Scalable Occupant-Centric HVAC Control in Accommodations Using Individual Preference and Global Thermal Comfort Database

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Abstract

To facilitate the practical implementation of occupant-centric HVAC control (OCC) that reflects individual thermal comfort, ensuring scalability and validating performance through real-world deployment are critical. This study proposes a scalable OCC framework tailored for accommodations, which generates an initial comfort model at check-in using a public thermal comfort database and guest profile data, then personalizes it during the stay based on temperature setpoint adjustments. The system was deployed in an accommodation facility in Japan and evaluated in a four-night field experiment with 20 participants. Results showed a 37% reduction in daily setpoint adjustments (from 4.9 to 3.1 times per person), suggesting enhanced thermal comfort. The findings demonstrate the effectiveness of the proposed framework and its potential for enhancement through broader deployment and data accumulation.

1. Introduction

Conventional HVAC (Heating, Ventilation, and Air Conditioning) systems aim to provide environments acceptable to the average people, often resulting in user dissatisfaction (Graham et al., 2021). The importance of occupant-centric HVAC control (OCC), which prioritizes individual thermal comfort, is increasingly recognized (Huang et al., 2024; Soleimanijavid et al., 2024). However, OCC approaches remain underutilized in real-world settings. Soleimanijavid et al. (2024) identified several barriers to adoption, including computational complexity, integration with Building Automation Systems (BAS), data availability and quality, scalability, and limited real-world implementation studies. To overcome these challenges, scalable OCC frameworks must demonstrate improved thermal comfort with minimal data and computational requirements. Although most OCC studies research has focused on multi-occupant spaces such as office, classroom, and conference room (Huang et al., 2024), the HVAC control resolution in such spaces is normally zone level, leading to a mismatch with thermal comfort modeling resolution (i.e., personal level). Ono et al. (2022) revealed that this mismatch can result in an 8% potential loss in thermal comfort improvement.

Given these limitations, accommodation settings offer promising opportunities for OCC. Guest rooms are generally occupied by one or a few guests, enabling finer control resolution than office spaces. However, accommodations pose unique constraints, such as limited guest information at check-in and short stays that restrict data collection. To address these, we propose a scalable OCC framework that utilizes available guest information, such as climate of residence, sex, and season to construct an initial comfort model based on a public thermal comfort database. This model serves as the starting point at check-in, and during the stay, guest interactions with the HVAC system (i.e., setpoint adjustments) are used to learn individual preferences. Although the short stay can limit the amount of data collected from individuals, setpoint adjustment histories can be more informative than survey-based feedback on thermal comfort when learning preference. We implemented this framework in an accommodation facility in Japan and conducted a field experiment to assess the control performance.

2. Method

2.1. Proposed Control Framework

Figure 1 illustrates the proposed OCC framwork in accommodations. During the preparation phase, seasonal base comfort models are constructed from a temperate-climate dataset, and temperature shifts (ΔT) are calculated based on climate, sex, and season. At check-in, the initial comfort model is generated by applying the appropriate ΔT to the

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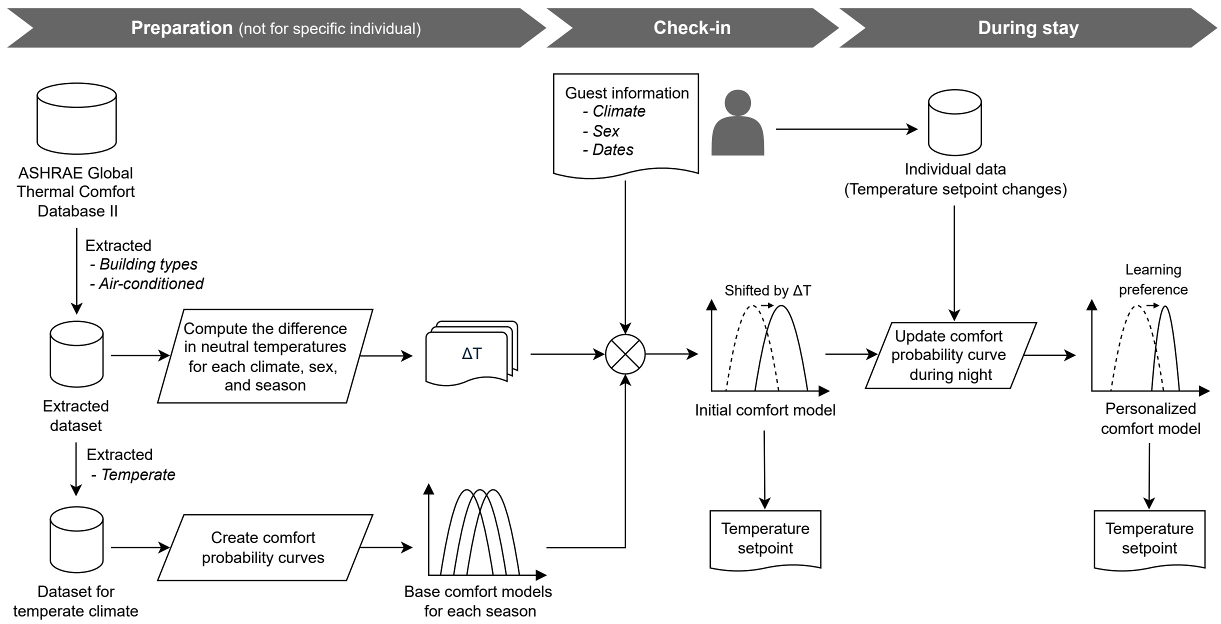

Figure 1. Proposed occupant-centric HVAC control framework in accommodations.

base model. During the guest's stay, the comfort model is updated every night based on the records of temperature setpoint adjustments. This framework might not work well if the guest stays only for one night, but it can be effective when staying for more than one night or for repeat guests.

2.1.1. Base and initial comfort models

To develop an intuitive thermal comfort model that probabilistically expresses the relationship between air temperature and thermal comfort, we adopted the modeling framework proposed by Jung and Jazizadeh (2019). The procedure is as follows: (1) From thermal preference survey results ("prefer warmer," "neutral," "prefer cooler"), the mean and standard deviation of air temperature corresponding to each response are calculated. (2) Each response category was assumed to follow a normal distribution. For "prefer warmer" and "prefer cooler,"half-normal distributions are used. (3) The overall comfort probability curve is derived from three comfort states corresponding to the three normal distributions based on a Bayesian network.

To construct the thermal comfort model, we extracted data entries from the ASHRAE Global Thermal Comfort Database II (Földváry Ličina et al., 2018) based on the following criteria: Indoor air temperature, outdoor air temperature, and thermal preference are recorded, office or school, and air-conditioned. A total of 35,632 data entries met these conditions. To keep the model simple, we constructed base comfort models for each season using data from the temperate climate, which had the highest data volume (Figure 2). Based on these models, the comfort temperature (defined as the temperature corresponding to 100% comfort probability)

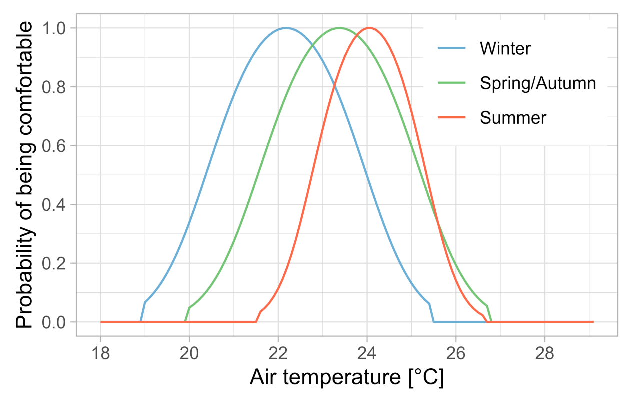

Figure 2. Base comfort models for each season.

was calculated. The resulting comfort temperatures were consistent with previous literature (Cena & de Dear, 1999): 24.2 °C in summer, 23.4 °C in spring/autumn, and 22.3 °C in winter. To extend this model to be an initial comfort model for a guest considering the climate, sex, and season, we applied horizontal shifts (ΔT) to the base comfort model. For each subgroup, the average temperature associated with thermal neutrality was calculated, and ΔT was defined as the deviation from the temperate-climate baseline.

2.1.2. Updating models based on individual data

Individual preference data are collected through temperature setpoint adjustments by guests. If the temperature setpoint is increased/decreased, thermal preference data is recorded as "prefer warmer" and "prefer cooler," respectively at that time. If the setpoint remained for an hour, the thermal preference of "no change" is recorded. The individual preference data are combined into the original database with a predetermined weight to have a comparable impact on comfort modeling and recalculate a comfort probability curve to obtain the personalized comfort model for the guest.

2.2. Case study

2.2.1. Study Building

The proposed OCC framework was implemented in an actual accommodation facility to evaluate its performance through a subjective experiment. The study building is located in Nagano, Japan, consisting of 20 guest rooms and several common areas such as a hall. Each guest room was individually air-conditioned using a Variable Refrigerant Flow (VRF) system, allowing guests to freely adjust the temperature setpoint during their stay.

2.2.2. Subjective Experiment

A subjective experiment was conducted in the guest rooms over a five-day, four-night period from August 20 to 24, 2024, to evaluate the OCC performance. 20 university students (10 male and 10 female) were participated for the experiment, with each assigned to a separate guest room. Because daily activities such as taking meals, bathing, and sleeping can influence perceived comfort, a consistent schedule was established for all participants throughout the experiment. Participants were instructed to remain in their guest rooms from 7:00 PM until 8:30 AM the following morning. The participants were asked to answer a survey on thermal comfort 5 times per day. Prior to the main experiment, a two-night, three-day preliminary experiment was conducted at each participant's home to help participants familiarize themselves with the experimental process and schedule.

Table 1 shows the experimental cases. Day 1 (NoOCC-A) was designated for learning individual preferences based on participants' temperature setpoint adjustment history, with the initial temperature set to 25 °C. On Days 2 and 3, a crossover experiment was conducted to compare fixed-setpoint operation at 25 °C (NoOCC-N) and OCC (OCC-N), with the two cases alternated between two groups of 10 participants each. During this phase, temperature setpoint adjustment was prohibited. On Day 4, participants were again allowed to adjust the temperature setpoint, and the number of temperature setpoint adjustments by participants was recorded while OCC was active (OCC-A). With OCC, the temperature satisfies more than a probability threshold (here, set to 80%) according to the comfort model is set to the setpoint to balance thermal comfort and energy efficiency viewpoints.

Table 1. Experimental cases.

Case name	Setpoint control strategy	Setpoint adjustment by guests
NoOCC-A	Initially set to 25 °C	Allowed
NoOCC-N	Constant at 25 °C	Not allowed
OCC-N	OCC	Not allowed
OCC-A	OCC	Allowed

3. Results and Discussion

A statistical analysis by the Wilcoxon signed-rank test was conducted for the subjective feedback on thermal comfort and thermal preference between Cases NoOCC-N and OCC-N (Figure 3). While the difference in thermal comfort was not significant, a trend toward improved comfort under the OCC condition (OCC-N) was observed. Regarding thermal preference, the proportion of responses indicating "no change (±0 °C)" increased significantly in OCC-N ($p < 0.001$). These results suggest that the OCC system effectively created environments perceived as comfortable by the participants, thereby reducing the need for temperature adjustments. Additionally, the mean temperatures over time and guest rooms for NoOCC-N and OCC-N were the same level, 24.3 and 24.1 °C, respectively, meaning that OCC would not lead to a significant increase in energy usage.

Figure 4 compares the number of temperature setpoint adjustments between NoOCC-A (Day 1) and OCC-A (Day 4). On Day 1, there were a total of 97 operations (4.9 times per person), while on Day 4, this dropped to 61 operations (3.1 times per person), marking a 37% reduction. Notably, adjustments to increase the temperature were reduced nearly in half. The individual adjustment behavior showed substantial variability in participants' sensitivity to their thermal environment. While two participants made no changes at all, others adjusted the temperature as many as 17 times in one day. Moreover, many participants performed both upward and downward adjustments within a single day, suggesting that fine-tuned adjustments were made in response to their activities such as bathing and sleeping. Figure 5 presents

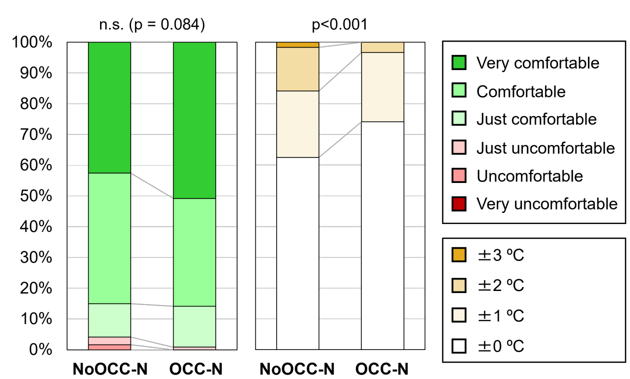

Figure 3. Subjective feedback on thermal comfort (left) and thermal preference (right).

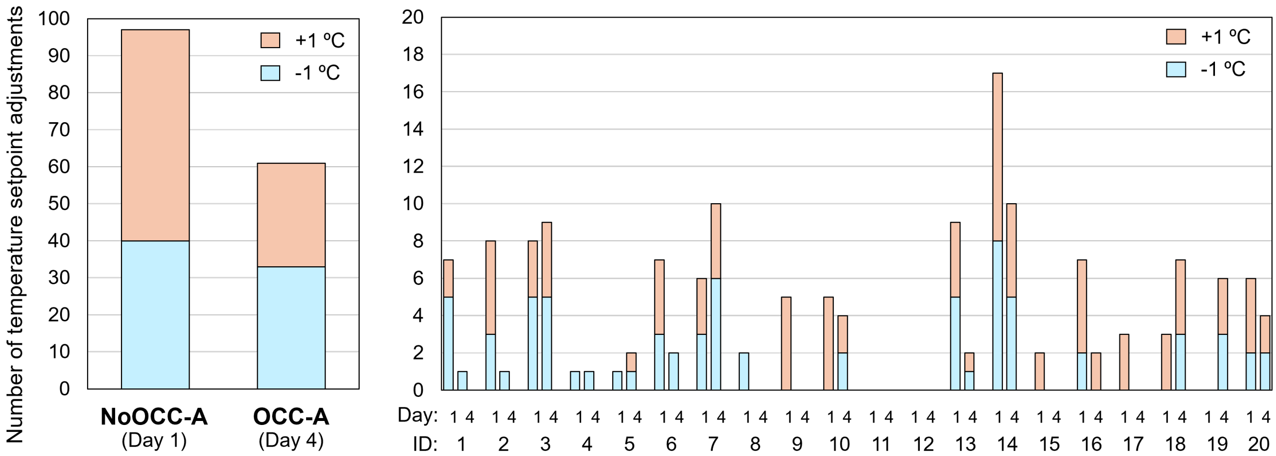

Figure 4. Number of temperature setpoint adjustments for the total of all participants (left) and each participant (right).

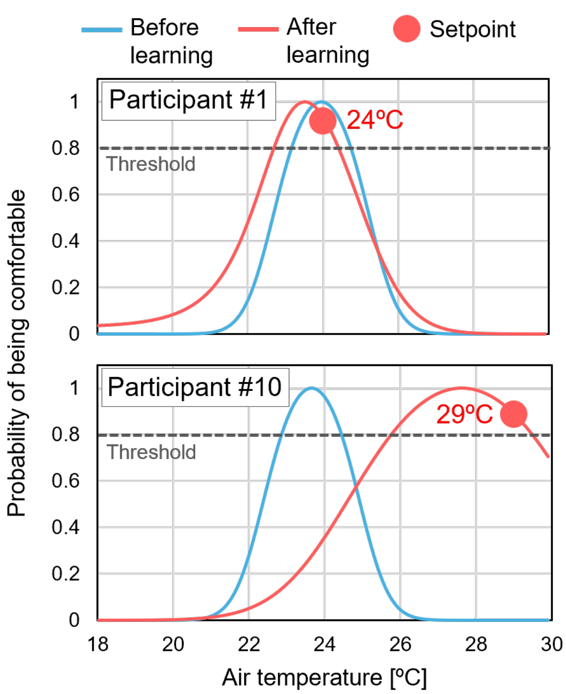

Figure 5. Comfort probability curves before and after learning individual preference for Participant #1 and #10.

changes in the comfort probability curves for two representative participants based on temperature adjustment history from Day 1. Participant #1, who lowered the setpoint temperature on Day 1, had a 24 ºC setting on Day 4 as a result of preference learning. Participant #10, who raised the setpoint temperature, had a 29 ºC setting on Day 4. These examples demonstrate that the system successfully learned individual preferences from setpoint adjustment history.

The number of preference data used for learning was between 11 and 18 per individual, which was much smaller than the required responses for accurate prediction suggested by Tartarini et al. (2022), 250–300 data points per person, indicating the importance of collecting informative data that effectively captures individual preferences. Supporting this, Tekler et al. (2024) showed that only two informative data points made substantial improvement in prediction performance of personal comfort models through active transfer learning. Likewise, temperature setpoint adjustments offer a more direct representation of user preference than conventional survey-based feedback, particularly when feedback is collected passively and without interaction with the HVAC system, contributing to effective personalization with minimal data. Additionally, the proposed OCC framework provides a practical advantage by eliminating the need for additional sensors, subjective feedback collection interfaces, and controllers, while OCC frameworks normally rely on occupancy sensors, subjective feedback on thermal comfort, and complex algorithms (Lei et al., 2022). This simplicity enhances both the scalability and ease of deployment of the proposed framework in real-world settings.

4. Conclusion

This study proposed and validated a scalable occupant-centric HVAC control framework for accommodation environments through a four-night field experiment with 20 participants. The results showed a 37% reduction in setpoint adjustments and a significant increase in responses indicating "no change" in thermal preference ($p < 0.001$), suggesting improved thermal comfort. The findings demonstrate the scalability of the proposed OCC framework that can be easily adopted in other accommodations with minimal data collection and guests' burden. While this initial deployment relied on the ASHRAE database, broader adoption will allow the system to be incrementally refined using accumulated real-world user data. This synergy between the scalable control framework and personalized data accumulation holds significant potential for advancing occupant-centric HVAC control in accommodations.

References

Cena, K. and de Dear, R. Field study of occupant comfort and office thermal environments in a hot, arid climate. *ASHRAE Transactions*, 105:204, 1999.

Földváry Ličina, V., Cheung, T., Zhang, H., de Dear, R., Parkinson, T., Arens, E., Chun, C., Schiavon, S., Luo, M., Brager, G., Li, P., Kaam, S., Adebamowo, M. A., Andamon, M. M., Babich, F., Bouden, C., Bukovianska, H., Candido, C., Cao, B., Carlucci, S., Cheong, D. K., Choi, J.-H., Cook, M., Cropper, P., Deuble, M., Heidari, S., Indraganti, M., Jin, Q., Kim, H., Kim, J., Konis, K., Singh, M. K., Kwok, A., Lamberts, R., Loveday, D., Langevin, J., Manu, S., Moosmann, C., Nicol, F., Ooka, R., Oseland, N. A., Pagliano, L., Petráš, D., Rawal, R., Romero, R., Rijal, H. B., Sekhar, C., Schweiker, M., Tartarini, F., Tanabe, S.-i., Tham, K. W., Teli, D., Toftum, J., Toledo, L., Tsuzuki, K., De Vecchi, R., Wagner, A., Wang, Z., Wallbaum, H., Webb, L., Yang, L., Zhu, Y., Zhai, Y., Zhang, Y., and Zhou, X. Development of the ASHRAE Global Thermal Comfort Database II. *Building and Environment*, 142:502–512, 2018. doi: 10.1016/j.buildenv.2018.06.022.

Graham, L. T., Parkinson, T., and Schiavon, S. Lessons learned from 20 years of cbe's occupant surveys. *Buildings and Cities*, pp. 166—-184, Feb 2021. doi: 10.5334/bc.76.

Huang, G., Ng, S. T., Li, D., and Zhang, Y. State of the art review on the hvac occupant-centric control in different commercial buildings. *Journal of Building Engineering*, 96:110445, 2024. doi: https://doi.org/10.1016/j.jobe.2024.110445.

Jung, W. and Jazizadeh, F. Comparative assessment of HVAC control strategies using personal thermal comfort and sensitivity models. *Building and Environment*, 158 (March):104–119, 2019. doi: 10.1016/j.buildenv.2019.04.043.

Lei, Y., Zhan, S., Ono, E., Peng, Y., Zhang, Z., Hasama, T., and Chong, A. A practical deep reinforcement learning framework for multivariate occupant-centric control in buildings. *Applied Energy*, 324:119742, 2022. doi: 10.1016/j.apenergy.2022.119742.

Ono, E., Mihara, K., Lam, K. P., and Chong, A. The effects of a mismatch between thermal comfort modeling and HVAC controls from an occupancy perspective. *Building and Environment*, 220:109255, July 2022. doi: 10.1016/j.buildenv.2022.109255.

Soleimanijavid, A., Konstantzos, I., and Liu, X. Challenges and opportunities of occupant-centric building controls in real-world implementation: A critical review. *Energy and Buildings*, 308:113958, 2024. doi: https://doi.org/10.1016/j.enbuild.2024.113958.

Tartarini, F., Schiavon, S., Quintana, M., and Miller, C. Personal comfort models based on a 6-month experiment using environmental parameters and data from wearables. *Indoor Air*, 32(11):e13160, 2022. doi: https://doi.org/10.1111/ina.13160.

Tekler, Z. D., Lei, Y., and Chong, A. Data-efficient comfort modeling: Active transfer learning for predicting personal thermal comfort using limited data. *Energy and Buildings*, 319:114507, 2024. doi: https://doi.org/10.1016/j.enbuild.2024.114507.