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Insights into Personalized Thermal Comfort through Innovative Data Collection: case study from HSB Living Lab

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Abstract. This study investigates personalized thermal comfort through ecological momentary assessment (EMA) and wearable-supported feedback within a cold-climate context. Conducted at the HSB Living Lab in Gothenburg, Sweden, the research integrates real-time subjective comfort responses collected via the Cozie app with high-resolution indoor environmental data. The study explores the gap between predictive thermal comfort models—such as PMV and in-situ human perception in a real-world setting. Three primary outcomes were achieved. First, the study evaluates the predictive accuracy of PMV against daily participant feedback, revealing significant mismatches, particularly in detecting thermal discomfort (i.e., preferences for "warmer" or "cooler" conditions). Second, it introduces thermal fingerprinting for each participant, visualizing comfort patterns through a combination of statistical modelling, environmental exposure, and perception-response correlation. Third, the study advances spatial analysis by introducing a 3D "comfort landscape" of the HSB Living Lab, color-coding rooms by average perceived discomfort and overlaying sun exposure patterns to uncover how orientation and time-of-day lighting conditions may affect thermal comfort. The findings highlight the limitations of conventional models in real-life applications and reinforce the need for occupant-centric, context-aware approaches to environmental control. Based on this integrated analysis, the study proposes strategies that consider spatial, behavioural, and seasonal dynamics—offering pathways to enhance both personal well-being and energy efficiency in shared living environments.

1. Background and Related Work

Recent research emphasizes a growing need for human-centered thermal comfort modeling in smart buildings, driven by increasing evidence that conventional models such as PMV (Predicted Mean Vote) do not adequately reflect real-world comfort experiences. Studies have shown that comfort is not merely a function of environmental parameters but is shaped by personal, behavioral, and contextual factors, including clothing insulation, activity level, and even psychological expectations [1]. The emergence of occupant-centric control systems and responsive building automation highlights the limitations of static models and the demand for adaptive, personalized thermal comfort frameworks [2]. Notably, a recent comparative study by [3] evaluated the predictive accuracy of PMV models as implemented in ISO 7730:2005 and ASHRAE 55:2023, finding that neither model consistently aligned with in-situ human perception across varied contexts. Their results reinforce the critique that standardized PMV algorithms often fail to capture individual comfort preferences and dynamic indoor conditions. As sensor networks, mobile-based ecological momentary assessment (EMA), and wearable technology enable real-time comfort tracking, the path forward lies in integrating this high-resolution occupant data into smart, adaptive thermal comfort systems that reflect the lived experience of building users. The adoption of EMA and Right-Here-Right-Now (RHRN) surveys has transformed how researchers collect and interpret thermal comfort data, offering a more granular, time-sensitive, and contextually rich understanding of occupant experience. Unlike retrospective or laboratory-based comfort surveys, EMA methods capture in-the-moment subjective responses, enabling direct correlation with dynamic environmental conditions and behavioral states [4,5]. This approach is especially valuable in residential and mixed-use living environments, where thermal conditions—and occupant activities—can fluctuate significantly throughout the day. EMA has been successfully implemented using mobile applications and wearables, reducing recall bias and supporting real-time comfort mapping [6,7,8]. The Cozie app, in particular, has gained traction as a tool for collecting self-reported comfort sensations in field studies, and has been validated across diverse settings including offices, homes, and living labs [9]. RHRN surveys deployed through platforms like Cozie allow participants to report not only thermal sensation but also preference and acceptability, thereby enriching the comfort dataset and supporting adaptive comfort model calibration [10]. These methods are foundational for occupant-centric building research, providing both temporal depth and subjective nuance that conventional sensor-based approaches alone cannot deliver.

An increasing body of research underscores the critical importance of spatial and temporal context in understanding and modeling thermal comfort. Comfort perceptions are not only shaped by static environmental conditions but also by where and when occupants experience thermal environments within a building. Spatial variables—such as room orientation, floor level, window placement, and exposure to direct sunlight—can lead to significant microclimatic variations even within the same structure [11,12]. Recent studies leveraging spatial mapping and GIS-integrated building analysis have demonstrated the potential of identifying thermal discomfort hotspots and adapting building control strategies accordingly [13]. Temporal patterns also play a vital role: comfort thresholds and preferences can vary not only across seasons but also between morning and evening, as metabolic rates, clothing levels, and outdoor conditions change [14]. In this context, Right-Here-Right-Now data combined with room-level environmental sensing enables researchers to uncover how comfort perception evolves throughout the day and across different spatial zones.

2. Methodology

This study was conducted at the HSB Living Lab in Gothenburg, Sweden—a full-scale residential research facility and innovation testbed [15]. The building comprises fully equipped students' and researchers' apartments and instrumented with sensors for tracking temperature, relative humidity, CO_2 levels, and other environmental conditions. A total of ten participants were recruited for this study, with an equal gender balance, and an age range of 20 to 35 years. Participants were distributed across different floors and orientations within the building—ranging from east- to west-facing rooms—enabling spatial comparisons related to solar exposure (e.g., morning vs. evening sun). The data collection period extended from September to December 2024, capturing a transition from early autumn to winter in a Nordic climate.

Thermal comfort data were collected through a combination of ecological momentary assessment (EMA) and continuous environmental monitoring. Participants used the Cozie app, an open-source platform designed for wearable and mobile-based field studies, to complete Right-Here-Right-Now (RHRN) surveys twice a day (morning, evening). Each survey captured thermal sensation (e.g., cold, neutral, hot), thermal preference (e.g., want cooler, no change, want warmer), and situational metadata including location, level of activity and clothing. The EMA approach enabled in-the-moment self-reporting, reducing recall bias and allowing for direct alignment with environmental conditions. In parallel, indoor environmental data were collected using permanently installed sensor systems in each participant's room, logging air temperature, relative humidity (RH), and CO_2 concentration at five-minute intervals. These sensor readings were matched to each participant's survey timestamp and spatial location, allowing for synchronized analysis of subjective comfort alongside objective indoor climate data. This dual-stream data collection strategy provided a high-resolution, temporally and spatially contextualized dataset to evaluate thermal comfort patterns in real residential settings.

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Figure 1. Study data flow overview.

To evaluate the relationship between predictive comfort models and real-world thermal perception, all data streams were carefully integrated and preprocessed. First, timestamp alignment was performed to synchronize each Cozie survey response with the nearest environmental sensor readings—specifically temperature, relative humidity, and CO_2 levels—recorded at five-minute intervals in participants' rooms. This integration enabled the calculation of PMV. The data were then aggregated daily and weekly, allowing for the identification of temporal trends in comfort responses and model accuracy. To support spatial and architectural analysis, each participant's room was linked to architectural floor plans of the HSB Living Lab and classified by solar orientation (e.g., morning vs. evening sun exposure). This spatial information was used to construct a 3D "comfort landscape", highlighting areas of persistent discomfort and correlating them with room characteristics.

3. Results

3.1. *Real-Time Comfort vs. Environmental Conditions*

As visualized in Figure 2, a heatmap of weekly average indoor temperatures per participant, comfort preferences were mapped onto measured conditions using directional arrows (↑ warmer, ↓ cooler). While most participants were exposed to temperatures between 20–23°C, their preferences varied significantly. For example, some participants (e.g., P05, P07, P13) expressed a desire for cooler environments despite experiencing the highest room temperatures, while others (e.g., P01, P03, P04) consistently preferred warmer conditions even at relatively low temperatures.

The divergence between measured temperature and preferred conditions highlights the subjective and context-dependent nature of thermal comfort. Even when indoor temperatures were held within traditionally accepted comfort bands (e.g., 21–23°C), a substantial portion of responses indicated discomfort or a desire for change. These findings reinforce the limitation of applying static thermal setpoints and underscore the need for dynamic, personalized comfort strategies in shared indoor environments. The results demonstrate that maintaining temperature within a fixed, standardized range (e.g., 21–23°C) does not guarantee occupant comfort across a diverse population. The observed divergence suggests that comfort setpoints should be redefined as individualized comfort zones, adaptable over time and space.

3.2. *PMV Model Evaluation and Prediction Accuracy*

To assess the reliability of conventional thermal comfort models, each participant's real-time survey responses were compared with calculated PMV values, generated using ISO 7730:2005 equations and indoor environmental sensor data. The goal was to determine whether the PMV index, based on environmental inputs and RHRN survey input (clothing, level of activity), could accurately reflect participants' actual thermal sensations and preferences. The comparison revealed that while PMV correlated moderately with reported thermal sensation for some participants, it performed inconsistently across the group. As shown in Figure 3, PMV–perception correlation coefficients (r) varied from weakly positive to near-zero for most participants. Moreover, PMV values tended to over-predict comfort neutrality and underestimated discomfort, particularly for those who frequently expressed a desire for "cooler" or "warmer" conditions despite PMV values suggesting neutral conditions (i.e., PMV ≈ 0).

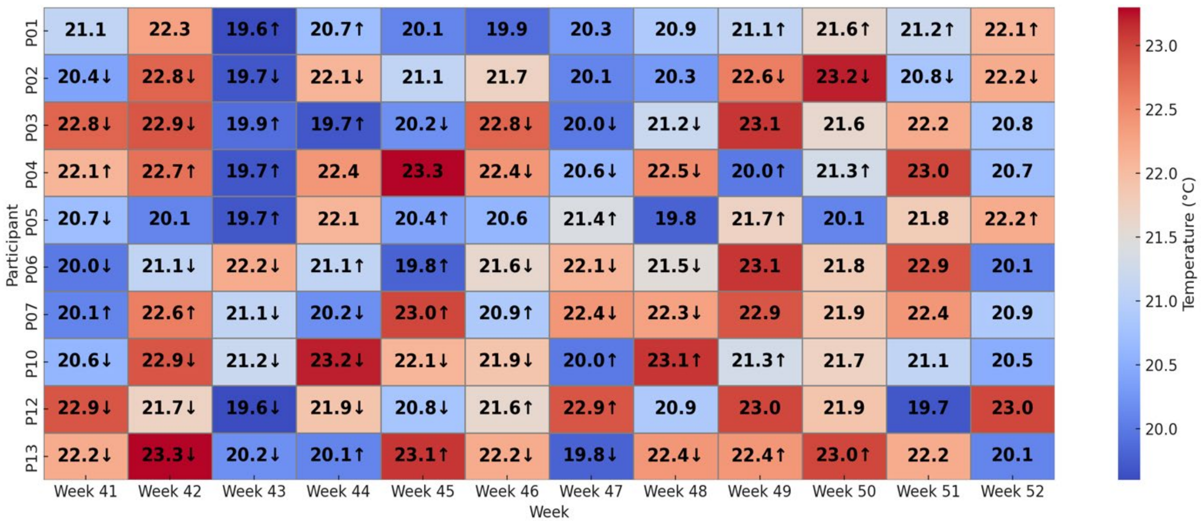

Figure 2. Weekly average indoor temperatures (°C) for each participant's room from Week 41 to Week 52
Arrows indicate thermal preference reported that week:
↑ = preference for warmer, ↓ = preference for cooler, no arrow = no change

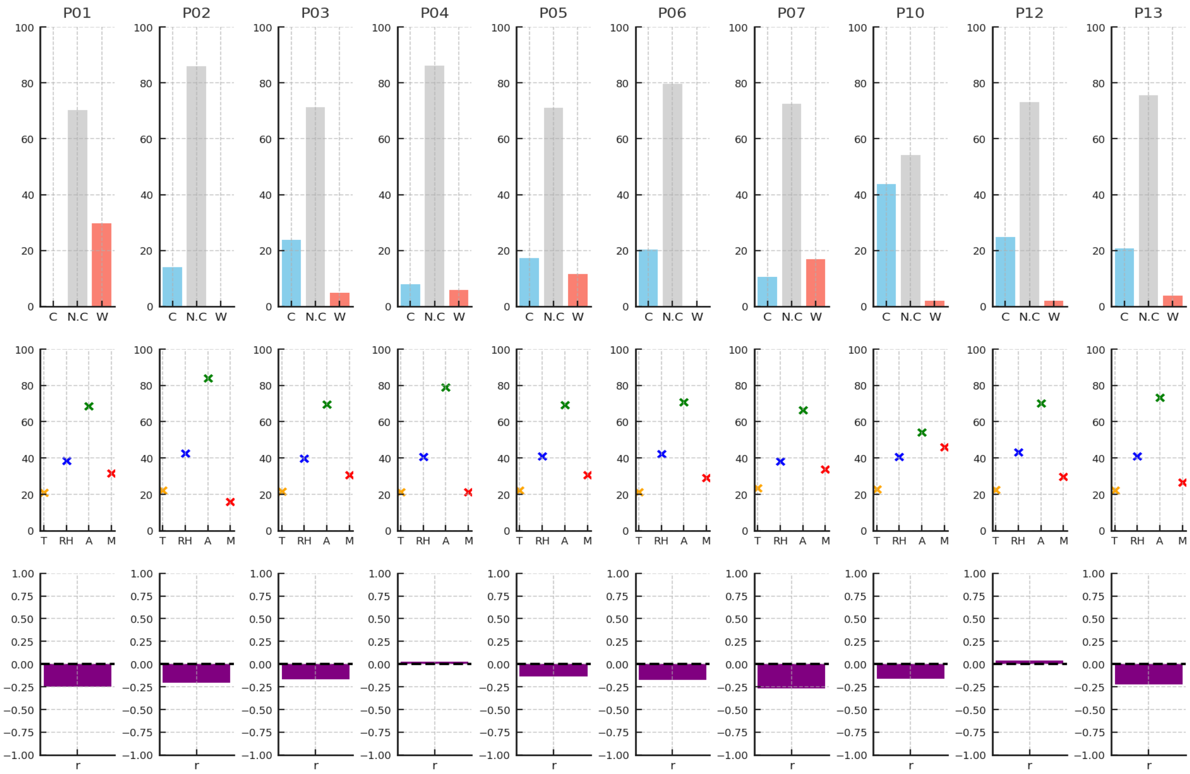

Figure 3. Personalized Thermal Comfort Profiles Based on PMV: Preferences, Environmental Conditions, Model Accuracy, and Perception Correlation per Participant.
Cooler (C), No Change (N.C), Warmer (W)
Temperature (T), Relative Humidity (RH) and PMV model evaluation Accuracy (A), Mismatch (M)
Correlation coefficient (r) between PMV values and reported thermal sensation.

In terms of classification, the model showed higher accuracy in predicting “no change” responses but struggled to capture thermal dissatisfaction. Mismatch rates for discomfort (preference for warmer/cooler) were notably high in participants such as P01, P03, and P07, where PMV repeatedly failed to detect perceived deviations from thermal neutrality. This aligns with prior critiques of PMV’s limitations in naturally ventilated or residential contexts, where occupant behaviour, clothing adjustment, and cultural expectations introduce variability unaccounted for by the model.
These findings confirm that while PMV remains useful as a general predictor of thermal trends, it lacks precision for individualized comfort prediction in adaptive, real-life environments. This further supports the need for alternative or extended modelling approaches—such as machine learning-based prediction—when aiming to integrate comfort data into responsive building systems.

3.3. 3D Comfort landscape

To explore how thermal perception is shaped by spatial and environmental context, we developed a 3D comfort landscape of the HSB Living Lab—mapping participant room locations, solar orientation, and aggregated comfort preferences during the warmest and coldest weeks of the study period. As visualized in Figure 4, the two diagrams represent snapshots of thermal conditions and participant preferences for Week 42 (left) and Week 51 (right). Week 42 was among the warmest, with several rooms experiencing indoor temperatures above 23 °C, while Week 51 marked one of the coldest periods, with indoor conditions dropping close to or below 20 °C in multiple rooms. Both diagrams are spatially oriented to reflect the actual layout of the building, with clear indication of solar paths across the day—from east-facing morning sun to west-facing evening exposure. In each diagram, rooms are color-coded according to thermal tendencies (cooler, neutral, or warmer), and icons indicate participants’ comfort preferences for that week. In the warmer week (Week 42, left), participants in west-facing or upper-level units (e.g., P07, P13) expressed a preference for cooler conditions, while some in shaded or lower-level units (e.g., P01, P06) were already indicating a need for additional warmth. By contrast, during the colder Week 51 (right), most participants shifted toward requesting warmer environments, particularly in rooms with limited solar exposure or lower average temperatures (e.g., P04, P06, P01).

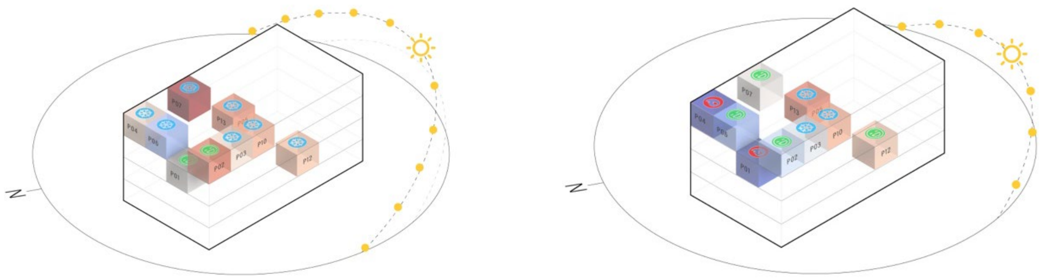

Figure 4. 3D Comfort Landscape of the HSB Living Lab: Spatial Distribution of Participants, Sun Exposure, and Thermal Preferences: Left diagram shows aggregated data for Week 42 and Right diagram for Week 51.

The contrasting comfort landscapes reveal how thermal perception is not solely driven by temperature, but also by spatial orientation, solar gain, and likely behavioural or physiological adaptation. The findings demonstrate that even with moderate indoor temperature variation, perceived comfort diverged significantly between participants and weeks. This reinforces the importance of spatially adaptive comfort strategies, such as aligning room assignments with known thermal preferences, or applying targeted HVAC zoning that dynamically responds to both room characteristics and occupant feedback.

4. Discussion

This study demonstrates the potential of combining ecological momentary assessment (EMA) with environmental sensing and spatial analysis to evaluate the performance of thermal comfort models in a cold-climate residential context. While PMV is widely adopted in standards like ISO 7730, our findings align with recent work [3] suggesting their limited accuracy in real-life, occupant-driven environments. Across over 1,200 RHRN surveys, we observed an average mismatch rate of 36% between PMV predictions and participants' thermal preferences—particularly underrepresenting discomfort when users desired “warmer” or “cooler” conditions. Thermal comfort patterns varied significantly with room orientation and sun exposure, as shown in the 3D comfort landscape. During Week 42 (warmest), west-facing rooms (e.g., P07, P13) were associated with cooling preferences, while in Week 51 (coldest), participants in shaded or lower-floor rooms (e.g., P01, P04) expressed a consistent need for warmth—even at temperatures near 20 °C, well within standard comfort zones. These findings support prior evidence that static setpoints fail to capture the spatial and temporal complexity of comfort perception.

The study was limited to ten participants within a single building during the autumn–winter season. Findings may not generalize to different climates, building types, or longer time spans. Future research should explore seasonal comfort transitions, behavioral adaptations, and machine learning-based prediction models that account for individual variability over time.

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