# INTERACTIONS BETWEEN THERMAL AND VISUAL (DIS-)COMFORT AND RELATED ADAPTIVE ACTIONS THROUGH CLUSTER ANALYSES

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## ABSTRACT

The objectives of this study are to analyze interactions between thermal and visual influences on comfort and behaviors and to present a clustering method based on the results of mixed-effect regression analyses for simulation and control purposes. Results show a) interactions between thermal and visual influences on comfort and behavior, b) the advantage of this method in creating independent and distinct patterns related to thermal comfort, visual comfort, and occupant behavior, and c) that the relationship between clusters e.g. between clusters of thermal and visual comfort or between thermal comfort and heating behavior is not significant.

## INTRODUCTION

Averaged models related to thermal comfort and occupant behavior are facing limitations in the context of building performance prediction and building operation. On the one hand, they are restricted in looking at unidimensional influences on behavioral actions, e.g. at the effect of indoor and outdoor thermal conditions on controls able to control thermal conditions (Haldi and Robinson, 2009), but not whether indoor visual conditions moderate such relationships.

In addition, researchers in the fields related to occupants' comfort and behavior recognized limitations in the application of averaged models for advanced building energy concepts. In order to show and model the diversity in both aspects, previous studies presented simplified and partly artificial classifications (e.g. active/passive occupants (D'Oca et al., 2014) or energy frugal/indifferent (Hong et al., 2015)) or data-driven distributions of behavioral patterns (Haldi et al., 2016). At the same time, looking at the individual level is also beyond practical application.

The objectives of this paper are a) to look at interactions between thermal and visual influences on comfort and behaviors related to one of these aspects and b) to introduce a data-driven method to define specific patterns (clusters) of perceptive (comfort votes) and behavioral responses.

These objectives are addressed through four research questions.

1) To what extent moderate visual parameters of the physical environment interactions with the thermal environment and vice versa?
2) What are characteristics of individual clusters of comfort and behavior in relation to thermal and visual aspects of the indoor environment?
3) Is there a relationship between the clusters a person is assigned to with respect to thermal perception, visual perception, thermal behavior, and visual behavior?
4) Is there a relationship between individual factors (e.g. demographics and psychological traits) and the probability of membership in a cluster?

## METHODS

### Datasets used

Two data sets were used for the following analysis. Both data sets derive from experimental studies with human subjects in a field laboratory, which provides working conditions in a realistic office setting with controlled indoor environments and connection to the outdoors.

The study leading to the first dataset, in the following referred to as data set A, is described in detail in previous publications (Schweiker et al., 2012; Schweiker and Wagner, 2016). During this study, 36 subjects were asked to work three full working days of 8 hours each in the field laboratory. All subjects were of student age and reacted to a public call for participants. None of the participants was connected to the research team. Subjects had to bring their own work and were asked to fill in questionnaires in average every 90 minutes. During these experiments, they were allowed to adjust their clothing levels, open windows, adjust the external blinds, use the ceiling fan, and interact with the artificial lighting.

The three days differed in the number of persons sharing an office room – one day, subjects were alone, another day, two persons were sharing the room, and a third day, four persons were sharing the room. The order of conditions was balanced.

For this paper, only the data from days with single-person (referred to as A1) and two-person offices (A2) was considered.

The second dataset (dataset B) derives from an unpublished experiment looking at the interaction between visual and thermal influences on people's perception and behavior.

For the first year of this study, 24 subjects were asked to work in the field laboratory for 4 full working days during 4 seasons, i.e. in total 16 working days. Half of the subjects were 32 years or younger, the other half were 50 years or older. In addition, half of them were female. As for the first study, subjects reacted to a public call for participants.

During the 4 working days in each season, subjects experienced 6 different conditions (two of them twice). These conditions varied in the degree of control subjects' had over thermal and visual aspects of the indoor environmental conditions. In all conditions, subjects were allowed to adjust their clothing levels. In three conditions, subjects were allowed to tilt the windows, adjust the blinds, and interact with artificial lighting. At the same time, the indoor thermal conditions were beyond their control and fixed in terms of the operative temperature to one of 20°C, 25°C, or 30°C. During the other three conditions, subjects were allowed to tilt or open the window, adjust the thermostat for heating or cooling. The indoor lighting level was beyond their control and fixed by means of automated blinds and artificial lighting in terms of the illuminance level to one of 300lx, 500lx, or 1,000lx.

For all experimental protocols, ethical clearance was obtained and all subjects gave their written informed consent prior to participating.

### Analysis procedures

The analysis procedures consist of four steps. All steps were done using the statistical software package R (R Development Core Team, 2012) and the packages lmer (Bates et al., 2014) and nnet (Venables and Ripley, 2002).

In the first step – related to research question 1 – the data from study B was analyzed by means of mixed effect logistic regression analysis in order to reveal interactions between visual and thermal environmental parameters on their effect on subjects' behavioral actions. For this analysis, classical Bernoulli models related to the state of a control object were used. The dependent variables – the interactive opportunities – were the window state (open/close), the state of the thermostat (heating on/off – note that only heating was considered due to a negligible number of cooling interventions), and the state of artificial lighting (on/off). As independent fixed effects were considered the operative temperature, the outdoor air temperature, the indoor illuminance level, and the global solar radiation together with their interaction terms. All independent variables were normalized based on their means and standard deviations. The subject identifier was considered as independent random effect. For this analysis, function glmer with family binomial and bobyga optimizer was used.

For the second to fourth step – related to research question 2 – both datasets were considered.

In the second step, mixed effect regression analysis was used to estimate the regression parameters related to a variety of models as presented in Table 1. In each model, the subject identifier was considered as independent random effect. In contrast to common approaches, which are solely looking at the resulting model fit, we stored the resulting intercept and slope for each model and each subject.

*Table 1: Dependent and independent variables considered for the mixed effect regression analysis.*

| Data | Dependent variable | Independent variable |
|---|---|---|
| A (A1/A2) | Thermal sensation (TS)<br>Thermal preference (TP) | Predicted Mean Vote (PMV) |
| | Window opening<br>Ceiling fan usage | PMV |
| B | TSV<br>TPV | PMV |
| | Window opening<br>Heating set point<br>Cooling set point | Outdoor air temperature |
| | Visual sensation (VS)<br>Visual preference (VP) | Indoor illuminance level |
| | Blinds usage<br>Lighting usage | Outdoor illuminance level |

In the third step, a cluster analysis (k-means) was applied on the stored values of regression parameters for intercept and slope for each subject. R function kmeans was used and the number of clusters was fixed to 4 due to the limited number of data points. This analysis leads to one cluster number for each subject and each dependent variable.

In the fourth step, multinomial logistic regression analysis was performed in order to investigate the influence of sex, age, and thermos-specific self-efficacy (specSE) on the membership in a particular cluster. According to Hawighorst, Schweiker, and Wagner (2016), “specSE describes peoples' expectations towards their competences to execute desired operations improving their perception of the thermal environment successfully”. Consequently, the dependent variable in this analysis was the cluster number, while the independent variables were age, sex, and the specSE. R function multinom was used for this analysis.

## RESULTS

Table 2 shows the normalization parameters for the four independent variables considered for the first analysis looking at moderating effects of visual and thermal conditions.

*Table 2: Normalization parameters.*

| Data point | Mean value | Standard deviation |
|---|---|---|
| Indoor operative temperature (Tin) [°C] | 25.2 | 3.06 |
| Outdoor temperature (Tout) [°C] | 15.5 | 8.12 |
| Indoor illuminance (Ev) [°C] | 1010 | 623 |
| Global solar radiation (Iglob) [°C] | 372 | 282 |

The mixed effect logistic regression analysis revealed that the independent variables and their interaction terms were highly significant at $p < 0.1$ with few exceptions. Due to the number of data points (192,343) this is not coming to a surprise. With effect sized being complex to be explored in multivariable models including interaction terms, the non-standardized effect sizes are presented graphically in Figures 1 and 2 for the analyzed heating and lighting behavior.

Figure 1 shows that the probability of heating switched on increases with decreasing outdoor temperatures. At the same time, there is a strong effect of visual parameters on the probability. With decreasing illuminance levels, the heating probability increases (blue line) and with decreasing global solar radiation, the probability decreases (green line). Thereby, the effect of indoor illuminance levels is higher than that of solar radiation.

In contrast, Figure 2 shows that the probability of lighting switched on does not depend strongly on thermal characteristics of the indoor and outdoor environment. In general, the probability of lighting being switched on is rather low, which can be explained by the working period (9:30 am to 4:30pm) and high percentage of glazing of the facility, so that most of the experimental time, indoor illuminance levels were sufficient for working.

Comparing the effect of indoor operative temperature with that of the outdoor temperature, the latter one shows a bigger influence on the lighting probability, while the former hardly changes it.

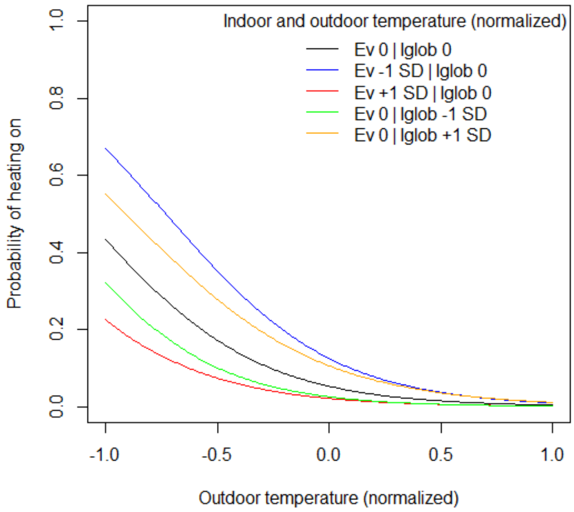


*Figure 1: Probability of heating switched on in relation to the outdoor temperature, indoor illuminance levels (Ev), and global solar radiation (Iglob). For explanation of normalized values see Table 2.*

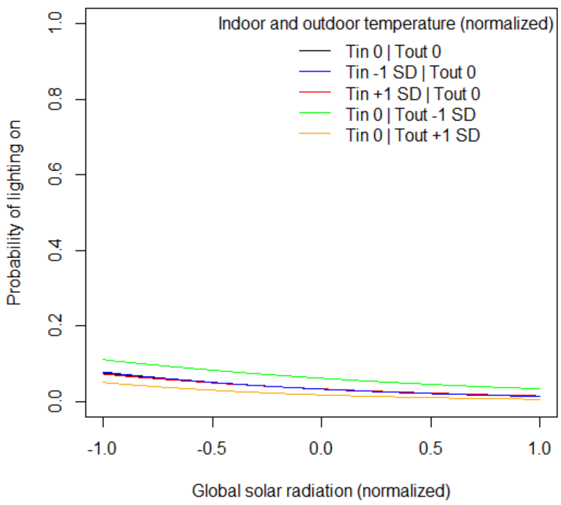


*Figure 2: Probability of lighting switched on in relation to the global solar radiation, indoor operative temperature (Tin), and outdoor temperature (Tout). For explanation of normalized values see Table 2.*

Figures 3 to 5 present exemplarily the outcome of the cluster analysis for the window opening behavior for dataset A1. The clusters identified based on the regression coefficient determined by mixed effect regression analysis shown in Figure 3 lead to distinct behavioral patterns as shown in Figure 4. These patterns differ in their $t_{50}$-value (e.g. cluster 4 has a probability of 0.5 at a PMV of -0.75, while the one of cluster 2 is at a PMV of +.4) and their slope, i.e. the range of the independent variable leading to a switching behavior (e.g. small for cluster 2 and large for cluster 4.

Similar distinct patterns were also found for the other dependent variables related to occupant's behavior and comfort perception (see Figure 5), but cannot be shown here due to space limitations.

In general, the number of 4 clusters was found to be meaningful in order to extract distinct patterns. A higher number of clusters would be possible, but led to rather small differences between individual behavioral patterns.

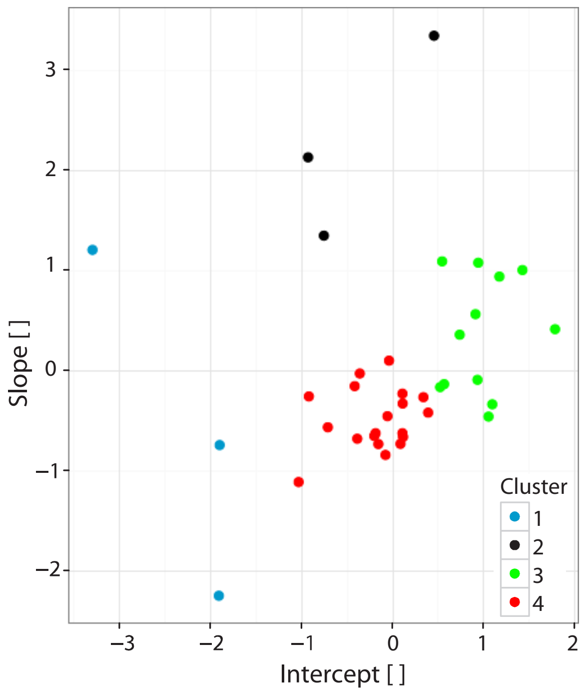


*Figure 3: Representation of the results of cluster analysis. Points show normalized intercept and slope for each participant for the window opening behavior in dataset: A1. Colors show the assigned cluster.*

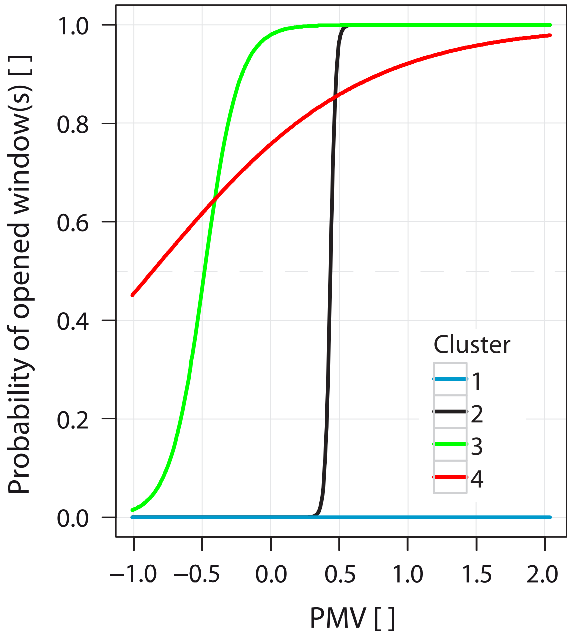


*Figure 4: Resulting behavioral patterns based on cluster analysis of window opening behavior presented in Figure 3.*

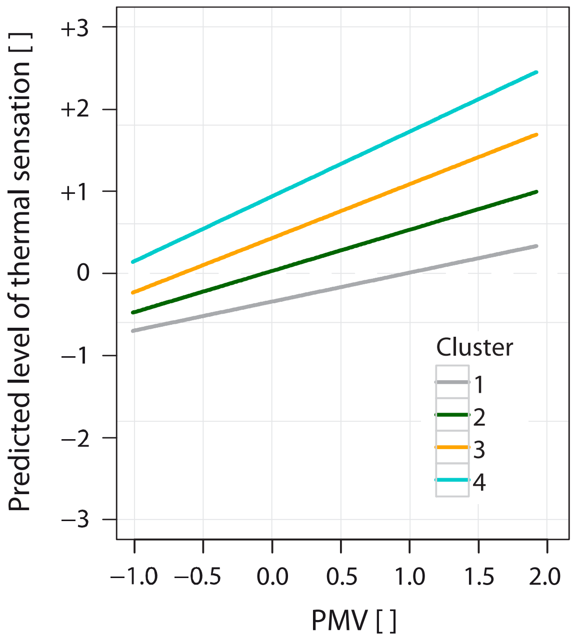


*Figure 5: Predicted level of thermal sensation for each cluster based on dataset: A1.*

Next, related to research question 3, we analyzed whether there is a relationship between the clusters a person is assigned to with respect to thermal perception, visual perception, thermal behavior, and visual behavior.

Figure 6 shows exemplarily the comparison of cluster a person is assigned to for thermal sensation and window opening behavior. The largest dot shows e.g. that a high number of persons assigned to cluster 4 in thermal sensation was assigned to cluster 3 for window opening behavior. However, there is also a high number of persons assigned to cluster 4 of thermal sensation and cluster 2 for window opening behavior.

Such comparison was done for all possible combinations of clusters. Table 3 summarizes the outcome of this analysis grouped into four categories of comparisons. The first category compares two types of perceptions within the same domain of comfort, e.g. thermal sensation (TSV) with thermal preference (TPC). The second category compares perception between the visual and thermal domain of comfort. The third group are comparisons between perceptions and behaviors, while the fourth and last group compares two types of behaviors.

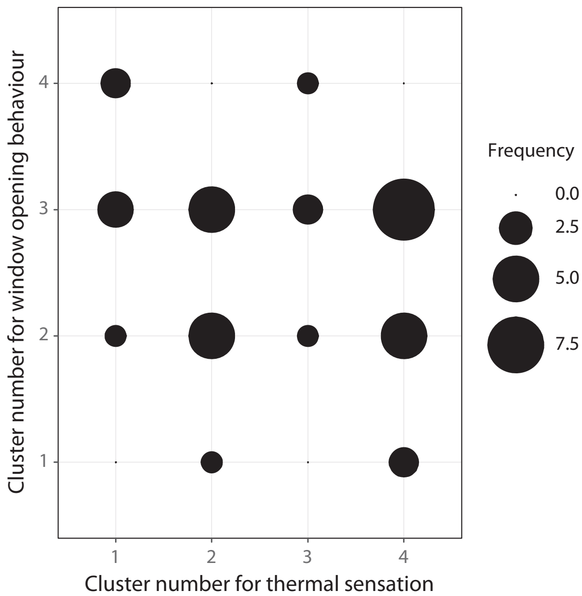


*Figure 6: Comparison of agreement between cluster for thermal sensation and window opening behavior for individual persons based on dataset: A1.*

*Table 3: Congruence between assigned clusters*

| | |
|---|---|
| **1) Sensation vs. preference**<br>*Example: TSV vs. TPV* | **2) Perception A (thermal) vs. perception B (visual)**<br>*Example: TSV vs. VSV* |
| Observed fit [%]:<br>22 (11 – 34)* | Observed fit [%]:<br>34 (29 – 38)* |
| **3) Perception vs. behavior**<br>*Example: TSV vs. window opening* | **4) Behavior A vs. Behavior B**<br>*Example: Window opening vs. fan usage* |
| Observed fit [%]:<br>24 (12 – 37) | Observed fit [%]:<br>25 (20 – 29)* |

In Table 3, for each group, the mean value for the percentage of persons being in the same cluster is shown together with the range.

A bit surprising, the observed fit is highest for the congruence between clusters of thermal and visual perception (group 2).

However, in general, the congruence is low (<50%), which questions the meaning of categorizing persons in general as active/passive or into other general categories. A meaningful approach would be to model a person in different behavioral patterns and comfort requirements.

The last aspect analyzed is related to demographic and personal factors leading to a higher probability of membership in a specific cluster.

Figures 7 and 8 present exemplary results of this analysis for the clusters shown in Figures 4 and 5, i.e. for window opening behavior (Figures 7 and 4) and thermal sensation (Figures 8 and 5).

As visible in Figure 7, there are significant differences in cluster membership between females and males and related to the value of specSE especially for clusters 2 and 4. The probability to belong to cluster 2 (characterized by opening the window at rather high values of PMV – see Figure 4), is higher for females and increases especially in females with a higher value of specSE, i.e. a higher confidence that ones action can change something in the thermal conditions. At the same time, the probability to belong to cluster 3 increases equally for females and males with lower specSE.

Figure 8 shows the relationship between the probability of membership in a specific cluster of thermal sensation and sex and specSE of a person. The probability to belong to cluster 4 (characterized by the lowest (closest to cold) thermal sensation given a specific PMV – see Figure 5) increases with a low value of specSE especially for females. At the same time, the probability to belong to cluster 1 (those stating the warmest sensations), increases slightly with increased specSE.

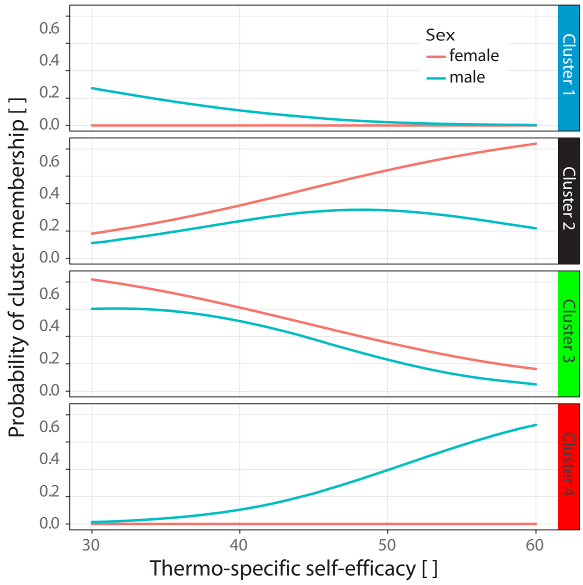


*Figure 7: Probability of cluster membership for window opening behavior (see Figure 4 for characteristics of cluster) in relation to sex and specSE of subjects for dataset: A1.*

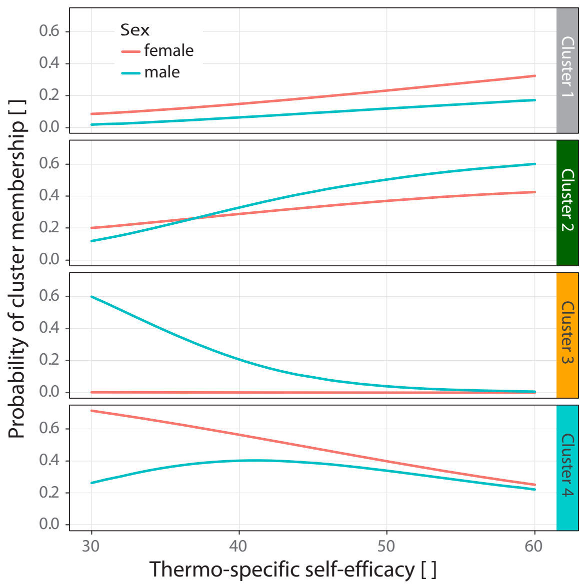


*Figure 8: Probability of cluster membership for thermal sensation (see Figure 5 for characteristics of cluster) in relation to sex and specSE of subjects for dataset: A1.*

## CONCLUSION

This study shows that modelling approaches presented so far lack complexity with regard to three aspects.

First, the analysis presented above reveals that there is a strong effect of visual characteristics of the physical environment on behavioral patterns affecting the thermal indoor environment. At the same time, the effect of thermal characteristics has a negligible effect on behavioral patterns affecting the visual indoor environmental conditions.

Second, the average model of occupant behavior appears to be oversimplified and the method presented above looks promising in revealing meaningful and distinct behavioral patterns which differ not only in the magnitude of influences triggering a behavior (signified by differences in $t_{50}$), but also the strength of reaction given changes in the indoor environmental parameters.

Third, this paper showed a very weak relationship between clusters, which signifies that e.g. there is no such thing such as an always passive occupant, but that the activeness of an occupant and their comfort requirements differ between types of behaviors and perceptions. Thereby, the analysis method presented here allows extracting the frequency of specific clusters and related behavioral patterns, which can be easily implemented in advanced building procedures such as agent-based models by equipping a specific percentage of agents with a specific pattern based on empirical data.

In addition, we showed that there are individual factors such as sex or factors from the field of psychology related to the perceived level of control which have an influence on the probability of cluster membership.

Limitations are certainly given due to the small sample size and need to be overcome with future studies.

Future studies also need to look e.g. at multiple behaviors at once in order to analyze whether despite the results shown here, the definition of an active occupant is valid when considering the totality of a person's reaction to changes in the indoor and outdoor, thermal and visual environmental parameters.

## ACKNOWLEDGEMENT

This study was funded by the German Federal Ministry of Economics and Technology (BMWi) with the project ID's: 0327241D, 03ET1035B, and 03ET1289B.

## REFERENCES

Mitchell, J.W., Beckman, W.A. 1995. Instructions for IBPSA Manuscripts, SEL, University of Wisconsin, Madison USA.

Bates, D., Mächler, M., Bolker, B. and Walker, S., 2014. Fitting Linear Mixed-Effects Models using lme4. *arXiv:1406.5823 [stat]*.

D'Oca, S., Fabi, V., Corgnati, S.P. and Andersen, R.K., 2014. Effect of thermostat and window opening occupant behavior models on energy use in homes. *Building Simulation*, [online] 7(6), pp.683–694. Available at: <http://dx.doi.org/10.1007/s12273-014-0191-6>.

Haldi, F., Calì, D., Andersen, R.K., Wesseling, M. and Müller, D., 2016. Modelling diversity in building occupant behaviour: a novel statistical approach. *Journal of Building Performance Simulation*, [online] pp.1–18. Available at: <http://dx.doi.org/10.1080/19401493.2016.1269245>.

Haldi, F. and Robinson, D., 2009. Interactions with window openings by office occupants. *Building and Environment*, 44(12), pp.2378–2395.

Hawighorst, M., Schweiker, M. and Wagner, A., 2016. Thermo-specific self-efficacy (specSE) in relation to perceived comfort and control. *Building and Environment*, 102, pp.193–206.

Hong, T., D'Oca, S., Turner, W.J.N. and Taylor-Lange, S.C., 2015. An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs framework. *Building and Environment*, [online] 92, pp.764–777. Available at: <http://www.sciencedirect.com/science/article/pii/S0360132315000761>.

R Development Core Team, 2012. *R: A Language and Environment for Statistical Computing*. [online] Vienna, Austria: R Foundation for Statistical Computing, Vienna, Austria. Available at: <http://www.r-project.org>.

Schweiker, M., Brasche, S., Bischof, W., Hawighorst, M., Voss, K. and Wagner, A., 2012. Development and validation of a methodology to challenge the adaptive comfort model. *Building and Environment*, 49(1), pp.336–347.

Schweiker, M. and Wagner, A., 2016. The effect of occupancy on perceived control, neutral temperature, and behavioral patterns. *Energy and Buildings*, 117, pp.246–259.

Venables, W.N. and Ripley, B.D., 2002. *Modern Applied Statistics with S*. Fourth ed. [online] New York: Springer. Available at: <http://www.stats.ox.ac.uk/pub/MASS4>.