Mind the Hazard: Modeling and Interpreting Comfort with Personalized Sensing

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ABSTRACT

Recent advances in personalized sensing and comfort feedback have spurred the development of data-driven comfort models tailored to individual needs. However, because current models treat sequential comfort feedback independently, they are subject to unstable predictions and limited interpretability, hindering their deployment in building management. This study introduces a dynamic modeling framework that utilizes a Neural Ordinary Differential Equations-based Continuous-time Markov Chain to model the transitions in comfort states over time. Our modeling approach, developed through a field study utilizing smart glasses and mobile app feedback, tracks occupants' comfort transitions across daily activities and contexts. The results demonstrate that this model not only predicts comfort states more accurately and stably than conventional classification models but also uniquely provides a representation of how the hazards of state transitions are influenced by changing ambient and contextual conditions. This approach, therefore, offers a new perspective on personalized building control, where predictions of comfort transition hazards can preemptively suggest building management interventions to avoid occupants experiencing discomfort. In addition, insights into how environmental and contextual characteristics relate to these hazards can guide holistic management strategies that dynamically balance comfort with energy targets in response to the occupants' activities and contexts.

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CCS CONCEPTS

• **Computing methodologies** → **Machine learning**; • **Human-centered computing** → *Human computer interaction (HCI).*

KEYWORDS

Indoor environment quality, Personalized comfort model, Wearable sensing, Continuous-time Markov Chain (CTMC), Neural Ordinary Differential Equations (Neural ODEs)

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1 INTRODUCTION

Management of occupant-centric buildings requires satisfying individual comfort requirements and intelligently balancing these with energy efficiency goals. Conventional comfort models, such as Fanger's Predictive Mean Vote (PMV) and the adaptive thermal comfort model, predict mean thermal sensations for a (large) group of people, but cannot account for dynamic and nonuniform environments or individual differences. Furthermore, some of the required inputs (e.g., clothing insulation in the PMV model) are difficult to accurately measure in practice [6].

Recent advances in Internet of Things technology, wearable sensors, and mobile applications have catalyzed a shift toward personalized comfort models [5, 10]. These models harness rich data streams and employ advanced machine learning models to predict comfort states based on these personalized data. The personalized comfort prediction can further inform subsequent building design [9] or enable personalized action recommendations for occupant-centric building management [11]. Currently, most personalized comfort models treat sequential comfort state feedback as independent incidents to satisfy the standard classification task formulation. However, this approach results in models that yield unstable predictions despite only moderate input variations, thus rendering them unreliable for operations requiring robust and accurate occupant comfort information. Specifically, when individual comfort predictions are used for personalized controls aiming to optimize both comfort and energy objectives, unstable results oscillating between 'comfort' and 'discomfort' states can lead to frequently switching or even conflicting actions, such as adjusting temperature setpoints up and down , or toggling window blinds. Such instability can significantly damage the credibility of the suggested actions and may even lead to complaints about building operations. As a result, neither comfort nor energy objectives are achieved. Furthermore, the lack of interpretability in these models makes it difficult to diagnose and improve their performance [5, 8, 10].

Inspired by previous research that employed survival analysis to track participants' reactions under dynamic thermal stimuli [3], we introduce a modeling framework that captures the dynamics of recurrent comfort state transitions in response to the varying environmental and contextual conditions with occupants' daily routines. Our appraoch uses a Neural Ordinary Differential Equations (Neural ODEs)-based Continuous-Time Markov Chain (CTMC) model [4], which generalizes binary survival analysis into multi-state transitions under complex interactions of condition features. The modeling framework we introduce was developed in a field study of occupant comfort using smart glasses ("AirSpecs") equipped with multiple bodily and ambient sensors [1, 2, 12]. The occupants also provided their longitudinal overall comfort state feedback alongside other social and physiological context information via a companion mobile app. Our analysis also investigates how environmental and contextual conditions influence comfort state transitions. To do this, we use Shapley value analysis to quantify feature importance [7]. We also demonstrate our model's unique capability to generate marginal hazards under one or multiple shifting conditions. Overall, our framework makes contributions in three key areas:

Stable prediction: A key motivation for this CTMC model is to enable stable predictions that gradually updates comfort state probability following the changes of underlying transition hazard over time, thereby overcoming the instability drawbacks inherent in independent incident classification. **Interpretation of transition hazard:** Our framework facilitates a comprehensive analysis of how the transition hazards are influenced by marginal and concurrent changes in ambient and contextual conditions. **Proactive and holistic management:** The representation and interpretation of transition hazard enables building management strategies that can propose interventions to avoid occupants experiencing discomfort and dynamically balance comfort with energy targets in response to the occupants' varying activities and contexts.

2 METHODOLOGY

2.1 CTMC Comfort Transition Model

This study employs CTMC to model transitions between various comfort states. In a CTMC, each state represents a distinct comfort level, with transitions governed by hazard rates that indicate how likely the comfort state changes to the other at any given time due to varying environmental and contextual conditions. A CTMC model is fundamentally defined by a set of forward and backward Kolmogorov equations. The forward equation predicts the transition probability between any two states over a given future time interval from the initial time, whereas the backward equation connects future transitions back to the initial time.

$$\textbf{Forward:} \quad \frac{dP_{ij}(s,t)}{dt} = \sum_k P_{ik}(s,t)\lambda_{kj}(t,x), \tag{1}$$

$$\textbf{Backward:} \quad \frac{dP_{ij}(s,t)}{ds} = -\sum_k \lambda_{ik}(s,x)P_{kj}(s,t). \tag{2}$$

Here, $P_{ij}(s,t)$ denotes the transition probability from state i at time s, to state j at time t. λ_{ij} is a critical concept in CTMC model, it represents the instantaneous transition rate, called the "hazard", i.e., the frequency of transitions per unit time between states i and j. This term reflects the tendency of a transition occurring before it actually happens, which can be especially useful in preventing transitions toward undesired states like discomfort. Hence, we will consistently use the term "hazard" to denote this instantaneous transition rate. These hazards typically vary over time t and with external factors x (e.g., environmental and contextual conditions).

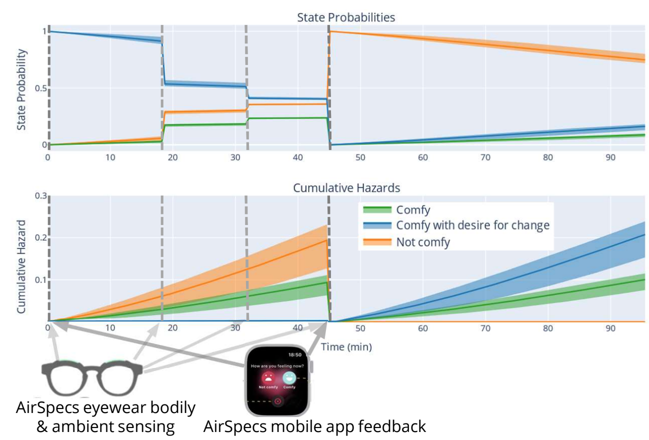

Figure 1: Illustration of how the CTMC comfort transition model works with streamed sensing and feedback. The model tracks comfort state probability (above) and the underlying transition hazard (below) to other states over time with 95% credible intervals (based on percentiles). The timings with sensing data and feedback updates are shown in dashed lines.

Identifying complex Kolmogorov equations directly from the data presents significant challenges. Typically, researchers assume a constant hazard (homogeneous CTMC) or adopt specific functional forms for the transition hazard, limiting the ability to model complex interactions between environmental and contextual conditions effectively. To overcome these limitations, we employ a deep learning-based framework, SurvNode. SurvNode integrates Neural ODEs to parameterize and dynamically solve the Kolmogorov equations via a neural network, enabling a data-driven, adaptive approach to model comfort transitions from streaming data. The framework aims to maximize the likelihood of state transitions at a given time based on observations. In our case, such observations are participant-reported comfort states over time. Additionally, SurvNode utilizes a Variational Autoencoder to compress high-dimensional data into a few normal random variables. By sampling these random variables, the model learns not only the transition hazards but also their credible intervals, indicating potential epistemic prediction errors arising from the variability and completeness of the collected data (as shown in Fig. 1). Further technical details of SurvNode are elaborated in [4].

Fig. 1 illustrates how the CTMC model is deployed to continuously predict and update state probabilities with streamed comfort feedback alongside contextual information and environmental measurements. When an occupant provides their comfort feedback, an initial state is determined with certainty. The model then propagates state probabilities with dynamic hazard and transition probabilities. As depicted, the model can update with new ambient measurements, which are much more frequently collected than feedback, predicting an increased probability and hazard of entering a "Not Comfy" state. Ultimately, the occupant confirms the discomfort state in subsequent feedback, and the model updates accordingly.

2.2 Field study and dataset overview

This model was developed using a dataset from a field study aimed at tracking occupants' recurring comfort transitions across various daily activities and contexts, including homes, offices, cafeterias, and libraries [1]. The study was carried out in three cities spread around the world, Boston (USA), Fribourg (CH), and Singapore (SG)—to capture environmental and individual preference variability. Ten participants were recruited at each site to participate for five consecutive days. For this study, a custom smart glasses platform called AirSpecs [2] was developed. AirSpecs are equipped with ambient air temperature and humidity sensors, an air quality sensor on a sideboard, lux sensors, and sensors for ambient noise levels (dBA). Digital skin temperature sensors located on the nose and temple provide data on both body thermal condition and cognitive loads. Additionally, a mobile and smartwatch app was developed to prompt participant surveys at irregular intervals (every 30-60 minutes) [12]. During these surveys, participants provided their overall binary comfort feedback ("Comfy" or "Not Comfy") along with their desire for change in one or more domains, including thermal, indoor air quality (IAQ), visual, and acoustic comfort. Participants also provided other contextual information, such as their current activity and physiological conditions.

Unfortunately, due to cloud storage failure, all data from Fribourg (CH) was lost. This loss is particularly regrettable as it further reduces the size of this dataset (684 feedback observations) and eliminates a valuable source of data representing a unique social and climatic context. Another notorious issue in comfort prediction is the class imbalance between discomfort and comfort states. To address this issue, where discomfort states are underrepresented [5, 8], we defined an intermediary state called "Comfy with desire for change." In this state, participants confirmed overall "comfy" but also expressed a desire to change in some environmental conditions. We further processed the measurements and survey data to extract features for subsequent models as described in Table 1.

2.3 Performance benchmark experiment setup

To benchmark our model's performance in predicting comfort states, we selected four commonly used baseline classification models: Random Forest (RF), Support Vector Machine (SVM), Logistic Regression (LR), and Multi-Layer Perceptron (MLP), and used F1 score as the evaluation metric. Because our model produces the

Table 1: Feature overview

Group	Feature	Note
Ambient	Ambient temperature (°C) Relative humidity (%) CO_2 index (%) VOC index (%) Sound level (dBA) Illuminance (lux)	Dowsampled AirSpecs measurements (one minute),exponential-weighted moving average to tackle noisy and missing data
Bodily	Temple temperature (°C)	
	Heart rate (s^{-1})	Empatica measurements, same processing
Dynamic context	Internal unease	Binary, reported desires for better mood or bodily condition in surveys
	Alone/Group	Binary
	Focus level	Categorical, defined by the time difference between actual and perceived survey interval
	#Past discomfort	Counts of past discomfort report within this day
Demo-graphic	BMI Age	-
	Country	Categorical, participant's study location

probability for each state, we employed the argmax function to determine the most likely prediction. This prediction accuracy evaluation reflects how well each model captures genuine variations in comfort levels due to changes in ambient and contextual conditions, but it does not account for each model's prediction stability.

Therefore, we progressively sampled random intervals between 5 and 20 minutes in bodily and ambient measurements between each pair of consecutive comfort feedback observations across the entire dataset. For these upsampled entries, we held the contextual features constant by employing backward-filling between observations. By doing so, if there is an actual transition between two observations, the upsampling allows us to pinpoint the transition time more precisely. However, multiple rapid transitions between different comfort states are very unlikely within the short intervals between two observations. All models then predicted comfort states for these upsampled entries. Ideally, a "stable" model should not predict more than one state transition between two actual observations on these upsampled entries. Hence, we define an "instability score"—a metric expressed as the percentage of instances where a model predicts more than one state change between each two feedback observations across the dataset. This metric indicates how prone a particular model is to changing predictions frequently. Since the three comfort states represent distinctly different comfort levels, unstable predictions oscillating among states may lead to overly frequent and conflicting actions in building operation.

Additionally, we conducted a feature importance analysis for both types of models. For this analysis, we utilized SHAP (Shapley Additive exPlanations), a tool that attributes the predictions of a machine learning model to its input features based on Shapley values from cooperative game theory [7]. This allows us to demonstrate how the unique ability of our model to predict marginal hazards under varying environmental and contextual conditions enhances our understanding of feature contributions.

Given the limited size of the dataset, we trained a single model for the participant group rather than individual models for each participant. Participants' differences were still accounted for in the model through dynamic contextual and static demographic and anthropocentric features. Thus, the model can still yield individual comfort prediction given each participant's distinct dynamic and static features. For the CTMC model, additional inputs also included the previous state from the last comfort feedback, and the relative daily start and end times of each comfort transition (i.e., i , s and t in Eq. 1 & 2). To ensure a fair comparison, we also included the previous state as an additional feature in the classification models. We split the dataset into training and testing sets at a ratio of 70% and 30%. For the classification models, to further address the class imbalance issue, we applied weighted oversampling to the raw data. During training, we did hyperparameter grid search using 5-fold cross-validation on the training set. For the CTMC model, we manually tested ten sets of network architecture hyperparameters, as the extensive training time precluded automatic network search. We did not oversample the minority classes as it may have distorted the state occupation distribution learned by the CTMC model.

3 RESULT AND DISCUSSION

3.1 Comfort state prediction

The results of the comfort state predictions are summarized in Table 2. With a relatively limited dataset size, all models produced a macro F1 score of approximately 0.6. While prediction performance should be improved, these results are still informative as they reflect typical performance at the “cold-start” stage for any personalized comfort model [10]. We observed that all classification models particularly struggle with the “Not Comfy” state. This issue may result from the aforementioned class imbalance issue in this minority state even with the application of the oversampling techniques.

Interestingly, our model exhibits superior performance in predicting the “Not Comfy” state. We infer that this is because our model explicitly learns the probability propagation from previous states as depicted in Fig. 1, not just the overall state distribution, as classification models do. This capability helps to capture scenarios where discomfort persists or emerges from a previously less comfortable state, such as “Comfy with desire for change.” Conversely, other classification models, despite also incorporating “previous state” as an informative input feature (as shown in Fig. 2.(a)), often yield unstable predictions and overlook such transitions due to the rarity of this class. As the instability scores in Table 2 indicate, SVM and LR maintain stable predictions since their simpler architectures ensure decision boundaries that are less prone to fluctuate with minor changes in input data. Despite its complex architecture, our CTMC model is capable of explicit transition modeling and achieves the lowest instability score.

Table 2: Performance benchmarking summary

	Comfy	Not comfy	Comfy with desire for change	Macro avg. F1	Instability
RF	0.77	0.51	0.65	0.64	6.26%
SVM	0.72	0.53	0.62	0.62	1.18%
LR	0.79	0.44	0.65	0.63	3.89%
MLP	0.72	0.27	0.6	0.53	8.29%
CTMC	0.72	0.62	0.57	0.64	0.17%

It is important to note that the imbalanced distribution of transition originals and destinies also affects our model's performance, potentially compromising accuracy in “Comfy” and “Comfy with desire for change” states. Additionally, as Fig. 1 shows, our model may identify a correct trend towards a particular state in underlying hazards but not always assign the highest probability to this state. Therefore, we argue that when deploying our model for personalized control, using the transition hazard to define objectives or rewards could guide controller actions more effectively than using comfort states alone. This approach not only offers richer information but also facilitates more proactive interventions, preventing discomfort before it fully manifests. Additionally, the credible intervals of hazards may serve as valuable indicators of epistemic uncertainty, further guiding the precision of intervention strategies.

3.2 Feature analysis

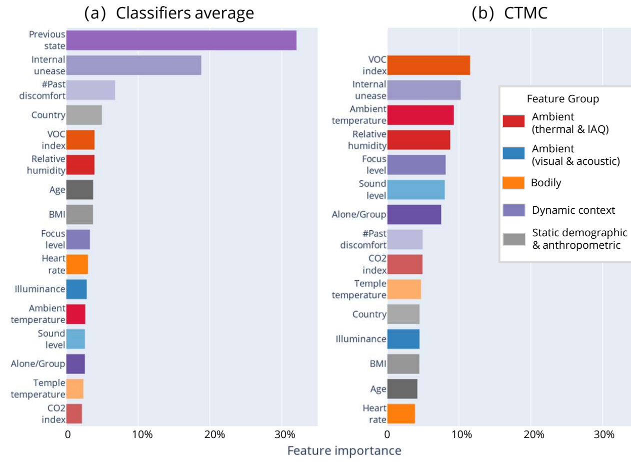

Figure 2: Feature importance from averaged value over all classification models (left); CTMC model (right). For the CTMC model, "Previous state" is not directly input as feature, so this space is left blank for better comparison of the other features. Color-coding indicating feature groups is labeled.

3.2.1 Overall Feature Importance. As Fig. 2 illustrates, ambient measurements—particularly thermal and IAQ—play a critical role in both model types. It is important to note that interpreting individual feature importance scores in this group can be challenging, as ambient temperature and humidity are interdependent, and both VOC and CO_2 indices primarily indicate the underlying ventilation condition. Dynamic contextual features, particularly each individual's internal unease, are also critical for both model types, underscoring the need to consider occupants' physical and physiological states beyond ambient conditions when developing personalized comfort models. A significant difference between the CTMC and classification models is that the CTMC assigns lower importance to demographic and anthropocentric characteristics of each individual. This may be because these characteristics are static for each participant, and thus offer limited information for dynamic state transitions. This limitation may prevent the model from capturing nuances across different occupants. We anticipate that this issue could be mitigated with larger datasets, allowing for the development of individual-specific models.

3.2.2 Marginal hazard analysis. Although SHAP also permits the calculation of how specific feature variations influence the model's output, interpreting these variations can be challenging and less intuitive compared to overall feature importance, particularly when analyzing the interactions between features. Conversely, our model uniquely enables analysis of how marginal hazards are influenced by variations in one or multiple input features. To demonstrate this, we analyze one of the most important measurements—ambient temperature—and two of the most important contextual conditions—internal unease and focus level. We vary these features while setting other contextual features to their mode values and measurement features to their mean values. Here, we focus on the participant group from Boston (US).

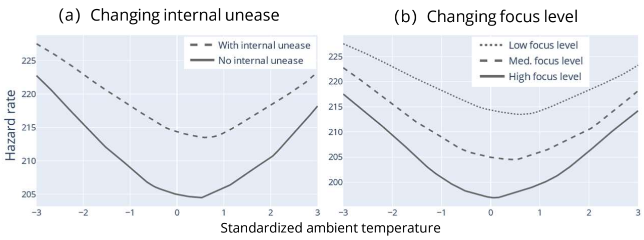

Figure 3: Marginal hazards from "Comfy" to "Comfy with desire for change" under shifting ambient temperature and two contexts: Left (internal unease); right (focus level).

According to Fig. 3, the model captures a reasonable U-shaped hazard pattern as the ambient temperature varies from low to high. Fig 3.(a) further shows that occupants experiencing internal unease are more inclined to seek adjustments in all ambient conditions. Fig 3.(b) depicts that the greater the focus on the current activity, the less likely occupants are to transition to less comfortable states and request changes. Both contextual conditions have the most impact on moderate temperatures, while in extreme temperatures, ambient conditions predominantly influence the transition hazards.

These results may trigger interesting designs that allow interaction between building operations and health & focus management apps. For instance, the building system can slightly tighten temperature setbacks when the occupant sets the apps to be engaged in concentrated activities. Then, when a short break and body relaxation are suggested to the occupant by the apps, the building system can enable more comfortable temperature setpoints to allow quick refreshing. The energy savings during concentrated periods can be displayed to the occupants as an additional reward besides productivity. Overall, such an interpretation of the synergy between ambient and contextual conditions could inform more holistic and dynamic personalized management strategies that trade off discomfort prevention and energy efficiency objectives in response to the routines and activities of the occupants.

4 CONCULUSION AND OUTLOOK

This study introduces a modeling framework that captures the dynamics of comfort state transitions across various daily activities and contexts using a deep-learning-based CTMC model. Our model demonstrates superior performance over traditional classification models, particularly in accurately predicting minority discomfort states and dynamically updating with shifting conditions. The ability to analyze transition hazards under changing ambient and contextual conditions positions this framework as a foundational tool for developing smart, personalized comfort management systems that preemptively address discomfort and optimize the balance between occupant comfort and energy efficiency.

The primary limitation of this study is the small dataset size, which restricts the robustness and generalizability of our findings. To address this, we are planning a larger-scale study using the same eyewear with a web app feedback pipeline. Although this research contrasts CTMC models with classification approaches, future work will explore integrating these models to leverage their complementary strengths. For instance, established semi-supervised learning paradigms and data augmentation techniques may better leverage abundant sensor data and address the sparsity of labeled comfort state observations, which in turn may enhance the CTMC modeling approach. Furthermore, while the inclusion of personal, contextual conditions has shown potential benefits, privacy concerns regarding data collection remain a challenge. Additionally, the deployment costs and efforts to maintain participant compliance suggest that exploring complementary data acquisition methods is necessary for wider application. For example, more easily accessible localized desk-level smart plugs, along with occupants' interaction records with thermostats and windows, may enable us to infer occupants' comfort states and social activities, allowing us to implement the proposed framework. In the end, this approach to creating more reasonable and practical comfort state predictions can enhance our understanding of individual comfort and provide more useful information for advanced and personalized building controls.

REFERENCES

[1] Patrick Chwalek, Sailin Zhong, Nathan Perry, Tianqi Liu, Clayton Miller, Hamed Seiied Alavi, Denis Lalanne, and Joseph A. Paradiso. 2024. Exploring Urban Comfort through Novel Wearables and Environmental Surveys. https://doi.org/10.48550/arXiv.2408.08323 arXiv:2408.08323 [cs]

[2] Patrick Chwalek, Sailin Zhong, David Ramsay, Nathan Perry, and Joe Paradiso. 2023. AirSpec: A Smart Glasses Platform, Tailored for Research in the Built Environment. In *Adjunct Proceedings of the 2023 ACM International Joint Conference on Pervasive and Ubiquitous Computing & the 2023 ACM International Symposium on Wearable Computing (UbiComp/ISWC '23 Adjunct)*. Association for Computing Machinery, New York, NY, USA, 204. https://doi.org/10.1145/3594739.3610796

[3] Matteo Favero, Igor Sartori, and Salvatore Carlucci. 2021. Human Thermal Comfort under Dynamic Conditions: An Experimental Study. *Building and Environment* 204 (Oct. 2021), 108144. https://doi.org/10.1016/j.buildenv.2021.108144

[4] Stefan Groha, Sebastian M. Schmon, and Alexander Gusev. 2021. A General Framework for Survival Analysis and Multi-State Modelling. https://doi.org/10.48550/arXiv.2006.04893 arXiv:2006.04893 [cs, stat]

[5] Weizheng Hu, Yong Luo, Zongqing Lu, and Yonggang Wen. 2019. Heterogeneous Transfer Learning for Thermal Comfort Modeling. In *Proceedings of the 6th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation (BuildSys '19)*. Association for Computing Machinery, New York, NY, USA, 61–70. https://doi.org/10.1145/3360322.3360843

[6] Joyce Kim, Stefano Schiavon, and Gail Brager. 2018. Personal Comfort Models – A New Paradigm in Thermal Comfort for Occupant-Centric Environmental Control. *Building and Environment* 132 (March 2018), 114–124. https://doi.org/10.1016/j.buildenv.2018.01.023

[7] Scott M. Lundberg and Su-In Lee. 2017. A Unified Approach to Interpreting Model Predictions. In *Proceedings of the 31st International Conference on Neural Information Processing Systems (NIPS'17)*. Curran Associates Inc., Red Hook, NY, USA, 4768–4777.

[8] Matias Quintana, Stefano Schiavon, Kwok Wai Tham, and Clayton Miller. 2020. Balancing Thermal Comfort Datasets: We GAN, but Should We?. In *Proceedings of the 7th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation (BuildSys '20)*. Association for Computing Machinery, New York, NY, USA, 120–129. https://doi.org/10.1145/3408308.3427612

[9] Andrew Sonta, Thomas R. Dougherty, and Rishee K. Jain. 2021. Data-Driven Optimization of Building Layouts for Energy Efficiency. *Energy and Buildings* 238 (May 2021), 110815. https://doi.org/10.1016/j.enbuild.2021.110815

[10] Federico Tartarini, Stefano Schiavon, Matias Quintana, and Clayton Miller. 2022. Personal Comfort Models Based on a 6-Month Experiment Using Environmental Parameters and Data from Wearables. *Indoor Air* 32, 11 (2022), e13160. https://doi.org/10.1111/ina.13160

[11] Stephen Xia, Peter Wei, Yanchen Liu, Andrew Sonta, and Xiaofan Jiang. 2023. RECA: A Multi-Task Deep Reinforcement Learning-Based Recommender System for Co-Optimizing Energy, Comfort and Air Quality in Commercial Buildings. In *Proceedings of the 10th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation (BuildSys '23)*. Association for Computing Machinery, New York, NY, USA, 99–109. https://doi.org/10.1145/3600100.3623735

[12] Sailin Zhong, Patrick Chwalek, Nathan Perry, David Ramsay, Clayton Miller, Denis Lalanne, Hamed Seiied Alavi, and Joseph Paradiso. 2024. Sensors and Sensibilities: Exploring Interactions for Habitat Comfort with an Environmental-Physiological Sensing Eyewear in the Wild. https://doi.org/10.2139/ssrn.4943028