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Comparative assessment of HVAC control strategies using personal thermal comfort and sensitivity models

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ABSTRACT

Research efforts have demonstrated the potentials of improving the performance of Heating, Ventilation, and Air-Conditioning (HVAC) systems by leveraging personalized thermal comfort preferences and profiles. However, there are remaining challenges for effective control in collective conditioning in multi-occupancy scenarios. In this study, we have investigated the impact of personal thermal comfort sensitivities – distinct individual reactions to temperature variations– on collective conditioning. To this end, we have explored whether taking the thermal comfort sensitivity into account influences the selection of temperature setpoints and the overall probability of achieving comfort. We have also examined the impact of different thermostat temperature resolutions (0.1, 0.5, and 1.0 °C) on these factors with a hypothesis that finer resolutions could aid in achieving improved overall thermal comfort. In doing so, we have proposed an agent-based control mechanism to simulate the multi-occupancy space, controlled by an HVAC agent to provide air conditioning for multiple human agents using three operational strategies to compare conventional strategies with our proposed approach. The first strategy relies on majority thermal votes, the second one relies on the gap between thermal preferences (i.e., preferred temperature) and ambient temperature, and the third strategy uses thermal comfort sensitivity in addition to preferences. The investigations were conducted by using stochastically modeled comfort profiles (six actual comfort profiles and 15 mathematically synthesized profiles from actual data). These profiles were used to model the behavior of human agents in diverse multi-occupancy scenarios, modeling two to ten occupants in a space for different thermostat temperature resolutions. Our investigations demonstrated that thermal comfort sensitivity plays a statistically significant role in collective conditioning as it resulted in changes of temperature setpoint in 86% of cases and a higher probability of achieving collective comfort.

1. Introduction

Heating, Ventilation, and Air Conditioning (HVAC) systems control almost half of building energy use in the US – 44.0% in commercial and 47.7% in residential buildings respectively [1,2] – with the aim of satisfying occupants' thermal preferences in indoor environments. American Society of Heating, Refrigeration, and Air Conditioning Engineers (ASHRAE) has specified that, in acceptable thermal environments, the majority (≥80%) of the occupants should find the thermal condition acceptable [3]. Specifically, the Predicted Mean Vote (PMV) model, which ASHRAE uses for HVAC design [3], states that 90% of occupants would be satisfied if the PMV-defined comfort zones are met (i.e., Predicted Percentage of Dissatisfied (PPD)). However, field studies have shown that only a small portion of buildings (11% among 215 buildings in the USA, Canada, and Finland) fulfilled such a goal [4]. The literature has pointed to a number of reasons for this suboptimal performance of the current HVAC systems. First, the comfort zone, defined by the PMV model, refers to the neutral vote (on a 7-point ASHRAE thermal sensation scale) according to controlled experimental studies [5] and does not necessarily represent occupants' diversity [6,7]. Therefore, this model might not be universally applicable [8]. Second, limitations in human-building interaction play a part. Office occupants often experience difficulties in controlling thermostats due to their ambiguous interfaces, authority concerns, and unknown locations [9,10]. Moreover, default temperature setpoints are often set by facility managers regardless of actual occupants' perspectives [11]. Accordingly, survey studies show that office occupants were less satisfied, compared to residential occupants [9,10].

To address these limitations, research efforts have focused on enabling intelligent and Human-In-The-Loop (HITL) HVAC operations in

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the past decade. Specifically, the advancements in information and communication technologies facilitated the collection of occupant thermal votes through electronic and real-time surveys as a major direction of research efforts in this field [7,12–22,50,51]. Furthermore, recent studies have explored the potentials of using physiological responses as input parameters to HVAC operations [23–26]. Therefore, occupants have been provided with a means of active participation in driving the control feedback of the HVAC operation by providing contextual information. These efforts have also paved the way for developing personalized comfort profiles (indicating an individual's properties like temperature preference with regard to thermal comfort) and comfort-aware HVAC operations [7,11,17–19]. In this way, individual thermal preferences (i.e., temperature values that most likely result in thermal comfort) could be identified by processing the historical thermal vote data. Such preferences have been used as feedback in the control loop of HVAC systems to provide improved thermal satisfaction and improve energy efficiency by avoiding over-conditioning [27–29]. In other words, compared to the conventional approach of generalizing occupants' characteristics (i.e., the PMV model), current research efforts are trying to make use of individual characteristics for improved HVAC operations.

Nonetheless, an outstanding question in this field is how to generate collectively acceptable conditions while using personalized thermal preferences. When multiple occupants share a space, served by a single HVAC air supply unit, which is common due to the use of thermal zones (spaces that are controlled by the same HVAC unit) [30], experiencing discomfort by some occupants is inevitable unless the thermal preferences of all occupants are close. When using personalized comfort profiles, achieving a satisfaction rate above 80% depends on the control strategy. A common approach is to use the average of thermal preference values as the control feedback parameter [31]. However, a noteworthy property in personalized comfort profiles is *the difference in response to temperature variations*, which we have defined as thermal comfort sensitivity. For example, one expresses discomfort quickly when the ambient temperature is increasing but has a high tolerance to lower temperatures. Another person could be sensitive to being cold while being more tolerant to higher temperatures [32]. Thermal comfort sensitivity manifests distinct features in personalized comfort profiles that have been observed in previous studies. Occupants have shown unbalanced reactions to temperature variations when providing thermal votes [27,31,33], which were also reflected in probabilistic modeling of thermal comfort profiles [7,17].

Accordingly, in this study, we hypothesized that these features could be leveraged for a more efficient control strategy. Specifically, our hypothesis states that when individual thermal comfort sensitivities of occupants are taken into consideration, different temperature setpoints with improved overall comfort could be achieved, compared to the cases that only rely on thermal preferences (i.e., the preferred temperatures). In addition, we have investigated the impact of HVAC systems' operable resolution of temperature setpoints in accounting for thermal comfort sensitivities. We considered 0.1 °C, 0.5 °C (~1 °F) and 1.0 °C intervals considering the resolution of available temperature sensors (often 0.1 °C [34]) and the commonly used resolutions (0.5 °C and 1.0 °C) in the literature [18,19,28,31]). To this end, our hypothesis is that the smaller the gap, the higher the probability of satisfied occupants. For example, for a preferred temperature of 24.5 °C, constraints in thermostat temperature resolution (e.g., having a 1 °C resolution) could pose a limitation to the realization of the optimal operational potential. Accounting for these hypotheses, we sought to investigate the following questions:

- Could leveraging individual thermal comfort sensitivities affect the control strategy by selecting a different temperature setpoint?
- Could leveraging the individual thermal comfort sensitivities improve individuals' thermal satisfaction in a multi-occupancy space?
- Does higher resolution of the sensing systems (i.e., smaller temperature setpoint intervals) facilitate in improving collective thermal satisfaction?

We have developed an agent-based model (ABM) to address these questions and to reflect the strategies for intelligent HVAC operation by accounting for personalized thermal comfort profiles and sensitivities, quantified through stochastic methods. Following the definition of generic ABM architecture, in this ABM, we have created individual elements (hereinafter agents), who independently possess their own characteristics, interact with each other, and respond autonomously to the variations of ambient conditions [35]. ABMs use a projection of natural language similar to when human users express their experiences [35] to allow for replication of real-world mechanisms. Hence, ABMs could be used as a powerful method to reflect individual characteristics of occupants (e.g., personalized comfort profiles and sensitivities) and simulate their behaviors in the context of different scenarios, in which they interact with HVAC systems [36,37]. To this end, we have adopted probabilistic and data-driven modeling techniques for simulating occupant behavior, which is reflected in the thermal comfort profiles.

The rest of the paper is structured as follows. The second section presents a review of previous collective conditioning strategies and their limitations. Section 3 elaborates on the methodology including the ABM and the mathematical modeling of human agents' behavior, designed to answer the aforesaid research questions. Section 4 presents the results of scenario analyses and the relevant discussions. Finally, the paper is concluded in Section 5 by presenting discussions, limitations, and future directions of this study.

2. Research background

Creating a collectively acceptable condition has been a long-lasting objective in the field of HVAC system operations. Accordingly, the objective of the PMV model, at the time of its development, was to identify system characteristics, for which the environmental and human-related factors result in feeling thermally comfortable by the majority of occupants [8]. However, individual differences in thermal perception and preferences have been shown to cause dissatisfaction and inefficient energy use during occupancy unless all the occupants of a thermal zone have similar preferences. Consequently, the personalization paradigm, which leverages the enhanced post-occupancy human-building interactions, was introduced to bring about strategies to improve collectively comfortable (or at least acceptable) conditions. Through our literature review [38], it has been noted that four operational strategies are introduced and the first approach leverages occupants' instantaneous thermal feedback [28,29]. In an example study, Murakami et al. [29] utilized occupants' instantaneous thermal votes (e.g., cooler, no change, or warmer) to shift the temperature setpoint depending on the thermal preferences that the majority of the occupants desired at each moment. This field study showed an energy saving potential of 20% while maintaining the percentage of satisfied occupants compared to the conventional operational strategy. Similarly, Purdon et al. [28] employed occupants' thermal feedback (i.e., votes) to evaluate the overall discomfort and selecte the temperature setpoint that minimizes the number of dissatisfied occupants. In their simulation study, energy savings of up to 60% were observed with a similar number of satisfied occupants. The second strategy uses occupants' feedback to update the PMV values. In an example study, Erickson and Cerpa [39] collected and averaged occupants' actual thermal votes, using the conventional 7-point thermal sensation scale (cold (−3) to hot (3)), to calculate the gaps between the average actual thermal votes and the calculated PMV values. Such gaps were used to update PMV-based thermal comfort estimations. Through field studies, it was demonstrated that this approach not only saved energy but also improved overall occupant thermal comfort, compared to the PMV-based operations. Compared to the first approach, the second one has made use of occupants' historical thermal votes for the benefit of operational strategies, which could reduce occupants' required dedication after a limited period of data collection [39].

The third operational strategy leverages individual thermal preferences, derived from personalized comfort profiles for collective conditioning. In contrast to the conventional control configuration (i.e., one thermostat in a thermal zone), Jazizadeh et al. [31] additionally installed temperature sensors in every room of a thermal zone, and then used an objective function to minimize the sum of gaps between the measured air temperature and the occupants' thermal preferences to adjust the thermostat setpoint. Through a field implementation, they have shown a 39% of energy saving (in the form of reducing daily average air flow) and improved users' thermal comfort. Finally, in a fourth operational strategy, Ghahramani et al. [33] created and leveraged zone level occupant discomfort profiles from multiple personalized profiles for multi-objective optimization. The personalized comfort profiles were converted into discomfort profiles and then combined. This study demonstrated 12.8% of additional energy savings compared to the 39% from their previous study [27] while maintaining the required comfort levels. More details on the spectrum of the operational strategies and their performance could be found in our comprehensive quantitative review paper on human-in-the-loop HVAC operations [38].

Despite studies on these operational strategies, the role of individual thermal comfort sensitivities in the control logic of HVAC systems is still unknown. As a common trend in the literature, in control strategies that leverage personalized thermal profiles, thermal comfort sensitivity has been uniformly applied. In other words, it is assumed that individuals have similar reactions to variations in temperature. ASHRAE states that at least a 3.0 °C (5.4 °F) of temperature variation is needed to provoke a change in thermal sensation [40,41]. As example studies, Klein et al. [40] and Kwak et al. [42,52] applied a generalized and linear thermal comfort sensitivity to human agents in their multi-agent-based simulation studies by referring to ASHRAE [5]. In another effort, Yang and Wang [42] utilized a normal distribution for human agents' comfort profiles, which still could not represent the difference in tolerances with respect to high and low temperature values due to their symmetrical form.

On the other hand, on the control side, the influence of operable temperature intervals (i.e., resolution) has not been thoroughly explored. Studies have not raised any questions on the influence of these intervals. They either did not specify the temperature setpoint interval [33,39], or they have used a single operable temperature interval (i.e., 0.56 °C or 1.0 °F) in configuring the optimal setpoint [18,19,31]. Purdon et al. [28] have discussed the impact of temperature step sizes in their control logic that searches to optimize the temperature setpoints according to occupants' comfort. They have identified a 1.0 °C step size as optimal compared to smaller and larger values. They have shown that depending on the initial temperature setpoint (i.e., the setback value) the use of small step sizes could be inefficient in reaching to the desired temperature even over a few hours. In this study, regardless of the control feasibility, we have looked at this problem from a different perspective. We have explored whether the temperature setpoint resolution could influence the probability of the overall comfort in multi-occupancy spaces.

As the trends in the literature show, this study contributes by developing a personalized comfort-driven HVAC operation that accounts for personal thermal comfort sensitivity in creating collectively acceptable indoor environments. Furthermore, we have evaluated the performance of different operational strategies that use personalized thermal comfort in comparison to the proposed approach. In doing so, we have compared the selected temperature setpoints and the overall occupants' satisfaction, derived from the operational strategy that leverages thermal comfort sensitivity against the strategies that ignore that factor. Furthermore, as noted, we have investigated the impact of varying operable temperature setpoint intervals on the temperature setpoint selection and collective occupants' satisfaction.

3. Methodology

In order to address the questions and test the hypotheses, we have developed an ABM simulation using MATLAB to reflect control strategies that account for the interaction between occupants and HVAC systems as shown in Fig. 1. The interactions were simulated using a scenario, in which HVAC operation is carried out using personalized thermal comfort profiles in multi-occupancy spaces. In this scenario, a human agent (a proxy of an occupant) provides its thermal votes to an Occupant Voting System (OVS) agent. Thermal votes could be selected among uncomfortably cool, comfortable, or uncomfortably warm with a degree of dissatisfaction. Hence, each data point contains information like uncomfortably cool at 21.5 °C with a specific magnitude of discomfort. The actions of the OVS agent include requesting a human agent for its thermal votes, collecting the human agents' thermal votes, and generating the thermal comfort profiles. The HVAC agents (a proxy of an HVAC system) request OVS agents for feedback to select the optimal temperature setpoint with the aim of maximizing human agents' thermal comfort in a space. Depending on the optimization method (i.e., operational strategy), the HVAC agent asks for different parameters from OVS agents and then searches the optimal temperature setpoint. In this ABM, we intentionally disregard the possible interaction between human agents (e.g., negotiating the temperature setpoint between occupants). In this study, we have only focused on the attributes associated with individuals' thermal comfort profiles and we assumed that the interaction dynamics between occupants could be reflected in their comfort profiles, developed over a long period of time. In other words, the impact of behavioral factors on thermal preferences have not been taken into account.However, as studies have shown [43,44], these interactions are important driving factors in energy management in buildings.

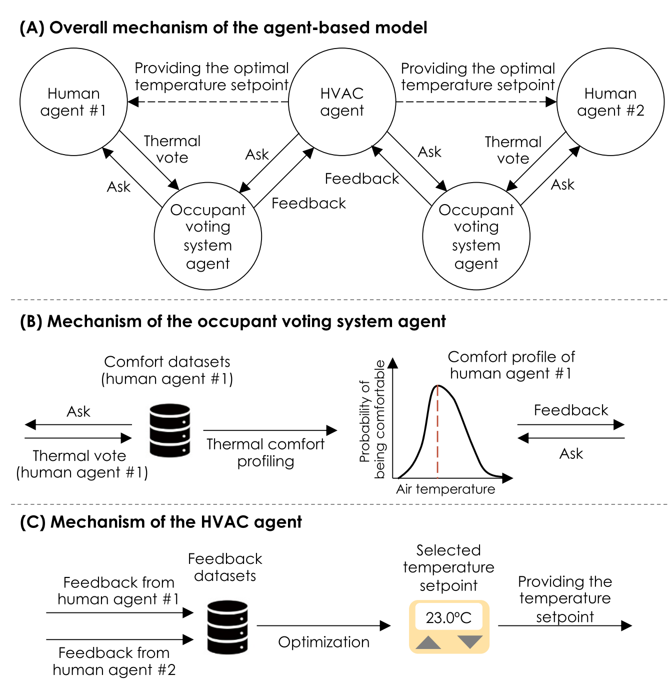


Fig. 1. Mechanism of the ABM in this study.

The following subsections elaborate on the specifics of the human, occupant voting system, and HVAC agents' modeling. Note that we have used air temperature as the sole control parameter in consideration of its substantial contribution to driving the thermal comfort votes [45]. Furthermore, in modeling the behavior of the HVAC agent, we assumed that temperature is uniformly distributed in space.

3.1. Populating comfort datasets for human agent modeling

In assessing the impact of thermal comfort sensitivity, it is important to consider the realistic comfort sensitivities of human subjects, collected through field observations. Accordingly, we have adopted real data sets from the literature to create thermal comfort profiles of occupants. In doing so, we have employed two sources of data: (1) actual thermal votes, extracted from previous studies [31,46] and (2) synthesized thermal votes, obtained from actual personalized comfort profiles, presented by Daum et al. [7]. The first source of the data was adapted given that these studies are the only ones that shared the raw thermal comfort data to the extent of our literature review. The second source was adopted to expand the datasets by simulating situations with a larger number of occupants. In the second source of data, the actual thermal votes were not presented in the paper explicitly. Therefore, we synthesized thermal votes based on the presented comfort profiles. The study presents six comfort profiles, created as probability distribution functions using datasets, collected through an electronic survey in a field study over a long period of time. We leveraged the mathematical representation of these six profiles to create a higher diversity in simulating the behavior of human agents.

From the first data source, we extracted six thermal vote datasets [31,46] by excluding one case in Jazizadeh et al. [31] as it did not represent votes, requesting warmer conditions. As shown in Fig. 2, the data collection in these two studies utilized a 100-point thermal preference scale (from −50 to 50) to reflect users' thermal preference votes. This scale presents a preferred level of change to achieve comfort – warmer with positive values, no change with zero, and cooler with negative values. We divided the votes into three classes; uncomfortably cool (from 6 to 50), comfortable (from −5 to 5), and uncomfortably warm (from −6 to −50). Several studies have shown that the three-category scale showed a better performance in comfort inference, compared to higher numbers of scales (e.g., 5 or 7 values) [38]. Moreover, as shown in Fig. 3, thermal votes from Pazhoohesh and Zhang [46] are aligned with the values in multiples of ten (−30, −20, −10, …, 30) except for the votes near zero. All the values in the vicinity of zero were utilized to represent a comfortable state. Therefore, we expanded the range for the comfortable state from −5 to 5 for consistency in data from both studies in the first source of data. Once the comfort profiles are shaped, to create a numeric representation for votes, we used +1 for uncomfortably cool votes, 0 for comfortable, and −1 for uncomfortably warm votes.

By using the thermal vote data, Daum et al. [7] used multinomial logistic models to create thermal comfort profiles (see Fig. 4A), which we used to create the second group of datasets. Similar to our data processing approach, they have used three types of thermal votes (too hot, comfortable, and too cold) for data collection and modeling. However, as noted, they have not presented the raw data. Therefore, we sampled thermal votes as shown in Fig. 4. Each model specifies the probabilities of being uncomfortably cool, comfortable, and uncomfortably warm with respect to each indoor temperature value with a sum of 100%. Leveraging these models, we utilized two random variables to synthesize the voting process (Fig. 4B): (1) the first random variable selects an indoor temperature within the range from 20 to 30 °C, representing the typical indoor temperature range that is usually controlled by HVAC systems [47], and (2) the second random variable takes a value in [0,1] to simulate the vote based on the area where the variable falls (uncomfortably cool, comfortable, and uncomfortably warm). In order to create human agents' datasets, we sampled 50

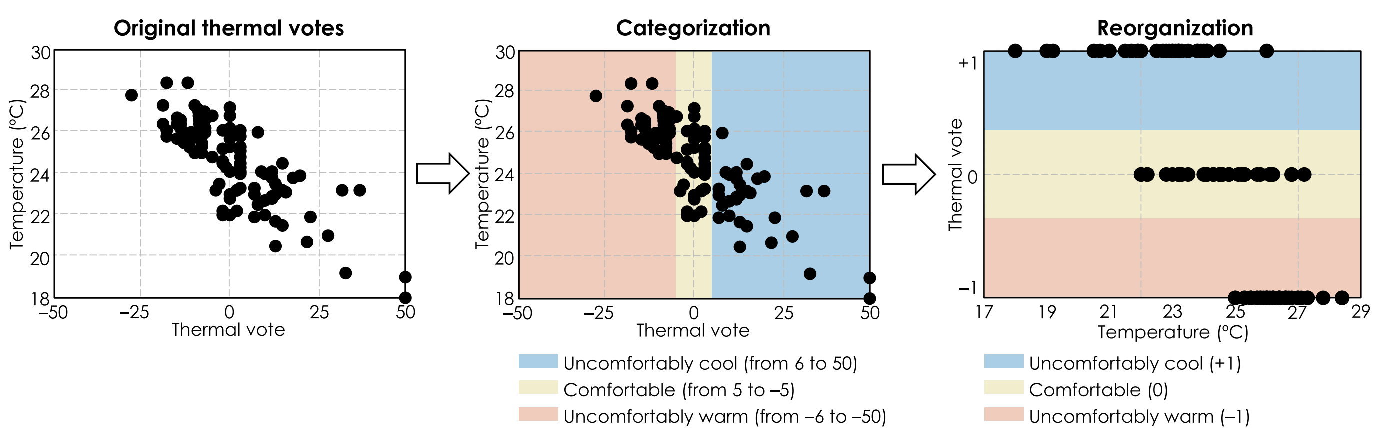


Fig. 2. Thermal vote categorization process (thermal votes are from Jazizadeh et al. [31]).

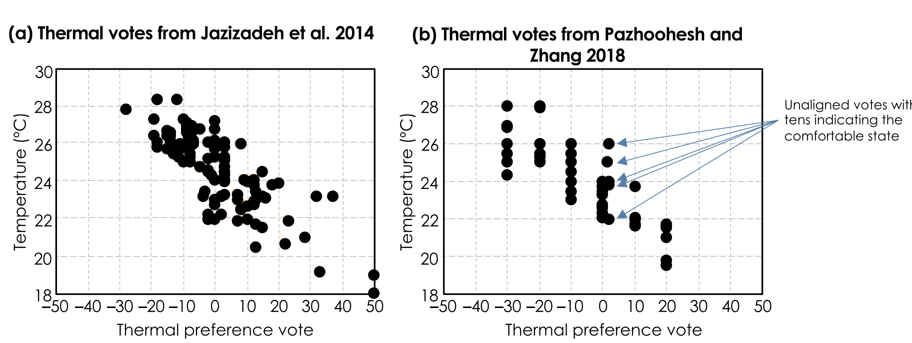


Fig. 3. Thermal preference votes from Jazizadeh et al. [31] and Pazhoohesh and Zhang [46].

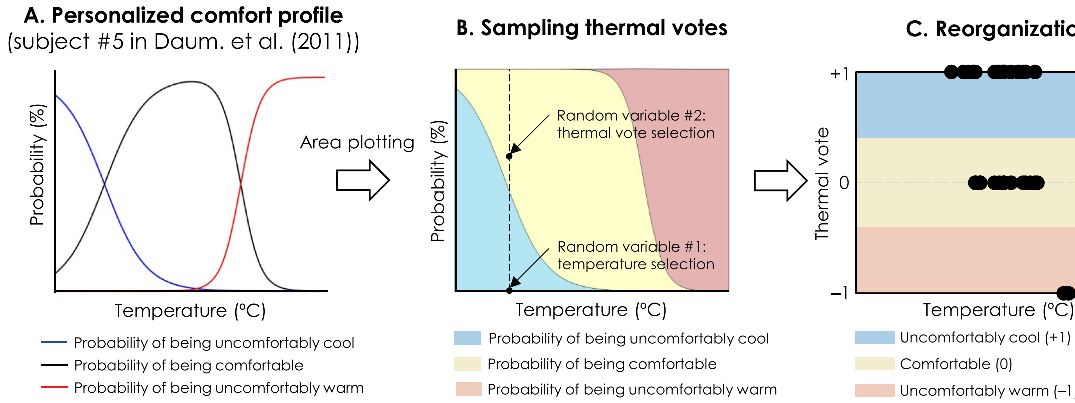


Fig. 4. Sampling thermal votes using personalized comfort profiles in Daum et al. [7].

thermal votes for each agent to simulate the process for thermal votes collection to match the number of thermal votes used in Refs. [31,46] for comfort profiling.

Note that when a human agent provides a new thermal vote to an OVS agent, the comfort profile of the human agent gets updated. However, we intentionally reduced the dynamics of our ABM to focus on the role of thermal comfort sensitivity in the operation of HVAC systems. Moreover, thermal votes, used in this study, reflect the dynamics of the human thermoregulation mechanisms such as change skin temperature (i.e., physiological) due to clothing insulation. All the studies we used as data sources for thermal votes [7,31,46] used field measurements without limiting the clothing insulation and therefore, they have accounted for the uncertainties associated with clothing insulation.

3.2. Personalized comfort profiling process using stochastic modeling

All the studies that have used thermal comfort votes for creating comfort profiles have shown vote overlaps under the same thermal condition. In other words, there are overlapping ranges of temperature, in which occupants have expressed comfort and discomfort in different occasions. This phenomenon could be seen in Fig. 4A. Therefore, in order to create a unified probabilistic thermal comfort profile to reflect the uncertainty of user experiences, we have adopted a stochastic modeling approach. To this end, we employed a Bayesian network modeling process for comfort profiling as proposed by Ghahramani et al. [17]. The method was adopted given that it leverages the probability distribution functions of comfortable and uncomfortable conditions to create one overall comfort profile that reflects thermal comfort sensitivity. We added a normalization step to assign the same scale to every comfort profile (from 0% to 100%).

The Bayesian network method creates the overall comfort profile by leveraging the Bayes rules and probability distributions of thermal perception across different ranges of temperature, associated with the three types of thermal votes. These thermal votes comprise the spectrum of occupants' individual comfort states (Fig. 5). In doing so, this method employs the range of air temperature that can be perceived as comfortable (Fig. 6 (a)) to create three probability distributions; uncomfortably cool, comfortable, and uncomfortably warm (Fig. 6 (b)). As shown in Fig. 6 (b), we have leveraged the overlapped parts, represented by three distributions, and created the overall comfort profiles as mathematically presented and shown in Fig. 6 (c) and (d).

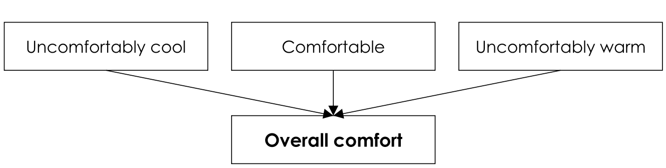


Fig. 5. Graphical representation of the Bayesian network [17].

For the probability distribution of comfortable votes $P(c|t)$, a normal distribution is used (Equation (1) and Fig. 6 (b)).

$$P(c|t) = f(t_c; \hat{\sigma}_c) = \frac{1}{\hat{\sigma}_c\sqrt{2\pi}} \exp\left(-\frac{(t_c-\mu_c)^2}{2\hat{\sigma}_c^2}\right) \tag{1}$$

where c means being comfortable, t_c represents any indoor temperature, for which a human agent has comfortable votes, μ_c is the mean of t_c values, and σ_c is the standard deviation of t_c values. This approach uses the normal distribution to represent different probability distributions of comfort. Therefore, we have verified the normality of the datasets used in this study as presented in the Results section. For the probability distribution of uncomfortably cool and warm votes that overlap with comfortable votes, two half normal distributions are employed (Fig. 6 (b)). For these half distributions, the probability of discomfort is maximum at both ends in the temperature range of interest. Hence, for example, the probability distribution of uncomfortably cool has its center at the minimum air temperature, which was also perceived as comfortable ($min(t_c)$). Equation (2) and Equation (4) show the half distributions and their related parameters. The mean values for these distributions are $min(t_c)$ and $max(t_c)$ for $P(uc|t)$ and $P(uw|t)$, respectively.

$$P(uc|t) = f(t_{uc}; \hat{\sigma}_{uc}) = \frac{\sqrt{2}}{\hat{\sigma}_{uc}\sqrt{\pi}} \exp\left(-\frac{(t_{uc}-min(t_c))^2}{2\hat{\sigma}_{uc}^2}\right) \ \forall \ t_{uc} \geq min(t_c) \tag{2}$$

$$\hat{\sigma}_{uc} = \sqrt{\frac{1}{n_{t_{uc}}} \sum_{1}^{n_{t_{uc}}} (t_{uc} - \min(t_c))^2} \tag{3}$$

Where uc means uncomfortably cool, t_{uc} represents any air temperature, for which a human agent had uncomfortably cool votes in the range of comfortable air temperature, $\hat{\sigma}_{uc}$ is the standard deviation of t_{uc} with respect to $min(t_c)$, and $n_{t_{uc}}$ is the number of t_{uc}.

$$P(uw|t) = f(t_{uw}; \hat{\sigma}_{uw}) = \frac{\sqrt{2}}{\hat{\sigma}_{uw}\sqrt{\pi}} \exp\left(-\frac{(t_{uw}-max(t_c))^2}{2\hat{\sigma}_{uw}^2}\right) \ \forall \ t_{uw} \leq max(t_c) \tag{4}$$

$$\hat{\sigma}_{uw} = \sqrt{\frac{1}{n_{t_{uw}}} \sum_{1}^{n_{t_{uw}}} (t_{uw} - \max(t_c))^2} \tag{5}$$

where uw means uncomfortably warm, t_{uw} represents any air temperature, for which a human agent has uncomfortably warm votes in the range of comfortable air temperature, $\hat{\sigma}_{uw}$ is the standard deviation of t_{uw} with respect to $max(t_c)$, and $n_{t_{uw}}$ is the number of t_{uw}. Using these three probability distributions and conditional probability rules, the overall probability distribution (i.e., comfort profile) is as presented by Equation (6).

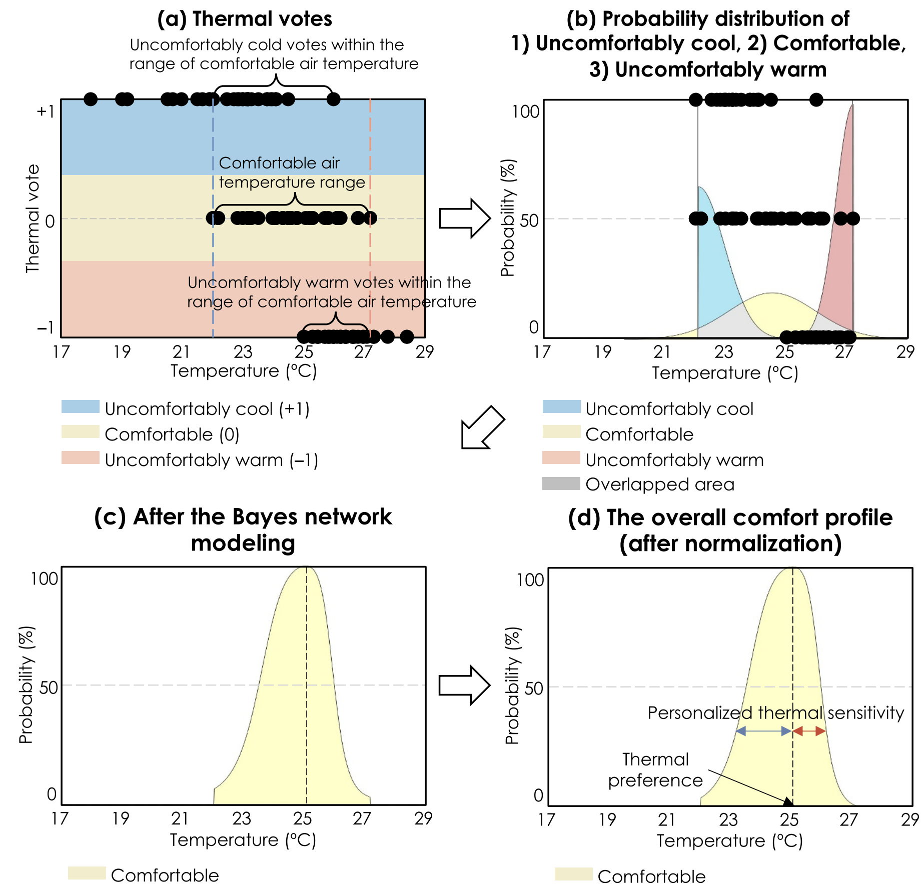


Fig. 6. Graphical representation of the comfort profiling process.

$$P(oc|t) = \frac{P(c|t)}{\omega_1 P(uc|t) + \omega_2 P(c|t) + \omega_3 P(uw|t)} \quad (6)$$

where P(oc|t) is the probability distribution of the overall comfort for a given temperature t, and ω_i, $i \in [1,2,3]$ are the weight factors for prior probabilities associated with $P(uc|t)$, $P(c|t)$, and $P(uw|t)$. The weight factors present prior probabilities in the Naïve Bayes formulation of Bayesian networks. In this approach, it is assumed that all probability distributions contribute to the overall comfort with the same weight [17]. An alternative approach in calculating the weight factors is to consider the frequency of votes in each thermal comfort vote category. However, the number of votes might reflect the number of exposures to different thermal conditions during the data collection. Therefore, in order to avoid biases due to the data collection process, we used the same weight factors for different categories of thermal votes in creating thermal comfort profiles. When $\hat{\sigma}_c$ is large, as illustrated in Fig. 6 (b), the $P(c|t)$ tails spread out beyond $P(uc|t)$ and $P(uw|t)$ despite the fact that comfortable votes have never been reported for those areas. When such situations happen, we change the $P(oc|t)$ value to zero for those tails as shown in Fig. 6 (c). In the last step, a min-max normalization is conducted:

$$P(oc|t) = \frac{P(oc|t) - min(P(oc|t))}{max(P(oc|t) - min(P(oc|t))} \quad (7)$$

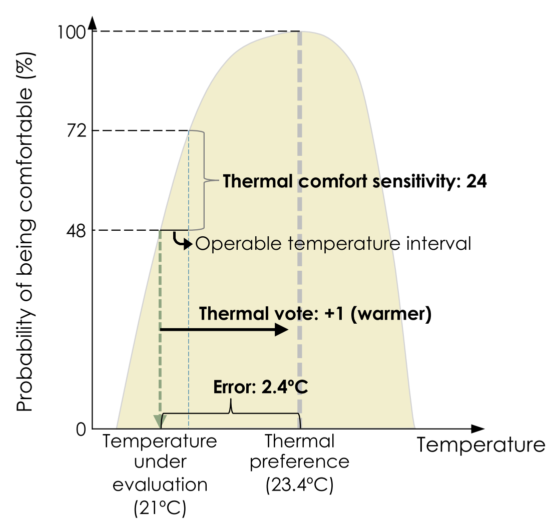
Fig. 6 shows each step of this comfort profiling method.

3.3. HVAC agent's conditioning logic

The HVAC agent was designed to implement three conditioning strategies to search for the collectively acceptable temperature set-points. In each strategy, the HVAC agent uses the following parameters to select the collectively acceptable temperature setpoint.

(1) Use of human agents' instantaneous thermal votes (inspired by Murakami et al. [29])
(2) Use of human agents' thermal preference values (inspired by Jazizadeh et al. [31])
(3) Use of human agents' thermal preference and sensitivity values

To clarify the parameters, Fig. 7 provides a graphical representation



Interval: Operable temperature setpoint variation
Strategy (1) – Thermal vote (Warmer, no change, cooler)
Strategy (2) – Error (Thermal preference – temperature (under evaluation))
Strategy (3) – Thermal vote (Warmer, no change, cooler)
+ Thermal comfort sensitivity (Probability variation)

Fig. 7. Graphical representation of the parameters that each strategy utilizes.

of the parameters which have been used in each strategy. Thermal preference stands for the temperature that has the maximum probability of comfort. Thermal votes are inferred from the comfort profiles by using Equation (8) (see Fig. 7 for illustration). For example, when an OVS agent uses human agent #1's comfort profile in a scenario that the evaluating ambient temperature is higher than the agent's thermal preference, the OVS agent sends a cooler preference vote to the HVAC agent and vice versa.

$$V_{i,T} = \begin{cases} -1, \; if \; T > TP_i (asking\ for\ cooler\ temperature) \\ 1, \; if \; T < TP_i \; (asking\ for\ warmer\ temperature) \\ 0, \; if \; T = TP_i (no\ change) \end{cases} \tag{8}$$

where T is the temperature, which is being evaluated, TP is a thermal preference, i is the index for human agents, and V is the thermal vote of human agents.

In order to quantify thermal comfort sensitivity, we have used the comfort probability differentials between temperature setpoint intervals (Equation (9) and Fig. 7).

$$TS_{i,T} = \begin{cases} CP_{T+t_{int}} - CP_T, \; if \; T < TP_i \\ CP_T - CP_{T-t_{int}}, \; if \; T > TP_i \\ 0, \; if \; T = TP_i \end{cases} \tag{9}$$

where CP is the probability of being comfortable, t_{int} is the temperature setpoint interval, and TS is thermal comfort sensitivity. For example, in a thermal comfort profile with a 48% probability of being comfortable at 21.0 °C and a 72% probability of being comfortable at 21.5 °C, the thermal comfort sensitivity is calculated as 24% of comfort gain by moving towards 21.5 °C. Fig. 7 illustrates this concept. In contrast, in another comfort profile, with a 40% probability of being comfortable at 21.5 °C and 50.0% of being comfortable at 21.0 °C, the thermal comfort sensitivity is calculated as 10% of comfort gain by dropping the temperature to 21.0 °C. As this example shows, the former profile manifests higher sensitivity to change in temperature. If these two profiles are present in the same room, the former profile should be prioritized when the temperature setpoint is selected between 21.0 °C and 21.5 °C.

Using the parameters presented above, in the first strategy, the HVAC agent requires a thermal vote from OVS agents to select the optimal temperature setpoint. It evaluates the potentials from the starting point, which is the setback temperature. The setback temperature is selected to ensure energy efficient operations. For example, in the warmer seasons, the setback is a higher temperature and vice versa. From this point, the HVAC agent changes the temperature setpoint depending on the majority thermal vote. An example has been given in Fig. 8, in which two human agents' comfort profiles with thermal preferences of 20.7 °C and 23.3 °C shared a thermal zone. Starting from a setback temperature of 19.0 °C, the HVAC agent monitors the sum of thermal votes at predefined temperature intervals (e.g., with a resolution of 1.0 °C) and selects the optimal temperature setpoint when the sum of votes is zero (at 21.0 °C). This strategy has been implemented using Equation (10) in a control loop.

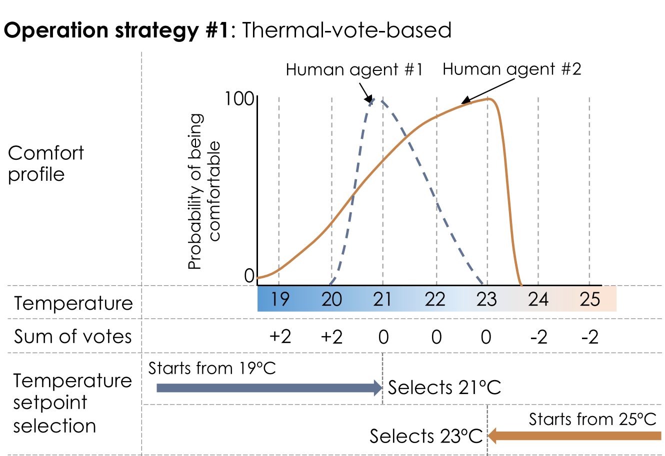


Fig. 8. Example of the first conditioning strategy.

$$T = \begin{cases} T + t_{int}, \; if \; \sum_i^n V_{i,T} \geq 1 \\ T - t_{int}, \; if \; \sum_i^n V_{i,T} \leq -1 \\ T, \; if \; \sum_i^n V_{i,T} = 0 \end{cases} \tag{10}$$

The iterations continue until one of the following conditions is met: (1) all the occupants are satisfied with the thermal conditions, (2) the sum of thermal votes become zero, or (3) the temperature selection process gets stuck in a loop between two temperature setpoints (at 21.0 °C, there are more votes for warmer, but 22.0 °C there are more votes for cooler). This third condition could be detected by looking at the history of the evaluated temperatures. To break the loop, assuming equal weight for each thermal vote, the algorithm chooses the temperature setpoint, which is closer to the initial temperature. The initial temperature is assigned as a setback temperature (18.0 °C and 28.0 °C in the winter and summer seasons, respectively) and temperatures closer to it are the energy efficient temperatures. Weighted thermal comfort votes could be also considered for different scenarios such as temporary vs. permanent occupancy although it is out of the scope of this study. Table 1 shows the pseudo code for this strategy.

The second strategy simulates a proportional control approach, which seeks to minimize the collective error between human agents' thermal preferences and operable temperature setpoints (Equation (11)). Although Jazizadeh et al. [31] pointed to uneven distribution of temperature in different rooms of a thermal zone as the rationale for installing room-level temperature sensors, in this study, we presumed that the temperature is uniformly distributed in multi-occupancy spaces. Therefore, the objective function is as follows:

$$error_{OT} = \sum_i^n |OT - TP_i| \tag{11}$$

where OT is operable temperature setpoint (e.g., 20.0, 21.0, …28.0 °C). The HVAC agent collects errors at each temperature setpoint from OVS agents as feedback and selects the setpoint, which has the minimum error. For example, when we have three human agents, who prefer 21.0 °C, 25.0 °C and 25.5 °C, and the HVAC agent can operate from 19.0 to 28.0 °C at an interval of 1.0 °C, the HVAC agent selects the temperature setpoint, which has the minimum sum of errors. Fig. 9 shows and illustration of this strategy and Table 2 shows its pseudo code.

The last strategy uses human agents' thermal votes and comfort sensitivities provided by OVS agents (Equation (12)). Similar to the first strategy, the HVAC agent collects the sum of thermal votes from OVS agents for finding the temperature setpoint closer to a majority vote. However, once achieving a zero value for the sum of thermal votes, the HVAC agent seeks to further finetune the temperature setpoint according to the human agents' thermal comfort sensitivities. One example has been given in Fig. 10. Comparing the human agents, the human agent #2 has a higher tolerance in response to temperature variation at the ranges, where the sum of thermal votes is zero (21, 22, and 23 °C). Therefore, the HVAC agent evaluates each human agent's thermal comfort sensitivity in the range of collective neutral vote. Moving from 21.0 °C to 22.0 °C, the HVAC agent observes a 48% loss of comfort for human agent #1 and 23% gain of comfort for the human agent #2. For the next interval, these values are 49% loss and 9% gain for human agents #1 and #2, respectively. Using these values and leveraging the third strategy, the HVAC agent balances the trade-off of comfort gain and loss by relying on thermal comfort sensitivity. In this example, the HVAC agent leans towards 21 °C.

The HVAC agent collects feedback from OVS agents by starting from the initial temperature and evaluates the next operable temperature setpoints as needed (Equation (12)). As noted, this searching process

Table 1
Pseudo code for the first conditioning strategy, which uses direct thermal votes.

```
Variables:
    T: Temperature which is being evaluated.
    HT: History of temperature setpoints, which have been evaluated (an array).
    PT: Temperature which is two iterations before T.
    interval: Temperature setpoint interval that an HVAC agent can change
    DT: Desired temperature (i.e., collectively acceptable temperature)
    Pi, i ∈ [1,2,3, ... ]: Thermal preferences of human agents (i is the number for each human agent).

while
    if length (HT) ≤ 2
        PT = 0
    else
        PT = HT(end − 2) ← Temperature which is two iterations before T
    if PT == T
        break (cycling between two temperature setpoints)
    end if
    for Every Feedback do ← Check each agent's thermal vote
        if T < Pi then
            Vi = +1
        else if T > Pi then
            Vi = −1
        else
            Vi = 0
        end if
    end for
    if sum(Vi, i ∈ [1,2,3, ... ]) == 0 then ← Check the sum of all thermal votes
        T = T
    else if sum(Vi, i ∈ [1,2,3, ... ]) > 0 then
        T = T + DT
    else sum(Vi, i ∈ [1,2,3, ... ]) > 0 then
        T = T − DT
    end if
    HT = [HT, T] ← Store the temperature setpoint which has been determined by the majority of thermal votes
end while
DT = T ← Desired temperature is found
```

Operation strategy #2: Error-based

Human agent #1: 21.0°C
Human agent #2: 25.0°C
Human agent #3: 25.5°C

Human agent's thermal preference										
Operable temperature (°C)	19	20	21	22	23	24	25	26	27	28
Error (Human agent #1)	2.0	1.0	0	1.0	2.0	3.0	4.0	5.0	6.0	7.0
Error (Human agent #2)	6.0	5.0	4.0	3.0	2.0	1.0	0.0	1.0	2.0	3.0
Error (Human agent #3)	6.5	5.5	4.5	3.5	2.5	1.5	0.5	0.5	1.5	2.5
Sum of errors	14.5	11.5	8.5	7.5	6.5	5.5	4.5	6.5	9.5	12.5

Fig. 9. Example of the second conditioning strategy.

might get stuck in two temperature setpoints. For example, at 21.0 °C, the sum of thermal comfort sensitivity is a positive value (i.e., moving to a warmer temperature setpoint) while the sum of thermal comfort sensitivity becomes a negative value at 22.0 °C. In this case, as discussed earlier, the temperature is set to a value, which is closer to the starting temperature value (i.e. set back temperature) given that all occupants have the same priority in the view of the HVAC agent. Table 3 shows the pseudo code for this strategy.

Regardless of the operational strategy, once the desired temperature setpoint is determined by the HVAC agent, the probability of thermal satisfaction for each human agent is extracted for comparison. For all three operational strategies, in our analyses, we used three operable temperature setpoint intervals of 0.1, 0.5, and 1.0 °C to assess the impact of the temperature setpoint resolution.

Table 2
Pseudo code for the second conditioning strategy – the use of thermal preference.

```
Variable:
    OT: Temperatures that an HVAC agent can set (e.g., 20°C, 21°C, 22° C,…)
    DT: Desired temperature (i.e., collectively acceptable temperature setpoint)
    Pi, i ∈ [1,2,3, ... ]: Thermal preferences of human agents (i is human agent index).
    error_i,j, i ∈ [1,2,3, ... ], j ∈ [OT]: Error between human agents' thermal preference and OTj
    minError ← the minimum error, which is initialized to a large value.

for each OTj in OT do
    for each feedback do ← Check each agent's error
        error_i,j = error_i,j + |OTj − Pi|
    end for
    if sum(error_i,j, i ∈ [1,2,3, ... ]) < minError
        minError = sum(error_i,j, i ∈ [1,2,3, ... ])
        DT = OTj
    end if
end for
```

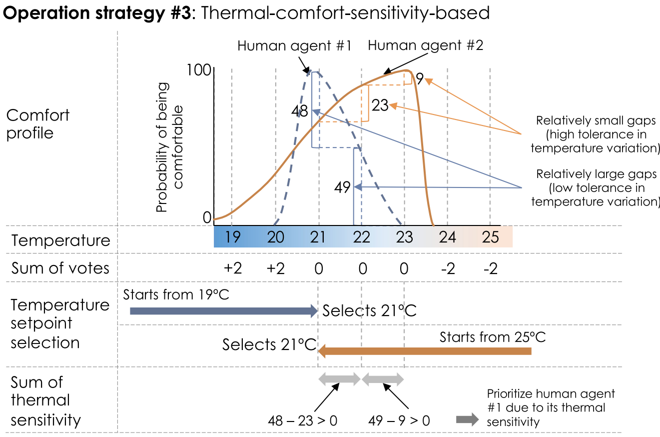


Fig. 10. Example of the third conditioning strategy.

$$T = \begin{cases} T + interval, & if\ \sum_i^n V_{i,T} \geq 1\ or \sum_i^n V_{i,T} = 0\ and \sum_i^n TS_{i,T} > 0 \\ T - interval, & if\ \sum_i^n V_{i,T} \leq -1\ or\ \sum_i^n V_{i,T} = 0\ and \sum_i^n TS_{i,T} < 0 \\ T, & if\ \sum_i^n V_{i,T} = 0\ and\ \sum_i^n TS_{i,T} = 0 \end{cases} \quad (12)$$

4. Results

4.1. Analyses with actual comfort datasets

In Fig. 11, the six thermal comfort profiles that were created by using direct extraction of thermal votes from prior studies have been illustrated. To verify the normality of six human agents' thermal votes, we conducted the Kolmogorov-Smirnov test, one of the commonly used normality method [48], and confirmed their normality (Table 4) with p-values less than 0.05 for all the cases. Note that the zeros in Table 4 are below $2.2251 \times e^{-308}$ and treated as zeros by MATLAB. It appeared that (1) human agents #1 and #3, (2) human agent #2 and 5, and (3) human agent #4 and 6 have similar thermal preferences. However, when it comes to thermal comfort sensitivity, human agent #3 had a better tolerance toward lower temperatures, compared to human agent #1. Human agent #2 had almost equivalent thermal comfort sensitivity to high and low temperatures in contrast to human agent #5, who had better tolerance to low temperatures. Human agent #4 was the most sensitive to temperature variations, and human agent #6 showed a better tolerance, compared to human agent #4.

Table 3
Pseudo code for the third conditioning strategy – the use of thermal vote and comfort sensitivity.

Variables:

T: Current temperature
HT: History of temperature setpoints, which have been evaluated (an array).
PT: Temperature which is two iterations before T.
OT: Temperatures that an HVAC agent can set (e.g., 20°C, 21°C, 22°C, …)
interval: Temperature interval that an HVAC agent can change
DT: Desired temperature (i.e., collectively acceptable temperature)
P_i, i ∈ [1,2,3, ...]: Thermal preferences of human agents (i is the number for each human agent).
TS_i, i ∈ [1,2,3, ...]: Thermal comfort sensitivity of human agents (i is the number for each human agent).
$CP_{i,j}$, i ∈ [1,2,3, ...], j ∈ [OP]: Comfort probability of human agents (i is the number for each human agent) at temperature j.

```
while
    if length (HT) ≤ 2
        PT = 0
    else
        PT = HT(end – 2) ← Temperature which is two iterations before T
    if PT == T
        break (cycling between two temperature setpoints)
    end if
    for each feedback do ← Check each agent's thermal vote and thermal comfort sensitivity
        if T < P_i then
            V_i = +1
            TS_i = CP_T+interval − CP_T
        else if T > P_i,j then
            V_i = −1
            TS_i = CP_T+interval − CP_T
        else
            V_i = 0
            TS_i = 0
        end if
    end for
    if ∑_{i=1}^n V_i < 0 then
        T = T + DT
    else if ∑_{i=1}^n V_i > 0 then
        T = T − DT
    else
        if sum(TS_i, i ∈ [1,2,3, ... ]) > 0 then
            T = T + DT
        else if sum(TS_i, i ∈ [1,2,3, ... ]) < 0 then
            T = T − DT
        else
            T = T
        end if
    end if
    HT = [HT, T] ← Store the temperature setpoint which has been determined by the majority of thermal votes
end while
DT = T ← Desired temperature is found
```

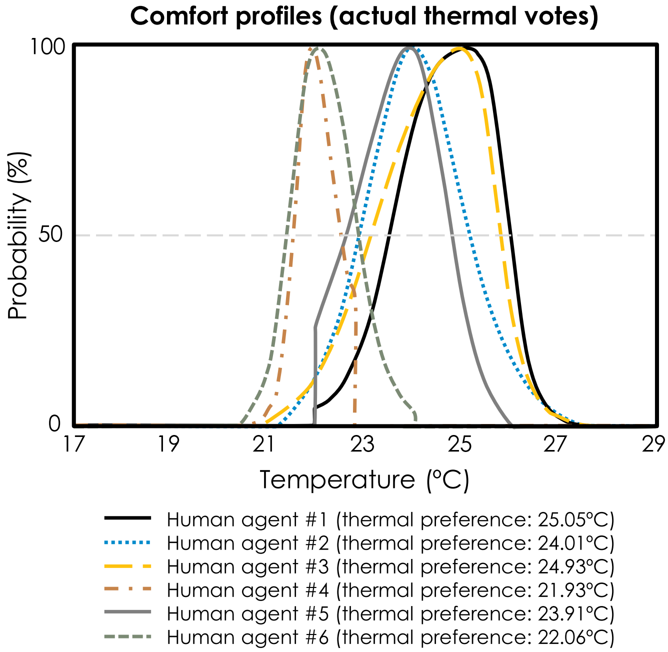


Fig. 11. Six human agents' comfort profiles based on actual thermal votes.

Table 4
P-values of each human agent's thermal votes derived from the Kolmogorov-Smirnov test.

Number of human agents	P-value		
	Uncomfortably cool	Comfortable	Uncomfortably warm
1	8.039xe^{-21}	2.079xe^{-31}	9.152xe^{-29}
2	1.645xe^{-15}	5.857xe^{-12}	2.735xe^{-32}
3	5.857xe^{-12}	8.039xe^{-21}	9.785xe^{-14}
4	2.156xe^{-08}	9.785xe^{-14}	0
5	0	9.785xe^{-14}	9.785xe^{-14}
6	8.882xe^{-16}	2.220xe^{-16}	2.156xe^{-08}

With these six human agents, different multi-occupancy cases were simulated to account for diverse scenarios. Scenarios, in which different combinations of two to five human agents interacting with a single HVAC agent, were simulated. The number of cases (N_C) in each multi-occupancy scenario can be computed by Equation (13), where k is the number of human agents in multi-occupancy spaces and n represents the maximum number of human agents (six in this case).

$$N_C = \frac{n!}{k!(n-k)!} \tag{13}$$

In the case with six human agents, we could only obtain a single output. Therefore, we eliminated that scenario because the statistical analysis was not possible. Through pair-sampled t-tests utilizing the number of cases, we have investigated the difference between the setpoints from the third and the first two strategies. Fig. 12 shows the selected temperature setpoints by three operational strategies for combinations of two human agents, 28.0 °C as initial setback temperature, and 1 °C as operable temperature setpoint interval. Even though Fig. 12 represents a limited number of scenarios in our analyses, it clearly demonstrates the differences among different operational strategies. Highlighting the impact of the initial temperature setpoint, the first operational strategy often selected 24.0 °C or 25.0 °C (80%) given that three human agents preferred temperatures above 24.0 °C. On the other hand, the second strategy often ended up with 23.0 °C (46.7%) to find an equidistance from human agents' thermal preferences. The third operational strategy, however, chose 22.0 °C with a higher frequency (46.7%). The high thermal comfort sensitivity of human agent #4 and #6 contributed to these results. Similar tendencies could be observed throughout different scenarios, in which other combinations of humans share the same thermal zone.

Table 5 shows the p-values from the paired-sample t-tests. With 0.95 significance level, 29 cases out of 48 cases (60.4%) showed statistically significant differences (the bold texts in Table 5). This demonstrates that thermal comfort sensitivity played a pivotal role in creating a collectively acceptable condition in a multi-occupancy space even for scenarios that three groups of human agents preferred similar temperatures.

The averaged probabilities of being comfortable, derived from human agents, were also compared as presented in Fig. 13. Generally speaking, the more human agents are present in a multi-occupancy space, the lower the probability of collective thermal satisfaction. The diversity in thermal preferences and comfort sensitivities across different human agents plays a part in this trend. As the results show, the third operational strategy outperformed the rest of the strategies. In some cases, the first operational strategy resulted in similar probabilities, but this strategy could be considerably affected by the initial temperature values (i.e., the starting point). When human agents can be grouped based on their thermal preferences (e.g., human agent #1 and #3 (with the thermal preference of 22.0 °C) vs. #4 and #6 (with the thermal preference of 25.0 °C)), the first strategy usually gets stuck with one group's thermal preference. We have illustrated this concept in Fig. 14. Hence, if the human agents in the group whose thermal preferences are far from the initial temperature are sensitive to thermal variations, the overall probability of being comfortable drops. In other

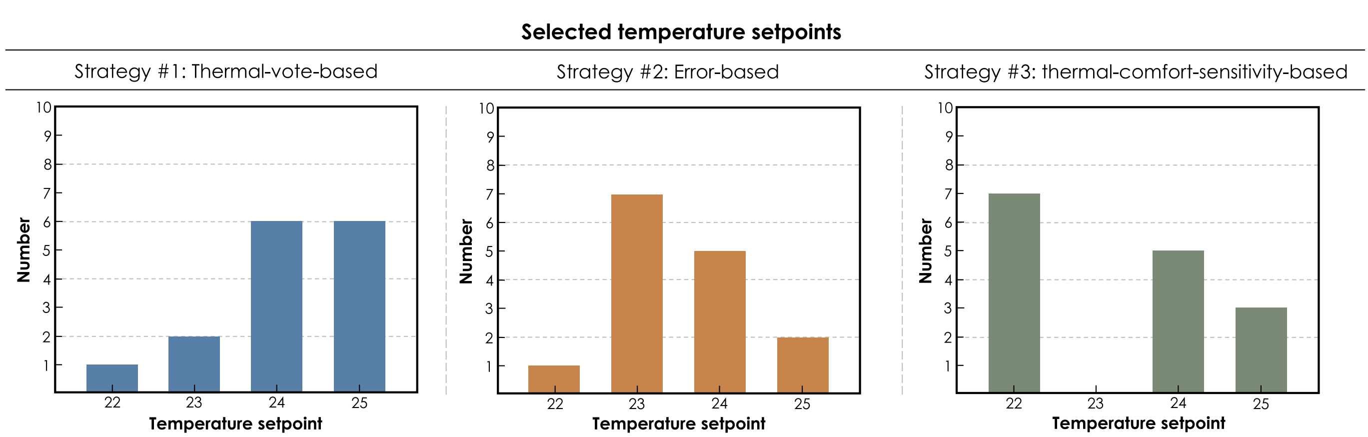


Fig. 12. Examples of the selected temperature setpoints from three operational strategies.

Table 5
P-values from paired-sample t-tests between the operational strategies (forgoing thermal comfort sensitivity in (#1 and #2) vs. accounting for thermal comfort sensitivity (#3)) for example actual thermal comfort profiles.

Number of human agents (Number of configurations)	P-values from pair-simple t-tests					
	Strategy #1 vs. #3			Strategy #2 vs. #3		
	Temperature setpoint interval (Initial temperature: 20.0 °C)					
	0.1 °C	0.5 °C	1.0 °C	0.1 °C	0.5 °C	1.0 °C
2 (15)	**.0062**	.1643	**.0192**	**3.927×e^{-04}**	**3.816×e^{-04}**	**9.199×e^{-04}**
3 (20)	**3.753×e^{-04}**	**3.379×e^{-04}**	**.0021**	.2406	.1893	.5409
4 (15)	**.0104**	.3343	**4.264×e^{-04}**	**.0492**	**.0359**	**.0061**
5 (6)	.1742	.0756	.0756	**.0151**	.1747	.1747
Initial temperature: 28°C						
2 (15)	**.0208**	.1502	**.0069**	**.0114**	.1189	.3636
3 (20)	**.0021**	**3.379×e^{-04}**	**3.753×e^{-04}**	.2406	.1893	.5409
4 (15)	**6.467×e^{-04}**	**3.973×e^{-04}**	**4.264×e^{-04}**	**.0341**	**.0359**	**.0061**
5 (6)	**.0250**	.0756	**.0756**	**.0151**	.1747	.1747

Bold texts are below 0.05 (statistically significantly different).

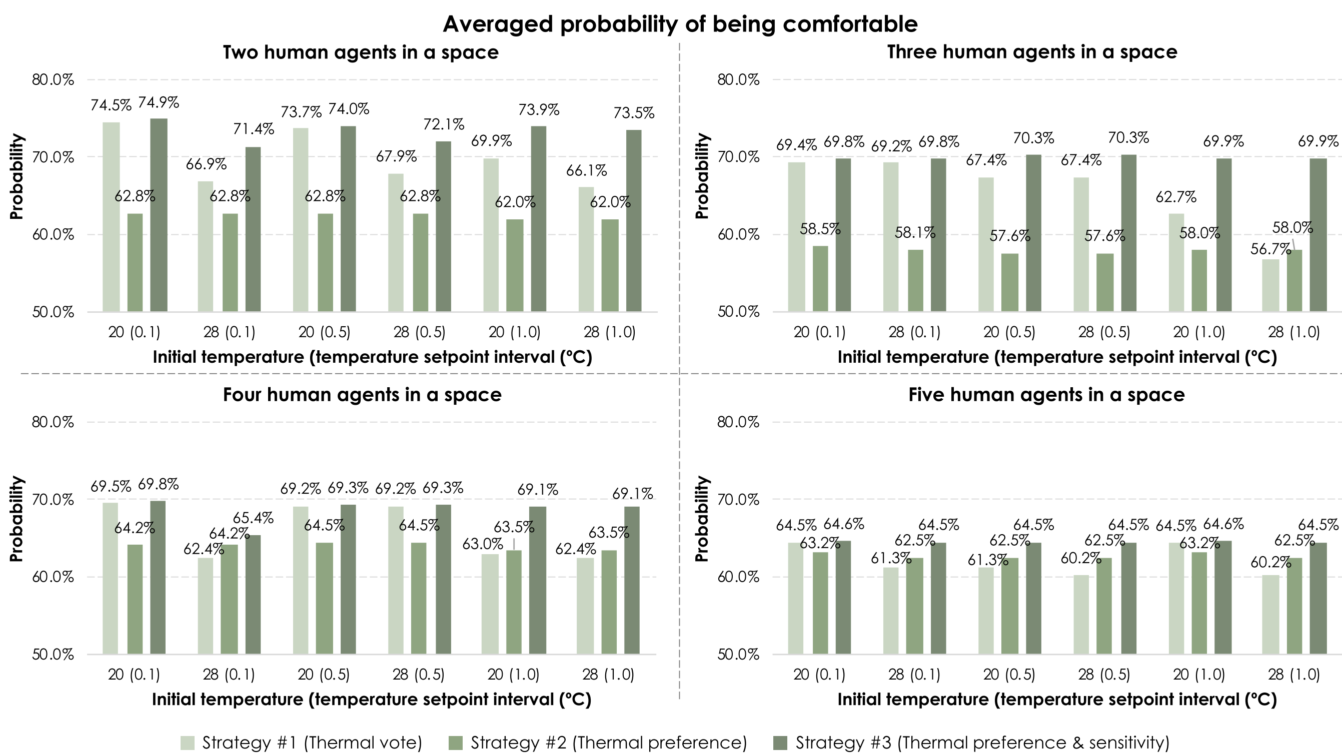


Fig. 13. Averaged probability of being comfortable for different multi-occupancy scenarios and control configurations: three operational strategies, two initial temperatures, and three operable temperature setpoint intervals.

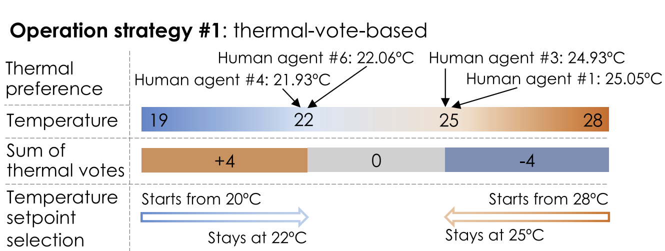


Fig. 14. Example of temperature setpoint selection process using the first operational strategy from different initial temperature values.

words, the performance of this strategy shows instability, compared to the rest.

The second strategy is not influenced by the initial temperature, but it has demonstrated the worst performance. Fig. 15 illustrates one of the reasons for the low performance: this strategy seeks to find the temperature setpoint that is equidistant from all the preferred temperatures by disregarding the sensitivity to temperature variations.

Lastly, investigating different temperature setpoint intervals shows that the use of 0.1 °C has the best performance in most scenarios and the use of 0.5 °C was the second best – that is, high flexibility in operable temperature setpoints provides better solutions to human agents.

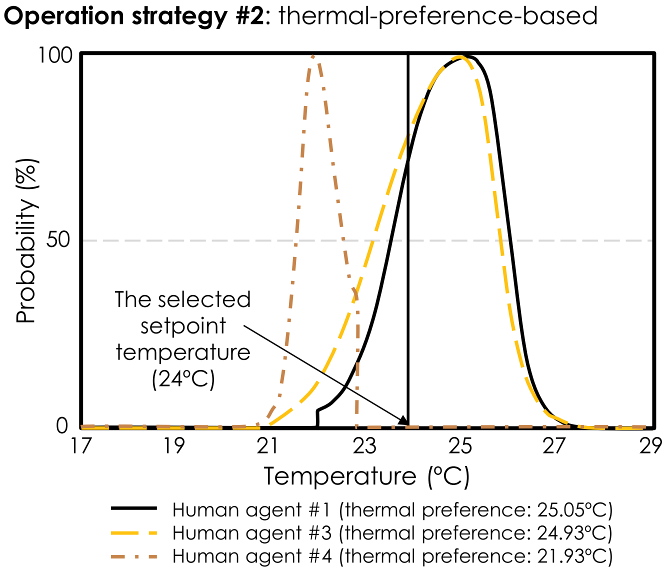


Fig. 15. Example of a selected temperature setpoint by the second operational strategy.

However, the gap between the overall probabilities derived from two intervals was insignificant (the highest gap was 0.9%, for scenarios with two human agents and the initial temperature of 20.0 °C). Therefore, the resolution of the temperature setpoints does not appear to be an important factor for the evaluated cases.

4.2. Analyses with synthesized comfort datasets

To further explore the importance of thermal comfort sensitivity, as noted earlier, we created 15 synthesized comfort profiles to represent more diverse human agents. Before applying the Bayesian network modeling process, we checked votes data for normality (Table 6). As noted, the second approach helped us evaluate more combinations of scenarios and cases, compared to the use of actual thermal profiles in Section 4.1. It is worth mentioning that since the original profiles in Daum et al. [7] were created using a large number of data points from each individual (6851 entries for 28 participants), our approach of randomly sampling 50 points from the original profiles results in creating 15 different comfort profiles. Unlike the actual thermal profiles, which could be grouped by preferences, in using synthesized profiles, we diversified thermal preferences. As shown in Fig. 16 thermal preferences were distributed across a temperature range from 20.05 to 27.31 °C, which is an acceptable range according to the field study by Klein et al. [40]. They utilized 242 thermal votes from permanent and temporary occupants of a building and presented a distribution of their thermal preferences (from 18.33 to 27.22 °C). In general, compared to the comfort profiles presented in Section 4.1, several human agents including #2, #8, #10, #11, and #12 had higher tolerances to temperature variations.

With 15 human agents, diverse multi-occupancy scenarios were simulated by using combinations from 2 to 10 human agents in a space. Similar operational strategies as presented in Section 4.1 were used in the analysis of this section. Table 7 shows the p-values for the *t*-test between the selected temperature setpoints by the third operational strategy vs. the first and second strategies. The number of cases (N_C) in each multi-occupancy scenario were computed by using Equation (13). In this case, almost for all the scenarios (97.2% of cases), statistically significantly different setpoints with a significance level more than 0.95 were observed. This is a clear increase, compared to the previous results (60.4%). In other words, when the diversity of thermal preferences and comfort sensitivities of human agents are taken into consideration, there is a high potential that the HVAC agent selects different temperatures setpoint. Note that the zeros in Table 7 are below $2.2251\times e^{-308}$ and are treated as zero.

When it comes to the average probability of collective comfort, as shown in Fig. 17, similar to what we observed before, the third strategy outperformed the other two strategies. These graphs also reveal that when the number of human agents in a thermal zone increases, the

Table 6
P-values of each human agent's thermal votes derived from the Kolmogorov-Smirnov test.

Number of human agents	P-value		
	Uncomfortably cool	Comfortable	Uncomfortably warm
1	$3.535\times e^{-10}$	$3.620\times e^{-18}$	$6.157\times e^{-20}$
2	$7.564\times e^{-10}$	$1.051\times e^{-21}$	$9.785\times e^{-14}$
3	$2.137\times e^{-16}$	$2.780\times e^{-17}$	$1.268\times e^{-14}$
4	$2.220\times e^{-16}$	$9.785\times e^{-14}$	$5.309\times e^{-27}$
5	$8.882\times e^{-16}$	$3.600\times e^{-33}$	$2.756\times e^{-09}$
6	$1.110\times e^{-16}$	$2.137\times e^{-16}$	$6.969\times e^{-28}$
7	$5.857\times e^{-12}$	$1.645\times e^{-15}$	$8.039\times e^{-21}$
8	$2.137\times e^{-16}$	$2.355\times e^{-24}$	$2.220\times e^{-16}$
9	$5.857\times e^{-12}$	$6.157\times e^{-20}$	$2.137\times e^{-16}$
10	$3.535\times e^{-10}$	$6.157\times e^{-20}$	$3.620\times e^{-18}$
11	$2.156\times e^{-8}$	$6.243\times e^{-35}$	0
12	0	$2.780\times e^{-17}$	$4.047\times e^{-26}$
13	$4.545\times e^{-11}$	$4.719\times e^{-19}$	$3.620\times e^{-18}$
14	$1.268\times e^{-14}$	$1.268\times e^{-14}$	$4.719\times e^{-19}$
15	$1.268\times e^{-14}$	$2.780\times e^{-17}$	$2.137\times e^{-16}$

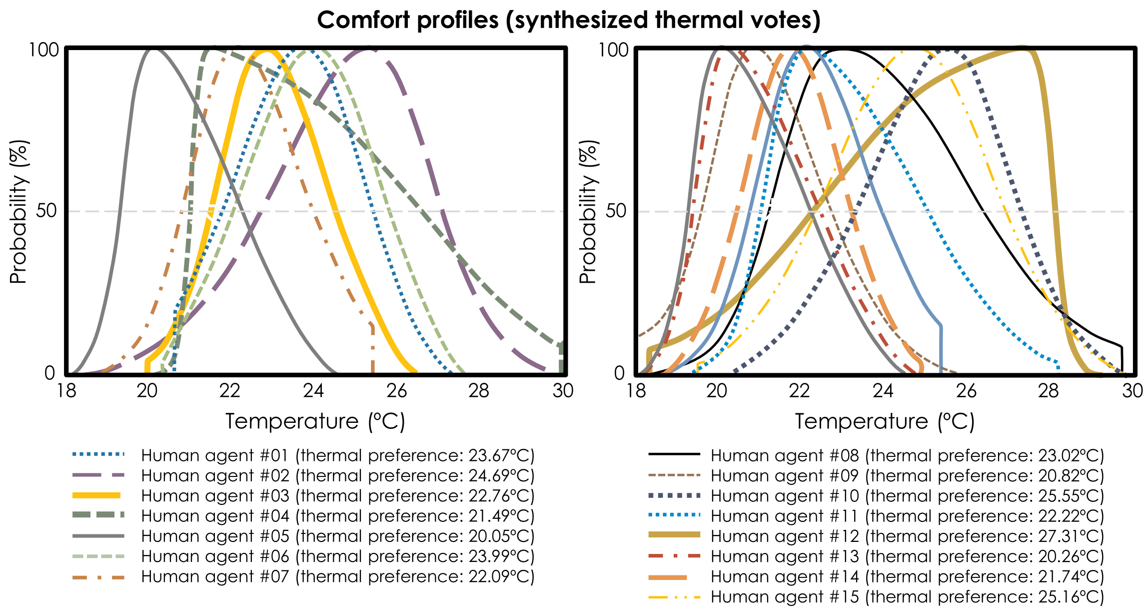


Fig. 16. Fifteen synthesized comfort profiles to represent human agents used in the analyses.

Table 7
P-values from paired-sample t-tests between the operational strategies (forgoing thermal comfort sensitivity in (#1 and #2) vs. accounting for thermal comfort sensitivity (#3)) for synthesized thermal comfort profiles.

Number of human agents (Number of cases)	P-value from pair-simple t-tests					
	Strategy #1 vs. #3			Strategy #2 vs. #3		
	Temperature setpoint interval (Initial temperature: 20 °C)					
	0.1 °C	0.5 °C	1.0 °C	0.1 °C	0.5 °C	1.0 °C
2 (105)	**$6.610\times e^{-17}$**	**$3.661\times e^{-13}$**	**$3.112\times e^{-09}$**	**$3.788\times e^{-04}$**	**.0137**	**0.0296**
3 (455)	**$2.601\times e^{-72}$**	**$1.487\times e^{-67}$**	**$1.308\times e^{-87}$**	**$4.357\times e^{-06}$**	**$2.951\times e^{-04}$**	.1290
4 (1365)	**$2.193\times e^{-198}$**	**$7.379\times e^{-108}$**	**$1.054\times e^{-75}$**	**$7.870\times e^{-23}$**	**$1.299\times e^{-17}$**	**$2.393\times e^{-12}$**
5 (3003)	**0**	**0**	**0**	**$7.216\times e^{-74}$**	**$8.093\times e^{-46}$**	**$1.185\times e^{-20}$**
6 (5005)	**0**	**$1.318\times e^{-233}$**	**$3.687\times e^{-154}$**	**$4.477\times e^{-115}$**	**$1.974\times e^{-130}$**	**$1.275\times e^{-85}$**
7 (6435)	**0**	**0**	**0**	**0**	**$3.746\times e^{-200}$**	**$8.328\times e^{-122}$**
8 (6435)	**0**	**0**	**0**	**0**	**0**	**$5.945\times e^{-208}$**
9 (5005)	**0**	**0**	**0**	**0**	**$2.620\times e^{-292}$**	**$4.194\times e^{-185}$**
10 (3003)	**0**	**0**	**0**	**0**	**$1.896\times e^{-271}$**	**$4.550\times e^{-141}$**
Initial temperature: 28 °C						
2 (105)	**$4.461\times e^{-13}$**	**$1.433\times e^{-10}$**	**$3.822\times e^{-08}$**	**$6.875\times e^{-05}$**	**.0415**	.6594
3 (455)	**$2.110\times e^{-68}$**	**$3.351\times e^{-73}$**	**$1.247\times e^{-55}$**	**$4.357\times e^{-06}$**	**$2.951\times e^{-04}$**	.1290
4 (1365)	**$6.801\times e^{-158}$**	**$3.598\times e^{-104}$**	**$1.553\times e^{-57}$**	**.004**	**$3.047\times e^{-11}$**	**$2.393\times e^{-12}$**
5 (3003)	**0**	**0**	**0**	**$7.216\times e^{-74}$**	**$8.093\times e^{-46}$**	**$1.185\times e^{-20}$**
6 (5005)	**0**	**0**	**$3.631\times e^{-225}$**	**$7.477\times e^{-104}$**	**$8.116\times e^{-126}$**	**$1.275\times e^{-85}$**
7 (6435)	**0**	**0**	**0**	**0**	**$3.746\times e^{-200}$**	**$8.328\times e^{-122}$**
8 (6435)	**$2.646\times e^{-55}$**	**0**	**$1.345\times e^{-43}$**	**0**	**0**	**$5.945\times e^{-208}$**
9 (5005)	**0**	**0**	**0**	**0**	**$2.620\times e^{-292}$**	**$4.194\times e^{-185}$**
10 (3003)	**.0132**	**$1.034\times e^{-28}$**	**$2.656\times e^{-51}$**	**0**	**$1.896\times e^{-271}$**	**$4.550\times e^{-141}$**

Bold texts are below 0.05 (statistically significantly different).

probability of collective comfort decreases, and the performances of different operational strategies converge. The influence of initial temperature on the first operational strategy was observed in this case as well. However, due to the differences between the thermal preferences and increases in the thermal tolerances, the variations between different configurations in the first and second strategies do not affect the performance as dramatic as we observed in Section 4.1. Similarly, the resolution of the temperature sensing system does not appear to have a significant impact on performance.

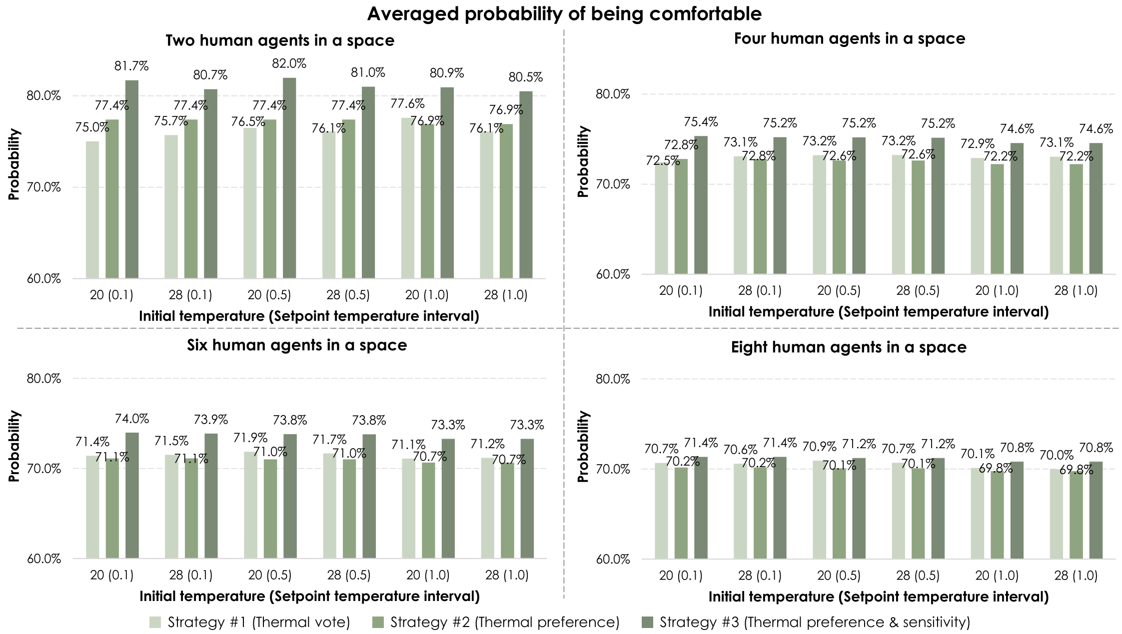


Fig. 17. Average probability of being comfortable in several multi-occupancy scenarios – each operation strategy, two initial temperatures, and three operable temperature setpoint intervals.

5. Discussion

The observations, in this study, could facilitate a more fundamental discussion on control strategies according to personalized thermal comfort in multi-occupancy spaces. According to these observations, one could ask (1) whether the air conditioning systems should provide an equally fair ambient condition for all the occupants or (2) providing a comfortable environment for the majority of occupants is a better strategy? Fig. 15 could be used as a clarifying example. In this figure, the HVAC agent could use comfort sensitivity to account for a fair and balanced temperature setpoint, or it could alternatively shift to meet the thermal preferences of two occupants and recommend adaptation strategies to the third occupant. In other words, there could be several possibilities to better serve multiple occupants in a space. A study by Shin et al. [49] proposed an approach to managing the *fairness* by HVAC systems in a multi-occupancy space. They have stated that a single optimized temperature setpoint could result in consistent dissatisfaction of some occupants and therefore selecting the majority vote or the mean (or median) temperature value might be unfair. Accordingly, they have proposed to minimize the accumulated discomfort by varying the temperature setpoint over time to meet the desire of all occupants at least for a period of time. In other words, in the case of examples in Fig. 15, their approach proposes to occasionally set the temperature setpoint according to the preference of the third occupant to be *fair*. Nonetheless, adjusting the clothing level or using local and personalized air conditioning systems could be recommended in case of having dissatisfied occupants while using an optimized temperature setpoint. In this study, we have explored the impact of different strategies including our proposed strategy that account for thermal comfort sensitivity and thus left further research into control fairness for future studies.

6. Conclusion

In this study, we have evaluated the performance of HVAC operational strategies that leverage personalized thermal comfort profiles as contextual information. In doing so, we have specifically investigated the role of thermal comfort sensitivity on HVAC operation in driving the temperature control setpoint and the average probability of collective thermal satisfaction. Simulating the interactions between occupants and HVAC systems through agent-based modeling, we compared three operational strategies by evaluating (1) the selected temperature setpoints, and (2) the average probability of collective thermal comfort in multioccupancy scenarios. Two of these strategies solely rely on thermal preferences, obtained from personalized thermal comfort profiles, while the third one accounts for thermal comfort sensitivity as well. We have further investigated the impact of temperature setpoint resolution in achieving higher overall thermal satisfaction. To this end, we explored three temperature setpoint resolutions of 0.1, 0.5, and 1.0 °C. The evaluated scenarios included combinations of occupants from 2 to 10 human agents by using six real-world and 15 synthesized thermal comfort profiles. Among all the evaluated scenarios, in 85.9% (134 out of 152) cases, statistically significant differences in temperature setpoints were observed when thermal comfort sensitivity was taken into consideration while the overall probability of having comfortable states increased. The results of the analyses demonstrated that the temperature setpoint resolution does not significantly influence the average collective satisfaction. We have also assessed the operational strategies, proposed by previous studies, which employ personalized comfort profiles. Therefore, this study also contributes to a better understanding of collective conditioning by using personalized comfort profiles.

There are also limitations in this study. As noted, this study was conducted under the assumption of having a uniform temperature distribution in a space, which is the reason that we did not specify the characteristics of the simulated spaces. Addressing the dynamic distribution of temperature in a thermal zone could potentially improve the operational strategies and it can be reflected in agent-based modeling by using computational fluid dynamics (CFD). Also, we have analyzed the performance of different strategies at the time when the environment has been stabilized. In the case of having field studies, HVAC systems' response time could affect the results. Moreover, as the number of occupants in a multi-occupancy space increases, as it is expected, the efficacy of integrating personalized thermal comfort profiles reduces and legacy operational methods could show the same outcome. Lastly, in investigating the impact of the temperature setpoint resolutions, we have considered values as low as 0.1 °C, which might not be feasible given the existing technologies. The reason for its inclusion was to investigate the impact of a hypothetical scenario, in which sensing systems could enable us to achieve that level of resolution. However, the results showed that the impact of such a high resolution is subtle, compared to generally operable temperature intervals (i.e., 0.5 °C and 1.0 °C). These findings could contribute to a better understating of temperature resolution impact even if it may be considered as hypothetical.

The proposed ABM model could be further developed to account for dynamic occupancy patterns, weighed comfort profiles, and real-world implementation. There could be a number of situations, where different weights can be assigned to different comfort profiles including permanent vs. temporary occupants, healthy vs. sick occupants, and adults vs. children occupants. The integration of the proposed operational strategy in this study could be reflected in the temperature setpoint configuration in real environments. The advancements of occupants' voting systems through mobile computing devices such as smartphones have paved the way for quantifying thermal comfort sensitivities. Accordingly, as the future directions of this study, we plan to leverage more complex agent-based-modeling to account for contextual information of the space, occupancy patterns, occupants' interactions, and energy consumption associated with different thermal comfort strategies and explore its integration into thermostat control logic.

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