Graphical Abstract

The effects of a mismatch between thermal comfort modeling and HVAC controls from an occupancy perspective

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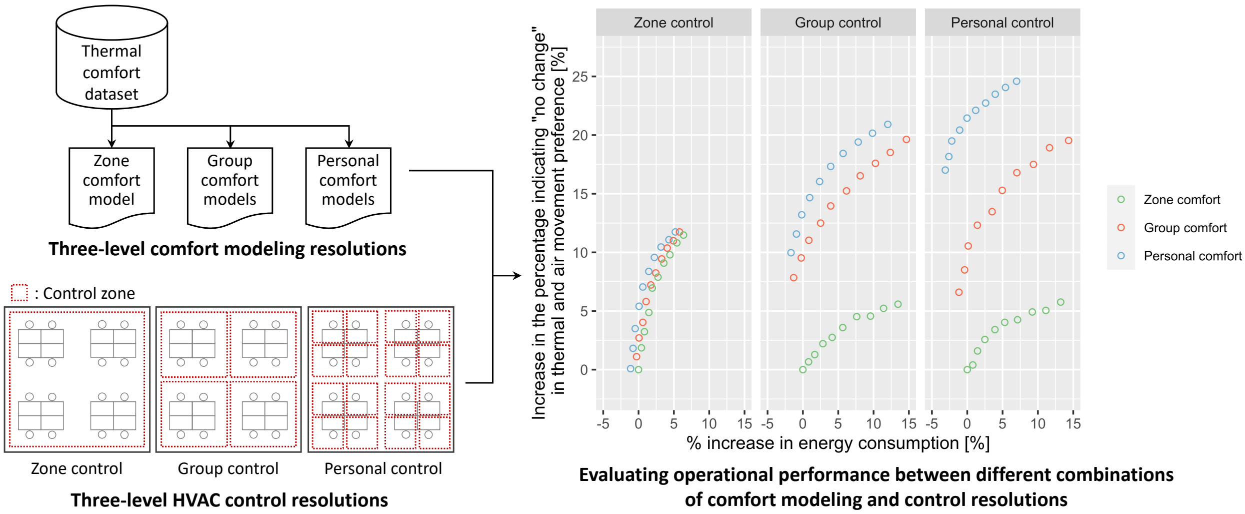

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Highlights

The effects of a mismatch between thermal comfort modeling and HVAC controls from an occupancy perspective

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- The interactions between thermal comfort models and HVAC controls were evaluated.
- Various occupancy resolutions of comfort models and HVAC controls were analyzed.
- More than 10% energy savings when HVAC operation considers a suitable comfort model.
- 6–12% decrease in occupants voting "no change" with mismatch in comfort and HVAC.

The effects of a mismatch between thermal comfort modeling and HVAC controls from an occupancy perspective

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ABSTRACT

Incorporating data-driven thermal comfort models into occupant-centric HVAC controls is crucial to meet occupants' preferences in thermal comfort. Although HVAC controls and thermal comfort modeling are highly inter-related, the interactions between their various resolutions require further study for a better understanding. This study aims to establish the effects of a mismatch between the occupancy resolutions of thermal comfort modeling and HVAC controls. We evaluated the energy and thermal comfort performance of different combinations of thermal comfort models and HVAC controls, focusing on their occupancy resolutions (zone, group, and personal thermal comfort models and zone, group, and personal HVAC controls). A mismatch between thermal comfort modeling and HVAC controls can result in a 6–12% decrease in occupants voting "no change" in thermal and air movement preference. Energy savings can be increased by more than 10% when considering a suitable comfort model for the HVAC control. The results demonstrate the importance of selecting a thermal comfort model with an appropriate occupancy resolution commensurate with the resolution of the HVAC controls.

1. Introduction

Thermal comfort is an essential factor for enhancing building occupants' health and productivity [4]. In determining how to manage and operate energy systems in buildings, generalized models such as the predicted mean vote (PMV), which represent the average characteristics of non-specific people, are typically used regardless of climate zones and building typologies. However, researchers have shown an increased interest in occupant-centric building design and operation [29]. Consequently, recent developments have called for incorporating subjective feedback from actual occupants in the development of thermal comfort models [18, 25]. To this end, recent years have seen thermal comfort models incorporating input variables such as occupant behavior [19], physiological data (e.g., skin temperature and heart rate) [23], and spatial data [1] to provide a more individualized estimate of occupants' preferences.

Studies have shown that incorporating personalized thermal comfort models into occupant-centric control frameworks can improve occupant thermal comfort because of their ability to cope with individual differences during HVAC operations [22, 16]. There are several occupant-centric control studies that have used data-driven thermal comfort models based on occupants' feedback and demonstrated improvements in operational performance. In a literature review, Xie et al. [38] reported that the medians of the improvements in energy savings and thermal comfort are 22% and 29%, respectively. However, Xie et al. [38] also reported that most studies used zone-level non-personalized controls, leading to challenges in mediating conflicts between individuals' thermal demands. This implies that personal thermal comfort models might not necessarily guarantee expected improvements in energy and thermal comfort performance when there is a mismatch between HVAC controls and thermal comfort models.

1.1. Occupancy resolution

Occupancy resolution was originally defined for occupancy data, such as presence, count, identity, and activity or tracking [26]. However, depending on its application, a higher occupancy resolution might not always lead to better outcomes [9]. Azimi and O'Brien [3] conducted a comprehensive review of occupancy sensing technologies and

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proposed a framework that selects the most appropriate occupancy sensing technologies based on the data requirements of the selected application. Their study found that occupant presence would suffice for conventional cooling and heating controls, while the number of occupants is crucial for demand control ventilation. Additionally, Gunay et al. [12] showed that the energy-saving potential of an occupancy-based occupant-centric control decreases as the occupancy resolution of HVAC controls decreases. Similarly, Hobson et al. [13] demonstrated that an occupancy-based occupant-centric control cannot work well when the spatial resolution of occupancy data is too low (e.g., building level). Likewise, selecting an appropriate occupancy resolution for HVAC controls and thermal comfort modeling is also crucial.

There exist different occupancy resolutions for HVAC controls and thermal comfort modeling strategies. Specifically, three different occupancy resolutions can be defined when discussing HVAC controls and thermal comfort modeling, respectively (Table 1).

Table 1
Definition and examples of three levels of occupancy resolution for HVAC controls and thermal comfort modeling, respectively.

Level	Definition of target occupants	HVAC control examples	Thermal comfort model examples
Zone level	A specific group of people who correspond to all the occupants in a space	- Zone air temperature control by VAV or CAV systems - Zone-level radiant temperature control by radiant cooling/heating systems	- Zone-level comfort profile
Group level	A specific group of people who form a subset of the total occupants in a space	- Subzone-level air movement control by ceiling fans - Subzone-level radiant temperature control by radiant cooling/heating systems	- Subzone-level comfort profile - Clustering by individual preferences
Personal level	A specific individual who is part of the occupants in a space	- Personalized air movement control by floor fans or ceiling fans - Personalized radiant temperature control by radiant cooling/heating systems - Personalized ventilation control - Personalized heater control	- Personal thermal comfort models

Occupancy resolution in the context of HVAC controls refers to the number of occupants in an HVAC control zone (zones that can be operated and controlled independently of one another). Each level of occupancy resolution can be realized by HVAC modulating devices such as terminal units, ceiling fans, and personal comfort systems. For instance, Ghahramani et al. [11] optimized the zone's setpoint temperature in a VAV system to reduce HVAC consumption while considering occupant thermal preferences. Lee et al. [20] implemented a self-tuned HVAC controller that controls a radiant floor cooling system with independently controlled loops to provide customized thermal preferences for the occupants served by different loops. Schiavon et al. [34] augmented an increase in setpoint temperature with personally controlled standing fans for reduced energy use and improvements in thermal comfort and perceived air quality. Zhang et al. [40] proposed using personal comfort devices such as a desktop fan and a cooling cushion to increase the upper limit of an occupant's thermal comfort. Amongst these examples, personal comfort systems would have the highest occupancy resolution because they offer individual occupants the ability to control their local environment [2, 32]. By contrast, a variable-air-volume (VAV) system that provides all occupants with a single thermostat to modulate the volume of air into a space would have the lowest occupancy resolution.

Occupancy resolution in the context of thermal comfort modeling refers to the number of occupants whose thermal responses are being aggregated by the model. Thermal comfort models can broadly be divided into three levels of occupancy resolution corresponding to zone, group, and personal. An example of a zone-level comfort model is the use of the PMV model to design the entire office space. Compared with zone comfort models, group and personal comfort models consider a specific group and person in the space, respectively. Group comfort models usually classify occupants into clusters within the zone based on their thermal preferences [14, 31, 21]. Zhao et al. [42] defined a group comfort zone derived from individual comfort zones based on multi-linear classifier to represent the range of comfortable thermal conditions for a group of occupants. There have been several studies investigating personal comfort models. Kim et al. [19] showed that personal comfort models significantly improved prediction accuracy compared to the conventional PMV model. Similarly, Li et al. [22] demonstrated that a comfort model personalized with individual physiological, behavioral, and environmental parameters was able to predict occupants' diverse preferences better.

1.2. Interactions between thermal comfort models and HVAC controls

Although the occupancy resolution of HVAC controls and thermal comfort models are closely related, their interactions require further study for a better understanding. Studies on HVAC controls usually assume a PMV thermal comfort model. Similarly, the benefits of utilizing personalized comfort preferences for HVAC control are typically evaluated using zone-level controls [11, 22, 16]. However, a higher occupancy resolution in HVAC control is likely to reap better building performance when matched with a higher occupancy resolution in thermal comfort modeling and vice versa. As Kim et al. [18] suggested, personal thermal comfort models would be more beneficial when combined with a high occupancy resolution of HVAC control since they could allow the system to adjust the local environment more precisely based on the predicted thermal responses.

Using a chamber room occupied by four subjects (i.e., zone-level control), Chen et al. [6] investigated the energy and thermal comfort performance for model predictive controls (MPCs) with a data-driven comfort model. Their results showed that using a data-driven comfort model provided an additional 25% energy savings compared with the PMV model without compromising thermal comfort. Similarly, Chaudhuri et al. [5] compared the energy-saving potentials between two general PMV-based models and five personal thermal comfort models at a single-occupancy room (i.e., personal-level control). Their results showed that the energy-saving potentials for the general models and personal comfort models compared to the baseline with a fixed setpoint were 17.3–25.9% and 16.0–34.4%, respectively. This implies that the performance improvement by a comfort-driven occupant-centric control could vary depending on the thermal comfort models, and personal comfort models do not always provide better performance than PMV-based models.

Regarding the occupancy resolution of HVAC controls, Jung and Jazizadeh [17] examined the influential parameters, such as the diversity in occupants' thermal comfort characteristics, thermal zone configuration, and the number of occupants in each zone, for comfort-driven HVAC control strategies. Importantly, their results showed that as the number of occupants in a zone increases, the improvement in energy and thermal comfort performance by personal comfort model-based controls decreases. This means that selecting a thermal comfort model with an appropriate resolution according to the occupancy resolution of HVAC controls could be crucial, avoiding unnecessary model complexity and data acquisition costs (e.g., sensing, data storage, and data processing).

However, a systematic understanding of the interactions between different occupancy resolutions of thermal comfort models and HVAC controls is still lacking. Therefore, the research question we want to address in this study is, *"What is the relationship between occupancy resolutions of thermal comfort modeling and HVAC controls and their subsequent effects on a building's operational (thermal comfort and energy usage) performance?"*. The aim of this study is to investigate the effects of a mismatch between the occupancy resolutions of thermal comfort modeling and HVAC controls.

2. Method

Figure 1 provides an overview of the framework used to investigate the relationship between occupancy resolutions of thermal comfort modeling and HVAC controls (hereafter, comfort modeling resolution and HVAC control resolution), which consists of the following three steps:

1. Using actual individual thermal preference data to create three different resolutions of thermal comfort models (i.e., zone, group, and personal).
2. For each combination of thermal comfort modeling and HVAC control resolution (i.e., $3 \times 3 = 9$ combinations), building operational conditions were optimized to maximize thermal comfort and minimize energy consumption.
3. Evaluate thermal comfort and energy usage performance across different combinations of thermal comfort modeling and HVAC control resolution.

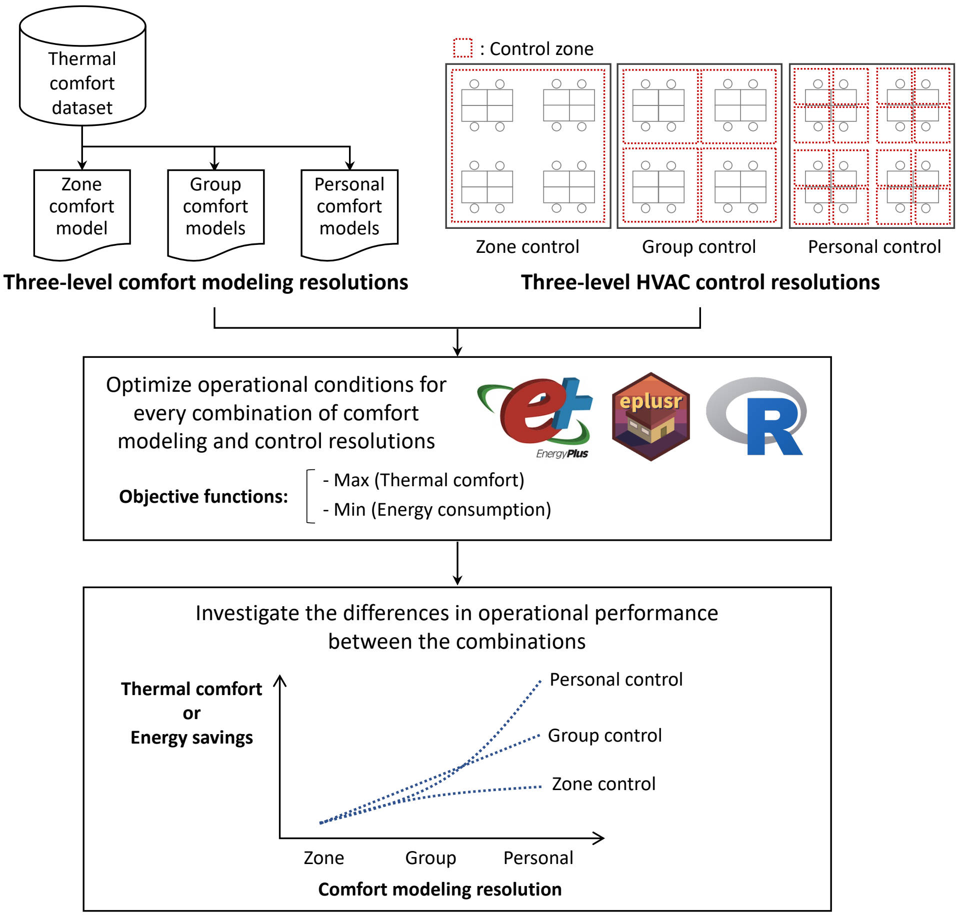


Figure 1: Framework to investigate the relationship between thermal comfort modeling and HVAC control resolution.

2.1. HVAC control resolutions

The HVAC system investigated is a VAV system with ceiling fans. The system achieves energy savings by raising the cooling setpoint (27°C–28°C) and offsetting any discomfort caused by the warmer temperature with elevated air movement provided through the ceiling fans [34, 27, 33]. As illustrated in Figure 2, three levels of control resolution were simulated by modeling the number of occupants sharing a single ceiling fan. In this case study, a total of sixteen occupants were assumed. Four occupants share a ceiling fan for group control, while each occupant has a ceiling fan for personal control. These setups were selected because of the availability of a thermal comfort dataset that contains individual thermal responses under various thermal conditions [28]. We also assume that the zone air temperature is uniform within the VAV control zone, and the air speed is uniform within the ceiling fan control zone.

2.2. Comfort modeling resolutions

2.2.1. Modeling of thermal comfort

A thermal comfort dataset collected by the subjective experiment [28] was used to develop the thermal comfort models in this study. The dataset consists of subjective responses under different thermal conditions (varying combinations of zone air temperature and air speed). The responses were collected 40 min after the subjects entered the experimental room to remove transient thermal responses. Table 2 summarizes the thermal comfort dataset. Thermal preference (TP) and air movement preference (AMP) were selected from various comfort metrics such as thermal/air movement sensation and acceptance. This is because thermal preference is a commonly used metric for personal comfort models [25] and the center of its scale, "no change," can be considered as "comfortable," unlike thermal sensation of which center is thermally neutral and not necessarily comfortable. In addition, when using devices that elevate air movement, such as ceiling fans, the impact of air movement preference on thermal comfort could be crucial. As

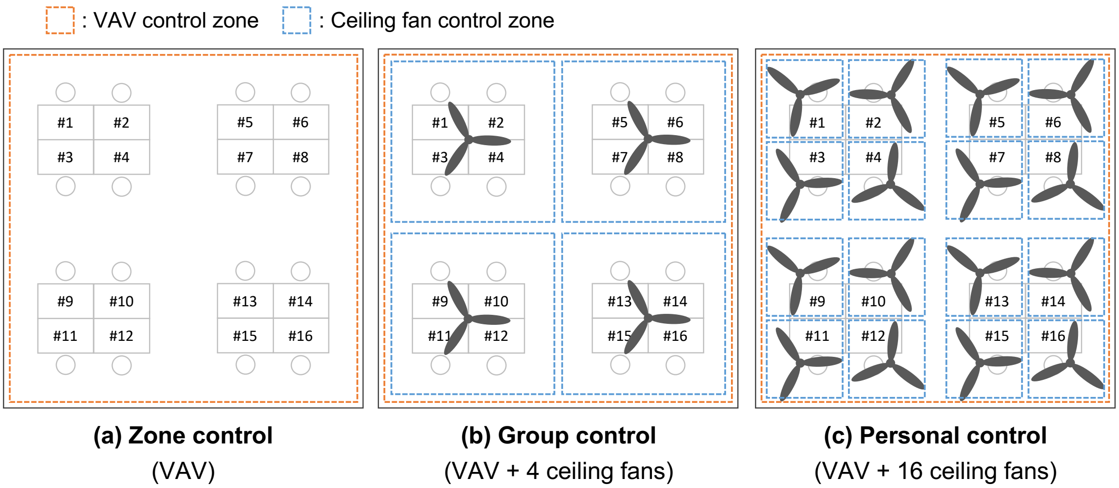


Figure 2: Three-level control resolutions combining a VAV box and ceiling fans.

shown in Figure 3, the experimental results indicate that people might have thermal and air movement preferences differently, although they mostly correspond with each other (e.g., TP = "no change" and AMP = "no change" at the same time). Consequently, this study considered both thermal and air movement preferences for a more realistic performance evaluation.

Table 2
Summary of the thermal comfort dataset from the experiment [28].

Number of subjects	Number of responses	Thermal conditions	Comfort metrics	
26	46 - 58 per subject (1,353 in total)	Air temperature: 24, 27, 30°C Ceiling fan mode: 0 (OFF), 3, 5 (mean air velocity: 0.07, 0.94, 1.87 m/s at 1.1 m above floor level)	Thermal preference: -2 (much cooler) -1 (slightly cooler) 0 (no change) +1 (slightly warmer) +2 (much warmer)	Air movement preference: -2 (much less) -1 (slightly less) 0 (no change) +1 (slightly more) +2 (much more)

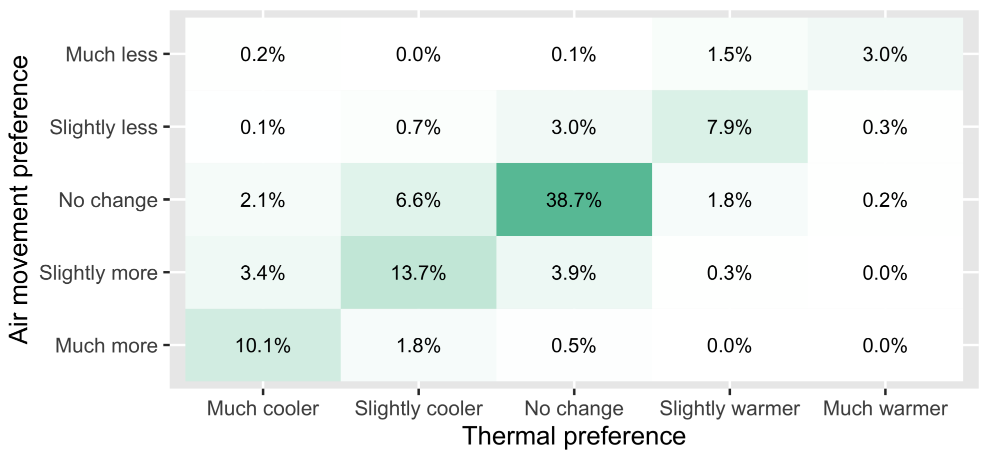


Figure 3: The percentages of subjective votes for each combination of thermal and air movement preferences.

Linear regression models were used to represent individual thermal and air movement preferences since they have been shown to capture relationships between subjective thermal responses and thermal conditions well [35, 37]. According to the setup of the control resolutions described above, actual thermal comfort data for 16 occupants are used to regress their thermal and air movement preferences individually with dependent variable, TP or AMP, and independent variables, air temperature and air velocity, as shown in Equation 1 and 2.

$$TP = a_1 + a_2 T_a + a_3 v_a + a_4 T_a v_a \tag{1}$$

$$AMP = b_1 + b_2 T_a + b_3 v_a + b_4 T_a v_a \tag{2}$$

where

T_a	: Air temperature [°C] ($T_a \in [22, 30]$)
v_a	: Air velocity [m/s] ($v_a \in [0.07, 1.87]$)
a_{1-4} and b_{1-4}	: Intercepts and coefficients

2.2.2. *Three-level comfort modeling resolutions*

Similar to the HVAC control resolution, three levels of comfort modeling resolutions were defined using the above linear regression models. In this study, the thermal comfort performance of HVAC controls is evaluated by the percentage of occupants voting "no change," which is achieved when $|TP|$ or $|AMP|$ is equal to or less than 0.5. Personal comfort models can then be expressed as Figure 4(a), which shows the area where $|TP|$ or $|AMP|$ is equal to or less than 0.5. The personal comfort models, which also serve as "ground truth" for the comfort evaluation, output 0 ("cooler" or "warmer") or 1 ("no change"). Accordingly, group and zone comfort models are derived from the personal comfort models by averaging the outputs (Figure 4(b) and (c)). Thus, the group and zone comfort models can predict the percentage of occupants voting "no change" under specific thermal conditions while not identifying the individual preferences.

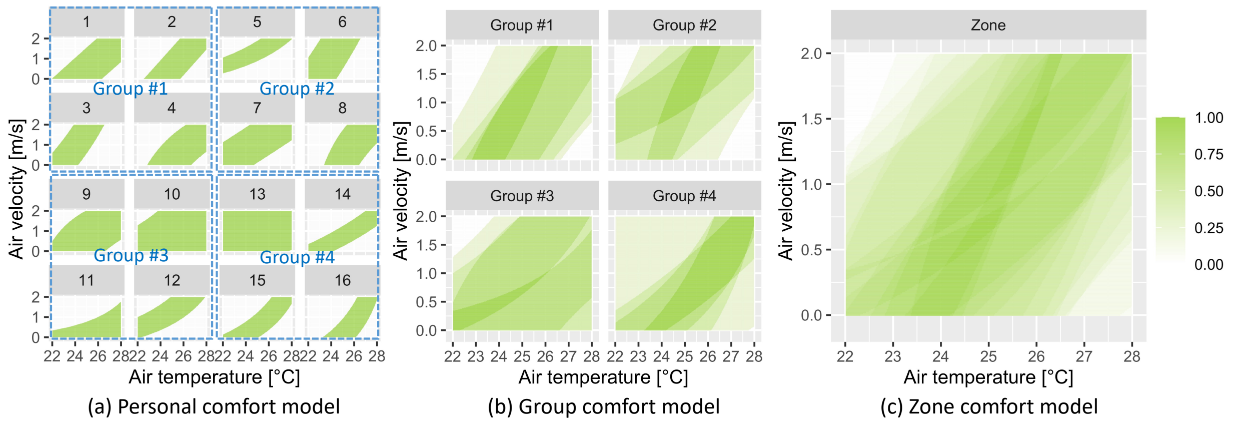


Figure 4: Three levels of comfort modeling resolutions. Personal comfort models are derived from the linear regression models and output 0 ("cooler" or "warmer") or 1 ("no change"). Group and zone comfort models output the average of corresponding personal comfort models.

2.3. Optimization framework

Multi-objective optimization was carried out by optimizing HVAC operations (zone air temperature setpoint and ceiling fan speed) to (1) maximize the percentage of occupants voting "no change" in thermal/air movement preference (Equation 3) and (2) minimize the energy consumption of the HVAC system (Equation 4). We also investigate the effects of considering only thermal preference compared to both thermal and air movement preference on the resulting optimal HVAC control. An occupant is considered as having a preference of "no change" if $|TP| \leq 0.5$ when considering only thermal preference. When using thermal and air movement preference as a metric, both $|TP| \leq 0.5$ and $|AMP| \leq 0.5$ need to be satisfied. The optimization is conducted at a daily resolution to reduce the computation time for the dynamic optimization of the hourly setpoint schedule.

$$max \left[P_{nochange} = 100 \frac{\sum_{t=1}^{24}(N_{nochange,t})}{\sum_{t=1}^{24}(N_{occupant,t})} \right] \tag{3}$$

$$min \left[E_{total} = \sum_{t=1}^{24}(E_{plant\_zone,t} + E_{AHUfan\_zone,t} + E_{ceilingfan,t}) \right] \tag{4}$$

where

$E_{AHUfan\_zone,t}$	: AHU fan energy consumption for the zone
$E_{ceilingfan,t}$	: Ceiling fan energy consumption for the zone
$E_{plant\_zone,t}$	: Plant energy consumption for the zone
E_{total}	: Daily total energy consumption
$N_{nochange,t}$	: Number of occupants voting "no change"
$N_{occupant,t}$	: Number of occupants
$P_{nochange}$	: Percentage of occupants voting "no change" in thermal/air movement preference over the day
t	: Time of day (hourly)

Algorithm 1 shows the pseudocode for the genetic algorithm-based daily optimization with `EnergyPlus` in `R` using the `eplusr` package [15]. The occupancy schedule used for the optimization is calculated by Occupancy Simulator [7]. The simulator generates stochastic occupancy schedules that can provide various combinations of thermal and air movement preferences within a group and a zone. Ceiling fan modes are determined only to maximize the number of occupants voting "no change" since ceiling fan power consumption is much smaller than the total energy consumption.

Algorithm 1: Pseudocode for the genetic algorithm-based daily optimization.

```
N_gen = number of generations (= 40);
N_ind = number of individuals (= 20);
N_day = number of days (= 31);
for day = 1 to N_day do
    if weekdays then
        for generation = 1 to N_gen do
            for individual = 1 to N_ind do
                set zone temperature setpoint schedule to EnergyPlus;
                run EnergyPlus simulation;
                for every simulation timestep t (hourly) do
                    if t ≥ 8 and t ≤ 19 then
                        if hvac control resolution == zone then
                            MODE_ceilingfan,t = off;
                        else
                            for every ceiling fan do
                                MODE_ceilingfan,t = argmax(N_nochange,t);
                            end
                        end
                    end
                    OBJ_comfort = sum(N_nochange,t)/sum(N_occupant,t);
                    OBJ_energy = sum(E_plant,t + E_AHUfan,t + E_ceilingfan,t);
                end
            end
            if generation == N_gen or change in average fitness < 1e-5 then
                break generation loop;
            else
                select, recombine, and mutate individuals for next generation;
            end
        end
    end
end
```

2.4. Case study

2.4.1. Building description

To quantify the effects that different thermal comfort modeling resolutions might have on the building's performance in the tropics, an EnergyPlus model that is representative of a large office building in Singapore is utilized. The model was developed by Duarte et al. [10] based on the Green Mark Scheme (Singapore's green building rating standard) in consultation with Singapore's Building and Construction Authority (BCA) and a consulting firm.

The reference model has a total floor area of 28,000 m^2 with 20 floors. The first three floors were modeled as car parks and the upper floors as open-plan offices. Each office floor was divided into four perimeter thermal zones, a core thermal zone, a staircase, and a restroom. Internal mass objects were defined to account for the thermal mass effects in interior zones. The cooling system consists of a water-cooled chilled water plant serving an air-handling unit at each floor. VAV terminals with no reheat were used at the zone level. All the main HVAC components, including the chiller, pumps, cooling coils, were properly sized based on the requirements of Singapore's green building standard and common industry practices.

For the optimization, we target an interior zone in the middle floor as shown in Figure 5. The interior zone is more suitable for the target zone than perimeter zones since the thermal comfort dataset used for thermal comfort modeling was collected without the impact of radiant environment (i.e., air temperature = radiant temperature). In addition, the conclusion would not be affected by the number of interior zones simulated in the optimization because they have the same operational conditions except the airflow interchange with the adjacent perimeter zones.

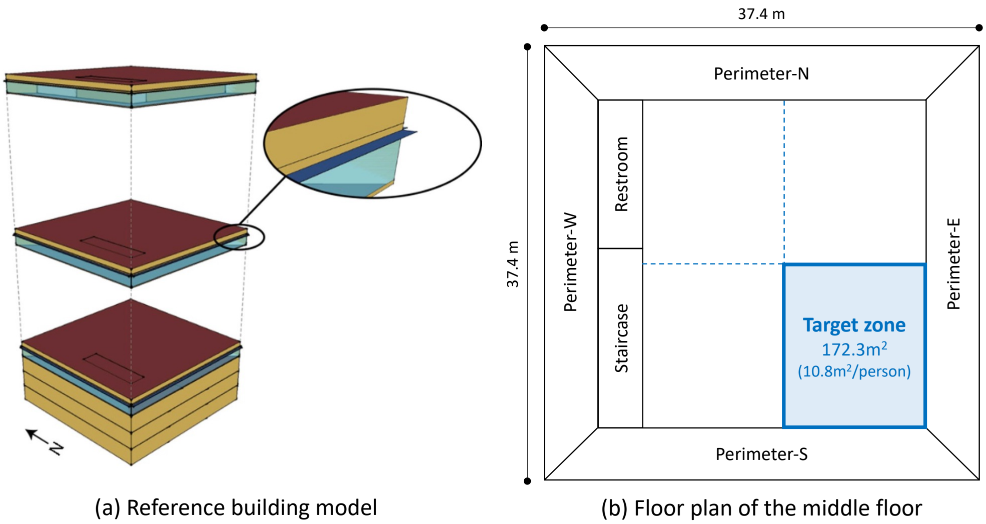


Figure 5: Reference building model [10] and target zone for optimization. The target zone is a quarter of interior zone at the middle floor.

2.4.2. Virtual experiments

Nine different combinations of thermal comfort modeling and HVAC control resolutions were evaluated (Figure 1) with the two types of comfort metrics (i.e., considering only thermal preference and both thermal and air movement preferences). The ranges of zone air temperature setpoint are differently set to 22–26°C for zone control and 24–28°C for group and personal controls to reduce the computation time because most occupants want "cooler" or "warmer" in thermal and air movement preference beyond the ranges according to the experimental data and the linear regression models.

Since we only optimize a part of the entire building, the plant and AHU fan energy consumption for the target zone is calculated following equations 5 and 6.

$$E_{plant\_zone,t} = E_{plant,t} \frac{Q_{zone,t}}{Q_{building,t}} \tag{5}$$

$$E_{AHUfan\_zone,t} = E_{AHUfan,t} \frac{V_{zone,t}}{V_{AHU,t}} \tag{6}$$

where

$E_{AHUfan,t}$	: AHU fan energy consumption
$E_{plant,t}$	: Plant energy consumption for the entire building
$Q_{building,t}$	: Cooling coil load for the entire building
$Q_{zone,t}$	: Cooling coil load for the target zone
$V_{AHU,t}$	: Supply air flow for the AHU
$V_{zone,t}$	: VAV air flow for the target zone

In addition, zone air temperature setpoints of the other zones are also changed according to the target zone's setpoints to eliminate the influence of the heat flux from the adjacent zones. For the simulation period, October is selected as the representative month since it is the nearest to the annual statistics in terms of the daily mean dry-bulb temperature and daily accumulative solar radiation based on the EPW weather data for Singapore.

3. Results

3.1. Linearity of thermal comfort models

Table 3 summarizes the linear regression results for thermal comfort models. The medians of root-mean-square errors (RMSE), which is calculated for each occupant, are around 0.5, demonstrating the model's capability to predict each occupant's thermal preference on a 5-point scale. In addition, p-values for T_a were mostly less than 0.01, while those for v_a and $T_a v_a$ were rarely less than 0.05. Only for occupant #10 and #11, T_a did not show the significance, indicating that they can be insensitive to the ambient temperature. Interestingly, even for the AMP model, T_a was more significant than v_a and $T_a v_a$, showing that the occupants can be more sensitive to the ambient temperature than the air movement in terms of air movement preference. In contrast, v_a and $T_a v_a$ were significant for some occupants, suggesting that these occupants can be sensitive to changes in air movement. Normality and homoscedasticity were also checked by observing fitted value-residual value and Q-Q plots.

Table 3
Summary of linear regression results including adjusted R^2, RMSE and p-value of coefficients.

Occupant #	Thermal preference model					Air movement preference model				
	Adjusted R^2	RMSE	p-value of coefficients[a]			Adjusted R^2	RMSE	p-value of coefficients[a]		
			T_a	v_a	$T_a v_a$			T_a	v_a	$T_a v_a$
1	0.736	0.390	**	-	-	0.739	0.380	**	-	-
2	0.731	0.505	**	-	-	0.793	0.488	**	-	*
3	0.753	0.474	**	-	-	0.695	0.492	**	-	*
4	0.573	0.483	**	-	-	0.652	0.460	**	-	-
5	0.721	0.541	**	**	*	0.855	0.356	**	-	-
6	0.543	0.622	**	-	-	0.657	0.506	*	**	**
7	0.481	0.540	**	-	-	0.554	0.574	**	-	-
8	0.585	0.589	**	-	-	0.627	0.533	**	-	*
9	0.579	0.404	**	-	-	0.642	0.447	**	-	-
10	0.207	0.319	-	-	-	0.221	0.363	-	**	**
11	0.663	0.491	-	**	*	0.732	0.412	-	**	*
12	0.514	0.689	*	-	-	0.724	0.497	**	-	-
13	0.206	0.541	*	-	-	0.468	0.475	*	-	-
14	0.782	0.499	**	-	-	0.829	0.518	**	-	-
15	0.800	0.499	**	**	*	0.732	0.448	**	-	-
16	0.705	0.665	**	*	-	0.657	0.524	**	-	-
Median	0.624	0.502	NA	NA	NA	0.676	0.482	NA	NA	NA

[a] **: < 0.01, *: < 0.05, -: ≥ 0.05

Figure 6 illustrates the areas where $|TP| \leq 0.5$ and/or $|AMP| \leq 0.5$ against air temperature (x-axis) and air velocity (y-axis). As can be seen in this figure, the areas are significantly different between individuals. For instance, occupant #6 prefers cool and breezy conditions, while #2 prefers warm and less breezy conditions. There are also "no preference" occupants like #10 and #13 who have low adjusted R^2 with the models (see Table 3). Figure 7 shows the number of occupants voting "no change" in thermal and/or air movement preference when the 16 occupants share the same thermal condition. It can be observed that the number rarely reaches 15 (94%), but the area where the number is equal to or greater than 13 (81%) is not narrow when only considering thermal preference or air movement preference. On the other hand, when considering thermal and air movement preference, the number is mostly equal to or less than 12 (75%), meaning that it is hard for zone control to provide the thermal condition where more than 75% of occupants vote "no change" in thermal and air movement preferences.

3.2. Significance of air movement preference

Before a detailed analysis of the optimization results, the significance of air movement preference on the occupants voting "no change" was evaluated. Figure 8 shows the comparison of the percentages indicating "no change" between the optimization results that considered only thermal preference and both thermal and air movement preference during optimization. As can be seen in this figure, when considering only thermal preference, the percentage for air movement preference was lower than that for thermal preference. This is because the optimal solutions tended to minimize energy

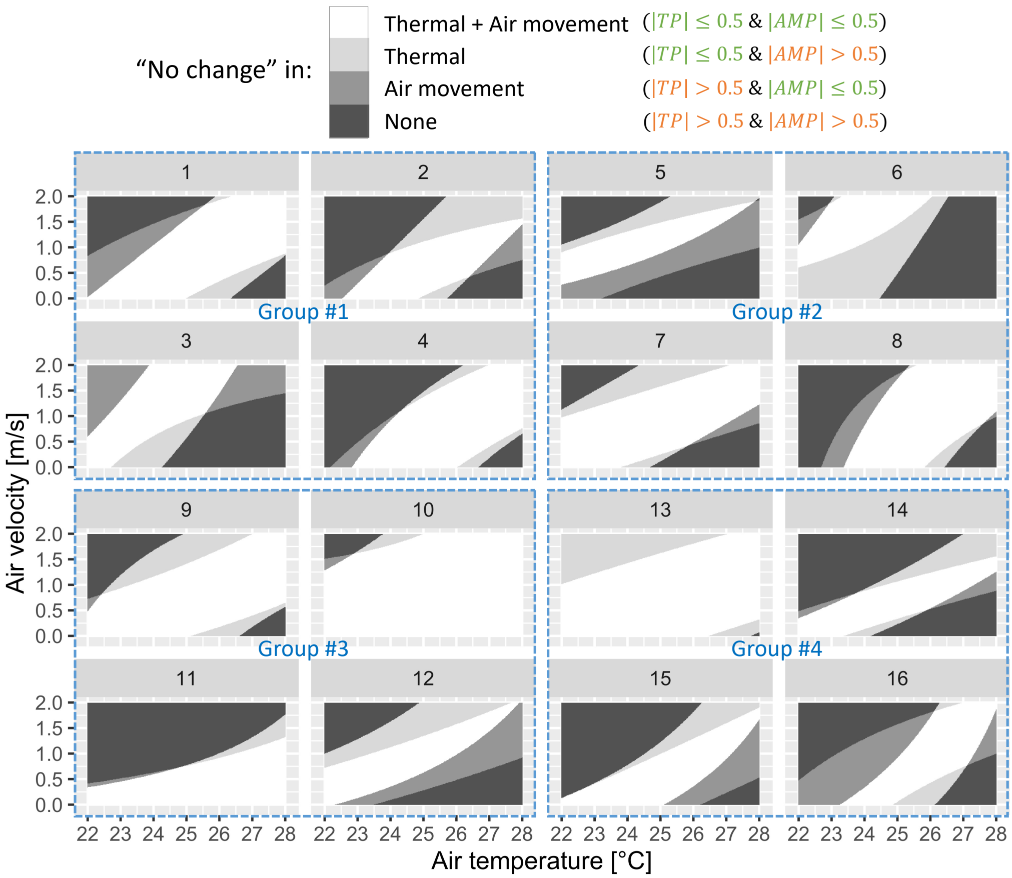


Figure 6: The areas where $|TP| \leq 0.5$ and/or $|AMP| \leq 0.5$ for 16 occupants calculated by the linear regression models. The grey color scale indicates that the occupant feels "no change" in both, either, and neither of thermal preference and air movement preference.

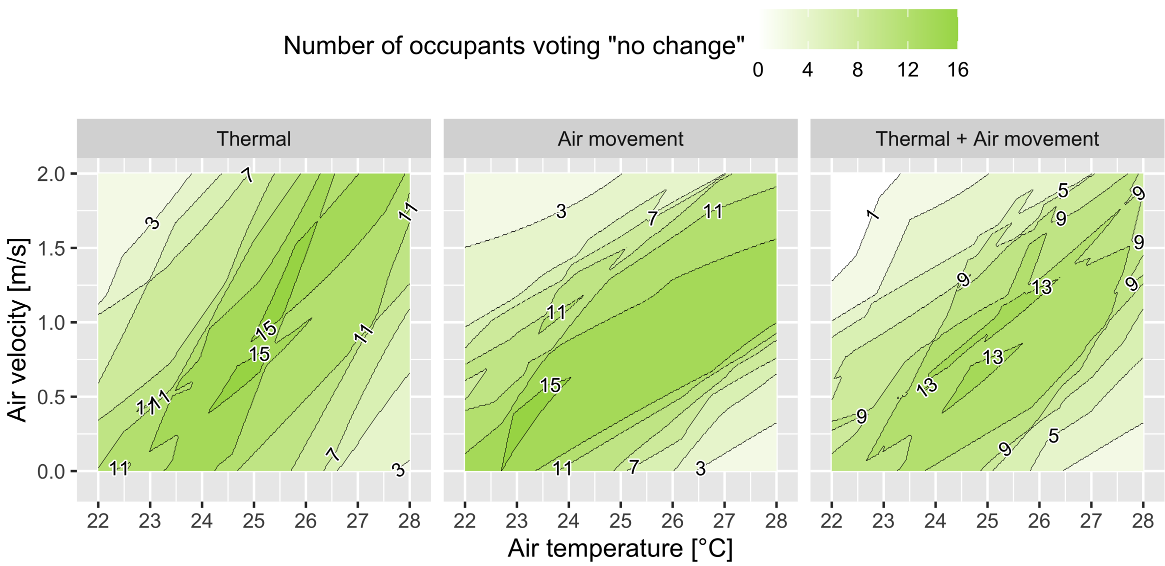


Figure 7: Number of occupants voting "no change" in thermal and/or air movement preference.

consumption by setting the zone temperature setpoint to the maximum possible and offsetting any thermal discomfort with high air speed. Consequently, air movement preference tends to be compromised. Not surprisingly, when both thermal and air movement preferences were considered during the optimization, the optimal solutions saw 18% and 32% improvement in air movement preference for group and personal controls, respectively.

For zone control, considering air movement preference as a metric slightly improved the percentage indicating "no change" in air movement preference, although there is no ceiling fan for zone control. This is because the air movement preference is strongly correlated with the air temperature (see Table 3), and the algorithm tried to find a best temperature to satisfy both thermal and air movement preferences without air movement. Thus, considering air movement preference for zone controls without elevated air movement is less significant than group and personal controls with elevated air movement, but still meaningful.

It is worth noting that the improvement in air movement preference increases as the occupancy resolution of HVAC controls increases (i.e., from zone through group to personal control), as can be seen in Figure 8. This can be attributed to what the areas where $|TP| \leq 0.5$ and/or $|AMP| \leq 0.5$ look like (Figure 6). Most occupants (#1, 2, 3, 4, 6, 7, 8, 9, 13, 14, and 16) have the area where $|TP| \leq 0.5$ but $|AMP| > 0.5$ at the bottom right (i.e., high temperature and low velocity). Therefore, when adjusting the thermal condition to satisfy only thermal preference with smaller energy consumption, air movement preference tends to be compromised with a high chance by personal control. On the other hand, group control tends to adjust the thermal conditions to the center, where most occupants feel "no change" in thermal and air movement preference when sharing the same thermal condition (Figure 7), rather than the bottom right, resulting in the slight improvement in air movement preference. This indicates that it could be more beneficial for HVAC controls with a higher occupancy resolution to consider air movement preference since they could have a higher risk of compromising air movement preference when considering only thermal preference.

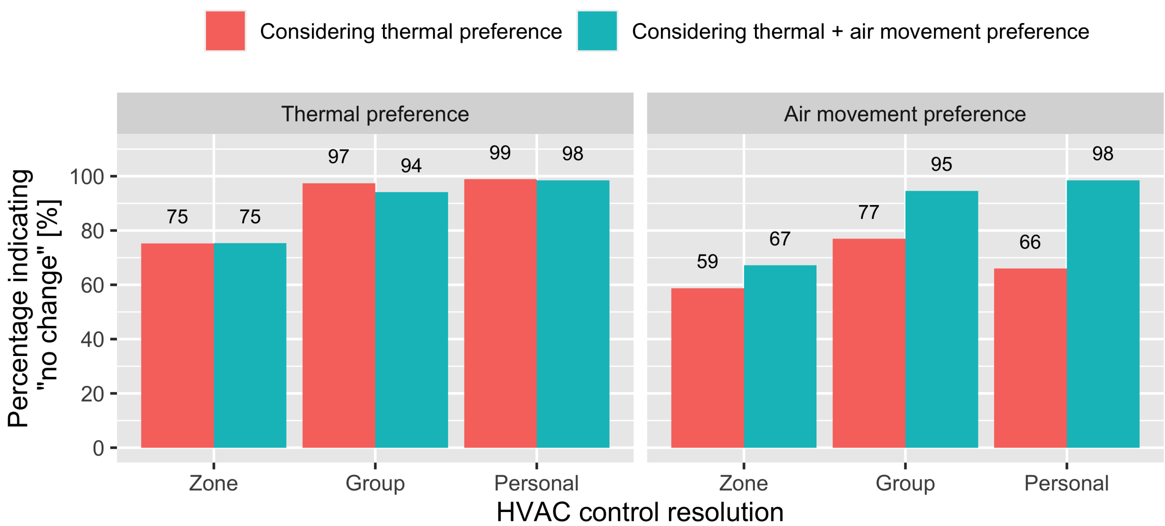


Figure 8: Comparison of the percentages indicating "no change" in thermal and air movement preference between considering only thermal preference and both thermal and air movement preference as a metric. Each bar indicates a representative solution with similar energy consumption for zone, group, and personal control with personal comfort model.

3.3. Comparison between different combinations of occupancy resolutions

Figure 9 plots the relationship between the two objectives (i.e., energy consumption and the percentage indicating "no change" in thermal and air movement preferences) for the Pareto fronts of each combination of the resolutions considering both thermal and air movement preferences during optimization. It can be observed that personal and group controls have higher percentages indicating "no change" with smaller energy consumption than zone control. This is because the elevated air movement by ceiling fans can increase the percentage indicating "no change," while the cooling load can be reduced by increasing the zone air temperature. As shown in Figure 10, the medians of zone air temperature for zone control were around 24°C, while those for the other two controls were 25–26°C.

Comparing group and personal controls, personal control with personal comfort model outperformed the other cases, while personal control with the other comfort models consumed larger energy than group control with the same models. This is because personal control consumes more energy for the larger number of ceiling fans. The ceiling fan energy was 7.6 kWh (1.4% of the total) for group control with group comfort model (i.e., the red triangle in Figure 9) and 20.3 kWh (3.9% of the total) for personal control with group comfort model (i.e., the red square in Figure 9). It was not significant but not negligible when comparing group and personal controls.

In addition, the percentage indicating "no change" for zone control was more sensitive to the energy consumption than the other controls. This is because the increase in the percentage indicating "no change" can be achieved only by lowering the zone air temperature for zone control. By contrast, group and personal controls have two operational variables, i.e., zone air temperature and group/personal devices (ceiling fans in this study). The difference in the operational variables also seemed to affect the spread of energy consumption. The spread of group and personal controls was larger than zone control. This is mainly because group and personal controls could have a broader range of zone temperature, especially to the higher side, since thermal conditions giving the same SET* can be realized by various combinations of air temperature and air speed.

The percentages indicating "no change" significantly differed between comfort modeling resolutions at the same control resolution for group and personal controls. This means that it is hard for a lower comfort modeling resolution to achieve the same percentage as a higher comfort modeling resolution. Thus, when comparing one objective at the same level of the other objective, the percentage indicating "no change" is easy to compare, but the energy consumption is difficult. Assuming a threshold of the percentage indicating "no change" as 80%, group or personal control with group or personal comfort model saved more than 10% energy than zone comfort model. This can be a potential loss in energy-saving performance caused by the mismatch between a higher control resolution and a lower comfort modeling resolution. Similarly, potential losses in the percentage indicating "no change" are mainly discussed in the rest of this subsection.

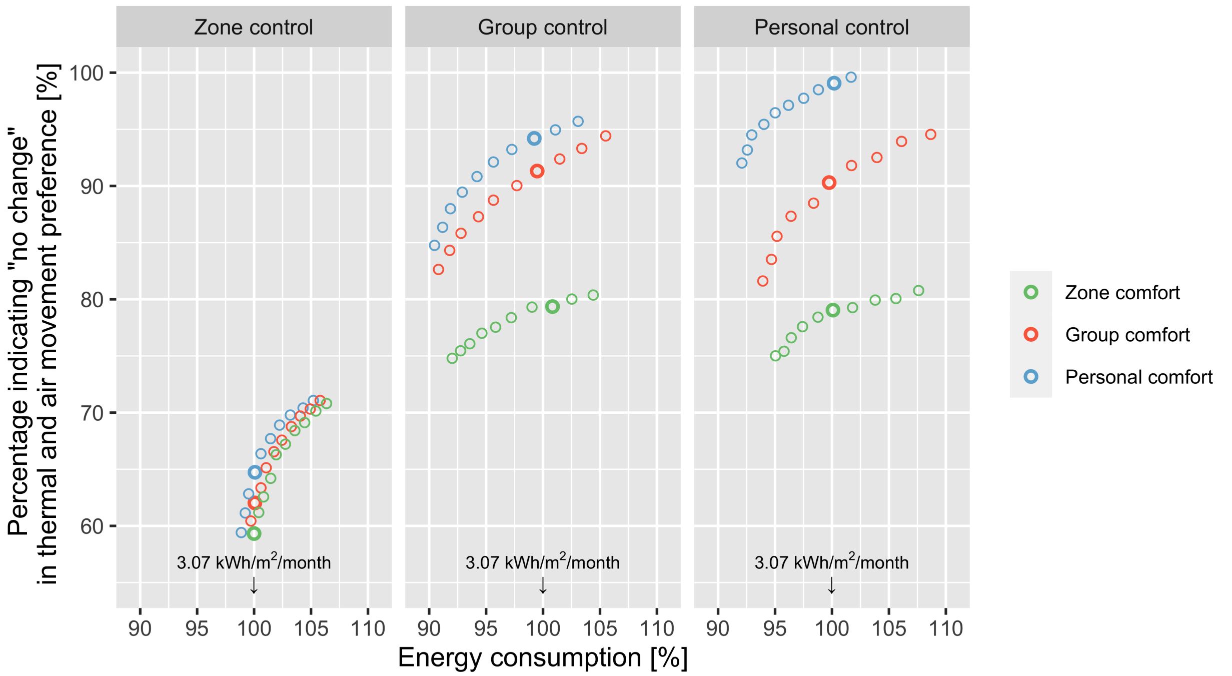


Figure 9: The relationship between energy consumption and percentage indicating "no change" in thermal and air movement preference for the Pareto fronts. X axis is the percentage to the minimum energy consumption among zone control-zone comfort model cases (i.e., the bold green circle in zone control).

Figure 11 illustrates the same results as Figure 9 in a different manner. This figure shows the relative values to the minimum energy solution of zone control cases. In this figure, we can see the relative difference between comfort modeling resolutions more directly. By using comfort models with a higher resolution for zone control, there was not much improvement in the percentage indicating "no change", mostly less than 5%. On the other hand, the percentages for group and personal controls improved by more than 10%. This makes sense because higher control resolutions

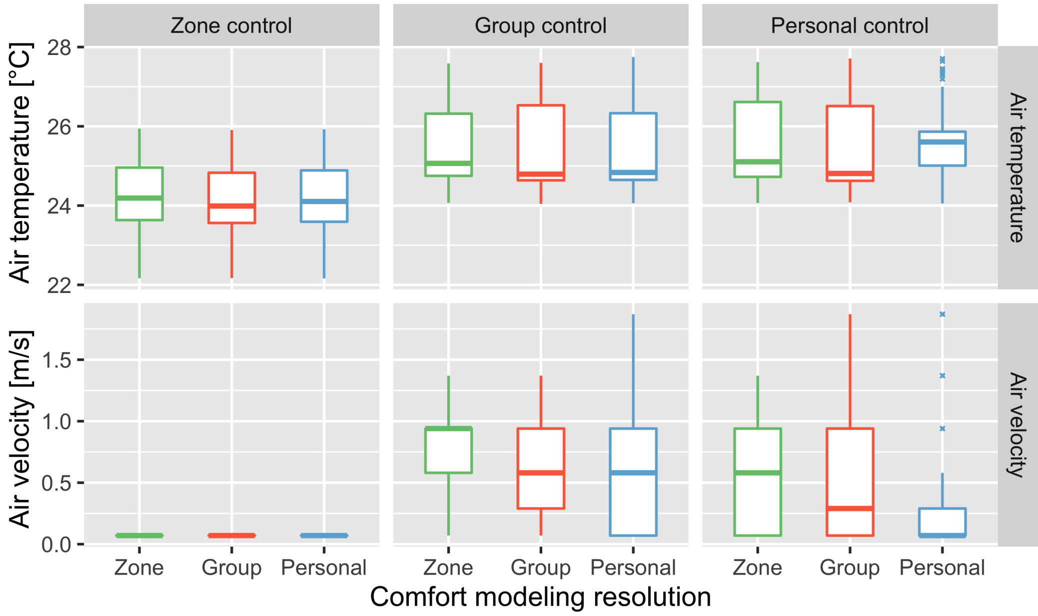


Figure 10: Boxplot of zone air temperature and velocity for representative solutions which are the nearest to the 100% energy consumption shown in Figure 9 (i.e., the bold points).

can potentially provide more preferable thermal conditions when combining comfort models with a higher resolution. However, the improvement from group to personal comfort model for group control, less than 5%, was smaller than the others. These results imply that a mismatch between a higher comfort modeling resolution and lower control resolution can result in less improvement in occupants voting "no change."

As can be seen in Figure 10, the thermal conditions are significantly different among the comfort modeling resolutions, especially for air velocity. For the personal control with personal comfort model, the interquartile ranges of air temperature and air velocity were lower and narrower than the other group and personal control cases. This is mainly because the zone temperature was lowered to satisfy the preference of some occupants who prefer cooler conditions, like occupant #6 (see Figure 6), while the other occupants wanted less air movement at the cooler conditions. Another reason for the lower air velocity is that the ceiling fans of individuals who were not present in the space were turned off like occupancy-based controls for personal control.

Figure 12 illustrates the occurrence of air temperature and air velocity for four individuals belonging to ceiling fan group #2 (occupant #5–8). The size of the circles indicates the number of hours that the occupant was exposed to the thermal condition (combination of air temperature and velocity) during the optimization period (i.e., for a month). For zone and group comfort models, the circles of four occupants correspond with each other since they shared the same thermal condition except for the hours when the occupant was not present. Optimal thermal conditions should be the bottom right (higher temperature and lower air velocity) in the white area ("no change" in thermal and air movement preference) since the objective functions are to minimize energy consumption and maximize the percentage indicating "no change". However, the difference in individual preferences makes it difficult for HVAC controls to find the best condition for the four occupants. When comparing the individual preferences in group #2, occupant #5 and #6 have the narrower areas satisfying both thermal and air movement preferences (i.e., white-colored areas in Figure 12) at relatively cooler and breezier conditions. In contrast, occupant #7 and #8 have the wider white areas. Therefore, as zone comfort model aggregates all the 16 occupants and is not specific to the group, using zone comfort model resulted in many occurrences outside the white areas for occupant #5 and #6 for both group and personal controls.

On the other hand, using group and personal comfort models allowed the thermal conditions to be more adjusted to the individual preferences of the occupants of group #2. However, regarding group control, the thermal conditions of group comfort model and personal comfort model almost overlapped, meaning that using personal comfort model did not much improve the percentage indicating "no change." This is because group control cannot adjust air temperature and velocity to the preferred conditions individually, even when the individual preferences are known from personal comfort models. Consequently, for group control, the improvement in the percentage indicating "no change" from group to personal comfort model was much smaller than that from zone to group comfort model, as can be seen in Figure 11. This can be a mismatch between a higher comfort modeling resolution and a lower control resolution.

For personal control, although thermal conditions can be individually controlled, using zone and group comfort models led to many occurrences outside the white areas for occupant #5 and #6. Of course, the thermal conditions for the four occupants were the same excluding their absent hours since the comfort models do not have "individual" resolutions. This can be considered as a mismatch between a lower comfort modeling resolution and a higher control resolution. In contrast, using personal comfort model allowed the thermal conditions to be almost controlled within the white areas, leading to much improvement in the percentage indicating "no change" even from group to personal comfort model as observed in Figure 11.

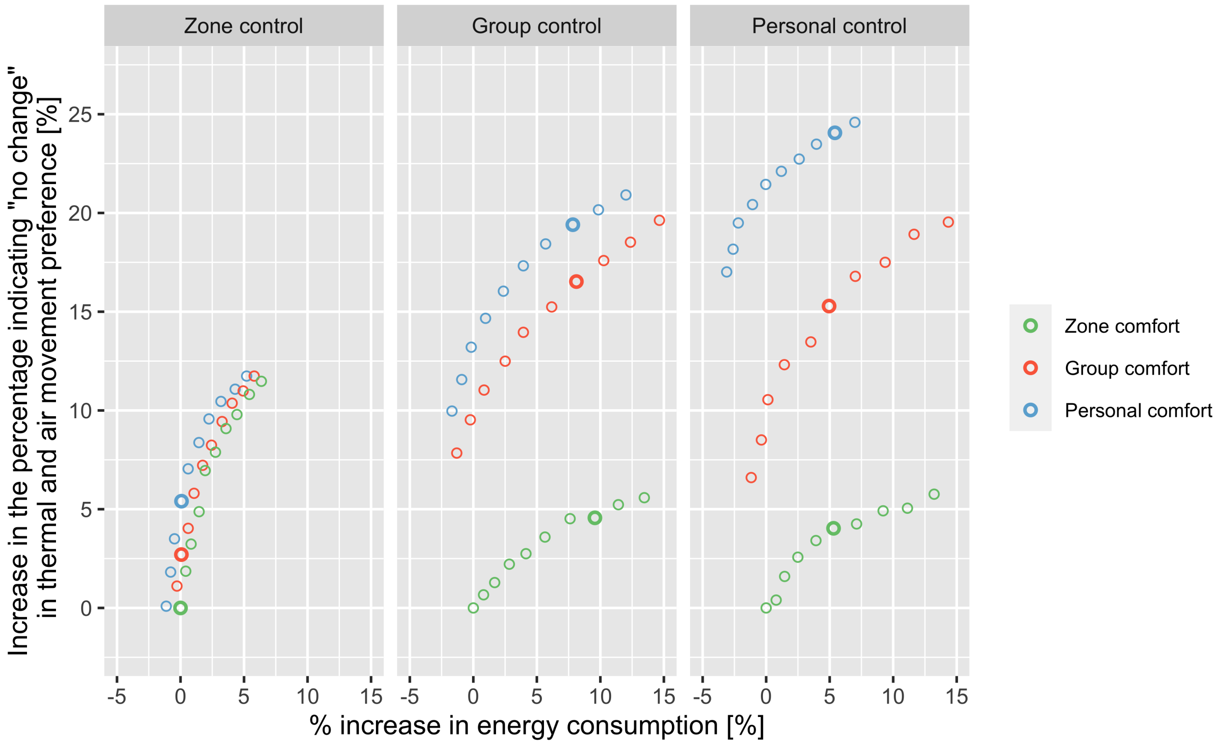
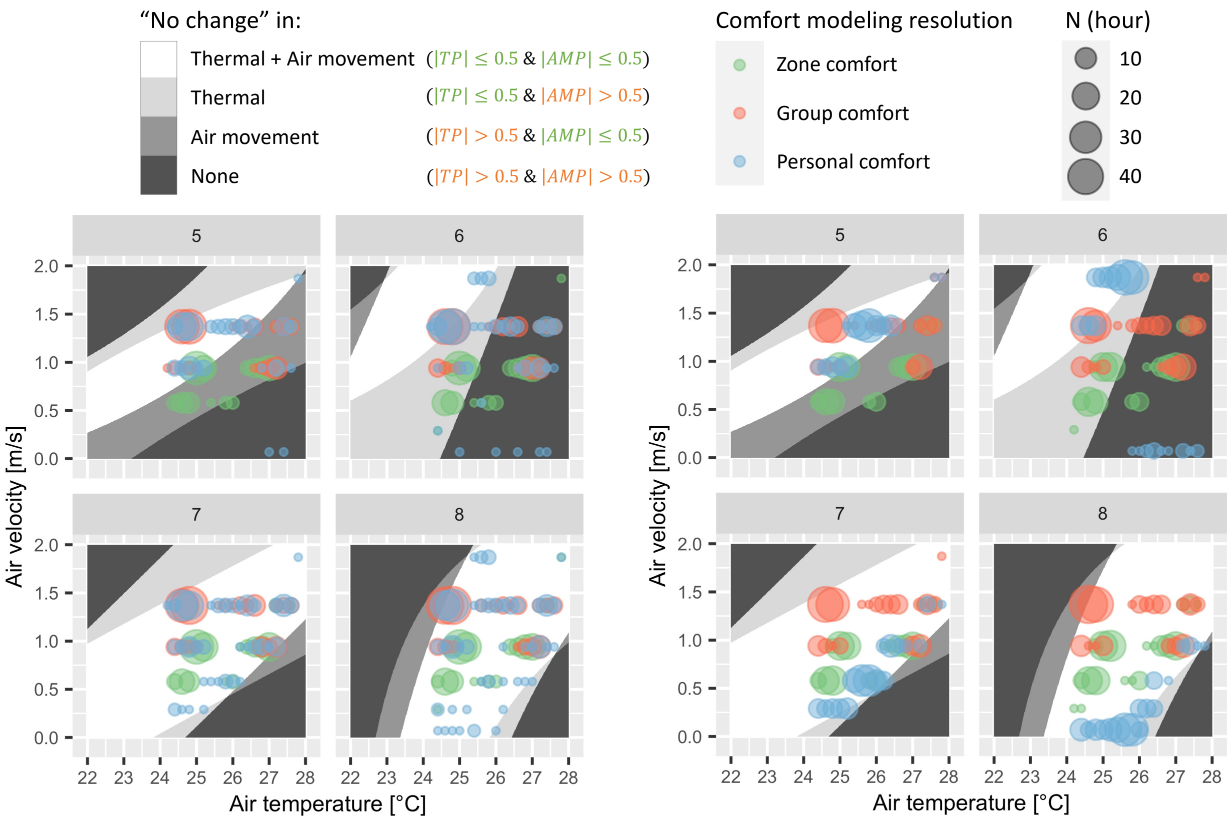


Figure 11: The relationship between % increase in energy consumption and increase in the percentage indicating "no change" in thermal and air movement preference.

4. Discussion

4.1. Potential loss caused by mismatch of occupancy resolutions

The most significant finding of this study is that a mismatch between the occupancy resolutions of thermal comfort models and HVAC controls can result in less improvement in the energy savings and occupants voting "no change" in thermal and air movement preference by a comfort-driven occupant-centric control. In other words, it is crucial to select a comfort model with an appropriate occupancy resolution according to the occupancy resolution of HVAC controls. Otherwise, a mismatch might result in a "potential loss" of the benefits of using finer HVAC controls and finer thermal comfort models. As discussed in subsection 3.3, when the occupancy resolution of comfort models is higher than HVAC controls (e.g., group control with personal comfort model), the control cannot adjust the thermal conditions to the preferred areas even though the occupants' preferences are known at a higher resolution. The improvement in the percentage indicating "no change" from zone to group comfort model for zone control was less than 3%, which was 8% smaller than those for group and personal controls when comparing the bold points in Figure 9. Similarly, the improvements from group to personal comfort model for zone and group controls were around 3%, which was



(a) Group control

(b) Personal control

Figure 12: The occurrence of air temperature and air velocity plotted on the areas indicating "no change" in thermal and air movement preference (see Figure 6) for ceiling fan group #2 (occupant #5–8). For the occurrence count, X axis is discretized by 0.2°C. Each graph illustrates how the thermal conditions were adjusted to meet the objective functions using comfort models with different resolutions.

6% smaller than that of personal control. This implies that a mismatch between lower control resolution and higher comfort modeling resolution can result in a 6–8% potential loss of the benefit of using finer comfort models.

On the other hand, when the occupancy resolution of comfort models is lower than that of HVAC controls (e.g., personal control with group comfort model), the thermal conditions are similarly controlled in the control zone, although the HVAC system is able to control the thermal condition individually. The percentage indicating "no change" of personal control with group comfort model was 9% lower than personal control with personal comfort model. Similarly, the percentage of group control with zone comfort model was 12% lower than group control with group comfort model. Moreover, the energy consumption of group or personal control with zone comfort model was more than 10% larger than group or personal comfort model. This implies that a mismatch between higher control resolution and lower comfort modeling resolution can result in a 9–12% potential loss of the benefit of using finer HVAC controls.

Although the above finding was derived from only a case study using a VAV system with ceiling fans, there is likely a similar relationship between comfort modeling and control resolutions even for different conditions in terms of climates, buildings, and systems. This is because the benefits of comfort models with higher resolutions seem to depend on the variance of individual preferences in a zone. The variance could be different between climates and buildings, but it can be true for any conditions that the variance would be higher when the occupancy resolution of HVAC controls becomes lower. For instance, Jung and Jazizadeh [17] reported a similar finding about the potential loss when combining a lower control resolution with a higher comfort modeling resolution. Their study showed that the improvement in thermal comfort with four occupants in a zone was 5–8% lower than that with two occupants by using personal comfort models. Similarly, the improvement with eighteen occupants was 3–7% lower than with four occupants. These are consistent with our results, although they used a different thermal comfort dataset and a different setup for the HVAC system that only controlled zone air temperature.

Additionally, Gunay et al. [12] and Hobson et al. [13] reported a similar mismatch between the occupancy resolutions of occupancy data and HVAC controls. Their studies indicated the importance of selecting suitable occupancy resolutions for occupancy data and HVAC controls to ensure the operational performance of occupancy-based occupant-centric controls. This suggests that occupant-centric controls need to be cautiously designed by considering the occupancy resolutions of inputs (e.g., occupancy data and occupants' feedback), control devices (e.g., HVAC and lighting), and metrics (e.g., thermal comfort modeling).

4.2. Thermal comfort models aggregating people

A conclusion that there can be a mismatch between zone control and personal comfort model seems to contradict the results of past studies, which have reported significant energy savings and thermal comfort improvements by using subjective feedback and thermal comfort models to determine an optimal zone temperature setpoint [6, 22, 43, 5]. However, they mostly used predetermined-setpoint controls or PMV-based controls as a baseline for the performance evaluation. In contrast, even zone comfort model, which was used as a baseline in this study, is a data-driven model targeting specific people occupying the zone. Thus, the thermal conditions can be optimized to meet the preferences of the specific people, unlike predetermined-setpoint controls and PMV-based controls, resulting in less improvements in occupants voting "no change" for group and personal comfort models at first glance. This implies that it could be sufficient to collect zone-level comfort data without individual labels and develop a thermal comfort model aggregating the occupants for optimizing zone control. In fact, studies have shown that a zone-level comfort profile and clustering model can successfully work for comfort-driven occupant-centric controls [11, 20].

From the optimization results, the percentage indicating "no change" for one-third (i.e., #3, 5, 6, 11, and 12) of the individuals were improved by the comfort models with a higher resolution, while those for the others were almost constant at 100% even with zone comfort models (Figure 13). Although only the percentages for thermal preference are shown here, similar results were observed for air movement preference. The one-third of individuals whose percentages indicating "no change" were improved have cooler preferences or narrow comfort zones (Figure 6). This suggests that aggregating people into zone or group comfort models by zone or group comfort profiles [11, 42] or clustering based on their preferences [21, 14, 31] could be an effective way to reduce efforts in data acquisition. For the occupants used in this study, two-thirds of them can be aggregated into a zone comfort model.

4.3. Importance of considering air movement preference

Another finding is that air movement preference plays an important role in a comfort-driven occupant-centric control, especially for elevated air movement systems with a higher control resolution. Although there are some studies that optimized the operation of an HVAC system with ceiling fans, they used the PMV model or thermal preference as a comfort metric, thus not considering individual air movement preference [36, 24]. Instead, they limited the operation of ceiling fans by linearly changing air speed within a range based on air temperature [36] and only controlling the on/off states [24] without exploring optimal air speed at each time step. The results of this study showed that the zone air temperature was mostly within a range of 25–26°C for personal control with personal comfort model (Figure 10), even though the zone air temperature can be more increased when only considering thermal preference. This implies that there is a comfortable range of air speed for each individual, although occupants in office buildings want more air movement [39, 8]. These results are in agreement with the finding by Schiavon et al. [34], which showed that 26°C with fans was the most comfortable condition for tropically acclimatized persons.

Moreover, our results indicate that the importance of air movement preference increases as the occupancy resolution of HVAC controls increases. The potential loss of the percentage indicating "no change" in air movement preference by not considering air movement preference during optimization was 8%, 18%, and 32% for zone, group, and personal control, respectively (Figure 8). This highlights the significance of incorporating air movement preference as well as thermal preference into occupant-centric controls with a higher occupancy resolution as metrics by a data-driven approach. In practice, individual occupant preference data can be collected using surveys and wearable devices [6, 22, 18, 14]. Thermal comfort models can then be developed based on the collected data considering the occupancy resolutions with the framework shown in Figure 1 and utilized to determine optimal setpoints by optimal control algorithms such as rule-based control [30], model predictive control [6, 20], and reinforcement learning-based control [41].

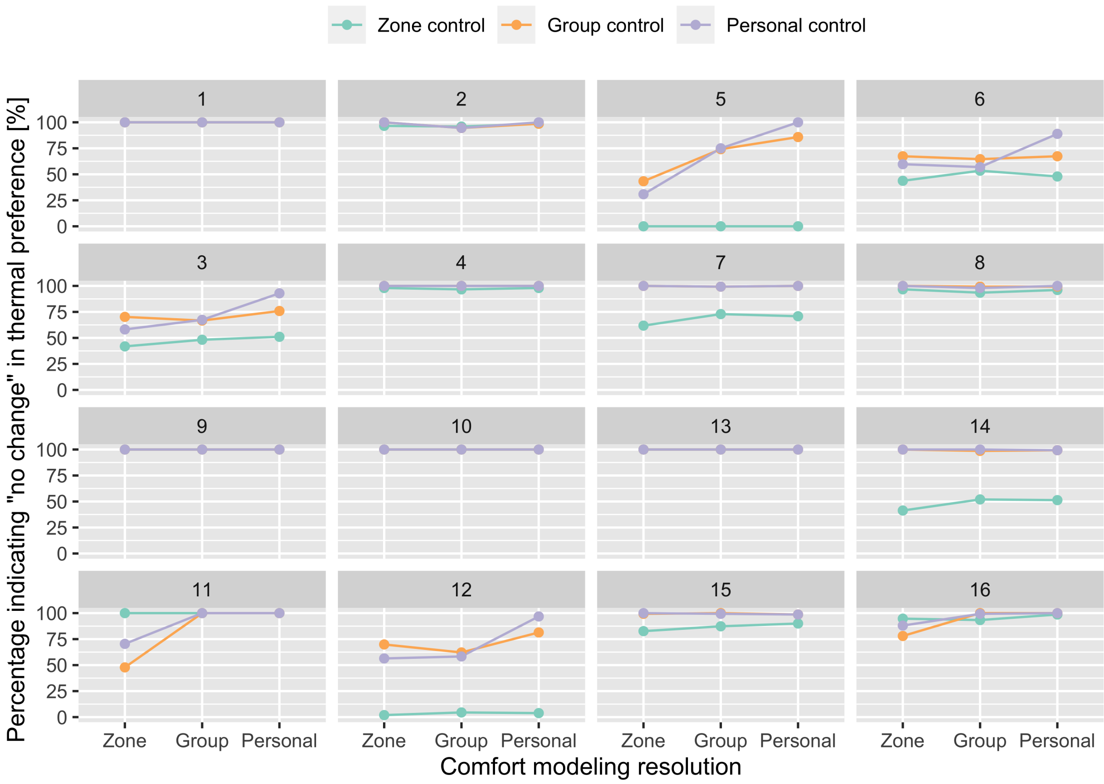


Figure 13: Percentage indicating "no change" in thermal preference for each occupant. The figure demonstrates how thermal comfort models with a higher occupancy resolution increased the percentage for each occupant.

5. Conclusion

This study was designed to evaluate different combinations of occupancy resolutions for HVAC controls and thermal comfort models to investigate the effects of mismatch between the occupancy resolutions. We conducted a simulation-based optimization study using data-driven personal comfort models to reflect individual thermal and air movement preferences. One of the significant findings is that a mismatch between the occupancy resolutions of HVAC controls and thermal comfort models can result in less improvements in energy savings and occupants voting "no change" by a comfort-driven occupant-centric control. This kind of potential loss can occur in both situations where control resolution is higher/lower than comfort modeling resolution because one with a lower resolution cannot fully exploit the capability of the other with a higher resolution. The results indicate that a mismatch can cause a 6–12% decrease in occupants voting "no change" in thermal and air movement preference. Moreover, energy savings can be increased by more than 10% when considering a suitable comfort model for the HVAC control. This implies the importance of selecting a comfort model with an appropriate occupancy resolution according to the occupancy resolution of HVAC controls. In addition, aggregating people into zone or group comfort models by zone or group comfort profiles or clustering can effectively reduce data acquisition costs for zone and group control. The results suggest that two-thirds of occupants can be aggregated into a zone comfort model. Another significant finding is that it is crucial to consider air movement preference as well as thermal preference, especially for elevated air movement systems with a higher occupancy resolution. This is because as the control resolution increases, the risk of compromising air movement preference could increase when only considering thermal preference. Without considering air movement preference during optimization, the percentage indicating "no change" in air movement preference can be potentially reduced by 8%, 18%, and 32% for zone, group, and personal control, respectively. These findings would be a basis to select a fit-for-purpose thermal comfort model for the HVAC controls that contribute to the improvement in building performance from an occupant-centric perspective.

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CRediT authorship contribution statement

Eikichi Ono: Conceptualization, Methodology, Formal analysis, Investigation, Visualization, Writing - original draft, Writing - review & editing. **Kuniaki Mihara:** Methodology, Data curation, Writing - review & editing. **Khee Poh Lam:** Writing - review & editing. **Adrian Chong:** Conceptualization, Methodology, Writing - review & editing, Supervision, Project administration, Funding acquisition.

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