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Bayesian inference of thermal comfort: evaluating the effect of “well-being” on perceived thermal comfort in open plan offices

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Abstract. The judgment of thermal comfort is a cognitive process which is influenced by physical, psychological and other factors. Prior studies have shown that occupants, who are generally satisfied with many non-thermal conditions of indoor environmental quality, are more likely to be satisfied with thermal conditions as well. This paper presents a novel approach that considers the effect of non-thermal building environmental design conditions, such as indoor air quality and noise levels, on perceived thermal comfort in open-plan offices. The methodology involves the use of Bayesian inference to relate the occupant’s thermal dissatisfaction in a building not only to thermal conditions and occupant metabolic factors (i.e., parameters of the original Fanger model), but also to measurable non-thermal metrics of indoor environmental quality. A Bayesian logistic regression approach is presented in this paper. The experimental context regards a prior indoor environmental quality measurement and evaluation study of 779 occupants of open-plan offices throughout Canada and the US. We present revised PMV-PPD curves for real-world offices that take into account both thermal and wellbeing IEQ parameters. The Bayesian inference analysis reveals that the occupant’s thermal dissatisfaction is influenced by many non-thermal IEQ conditions, such as indoor CO₂ concentrations and the satisfaction with the office lighting intensity.

1. Introduction

Today, dissatisfaction with indoor thermal conditions is known to be one of the most common sources of complaints by occupants of commercial buildings with respect to indoor environmental quality (IEQ) [1]. These complaints are not without merit, either. When building occupants are found to be dissatisfied with their thermal environment, it has been observed that their overall health, productivity, well-being, and satisfaction with the workplace are adversely affected [2-6].

This study aims to fill a prevailing research gap with respect to standard models of thermal comfort in that models have not always accurately predicted true thermal comfort observations from field studies [15]. As salient models such as the Fanger PMV-PPD model or Adaptive Comfort model only take into account thermal factors when predicting thermal comfort, the increasing awareness of the interdependencies between perceived thermal comfort and overall IEQ, as observed in the papers cited above, suggests that correlating thermal comfort prediction to *non-thermal* metrics of IEQ may be beneficial. It is therefore the objective of this paper to evaluate the effect of non-thermal IEQ parameters, such as lighting intensity, acoustic performance, and indoor air quality, on the perceived thermal comfort within office spaces.



1.1. Well-being IEQ factors affecting overall comfort

ASHRAE defines thermal comfort as “the condition of the mind in which satisfaction is expressed with the thermal environment” [7]. While there does not appear to be a dispute in literature whether thermal comfort can be attributed to thermo-physical parameters of the human body, as defined by Fanger’s PMV model, it is nevertheless increasingly accepted that thermal comfort can be influenced by personal differences in mood, culture and other individual and social factors [6,8].

Until recently, systematic performance criteria for IEQ, which takes into account both psychological and physical indicators of IEQ, have not been explicitly expressed in prevailing building codes and standards. However, in 2014, the International WELL Building Institute launched the WELL building standard, a building performance accreditation scheme focusing solely on the health, comfort and wellness of building occupants [9]. The emergence of the WELL standard occurred in tandem with recent research exploring the interdependencies between thermal comfort, IEQ, and building design. For instance, Wagner et al. [10] conducted a field study on occupant’s thermal comfort and their general satisfaction with the workplace (which included satisfaction with air quality, noise and daylight) in office buildings. They found that occupants who are generally satisfied with many non-thermal metrics of IEQ are more likely to be satisfied with thermal conditions as well. In previous studies by Huang et al., Rupp et al., Al Horr et al., and Kamaruzzaman et al. [11-14]; the authors found that acoustic and visual comfort, biophilia, indoor air quality and office layout can affect overall occupant comfort and satisfaction. Jamrozik et al. [6] studied the effect of six well-being factors on the occupant’s satisfaction in a living lab experimental setup. They found that the perceptions of environmental conditions which were not varied were also affected. This finding suggests that building occupants’ perceptions of environmental conditions may be holistic: dissatisfaction with one set of environmental conditions may affect occupants’ perception of the whole environment and result in dissatisfaction with a physically unrelated set of environmental conditions.

1.2. Bayesian modelling of Thermal Comfort

Bayesian processing, which refers to the computational modelling of Bayesian problems, has been used effectively in recent years to improve the characterization of thermal comfort probability distributions using new observational data. They incorporate previous knowledge on thermal comfort distributions from past research into the current estimation of model parameters and provide a robust manner of updating these parameters as more data becomes available. For example, Langevin et al. [15] developed an updated curve for the PMV-PPD relationship using Bayesian analysis on datasets from both laboratory and field settings using Fanger lab-based raw data as a prior for the field-based ASHRAE RP-884 datasets [16]. Jensen et al., [4] developed a model which correlates the indoor temperature with the mental performance of office employees using a Bayesian Network approach. They used data from RP-884 to build a correlation between thermal sensation votes and indoor air temperature.

2. A Novel Mathematical Bayesian Framework of Thermal Comfort

This paper seeks to quantify the effect of non-thermal IEQ conditions, such as indoor lighting levels, and CO₂, on metrics of perceived thermal comfort. The research underlying this paper proposes a novel Bayesian framework for the instantaneous evaluation of occupant thermal dissatisfaction, taking into account measurements of non-thermal and thermal IEQ conditions. One incarnation of the framework is specifically proposed and evaluated: an expansion of the Fanger PMV model in a manner that allows for the probability of thermal dissatisfaction, $p(D)$ or ‘PPD’ in the PMV model’s terminology, to be related not only to the original Fanger model terms, $\theta = \{T, RH, MRT, V, met, clo\}$, but also to several non-thermal IEQ parameters defined by separate set of terms, *WELL*. For the Fanger: T = air temperature (°C), RH = relative humidity (%), MRT = mean radiant temperature (°C), V = air velocity (m/s), met = the Fanger metric of metabolic rate, and clo = the Fanger metric of clothing insulation levels. In the Bayesian framework, posterior predictions of thermal dissatisfaction can be determined as follows:

$$p(D | \theta, WELL) = \frac{p(WELL | D) * p(\theta | D) * p(\theta)}{p(\theta, WELL)} \quad (1)$$

2.1. Field data source

Field IEQ data are drawn from the Cost-effective Open-Plan Environment (COPE) field study database made available for this research by the National Research Council of Canada (NRC). The database consists of IEQ data collected from 779 workstations and their occupants in nine buildings between 2000 and 2002 across Canada and the United States [17]. The IEQ data consists of over 4 physical measurements of thermal conditions, such as temperature and relative humidity, and additionally 12 measurements of non-thermal conditions, such as noise levels and CO₂ concentrations. A measurement for all parameters was made at each workstation in parallel to an occupant questionnaire that evaluated occupants' instantaneous satisfaction with some thermal and non-thermal conditions. For this study, a broad set of non-thermal measurements and questionnaire answers are used to characterize conditions of air quality, lighting, acoustics, and interior design. These are defined by the set $WELL = \{CO_2, CO, N, SII, DH, LS\}$, where CO_2 = indoor air CO₂ concentrations (ppm), CO = indoor air CO concentrations (ppm), N = A-weighted indoor noise levels (dBA), SII = speech intelligibility index, DH = workstation partition desk height (m), LS = surveyed occupant satisfaction with indoor light levels (a Likert scale from 1 to 7). In addition, the COPE dataset also contains occupant responses to the question of thermal satisfaction, TS , measured on a Likert scale from 1, 'very dissatisfied', to 7 'very satisfied'. Distributions of TS data per building and for the entire COPE database are shown in figure 1. Figure 2 illustrates data for all θ and $WELL$ parameters, as derived from the COPE dataset. Distributions of each metric per building in the COPE dataset are also shown. The probability density functions of each parameter are only generated for the purposes of comparison in figure 2 and are not used further in this study.

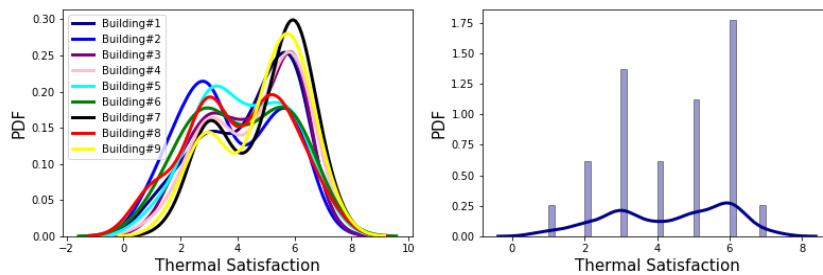


Figure 1. Probability Distributions of thermal satisfaction across all buildings

2.2. Bayesian logistic regression

Logistic regression belongs to a class of Generalized Linear Models (GLMs) that can be used to predict the relationship between one non-continuous dichotomous (binary) dependent variable and one or more independent variables. In this paper, a Bayesian logistic regression model is developed to represent eq (1) and is applied to the COPE database. The model predicts the linear relationship between thermal dissatisfaction (D), Fanger thermal conditions (θ) and non-thermal parameters ($WELL$) drawn from the dataset. By considering β as a set of regression model coefficients, $p(D | \theta, WELL)$ is estimated as:

$$p(D | \theta, WELL) = \frac{1}{1 + e^{-[\sum_{\theta}(\beta_{\theta} \cdot \theta) + \sum_{WELL}(\beta_{WELL} \cdot WELL) + \beta]}} \quad (2)$$

The probability of dissatisfaction, $p(D)$, is modelled as a dichotomous dependent variable and the 10 $WELL$ and θ parameters are modelled as continuous independent variables. Observed data for $p(D)$ is inferred from the COPE dataset by assuming that for each survey response, i :

$$D_i = \begin{cases} 1 \text{ or dissatisfied} & \text{if } TS < 4 \\ 0 \text{ or satisfied} & \text{if } TS \geq 4 \end{cases} \quad (3)$$

2.3. Model descriptions

Two different logistic models are generated in this study. First, the conditional probabilities of thermal dissatisfaction given thermal and non-thermal IEQ parameters are regressed using ten IEQ variables drawn from the COPE database, such that posterior distributions of $p(D | \theta, WELL)$ are inferred.

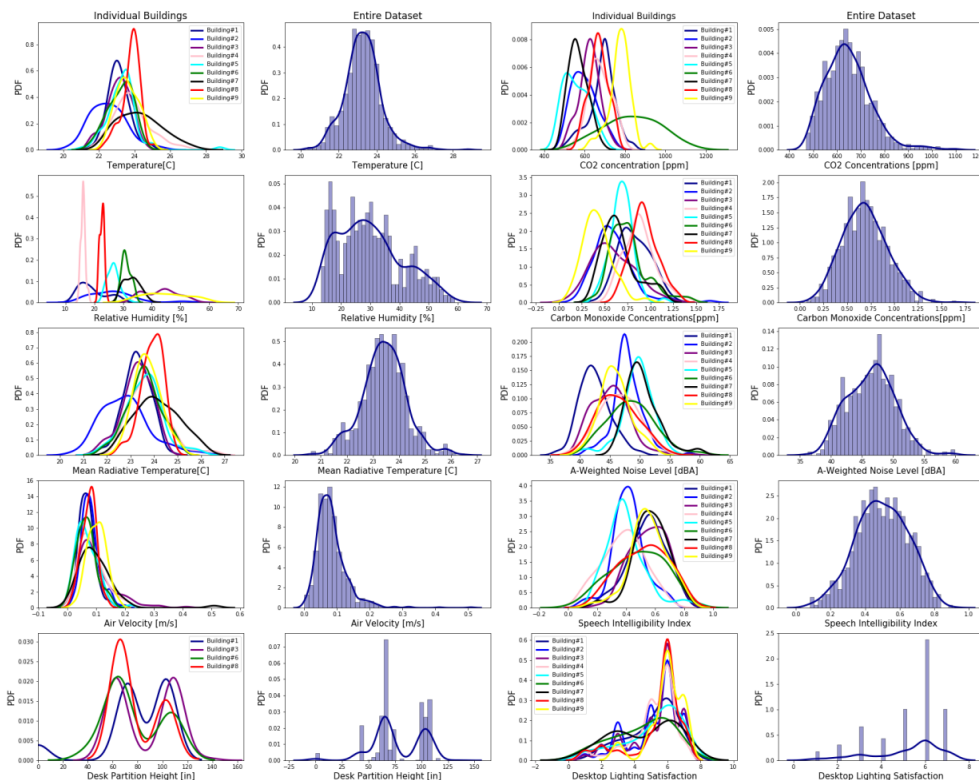


Figure 2. Probability distributions of Fanger and WELL parameters across all buildings

The second model seeks to update the relationship between thermal dissatisfaction and predicted mean vote (PMV) by inferring posterior distributions of $p(D|PMV, WELL)$. For this case, PMV is calculated from measured values of values of θ and recommended values of ‘clo’ and ‘met’ for office spaces as per ANSI/ASHRAE 55 Standard- table 5.2.2.A and table 5.2.1.2 respectively [7].

2.4. Sampling of posterior distributions

The Bayesian statistics Python library, PyMC3, is used to infer the posterior probability of occupant’s dissatisfaction for all the models presented. 5000 samples are drawn from the posteriors using the NUTS sampler, a type of Markov Chain Monte Carlo (MCMC) sampling method.

Weakly informative priors for the model regression parameters β are used, as recommended by Gelman et al. [18]. The following model parameters are modelled as having a first order linear relationship with $p(D)$: T, RH, MRT and CO₂. The following parameters are modelled as having a quadratic relationship with $p(D)$: V, CO, N, SII, DH, LS. The order of the correlations has been determined by trial and error.

3. Results and Discussion

3.1. Relationship between occupant’s thermal dissatisfaction and non-thermal well-being IEQ

Figure 3 shows the results from the first set of logistic regression models that predicts the correlations between thermal dissatisfaction $p(D)$ given a fixed set of Fanger thermal conditions, θ_0 , (equivalent to $PMV \approx 0$) and WELL parameters. $\theta_0 = \{T = 24 \text{ }^\circ\text{C}, RH = 25\%, MRT = 23.5 \text{ }^\circ\text{C}, V = 0.05 \text{ m/s}\}$, and $PMV(\theta_0, met = 1, clo = 1) = 0$. The results yield an observable relationship between surveyed thermal dissatisfaction and several WELL parameters. For example, it is observed that indoor air CO₂ and thermal dissatisfaction are positively correlated; more occupants are thermally dissatisfied at higher indoor CO₂ concentrations than at lower indoor CO₂ concentrations.

Similarly, it is shown in figure 3 that when the qualitative satisfaction with desktop lighting is higher, the dissatisfaction with the thermal conditions decreases significantly. The A-weighted noise levels and speech intelligibility index are also showing a positive and negative correlation respectively,

which mean that occupants experiencing higher noise levels would tend to be less satisfied with thermal conditions as well. The desktop partition height also observes an apparently high positive correlation with the probability of dissatisfaction, as shown in figure 3. One of the more interesting parameters is that of indoor air carbon monoxide concentrations, which show an inverse correlation with $p(D)$.

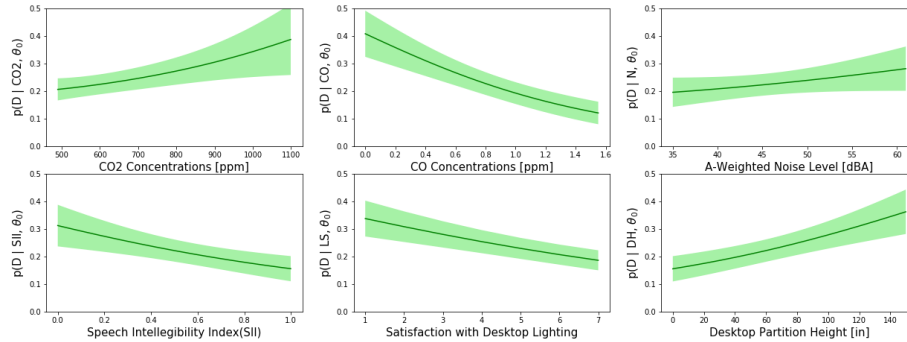


Figure 3. Probability $p(D | \theta_0, \text{WELL})$, where $\theta_0 = \{T = 24 \text{ }^\circ\text{C}, RH = 25\%, MRT = 23.5 \text{ }^\circ\text{C}, V = 0.05 \text{ m/s}\}$ and $PMV(\theta_0, met = 1, clo = 1) = 0$. Solid green lines indicate mean predicted value from all samples, with shaded green bands indicated the standard error.

The significance of these results suggests further analysis of the COPE dataset, and similar future datasets capturing non-thermal IEQ data, are warranted. The observable correlation between metrics such as desk partition height, carbon monoxide levels, and thermal dissatisfaction are striking, and not altogether easy to comprehend. On one hand, in defence of the model's robustness, sensor measurements of CO in the COPE dataset are distributed relatively evenly across the surveyed buildings in the COPE dataset, but it is not wholly clear if CO concentrations may be an indicator of a primary issue driving its observed impact on perceived thermal dissatisfaction. Without identifying the source of CO concentrations, one cannot wholly conclude that thermal discomfort is correlated directly to CO. A similar view must be taken for all considered parameters, suggesting that in a future work, the interdependency of WELL parameters will be examined.

3.2. WELL-adjusted relationship between PMV and thermal dissatisfaction $p(D)$

Figure 4 shows the results from the second set of modelling which predicts an adjusted relationship between estimated PMV and the thermal dissatisfaction given non-thermal WELL parameters, $p(D | PMV, \text{WELL})$. It is seen from the results that at $PMV = 0$, non-thermal parameters do appear to disrupt perceived thermal satisfaction. For example, at $PMV = 0$, the likelihood of thermal dissatisfaction increases from 0.3 to over 0.4 if the CO_2 levels increases from 600 to 900 ppm. If these observations are found to be repeatable in other contexts, the implications of such correlations are significant. If, in the future, it is possible to directly affect thermal satisfaction through improvement of non-thermal conditions in indoor spaces, it will encourage new thinking in regard to how to most cost-effectively deliver heating and cooling services in the built environment.

4. Conclusion

This paper presented a novel methodology for the evaluation of thermal comfort which includes not only thermal IEQ parameters, but also non-thermal indoor building design conditions. Bayesian logistic regression is applied to a prior field experimental IEQ data in order to predict the relationships between occupant thermal dissatisfaction and 10 thermal and non-thermal IEQ parameters.

The models' results revealed an observable correlation between thermal dissatisfaction, as experienced by occupants of open-plan office spaces, and non-thermal IEQ parameters such as CO_2 concentrations, lighting, noise and speech levels and also the height of the desktop partition. Our exploration of the relationship between PMV and thermal dissatisfaction, analogous to the classic PPD-PMV relationship of the Fanger model, reveal a potentially important finding, that occupant thermal satisfaction may be measurably improved by improving 'well-being'-related conditions in the built environment. As has been discussed, however, a deeper analysis of these findings is warranted and will

continue in the future, particularly to investigate whether there are underlying primary causes for the correlations presented. The results will be used to inform a future sensor and survey measurement process of office spaces at the University of British Columbia, which will take place across 2019 and 2020.

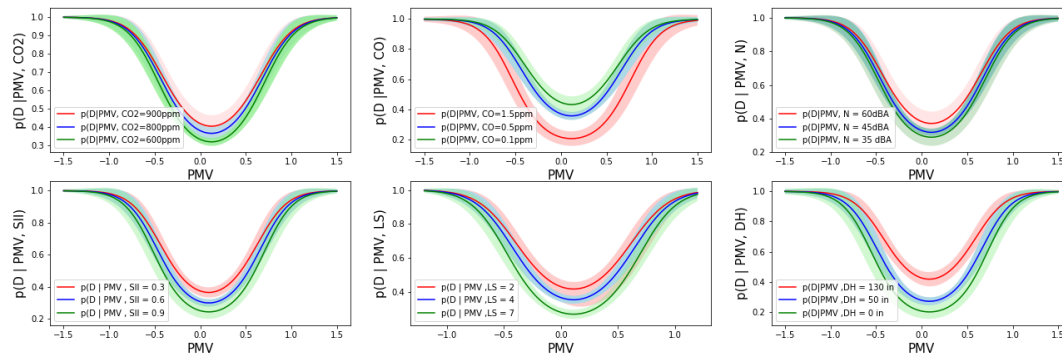


Figure 4. WELL-adjusted relationship between PMV and thermal dissatisfaction $p(D)$

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