Towards Improved Thermal Comfort Predictions for Building Controls: Hierarchical Bayesian Modelling of Indoor Environmental Design Conditions

Sarah Crosby
sarah.crosby@mech.ubc.ca
Department of Mechanical Engineering, University of British Columbia.
Vancouver, BC, Canada

Adam Rysanek
School of Architecture and Landscape Architecture,
University of British Columbia
Vancouver, Canada
arysanek@sala.ubc.ca

ABSTRACT

This paper updates the findings of a prior work that found evidence to suggest that predictions of thermal comfort can be improved by adding measurements of indoor CO_2 concentrations. This work first updates these findings by adding 150 new samples of IEQ measurements collected from occupants of office spaces at the University of British Columbia in 2019. This paper then formulates and proposes a novel Hierarchical Bayesian model, trained on the expanded field dataset, that predicts thermal satisfaction based on thermal IEQ metrics and measurements of CO_2 levels. Posterior predictive results revealed a robust and statistically significant correlation between perceived thermal comfort and indoor CO_2 levels. Cross-validation and posterior checks revealed stronger evidence that including indoor CO_2 concentrations as an independent variable when predicting thermal satisfaction improves its prediction accuracy. The proposed model can be integrated into building control systems to predict thermal comfort in office spaces based on thermal conditions and ventilation rates, which improves the prediction accuracy of thermal comfort, mitigate the performance gap between predictions and observations of thermal comfort, and may result in energy savings while not sacrificing indoor air quality and well-being, an important challenge to building controls.

CCS CONCEPTS

• **Computing methodologies → Modeling and simulation**; *Model development and analysis.*

KEYWORDS

Thermal comfort, Bayesian modelling, Occupant Thermal Satisfaction, Uncertainty Quantification, Machine learning, Building ventilation, Building controls

ACM Reference Format:

Sarah Crosby and Adam Rysanek. 2021. Towards Improved Thermal Comfort Predictions for Building Controls: Hierarchical Bayesian Modelling of Indoor Environmental Design Conditions . In *The 8th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation (BuildSys '21), November 17–18, 2021, Coimbra, Portugal.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3486611.3491128

BuildSys '21, November 17–18, 2021, Coimbra, Portugal

ACM ISBN 978-1-4503-9114-6/21/11…$15.00
https://doi.org/10.1145/3486611.3491128

1 INTRODUCTION

Indoor thermal comfort, defined as "the condition of the mind in which satisfaction is expressed with the thermal environment" [1], is a state of mind, rather than a state of condition, where its judgment is a cognitive process influenced by, not only measurable environmental conditions but also occupant's well-being and overall satisfaction [6, 14]. In recent years, it has been increasingly observed that occupants' thermal comfort can be influenced by individual differences in mood, well-being, and overall satisfaction [6, 9–11, 14, 16]. It has been argued that, if it is accepted that occupants' judgment of thermal comfort is a cognitive process, then perceived thermal comfort may be affected by the psychological effect of many physical conditions that occupants encounter in the built environment, not only thermal conditions [6].

Recently, emerging studies have found evidence in support of the multi-perceptual and multi-domain nature of thermal comfort, as well as the existing correlations between occupants' perception of thermal comfort [5, 9–11, 17]. For instance, Jokl et al. [11] found that one's optimal operative temperature for thermal comfort is correlated with one's general mood and feelings. Jamrozik et al. [10] showed that the occupant's perception of thermal comfort is holistic: the dissatisfaction with one type of environmental conditions affects occupant's perception of the whole environment and leads to dissatisfaction with the thermal environment and other unrelated metrics of IEQ. Further, it has been found that occupants' perceived thermal dissatisfaction increases with increased noise levels [9, 15, 16]. Gauthier et al. [7] have found a modest correlation between increased CO_2 concentrations and occupant's thermal dissatisfaction.

Although prevailing thermal comfort models have been used in building international codes for some time, it has been found that they have many limitations when applied to buildings' control systems [12] and show poor predictive performance when applied to individuals [2]. Research has shown that it has been possible to find discrepancies between standard model-predicted thermal comfort and thermal comfort observations, which affect building operations and controls [13]. It has been suggested that this performance gap could be filled by including new parameters in thermal comfort models, such as measurements of CO_2 concentrations [7].

Crosby et al.[4] investigated the correlations between thermal comfort and thermal and non-thermal parameters of IEQ. They applied Bayesian regression on the COPE dataset, a prior dataset of objective and subjective IEQ measurements collected from about 800 occupants of open-plan offices in nine buildings across Canada and the United States [18]. Crosby et al. have found that occupant's perceived thermal satisfaction is significantly correlated with indoor CO_2 levels. Furthermore, they demonstrated that adding measurements of indoor CO_2 concentrations to thermal comfort models provide better predictive accuracy than models that would not include these parameters.

2 NOVELTY AND SCOPE OF WORK

Aiming to mitigate the performance gap between observations and predictions of thermal comfort that affect building control systems, this paper: 1- Updates and verifies the prior findings of Crosby et al. by adding 150 new samples of IEQ measurements collected from a recent IEQ field study of open-plan offices carried out at the University of British Columbia (UBC) in 2019 and 2020. 2- Tests the significance and statistical robustness of the correlations between perceived thermal satisfaction and CO_2 concentrations. 3- Demonstrates that prediction accuracy of thermal satisfaction can be improved upon the addition of measurements of indoor CO_2 concentrations. 4- Formulates a new Hierarchical (or multi-level) predictive Bayesian model of thermal comfort, trained on the expended IEQ dataset, which can be used by building experts to improve the prediction accuracy of thermal comfort for building operations. The new proposed model can be integrated into building control systems to predict thermal comfort in office spaces based on thermal conditions and ventilation rates, which may result in energy savings while not sacrificing indoor air quality and well-being, an important challenge to building control systems, particularly now in a post-COVID-19 world.

3 METHODOLOGY

3.1 A Hierarchical Bayesian Framework of Thermal Comfort

Adopting Bayesian modelling in thermal comfort predictions provides a mechanism that is capable of integrating different IEQ datasets into one single thermal comfort model. This is achieved by providing a robust manner of updating prior knowledge on thermal comfort distributions from past research into the current estimation of model parameters. This reflects the scientific *learning cycle* where prior estimates are updated as new data becomes available [3]. In Crosby et al. [4], a Bayesian framework for inferring the probability of an occupant feeling thermally satisfied $p(S)$ as a function of thermal IEQ metrics, $\mathbf{F}$, and non-thermal IEQ conditions, $\mathbf{W}$, is described. This paper revisits this prior work and proposes a new hierarchical Bayesian framework for inferring occupants' thermal satisfaction $p(S)$. When dealing with differently-sized independent datasets, hierarchical modelling allows regression models to be fit to the datasets while accounting for unexplained variations among the datasets themselves and being able to fit a diverse array of data patterns. In Bayesian inference, hierarchical modelling often outperforms traditional (non-hierarchical) regression techniques

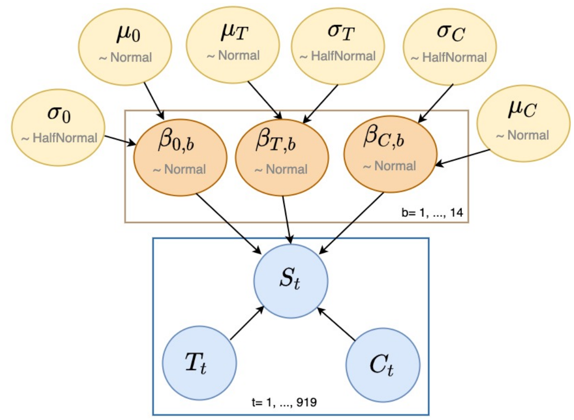

Figure 1: Network diagram of hierarchical logistic regression model for $p(S \mid T, C)$

with regards to model fitness and identifying true model parameters, particularly when managing multiple independent datasets [8]. Within the COPE and UBC extended dataset, there is a total of 13 unique subset field studies of individual buildings, b, (nine independent field trials within the COPE dataset, and four for the UBC set). Figure 1 illustrates a network diagram which details a hierarchical model of predicting thermal satisfaction, S as a function of indoor air temperature, T, and indoor CO_2 concentrations, C, $p(S \mid T, C)$, inferred from the entire COPE + UBC dataset. The subscript t refers to observed data from each individual test subject, of which there are 919 total in the combined datasets. β_0, β_T, and β_C are the model regression coefficients.

3.2 Updating the Prior Findings and Sampling of Posterior Distributions

As this paper seeks to test the statistical significance and robustness of the previous findings, a large field study has been conducted at the University of British Columbia (UBC) to determine whether the evidence base for the prior findings is improved upon the addition of new data. The new IEQ study utilizes modernized instrumentation under the auspices of more modern indoor building environments and building systems compared to the COPE field study of the early 2000s. The UBC dataset consists of instantaneous physical measurement of IEQ coupled with responses from an IEQ questionnaire collected from 150 workstations in four buildings between 2019 and 2020 from open-plan offices. The IEQ survey collects "right-here-right-now" occupant's satisfaction responses.

The UBC IEQ dataset is added to the COPE dataset and the hierarchical Bayesian framework (presented in section 3.1) is used to predict the correlation between perceived thermal satisfaction, $p(S)$, and indoor CO_2 concentrations, C, and to test whether, based on the updated dataset, the previous observations are reinforced. Posterior estimates of β are inferred for each building subset b. Each β is assigned a prior normal distribution of mean μ and variance σ (as shown in Figure 1). A Monte Carlo sampling process (i.e., NUTS algorithm) attempts to converge on identical posterior distributions for each field study-specific β, such that one observes all field study-specific β's sharing approximately the same posterior distribution.

4 RESULTS AND DISCUSSION

4.1 Posterior Predictions of Thermal Satisfaction

Figure 2 displays the posterior predictive results of the Bayesian hierarchical regression process, 1000 samples of $p(\beta \mid \text{field data})$ are drawn to generate 1000 samples of a candidate regression model of $p(S \mid T, C)$. Posterior predictions inferred from only the COPE dataset are shown in orange and predictions drawn from the combined COPE & UBC dataset are shown in blue. Indoor air temperature is kept fixed at, T=23.5 °C, which is the observed median measured indoor air temperature across both datasets.

As the regression coefficients of the model, β, are probabilistic, there is a range of fit of the model. The median posterior predicted probability of thermal satisfaction is denoted by a solid line and the 95% credible interval of thermal satisfaction predictions are shown as upper and lower dotted lines around the median. Figure 2 also presents the individual probability density of observed CO_2 concentrations for both the COPE (in orange) and COPE+UBC (in blue) datasets. Figure2 shows a significant correlation between

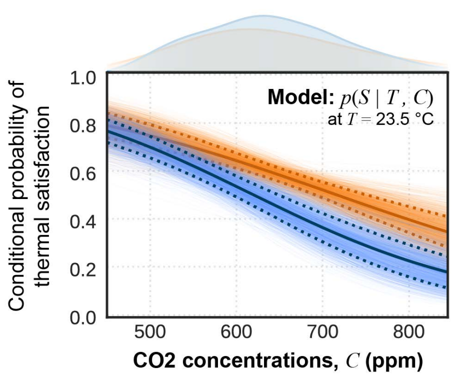

Figure 2: Posterior Predictions of the probability of thermal satisfaction $p(S \mid T, C)$ inferred from COPE (in orange) and COPE+UBC combined dataset (blue)

thermal satisfaction and indoor CO_2 levels which reinforces the observations made in the prior study. For instance, at 23.5°C, a decrease in indoor CO_2 concentrations from 800 ppm to 500 ppm was associated with an increase in the mean probability of thermal satisfaction from 0.2 to 0.8.

4.2 Model Checks and Cross-Validation

Leave-one-out Cross-Validation (LOO-CV) and the Watanabe-Akaike Information Criteria (WAIC) scores are performed to select the best-performing model and compare their predictive accuracy. Models with lower WAIC and LOO scores are a better fit to data when comparing the fit of different models to a dataset. A Null hypothesis is selected to establish our model comparison, which is selected to be the model that most closely fits the observed data but only includes thermal IEQ parameters. This first step reveals that the

Table 1: Values of Δ WAIC and Δ LOO for $p(S \mid T, C)$ Bayesian model inferred from COPE and COPE+UBC results

p(S | T,C)	COPE	COPE+UBC
Δ WAIC	8.1	11.9
Δ LOO	8.1	11.9

best representation of $p(S)$ as a function of only thermal parameters, as inferred from the COPE and UBC datasets, is the model that includes indoor air temperature, T as an independent variable i.e. $p(S \mid T)$.

The WAIC and LOO-CV scores for the developed model are calculated and the difference between the WAIC and LOO scores of the Null hypothesis and that of the CO_2 Bayesian model, Δ WAIC and Δ LOO respectively, for both COPE and COPE+UBC datasets are summarized in Table 1. The sign of the difference in WAIC scores compared to the Null hypothesis indicates the significance of the model: if the difference is positive, it means the model shows improvement in prediction accuracy of $p(S)$ over the Null the hypothesis, and the absolute value of the difference reflect the degree of which the model provides an improvement in prediction accuracy over the Null hypothesis. The results reveal stronger evidence, compared to Crosby et al. [4], that CO_2 is a credible predictor of perceived thermal satisfaction. It is observed from the WAIC and LOO-CV scores that $p(S \mid T, C)$ model provides improved predictive accuracy over the Null hypothesis for thermal satisfaction. It is also revealed that adding the UBC dataset makes the previous findings more significant and robust. This suggests that by including measurement of CO_2 concentration levels, it is possible to improve the prediction accuracy of thermal satisfaction in open-plan offices.

4.3 Proposing a New Predictive Thermal Comfort Model for Building Controls

Model checks and validation techniques revealed and reinforced the previous findings, that including measurements of CO_2 levels is proved to increase the prediction accuracy of thermal satisfaction in open-plan offices. In this section, we propose and formulate a new predictive model, derived from the hierarchical Bayesian regression of the expended dataset. The proposed model predicts the probability of thermal satisfaction, $p(S \mid T, C)$, as follows:

$$p(S \mid T, C) = \frac{1}{1 + e^{-\Gamma}}$$
$$\Gamma = [(\beta_T \;.\; T) + (\beta_{T^2} \;.\; T^2) + (\beta_C \;.\; C) + \beta_o] \quad (1)$$

Where T = air temperature (°C), C = indoor CO_2 levels (ppm), β_C, β_T, and $\beta_T 2$ are the model parameters for C, T, and T^2 respectively, and β_0 is the constant coefficient. C is modelled as having a first-order linear relationship with $p(S)$ and T is modelled as having a quadratic relationship with $p(S)$. The choice of these relationships was made on a trial-and-error basis and evaluation of model selection criteria. Figure 3 displays the model parameters' posterior probability distributions (β) drawn from the Markov Chain Monte Carlo sampling. The maximum a posteriori estimation (MAPE) and the 95% credible interval (highest posterior density, HDI, interval)

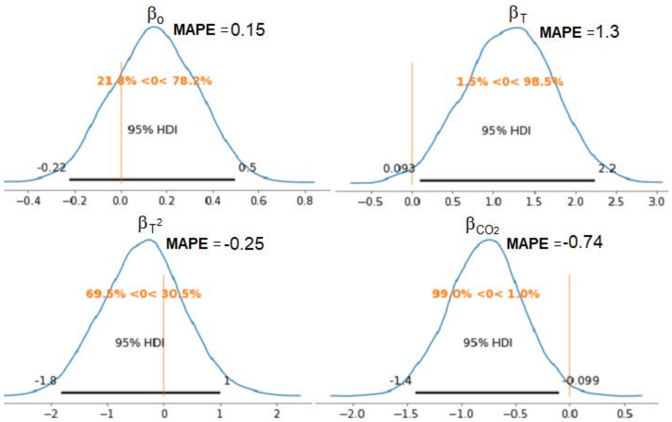

Figure 3: Posterior traces of the $p(S \mid T, C)$ model parameters (β). For each model parameter: its maximum a posteriori estimation (MAPE) is displayed along with the corresponding 95 % credible interval.

of each β are displayed. The significance of the effect of the model parameter on thermal satisfaction increases as the maximum a posteriori estimation (MAPE) deviates from 0 (displayed as a vertical orange line).

It is revealed from Figure 3, that the CO_2 model parameter credibly deviates from 0, which is evident from the $(p(\beta_{CO2}) < 0) =$ 99.0%. This observation suggests that the CO_2 measurements affect the predictions of thermal satisfaction in a statistically significant manner. The thermal comfort predictive model that we are proposing is a probabilistic model which predicts the thermal satisfaction as a probabilistic distribution with model parameters' uncertainty bounds presented above. For future use of the model, we recommend sampling from our model, presented in Eq.1, instead of using the deterministic formula for more accurate predictions.

5 CONCLUSION

A new hierarchical Bayesian model was developed in this work to investigate the relationship between thermal satisfaction and indoor CO_2 levels. Posterior results revealed that the effect of CO_2 on predicted thermal satisfaction is evident and significant. Model selection and cross-validation checks revealed that including measurements of indoor CO_2 concentrations as an independent variable when predicting thermal satisfaction significantly improved its prediction accuracy. Aiming to mitigate the performance gap between observations and predictions of thermal comfort, a novel predictive thermal comfort model was proposed to quantitatively predict thermal satisfaction given psychometric IEQ metrics and measured values of CO_2 concentrations.

The new model can be integrated into building controls to predict thermal comfort in office spaces based on thermal conditions and ventilation rates to improve the prediction accuracy of thermal comfort. This research has suggested that an office with high amounts of fresh air can provide the same level of thermal comfort at higher/lower temperatures than an office with 'typical' fresh air ventilation rates. Establishing these relationships in a manner in which building designers can account for these effects is important. Therefore we recommend expanding measurements in future thermal comfort field studies to include measurements of indoor CO_2 levels. More data is needed to investigate the generalizability of the findings and whether measurements of indoor CO_2 concentrations may improve personalized models of thermal comfort.

Cost-effective/off-the-shelf sensors of CO_2 are becoming more commercially available and common to see installed in commercial and residential buildings. One possible implication of this work is that additional monitoring of indoor CO_2 concentrations could improve thermal comfort compliance estimates, and may result in energy savings while not sacrificing indoor air quality and well-being, an important challenge to building control systems, particularly now in a post-COVID-19 world.

REFERENCES

[1] ASHRAE. 2013. Standard 55-2013 - Thermal Environmental Conditions for Human Occupancy. *Ashrae* 8400 (2013), 58. https://doi.org/ISSN1041-2336

[2] F. Auffenberg, S. Stein, and A. Rogers. 2015. A personalised thermal comfort model using a Bayesian network. *In Twenty-Fourth International Joint Conference on Artificial Intelligence* (2015).

[3] S. L. Choy, R. O'Leary, and K. Mengersen. 2009. Elicitation by design in ecology: using expert opinion to inform priors for Bayesian statistical models. *Ecology* 90 (2009), 265–277.

[4] S. Crosby and A. Rysanek. 2021. Correlations between thermal satisfaction and non-thermal conditions of indoor environmental quality: Bayesian inference of a field study of offices. *Journal of Building Engineering* 35 (2021), 102051.

[5] S. Crosby and A. Rysanek. 2021. Extending the Fanger PMV model to include the effect of non-thermal conditions on thermal comfort. *In proceedings of eSIM conference 2020, Vancouver, Canada.* (2021).

[6] N. Djongyang, R. Tchinda, and D. Njomo. 2010. Thermal comfort: A review paper. *Renewable and Sustainable Energy Reviews* 14, 9 (2010), 2626–2640.

[7] S. Gauthier, B. Liu, G. Huebner, and D. Shipworth. 2015. Investigating the effect of CO2 concentration on reported thermal comfort. *in: Proceedings of CISBAT 2015 International Conference on Future Buildings and Districts* (2015).

[8] A. Gelman. 2006. Multilevel (hierarchical) modeling: what it can and cannot do. *Technometrics* 48, 3 (2006), 432–435.

[9] L. Huang, Y. Zhu, Q. Ouyang, and B. Cao. 2012. A study on the effects of thermal, luminous, and acoustic environments on indoor environmental comfort in offices. *Building and Environment* 49, 1 (2012), 304–309. https://doi.org/10.1016/j.buildenv.2011.07.022

[10] Anja Jamrozik, Christian Ramos, Jie Zhao, Joleen Bernau, Nicholas Clements, Tracee Vetting Wolf, and Brent Bauer. 2018. A novel methodology to realistically monitor office occupant reactions and environmental conditions using a living lab. *Building and Environment* 130, December 2017 (2018), 190–199. https://doi.org/10.1016/j.buildenv.2017.12.024

[11] M. V. Jokl and K. Kabele. 2006. Optimal (Comfortable) Operative Temperature Estimation Based on Physiological Responses of the Human Organism. *Acta Polytechnica* 46, 6 (2006), 3–13.

[12] J. Kim, S. Schiavon, and G. Brager. 2018. Personal comfort models–A new paradigm in thermal comfort for occupant-centric environmental control. *Building and Environment* 132 (2018), 114–124.

[13] J. Langevin, J.and Wen and P. Gurian. 2013. Modeling thermal comfort holistically: Bayesian estimation of thermal sensation, acceptability, and preference distributions for office building occupants. *Building and Environment* 69 (2013), 206–226.

[14] Z. Lin and S. Deng. 2008. A study on the thermal comfort in sleeping environments in the subtropics—developing a thermal comfort model for sleeping environments. *Building and Environment* 43 (2008), 70–80.

[15] N. Pellerin and V. Candas. 2003. Combined effects of temperature and noise on human discomfort. *Physiology and Behavior* 78, 1 (2003), 99–106.

[16] N. Pellerin and V. Candas. 2004. Effects of steady-state noise and temperature conditions on environmental perception and acceptability. *Indoor air* 14, 2 (2004), 129–136.

[17] M. Schweiker, E. Ampatzi, M. S. Andargie, R. K. Andersen, E. Azar, V. M. Barthelmes, C. Berger, ..., and L. P. Edappilly. 2020. Review of multi-domain approaches to indoor environmental perception and behaviour. *Building and Environment* (2020).

[18] J. A. Veitch, K. E. Charles, K. M. Farley, and G. R. Newsham. 2007. A model of satisfaction with open-plan office conditions: COPE field findings. *Journal of Environmental Psychology* 27, 3 (2007), 177–189.