysis of dTSV on dTo of all the day-surveys.

The estimated regression coefficient (b) is then corrected to account for measurement error in the operative temperature, using equation 1 (Humphreys and Nicol, 2000).

$$b_{adj} = b\ (\sigma^2_{dTo})/\ (\sigma^2_{dTo} - \sigma^2_{err}) \tag{1}$$

Where σ^2_{dTo} is the variance of the variable dT_o and σ^2_{err} its error variance. This error can be attributed to sensor limitations and to its positioning in relation to the survey respondent. The sensor limitations are hard to estimate, and the positioning error can only be approximated if there is available data for this to happen. In the absence of more appropriate data for this approximation, Humphreys et al. (2013) used the vertical difference of 1m between the globe sensors on the measuring stations in the ASHRAE database and got a value for the error variance of 0.158 K^2. The error variance is estimated here from the logged temperatures in the classrooms.

The significance of the differences in the estimated regression coefficients was assessed with t-testing and validated by running regression models with interaction terms on the raw data (Potthoff analysis).

3. Results

For the analysis, inconsistent cases (strongly contradicting thermal sensation and preference votes) were excluded (6% of the sample). More details about the exclusion criteria can be found in Teli et al. (2013). A total of 4,851 thermal sensation votes (TSV) are used for the estimation of thermal sensitivity.

3.1. **Cluster analysis**

The clustering analysis units were defined as the 25 classrooms and the variables were defined as the monthly mean of 5-minute air temperature recordings. As introduced in section 2, the analysis was twofold. A review of the scree plot determined the number of clusters, which was set at 3. Then K-means clustering and Ward's minimum variance methods were applied. Both methods resulted in the same group membership, as described in Table 2 and shown in Figure 2. Cluster 1 consists of 3 classrooms from the lightweight UK school U1 and all 6 classrooms from the Swedish school S1. Cluster 2 consists of 5 classrooms from U1 and 3 from U2. Finally, cluster 3 consists only of classrooms from the medium-weight school U2.

Table 2 Membership of classrooms by clusters (cluster 1: blue, cluster 2: green, cluster 3: yellow)

U1	1	2	3	4	5	6	7	8			
U2	9	10	11	12	13	14	15	16	17	18	19
S1	20	21	22	23	24	25					

Figure 2 shows the monthly mean of 5-minute air temperature profiles of the classrooms (thin lines) and the clusters (thick lines). Cluster 1 has the highest mean temperature ($T_{a\text{-}mean}$=24.2 ^oC), cluster 2 follows with $T_{a\text{-}mean}$= 22.6 ^oC and finally cluster 3 with $T_{a\text{-}mean}$=21.2 ^oC.

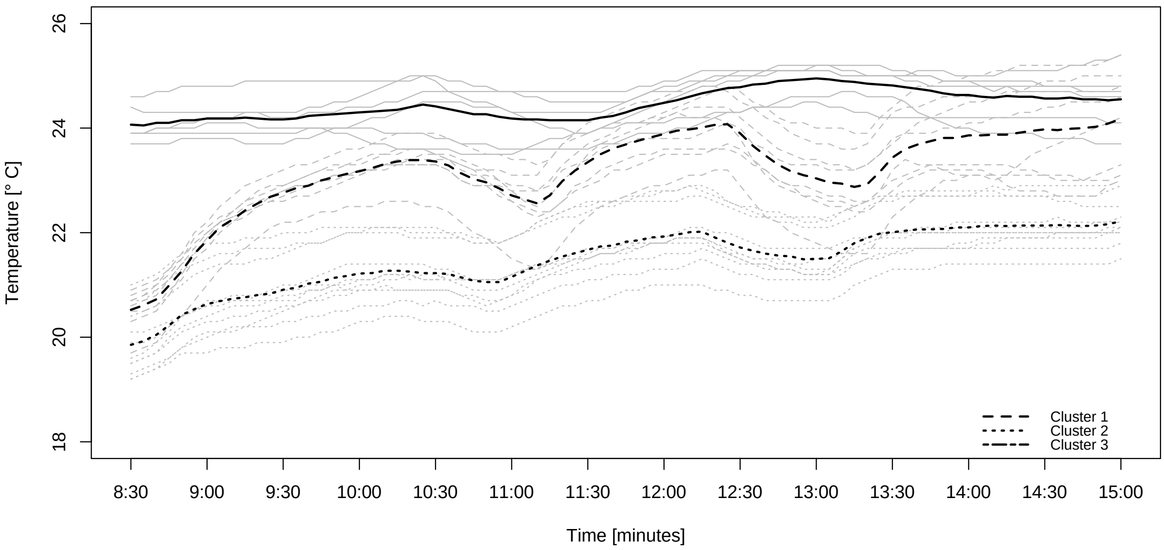

Figure 2. Monthly mean of 5-minute air temperature profiles of the 25 classrooms and the 3 clusters

Further cluster analysis applied the same method for the same unit ('classroom') but a different variable. Here, the interest lies in the temperature difference experienced over 15 minutes. As the classrooms have similar occupancy (heat gain), the difference in monthly mean temperature over 15 minutes mainly lies in fabric performance, gains and ventilation, including window opening behaviour. As introduced in section 2, the analysis was twofold. The number of clusters was set at 3. K-means clustering and Ward's minimum variance methods resulted in the same group membership. Interestingly, classrooms were grouped by their associated schools, as described in Table 3 and shown in Figure 3.

Table 3 Membership of classrooms by clusters (cluster 1: blue, cluster 2: yellow, cluster 3: green)

U1	1	2	3	4	5	6	7	8			
U2	9	10	11	12	13	14	15	16	17	18	19
S1	20	21	22	23	24	25					

Figure 3 shows the difference over 15 minutes of monthly mean of 5-minute air temperature profiles of the classrooms (thin lines) and the clusters (thick lines). Cluster 1 has the largest range in temperature difference ($dT_{a\text{-}mean}$=1.5^oC), cluster 2 follows with $dT_{a\text{-}mean}$=0.7^oC and finally cluster 3 with $dT_{a\text{-}mean}$=0.3^oC.

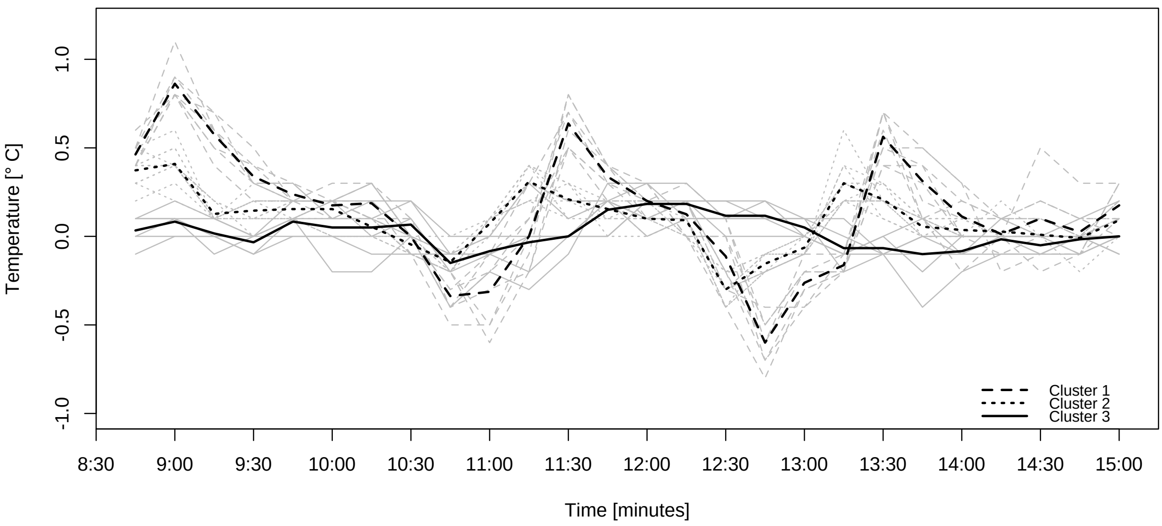

Figure 3. Difference over 15 minutes of monthly mean of 5-minute air temperature profiles of the 25 classrooms and the 3 clusters

Following the above results, thermal sensitivity is reviewed by the clusters established in both methods; (1) 3 clusters of monthly mean of 5-minute air temperature profiles (refer to Table 2) and (2) 3 schools (refer to Table 3).

3.2. **Thermal sensitivity**

For each day visit to each school and each thermal sensation response (TSV), the variables dTSV and dT_o were calculated. Table 4 summarizes the results from the regression analysis of dTSV on dT_o to derive the regression coefficients (b) for the entire dataset, by school and by cluster. The resulting regression coefficients are first compared without the adjustment for the error in the predictor variable.

As can be seen, for all schools combined the regression coefficient is 0.28/K (Figure 4). This is close to the value Humphreys et al. (2013) derived from the NV buildings at the SCATs database (0.308/K) and considerably lower than the overall regression coefficients for SCATs and ASHRAE databases (all building types) of 0.38/K and 0.37/K respectively.

Table 4. Regression coefficients (b, thermal sensitivity) by building and by cluster

Dataset	**N**	**Variance of dTo (°C^2)**	**Error variance of dTo (°C^2)**	**b**	**Standard error of b**	**R**	**p-value**	**Adjusted b**
All schools	4581	0.756	0.227	**0.277**	0.022	0.181	<0.001	0.396
By school								
U1	1224	0.762	0.154	**0.194**	0.045	0.122	<0.001	0.243
U2	1511	0.912	0.118	**0.389**	0.040	0.248	<0.001	0.447
S1	2116	0.642	0.222	**0.220**	0.032	0.152	<0.001	0.336
By cluster								
cluster 1	2566	0.739	0.199	**0.194**	0.028	0.139	<0.001	0.266
cluster 2	1190	0.685	0.141	**0.408**	0.049	0.236	<0.001	0.513
cluster 3	1095	0.680	0.118	**0.247**	0.054	0.138	<0.001	0.299

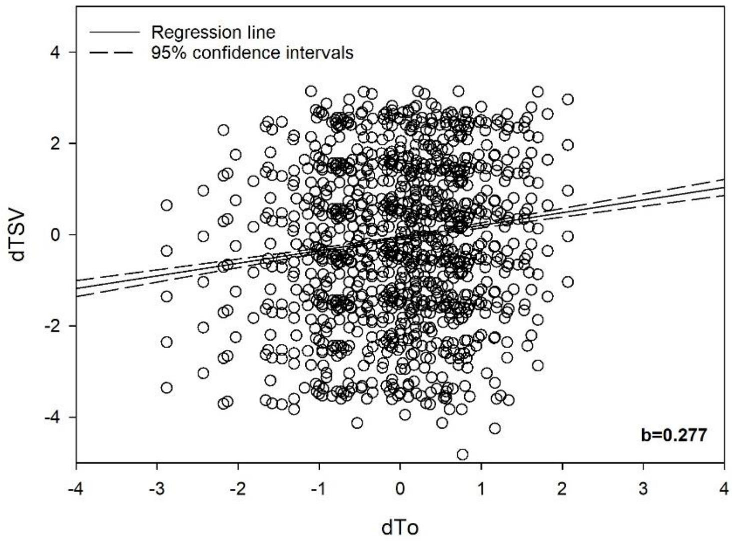

Figure 4. Regression of the day-surveys in the entire school sample.

Looking at the breakdown by school, differences can be seen. The regression coefficient for school U2 is 0.39/K, nearly double those of schools U1 and S1 (0.19/K and 0.22/K respectively), and these differences are statistically significant ($p < 0.05$). The difference between schools U1 and S1 is small and not statistically significant.

The breakdown by cluster gives a similar result but with very different groups. This time, cluster 2 has the highest regression coefficient (0.41/K) and the differences with the other two clusters is statistically significant ($p < 0.05$). Cluster 2 consists of 5 classrooms from school U1 (which had b= 0.19/K) and 3 classrooms from school U2 (b= 0.39/K). Cluster 3, with all classrooms from school U2, has b=0.25/K, which is much lower than the entire school's regression coefficient (b= 0.39/K). In both cases we get statistically significant differences, but the sample has been grouped in different ways.

The second part of the day-pooling method involves the correction of the regression coefficient for error in the measurement of the room temperature. It is therefore important to estimate its value. In this study, the estimation of error variance is based on air temperature measurements in two locations in the surveyed classrooms: at the centre of the classroom, where the thermal comfort instrument was placed, and at one of the side walls, where the data logger was installed. In most cases, the desk distribution in the classrooms covered this distance and therefore the error is considered representative. The average distance between the two locations was approximately 4m. The air temperature is used as a proxy for the operative temperature here, since only the air temperature was measured at the second location and the difference between T_o and T_a was overall small.

The estimation of the error variance was made for the three schools separately and then combined. The variance of the air temperature difference in the classrooms was lowest in school U2 (0.118 $^oC^2$) and highest in school S1 (0.222 $^oC^2$). The difference is quite large and likely related to the buildings' characteristics. Most of the surveyed Swedish classrooms are housed in repurposed villas (Figure 1) and have at least two walls connected to outdoors, leading to higher temperature differences between the walls and the centre of the classrooms. Such differences in the error variance of the room temperature are to be expected between different building/room samples. If the sample is treated as one, the error variance is estimated at 0.227 $^oC^2$.

The last column of Table 4 shows the estimated adjusted regression coefficients using the corresponding error variance. For the clusters, a weighted average of the error variance according to the number of classrooms from each school was used. The results confirm the observation of Humphreys et al (2016) that the estimate of the adjusted regression coefficient is sensitive to the error-variance in the predictor variable. The adjusted regression coefficients are between 15-53% higher than before the adjustment, depending on the dataset (all schools, school, cluster). For the entire dataset, the adjusted regression coefficient is 43% higher than before the adjustment.

Another aspect to consider is whether season affects the resulting thermal sensitivities. The only school where surveys were conducted in winter was the Swedish school, so the analysis is done on the S1 sample. As can be seen in Table 5, the regression coefficient for spring/summer is 40% lower than in winter. The difference did not reach statistical significance with p=0.073, which however is overall low. It appears that there is scope for further investigation on the influence of season on thermal sensitivity.

Table 5. Regression coefficients (b, thermal sensitivity) by season in the Swedish sample

Dataset	**N**	**Variance of dTo (°C^2)**	**Error variance of dTo (°C^2)**	**b**	**Standard error of b**	**R**	**p-value**	**Adjusted b**
S1-winter	2116	0.642	0.222	**0.285**	0.050	0.182	<0.001	0.436
S1-spring	1148	0.673	0.222	**0.169**	0.041	0.126	<0.001	0.252

4. Discussion

If the sample in this study is treated as one, representing the same building type (school) and main ventilation type (NV/no cooling), then according to Rupp et al. (2019) we should use the value 0.4/K for the Griffiths constant to estimate comfort temperatures. If the three schools are treated separately, then in school U1 thermal sensitivity is lower by approximately 40%, while in school U2 15% higher and in S1 approx. 15% lower. If the sample is divided by cluster (indoor temperature profiles experienced), the differences from the value 0.4 are -33%, +30% and -24% for clusters 1, 2 and 3 respectively. These differences are substantial, considering that the samples are from the same building type, main ventilation type and the surveys were conducted with the same research protocol.

An assumption when grouping the sample by building type or ventilation mode is that occupants experience similar conditions and have similar levels of adaptation. The results of this study however do not confirm this assumption, with significant differences in thermal sensitivities within the same building and ventilation type. The day-pooling method itself is based on an important assumption, i.e. that there is minimal to no adaptation during a working day. Although this may be close to reality for some office and school environments on which the assumption was based, it may be rather unrealistic for others, such as homes or buildings with large within-day temperature variations that instigate adaptive behaviours.

Based on Rupp et al. (2019), Griffiths constant should be treated as a variable. This study shows that the estimation of occupants' thermal sensitivity is rather sensitive to sample grouping, both in relation to the estimation of the regression coefficient and the error variance of the room temperature. It is therefore important to reflect on how reliable the resulting thermal sensitivities would be from single comfort study samples. A further issue to address is to what extent treating Griffiths constant as a variable contributes to more accurate estimations of people's comfort temperature. On a more general note, the validity in the Griffiths method needs to be revisited as an issue with large methodological implications for contemporary thermal comfort research.

5. Conclusions

Based on the findings of this study, thermal sensitivity varies within the same building type and ventilation mode as well as between buildings. It appears that building/space characteristics other than ventilation mode and within-day adaptive behaviour, which perhaps cannot be assumed as minimal, influence occupants' thermal sensitivity. The estimation of occupants' thermal sensitivity appears to be very sensitive to the room/building context. Grouping surveys by building type and ventilation mode for comparing the resulting regression coefficients is likely to bring statistically significant results if adequately large datasets are used but it does not necessarily mean that the resulting regression coefficients can be used with confidence in other samples of the same building/ventilation type.

Based on the findings from this analysis, there are fundamental and methodological issues to investigate before a robust recommendation on the estimation of occupants' thermal sensitivity in different contexts.

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