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Research article

# Classification of thermal environment control indicators according to the thermal sensitivity of office occupants

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ABSTRACT

The control that have the greatest influence on comfortable in the office occupants are the heating, ventilation, and air conditioning (HVAC) system operation and the thermal environment. However, comfortable HVAC operation is difficult in the office space characterized by a recommended standard thermal environment or a centralized HVAC system. To consider the occupant's thermal comfort to the greatest possible extent, must establish a method to quantify the variables related to the occupant's thermal comfort. This study aims to group occupants in Thermal sensation vote (TSV) clusters and perform sensitivity analysis (SA) on the relationship between thermal environmental factors in an office building and each cluster's TSV to establish the typology of the control indicators for each cluster. A total of 10 field experiments were conducted in the same office. This field study was carried out 2022. The indoor thermal environmental parameters, the subjective evaluation of the thermal comfort of the resident and the operation pattern of the heating system were monitored at the same time. A total of 4,200 datasets related to indoor thermal environmental parameters and a total of 1,680 datasets related to occupants' thermal comfort were collected and analyzed. The results of this study show that people have different levels of adaptability and sensitivity to a given thermal environment. This study founded distinguishable similarities in their thermal sensation traits and grouped similar TSV values into five clusters that responded differently to the same thermal environment. Each cluster showed different TSV and Thermal comfort vote (TCV) patterns, which allowed us to classify the groups that had sensitive responses to the thermal environment and those that did not. This study was determined different control indicators and guidelines for the divided groups according to thermal sensitivity.

## 1. Introduction

In the thermal comfort model, developed by Fanger [1], the term thermal comfort is defined as a "a state of mind in which satisfaction is expressed with the thermal environment" [2]. Thermal comfort is widely recognized as one of the main features requiring consideration in building design and operation [3,4]. Thermal comfort is highly correlated with the energy demand and consumption [5], as well as being strongly influenced by variables related to the indoor thermal environment and individual indicators. Occupants have a natural tendency to perform adaptive behaviors to maintain their thermal comfort, such as adjusting the

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**List of acronyms and abbreviations**

| | |
|---|---|
| TSV | Thermal sensation vote |
| TCV | Thermal comfort vote |
| ASHRAE | American; Society of Heating, Refrigerating, and Air-Conditioning Engineers |
| HVAC | Heating, ventilation, and air conditioning systems |
| ERVs | Energy Recovery Ventilation system |
| Clo | Clothing insulation |
| Met | Metabolic rate |
| BMI | Body mass index |
| SD | Standard deviation |
| T | Indoor air temperature (°C) |
| RH | Relative humidity (%) |
| PMV | Predicted mean vote |
| PPD | Predicted percentage of dissatisfied (%) |
| k-MEANS | k-means Cluster Analysis |
| SA (*SC*) | sensitivity analysis *(sensitivity coefficient)* |
| SRC (SRC/SRRC) | Regression coefficients/Standard regression coefficient |
| $SRRC_y$ | *Standard regression coefficient of y* |
| $\sigma_y$ | Standard deviation of y |
| $m_y$ | Mean of y |
| mTSV | Mean thermal sensation vote |
| mTCV | Mean thermal comfort vote |
| $\delta^2_{TSV}$ | Change in TSV (variance) |
| $\delta^2_{T}$ | Change in temperature (variance) |
| $\delta^2_{H}$ | Change in humidity |
| $\delta^2_{C}$ | Change in $CO_2$ |
| $\delta^2_{PMV}$ | Change in PMV |
| $\delta^2_{PPD}$ | Change in PPD |
| $\Delta OP$ | Change in output |
| $OP_{BC}$ | Output of base case |
| $\Delta IP$ | Change in input |
| $IP_{BC}$ | Input of base case |
| T.C–C | Thermal Cool Comfort |
| T.H–C | Thermal Hot Comfort |
| T.C–U | Thermal Cool Uncomfortable |
| T.H–U | Thermal Hot Uncomfortable |
| POBM–CSA | Personalized occupant behavior model with a cost sensitivity analysis |

HVAC system, curtains/blinds, or clothing; consuming hot or cold beverages; and opening/closing windows and doors [6–9].

The thermal environment of an office correlates not only with occupants' comfort, health, and safety, but also with their work efficiency [3,10,11]. The factors that have the greatest influence on work efficiency are the heating, ventilation, and air conditioning (HVAC) system operation and the thermal environment (44.1 %); therefore, personalized thermal control is crucial for improving work efficiency [12–14]. However, personalized HVAC operation is difficult in a shared office space characterized by a recommended standard thermal environment. In Korea, only non-autonomous environment is provided in large office buildings to save energy. This is referred to as centralized control in Korea. In such a centralized HVAC system, in which all occupants are exposed to the same thermal environment irrespective of individual thermal traits, some occupants may experience thermal comfort. The adaptive behavior of an office occupant is allowed to consuming beverages or adjusting their clothing but the occupant have limited to the control of HVAC system; maintaining an indoor thermal environment that can satisfy all occupants is therefore difficult. To consider the occupant's thermal comfort to the greatest possible extent, must establish a method to quantify the variables related to the occupant's thermal comfort. In other words, a method should be developed to alleviate the thermal comfort of office occupants [15].

Occupant thermal sensitivity analysis is a relatively new research field. Rupp [16] quantified occupant sensitivity to indoor temperature changes and investigated whether the thermal sensitivity depends on situational variables, including the building type, ventilation mode, outdoor climatic variables, and gender. Ryu [17] defined occupant indoor thermal sensitivity in Korean residential environments. Studies estimating occupant thermal comfort temperatures generally use thermal sensitivity analysis based on Griffith's method (regression analysis) [6,17–19].

However, previous studies have overlooked the complex relationship between the office thermal environment and the thermal comfort needs of individual occupants. The office thermal control system has limitations in satisfying individual thermal comfort requirements. Although the thermal comfort needs of each individual vary, there are common group-specific traits. Gauthier [20] clustered office occupants according to their thermal sensation votes (TSV) and defined the characteristics of each TSV cluster. Based on this analysis, this study was clustering according to individual office occupant TSV [16], defining each cluster of occupants sharing common traits as an analysis unit.

Sensitivity analysis (SA) can be used to address this problem. SA is a method generally used to quantitatively compare the changes in the output value according to changes in the input variables, which enables an evaluation of the degree of influence and relative importance that input variables have on the output value. SA can also partially reduce the uncertainty of the output value to a small threshold value by adjusting the input variables [21]. Owing to these advantages, SA is widely used in building simulations and observation studies. In a study on SA and the optimization of building operations, Gunay [22] performed SA to evaluate the influence that general operator decisions have on energy efficiency and comfort performance. Bre et al. [23] conducted a study on optimizing residential building design using SA and a genetic algorithm. In their study, SA was performed to optimize the thermal and energy performance of residential buildings. Through their study, they emphasized the efficiency and effectiveness of design optimization, thus improving the thermal and energy performance. To realize an occupant-centric building, Li [24] improved the occupant-centric building operation methodology by deriving personalized behavioral patterns using a personalized occupant behavior model with a cost sensitivity analysis (POBM–CSA). SA is widely used as a suitable approach for building operation and control optimization, as well as to support decision-making, by analyzing the thermal comfort and sensation votes (TCV and TSV) of the building occupants. K-means, a representative clustering algorithm, has high calculation efficiency and can deal with larger-scale data than hierarchical cluster analysis. K-means clustering is a method of making groups (types) by connecting common features or similar values, and it is mainly used to understand relationships among a large amount of complex data.

Most recent studies investigating the factors that directly influence the thermal comfort of occupants have focused on temperature (e.g., indoor air temperature, operating temperature, mean radiant temperature, and globe temperature) out of numerous thermal environmental factors [25]. As occupant comfort is subjective, exploring the variables that influence TCV and defining their relationships with the thermal environment are important. This highlights the need to examine the effects that various thermal environmental factors have on occupant thermal comfort.

As occupants have diverse thermal traits, there is no uniform definition, and the variables (thermal environment) exert different degrees of influence on individual occupants. Therefore, essential comprehensive research must examine the relationships between an occupant's TCV and the various thermal environmental variables to determine which variables have direct effects on the TCV of an occupant. In this context, this study aims to group occupants in several TSV clusters and perform SA on the relationship between thermal environmental factors in an office building and each cluster's TSV to establish the typology of the control indicators for each cluster. The study presents an optimized thermal environmental control for each TSV cluster, with the expected outcomes of simultaneously reducing building energy consumption and maintaining the thermal comfort of the occupants. Furthermore, results on the relationship between the thermal comfort of occupants and the indoor thermal environment can be used as a reference for developing optimized control technology for zoning of the building toward a reduction in its energy consumption across different building systems.

The main purpose of this study is to provide indicators for building control and energy-saving systems by clustering the changes in the indoor thermal environment and the thermal comfort of its occupants, as well as identifying the interactions among the indoor thermal environmental factors based on the sensation traits of the various TSV clusters. Therefore, this study was the following research questions to achieve the three objectives of this study:

1) Can various occupants be clustered into groups with common traits according to their TSV?
2) Can clustering reveal the relationship between the thermal environment and thermal comfort?
3) Develop an appropriate method for thermal environment control based on the thermal sensation traits of the derived groups?

## 2. Materials

Data for the objective physical factors and subjective personal factors were collected through field experiments using a mixed-method approach [26–28]. The environmental factors, which are the physical factors affecting the thermal comfort of indoor occupants, were set as variables. The indoor air-temperature and relative humidity (RH) [29] is basics thermal aspects of indoor environments. The used worldwide as indicators of indoor thermal environment satisfaction are predicted mean vote (PMV), and predicted percentage of dissatisfied (PPD). Studies have not only examined the PMV and PPD, along with the TCV [30,31], but research on $CO_2$ [32,33], recognized as an important determinant of indoor air quality, has also been conducted in conjunction with the TSV [34]. Therefore, based on previous studies [29–34], set five factors (i.e., the indoor air-temperature, RH, $CO_2$, PMV, and PPD) as the variables related to occupant thermal comfort.

Data on personal factors were collected using TCV and TSV questionnaires to examine the clothing insulation (Clo) and metabolic rate (Met) of the participants. Physical factor data were obtained from objective measurements using instruments, and personal factor data were subjective data obtained from questionnaire surveys. Participants provided ethical consent to all process steps, including data analysis, sharing, storage, and requirements.

### 2.1. Field data collection

The field survey was conducted in an office building located in Daegu, Korea. The building has a front curtain wall. High-efficiency HVAC is ensured with airtight windows, low-E double-pane glass, and insulation film. The test space in this building was approximately 133 $m^2$ (15.78 m × 8.46 m). Energy-saving facilities and equipment support the thermal maintenance of this building. An installed energy recovery ventilation system prevents indoor air pollution and maintains air cleanliness.

The thermostats in the office building accommodating the test space were set to 22 °C. In 2018, the Korean government recommended maintaining the set heating temperature of buildings below 20 °C [35]. However, ongoing studies have suggested that a set temperature of 20 °C has limitations as a one-dimensional approach to simple HVAC energy demand reduction [36]. Therefore, the target building centrally controls the heating system at 22 °C, considering both the energy and work efficiencies.

Fig. 1 shows the measurement instruments for objective data collection and the positions of the participants. Table 1 presents the details of the measurement instruments used in this study.

A total of 10 field experiments were conducted in the same space (office) in February 2022. In this study, one experiment was performed for 4 h. The participants participated in the experiment for 3 h and 30 min after the explanation of the experiment, stabilization of the heart rate, and physical recovery for 30 min. During the field experiment, outdoor conditions had an average temperature of 3.6 °C, a maximum temperature of 9.5 °C, and a minimum temperature of −1.7 °C. A total of 15 experiments were carried out, but only the data from days with no significant difference in conditions were used. Consequently, only the data from ten experiments were used for research. The experiments were performed during the same time period each day (08:00 to 12:00).

The instruments used to measure the environmental variables were placed in the center of the room (at a height of 0.6 m from the floor) and placed in the same location as in Fig. 1. Thermal environmental data (i.e., the temperature, RH, $CO_2$, PMV, and PPD) were recorded every 10 min [37]. As a result, a total of 840 datasets were collected, from which a total of 4,200 data were derived. Reflecting the characteristics of an office building, the mean Clo and Met were measured at 1.0 col and 1.2 met, respectively [38].

### 2.2. Participants and questionnaires

The participants (N = 42, 22 male and 20 female) were instructed to avoid alcohol consumption, smoking, and intense physical activity for at least 24 h before each experiment. For participants, unspecified individuals were selected. All of them were healthy and did not take any prescribed medications. They were requested to avoid alcohol, smoking, and vigorous physical activities at least 12 h before the experiment. The Clo and Met were measured at similar levels, such that the effect of their differences on the experimental results [39] was insignificant. Table 2 lists the general characteristics (i.e., gender, age, weight, and height) of the participants obtained using a questionnaire.

Participants entered the test space 30 min before the experiment began to have sufficient time for acclimation. They began by responding to the TCV and TSV questionnaires at 10 min intervals, i.e., the same intervals used to measure the thermal environmental data.

Fig. 2 indicates the participants were asked to rate the TSV and TCV questionnaire items on a seven-point thermal sensation scale (−3 = Cold, 0 = neutral, and +3 = Hot) and a seven-point thermal comfort scale (1 = very uncomfortable, 4 = neutral, and 7 = very comfortable) according to the ASHRAE Standards [29,40]. For each participant (occupant), 40 subjective data points (20 TCV and 20 TSV) were collected for a total of 1,680 TCV and TSV data.

## 3. Methods and results

### 3.1. Changes in physical and subjective factors

The scatter plots in Fig. 3 represent the thermal environmental factors and occupant thermal comfort factors.

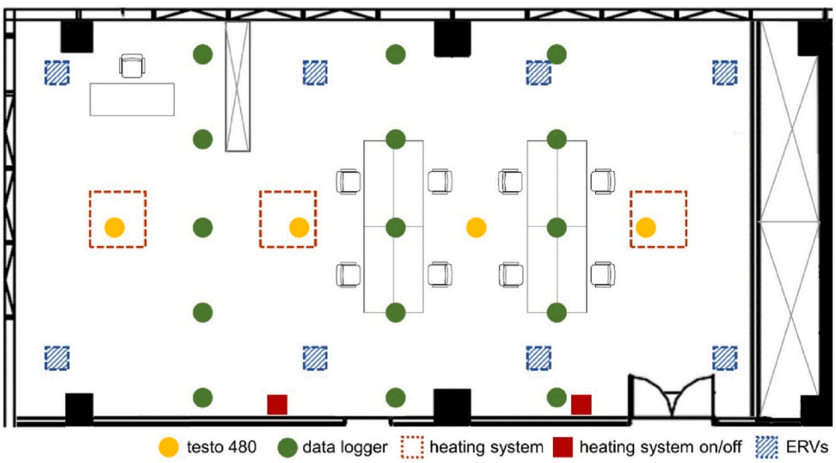



**Fig. 1.** Measurement instruments for objective data collection and the positions of the participants. *Note:* ERVs: Energy Recovery Ventilation system.

**Table 1**
Details of the measurement instruments used.

| Model | Parameters | Range | Precision | Resolution |
|---|---|---|---|---|
| data logger | Temperature | 0–50 °C | ±0.1 °C | 0.1 °C |
| & testo 480 | RH | 0–100 % RH | ± (1.8 % RH + 0.7 % of measured value) | 0.1 % RH |
| testo 480 | Turbulence | 0–5 m/s | ± (0.03 m/s + 4 % of measured value) | 0.01 m/s |
| | Radiant heat | 0–120 °C | −40 to 1 000 °C | – |
| | $CO_2$ | 0–10 000 ppm | ± (75 ppm + 3 % of measured value) | 1 ppm |
| | PMV | −3 to +3 | – | |
| | PPD | 0–100 % | – | |
| | User input for Clo | 1.0 (Clo) | – | 0.1 Clo |
| | User input Met | 1.2 (Met) | – | 0.1 Met |

*Note:* RH: Relative humidity (%), PMV: Predicted mean vote, PPD: Predicted percentage of dissatisfied (%), Clo: Clothing insulation, Met: Metabolic rate.

**Table 2**
General characteristics of the participants obtained using a questionnaire.

| Gender | N | Age (year) | | Height (cm) | | Weight (kg) | | BMI (kg/m$^2$) | | Clo | | Met | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Mean | ±SD | Mean | ±SD | Mean | ±SD | Mean | ±SD | Mean | ±SD | Mean | ±SD |
| Male | 22 | 27.27 | 3.13 | 176.4 | 4.76 | 76.63 | 11.54 | 24.55 | 3.06 | 0.98 | 0.050 | 1.1 | 0.3 |
| Female | 20 | 29.3 | 3.06 | 167.4 | 5.10 | 64.25 | 9.32 | 22.88 | 2.93 | 1.1 | 0.040 | 1.1 | 0.1 |
| Total | 42 | 28.23 | 3.22 | 172.1 | 6.69 | 70.73 | 12.15 | 23.75 | 3.08 | 1.04 | 0.045 | 1.2 | 0.2 |

*Note:* RH: Relative humidity (%), PMV: Predicted mean vote, PPD: Predicted percentage of dissatisfied (%), Clo: Clothing insulation, Met: Metabolic rate, BMI: Body Mass Index = weight/(height2), normally between 18 and 25 kg/m$^2$, SD: Standard deviation, N: Number.

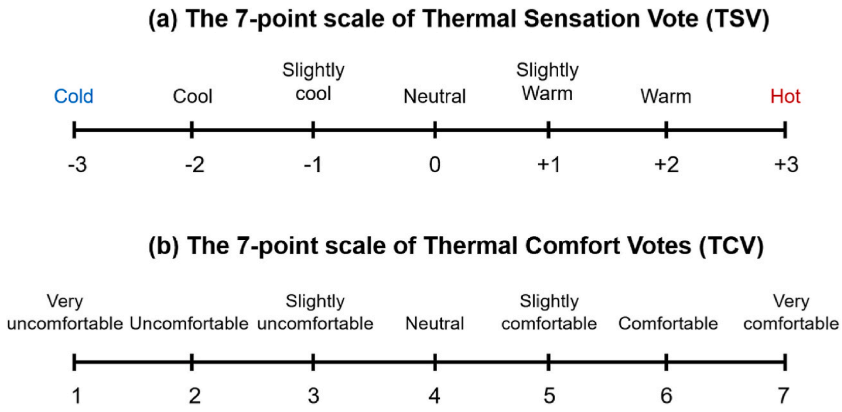
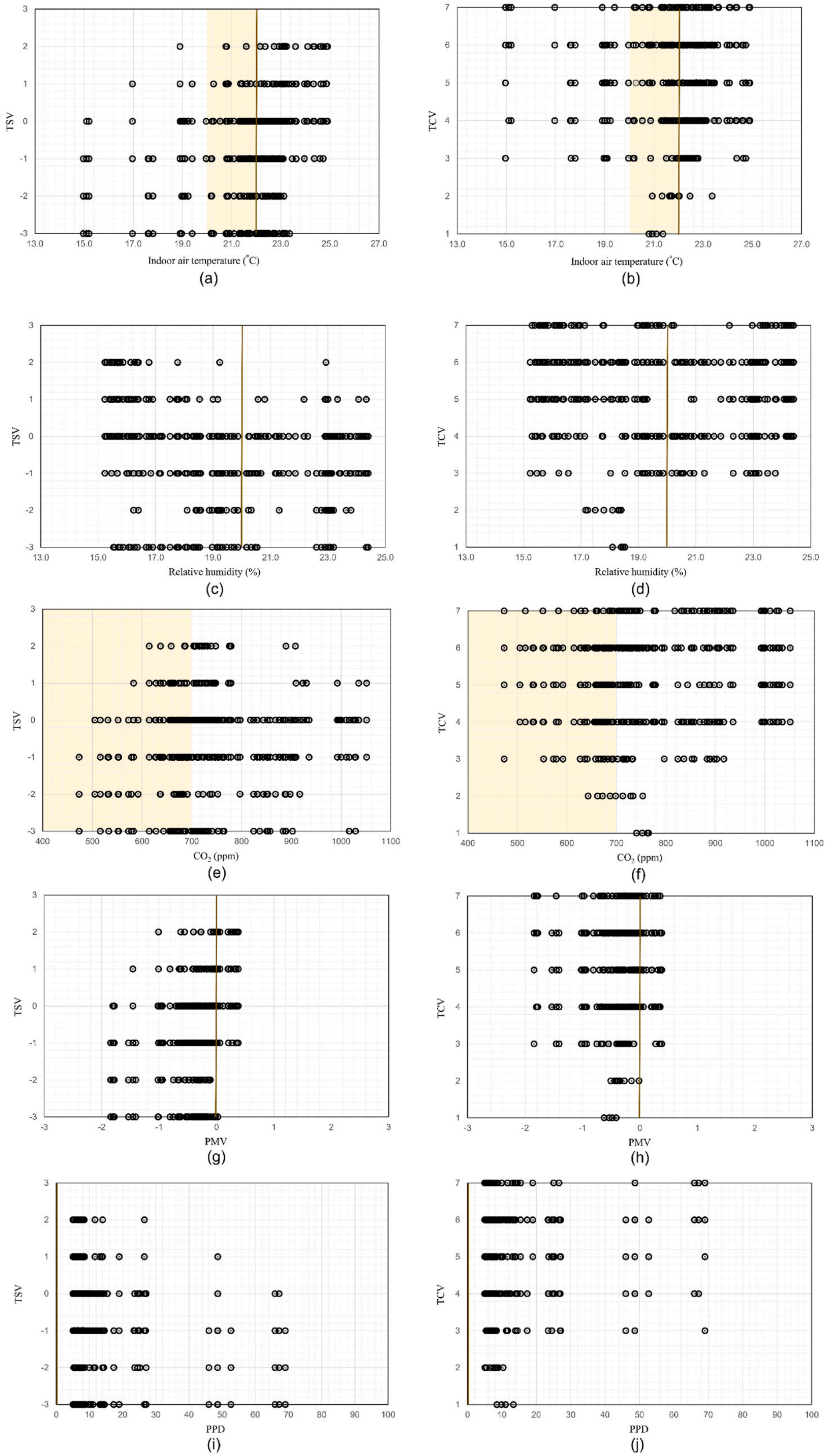



**Fig. 2.** The 7-point vote scales.

Fig. 3 indicates the optimal ranges of the thermal environmental factors, namely the temperature (Fig. 3 (a, b)), RH (Fig. 3 (c, d)), $CO_2$ (Fig. 3 (e, f)), PMV (Fig. 3 (g, h)), and PPD (Fig. 3 (i, j)). The Korean standards for the optimal ranges are as follows: indoor dry bulb temperature of 20–22 °C; RH ≥ 20 %; $CO_2$ of 400–700 ppm; and PMV and PPD = 0 (ISO 7730 standard). The TCV and TSV values were obtained from the participants. A TCV value closer to 7 indicates that the occupant feels more comfortable; a TCV value closer to 1 indicates that the occupant feels more uncomfortable. A TSV value closer to +3 indicates that the occupant feels warmer; a TSV value closer to −3 indicates that the occupant feels colder.

First, numerous cases did not achieve the optimal range for the indoor dry bulb temperature and TSV (20–22 °C). A significant temperature decrease was also observed when the heating system was turned off in compliance with the office building lunch break policy. Even within the optimal range for the indoor dry bulb temperature, many occupants responded with “Uncomfortable” (TCV) or “Cold” (TSV). For the RH, many occupants responded “uncomfortable” or “Cold” at a range of 20 % or less, which is below the optimal level. Similarly, the responses for more than half of the occupants were outside the optimal $CO_2$ range while some occupants responded with “Cold” within the optimal TSV range. The number of PPD result values distributed outside the optimal range was the highest among the five thermal environmental factors. In contrast, the number of PMV results within the optimal range was higher than that of the other factors. In addition, the TCV for a “comfortable” PMV (7) composed a high percentage. However, the PMV was distributed more densely toward Cold (−3), rather than toward Hot (3), which suggests that the occupants felt uncomfortable due to a perceived cold environment.

The analyses revealed that most of the TSV and TCV values were distributed outside of the optimal range. When verified against the




*(caption on next page)*

**Fig. 3.** Represent the thermal environmental factors and occupant thermal comfort factors the scatter plots: (a) temperature and TSV, (b) temperature and TCV, (c) RH and TSV, (d) RH and TCV, (e) $CO_2$ and TSV, (f) $CO_2$ and TCV, (g) PMV and TSV, (h) PMV and TCV, (i) PPD and TSV, (j) PPD and TCV. *Note:* TSV: Thermal sensation vote, TCV: Thermal comfort vote, PMV: Predicted mean vote, PPD: Predicted percentage of dissatisfied (%).

Korean standards for the related optimal ranges, most of the dry bulb temperature results were outside of the optimal range, which was also the case for the RH, $CO_2$, PMV, and PPD, where the PPD had the highest number of results that deviated from the optimal range.

A simple scatter-plot graph showing such a wide distribution has limitations when analyzing the relationship between the thermal environment and the thermal comfort of the occupants. This highlights the need for the development of a method to properly analyze the relationship between the thermal environment and thermal comfort.

### *3.2. Clustering of thermal environment and thermal comfort*

Building occupants have various thermal preferences under the same environmental conditions [41,42]. Despite this diversity, there are common traits across the thermal comfort characteristics of the occupants, as confirmed by the TCV-based control methods [37,43,44]. Therefore, the occupants were clustered in this study based on the common traits derived according to the thermal sensitivity of the occupants.

In the ASHRAE 55 [2] adaptive model for thermal comfort, the regression coefficients obtained from the linear regression analysis between the indoor operative temperature (independent variable; X) and mean TSV (dependent variable; Y) represent an occupant's sensitivity to a change in the temperature. In other words, a higher regression coefficient indicates a higher thermal sensitivity of the occupant to a change in the temperature. In contrast a lower regression coefficient indicates that the occupant has a reduced thermal sensitivity to a change in the temperature. This suggests that the TSV has less of an influence when its value is close to 0 (neutral). Moreover, the equation derived from the regression analysis can be solved for a thermal sensation (y-value) of 0 (i.e., the neutral condition in the ASHRAE seven-point thermal sensation scale), thus determining the neutral temperature of a group of occupants [21]. This has been recognized as an effective method (field studies) to calculate the thermal comfort temperature [6,45,46]; as such, it is widely used for different building types, such as office buildings, educational facilities, and housing facilities [6,45–47]. Previous studies have confirmed the feasibility of research on the indoor thermal environment and the thermal comfort of its occupants.

TSV clusters can be formed according to the thermal sensation traits based on the changes in the indoor thermal environment. Clustering collectively refers to methods that group data into several clusters based on the concept of similarity. The clustering method used in this study was k-means clustering (k-MEANS), which is commonly used to cluster a given dataset according to the mean and standard deviation of the perceived values [48–50]. The cluster analysis method was widely used in thermal comfort studies [51,52]. In addition to the area of thermal comfort, cluster analysis is widely used in medicine, information technology [53–55]. Despite all this research in different areas, studies involving thermal environment are few, and there are no studies applying cluster analysis [56]. In

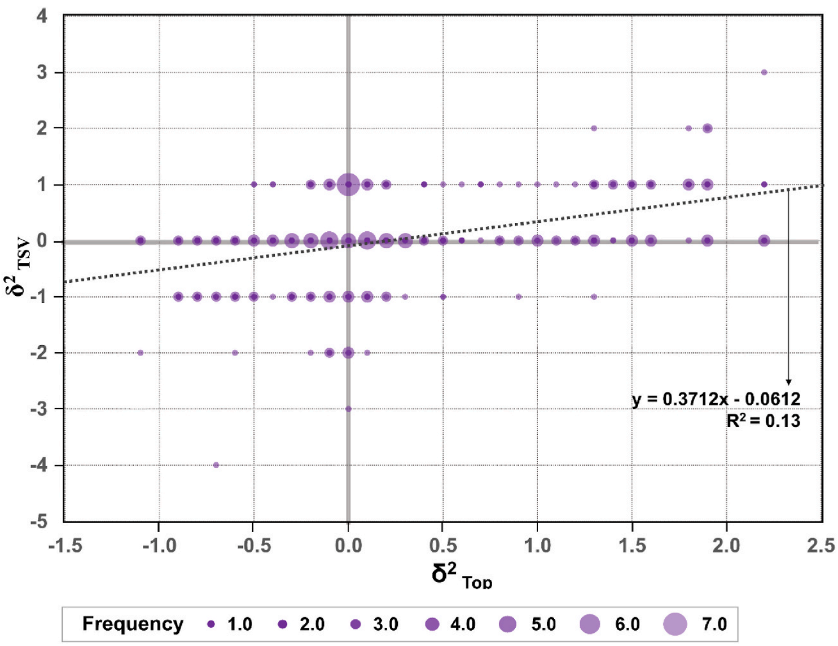



**Fig. 4.** Represents changes in the preferred level toward a state of comfort. *Note:* $\delta^2_{TSV}$: Change in TSV (variance), $\delta^2_T$: Change in temperature (variance).

case, the clustering results can synthesize the characteristics of the occupant class based on appropriate attributes [57]. k-MEANS is a representative clustering algorithm with high computational efficiency and an enhanced data processing capacity, as compared with hierarchical cluster analysis. A disadvantage of the k-MEANS algorithm is the risk of subjectivity when setting the number of clusters to be formed. To address this drawback, this study was the k-MEANS algorithm based on analyses conducted in previous studies [20,58]. We then performed clustering after three verifications to ensure the performance of the k-value (number of clusters). An SA can then be performed on the cluster derived according to a predefined methodology to evaluate the influence and importance that the input variables have on the output value. One drawback of K-means is that it requires somewhat subjective judgment in specifying the number of clusters to be made in advance. To supplement this issue, previous studies were referred to. In addition, to ensure the performance of the k value based on the analysis, three validations were performed and then the optimal number was determined through relationship analysis.

In this study, the input variables were the indoor thermal environmental factors. Prior to SA, the temperature was set as the key factor representing the five thermal environmental factors, which was used to cluster the TSV values [59,60].

The value of the input variable, x ($\delta^2_T$), was the change in the temperature factor, whereas the output value ($\delta^2_{TSV}$) was set as the change in the TSV value. The data values were calculated based on the difference between the temperatures measured at baseline and the first TSV value.

Fig. 4 shows the results of these calculations.

The change in the temperature ($\delta^2_T$) is the x-axis, whereas the change in the TSV value ($\delta^2_{TSV}$) is the y-axis. The centroid (0,0) was interpreted as a "neutral sensation" and "no change" regarding the TSV and temperature, respectively [20]. This TSV scale represents changes in the preferred level toward a state of comfort. A higher positive value indicates a more comfortable and warmer environment, 0 indicates a neutral environment with no change, and a higher negative value indicates a more uncomfortable and colder environment [61].

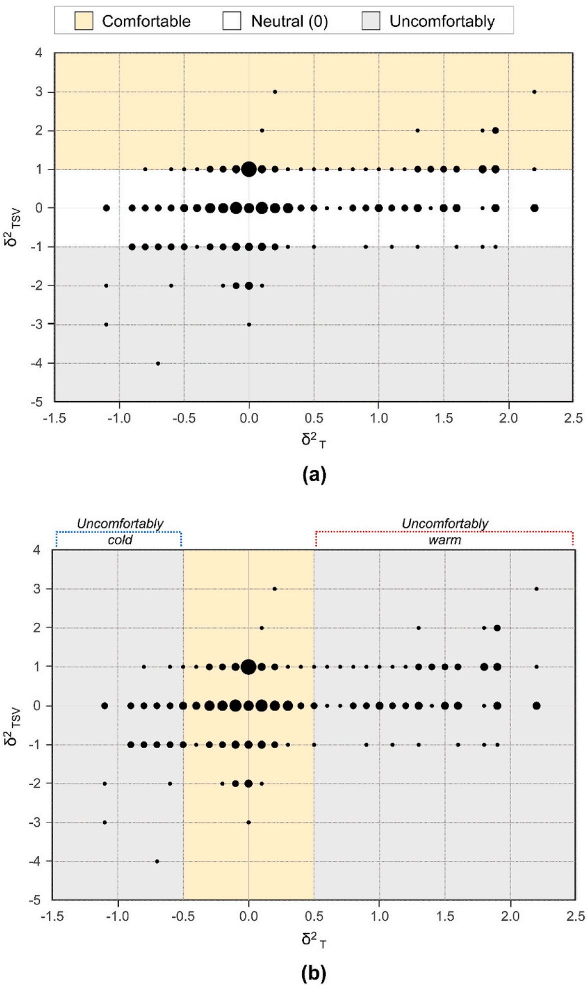



**Fig. 5.** Comfortable optimal ranges: (a) comfortable optimal ranges of output value ($\delta^2_{TSV}$), (b): comfortable optimal ranges of input value ($\delta^2_T$). *Note*: $\delta^2_{TSV}$: Change in TSV (variance), $\delta^2_T$: Change in temperature (variance).

As a result of deriving the x and y values every 10 min during the experiment, we found that the values were densely distributed between −1 and + 1 along the x-axis, especially near the centroid (0,0) (=neutral). Even at a y-value of +1 (= slightly warm), there were a wide range of temperature changes (x-axis), ranging from −0.5 to +1.6.

The fitted value (y) in the regression equation for the entire group was y = −0.06 + 0.37 * x, with an $R^2$ linear (L) value of 0.134. Combining the x and y values, the highest frequency (7.0) was derived from an x and y value of 0 and 1 while the second highest frequency (5.0–6.0) occurred within an x value range of −0.5 to +0.5 and y-value of 0. The results at a y-value of 0 generally showed a higher frequency than the results at other y-values. Unlike the y-values, which showed lower frequencies with an increase in the distance from reference (0.0), the x-values showed diverse frequencies.

Fig. 5 plots the comfortable optimal ranges. In $\delta^2_{TSV}$ (a), +1 to +4 is a comfortable range, −1 to +1 is a neutral range, and −5 to −1 is an uncomfortable range. In $\delta^2_T$ (b), −0.5 to +0.5 is a comfortable range, where the area to the left (−) is an uncomfortable cold range and the area to its right (+) is an uncomfortably warm range. Fig. 5(a) shows that most of the values are distributed within the neutral range (+1 to −1), whereas Fig. 5(b) shows that most of the values are distributed within the range between −0.5 and + 0.5, i.e., the comfortable range.

Performed clustering after three verifications to ensure the performance of the k-value (number of clusters).

1) Data and individual variables were obtained using statistics. Among the derived results, the TSV and temperature data were clustered with k-MEANS. Here, δ2TSV was the change in the TSV, where the baseline value was used as the reference value of each participant. The data for each participant were clustered.
2) Hierarchical cluster analyses were then performed on the changes in the TSV (δ2TSV) and temperature (δ2T) in preparation for k-means. The clustering method was selected based on previous studies; clustering was performed using an intergroup connection method [62,63]. Based on the differences in the measurement units of the cluster variables, individual distances were calculated after standardizing the variables. The average connection method was then used to derive the dendrograms.
3) After reviewing the dendrogram-derived results, the optimal number of clusters was set to five. Scatter plots (Fig. 6) were generated using the internal agreement [20] between the changes in the temperature (δ2T) and TSV (δ2TSV). Linear values were obtained for the five clusters using a regression line fitting analysis.

As a result of the analysis, cluster 4 (C4) was identified as the cluster with the highest number of cases (n = 364), followed by C5 (n = 178), C1 (n = 142), C3 (n = 60), and C2 (n = 54). The mean values of $\delta^2_T$ and $\delta^2_{TSV}$ were 1.5 and 0.3, respectively, for C1; 1.3 and 2.2 for C2, respectively; −0.3 and −2.3 for C3, respectively; 0 and 0.1 for C4, respectively; and −0.4 and −0.6 for C5, respectively. Of the five $\delta^2_T$ clusters, C1 showed the value closest to “Hot” (+3), followed by C2. C4 was neutral, whereas C3 was slightly closer to “cold” (−3) than C5. The values of $\delta^2_{TSV}$ for C1 and C3 fell within the range of ±2, which were more varied than the other clusters (range: ±1), suggesting that C1 and C3 were clusters with a higher sensitivity to changes in $\delta^2_{TSV}$.

The relationship between the two variables (i.e., $\delta^2_T$ and $\delta^2_{TSV}$) was predicted using the slopes of the regression lines; the prediction accuracy was analyzed using the linearity of the regression line. A straight line, which minimizes the squared sum of the difference between the actual y value and the y value on the straight line with a given x-value, was adopted as the regression line. Fig. 7 plots the linear values of the clusters derived using the regression equation required for prediction by minimizing the prediction error.

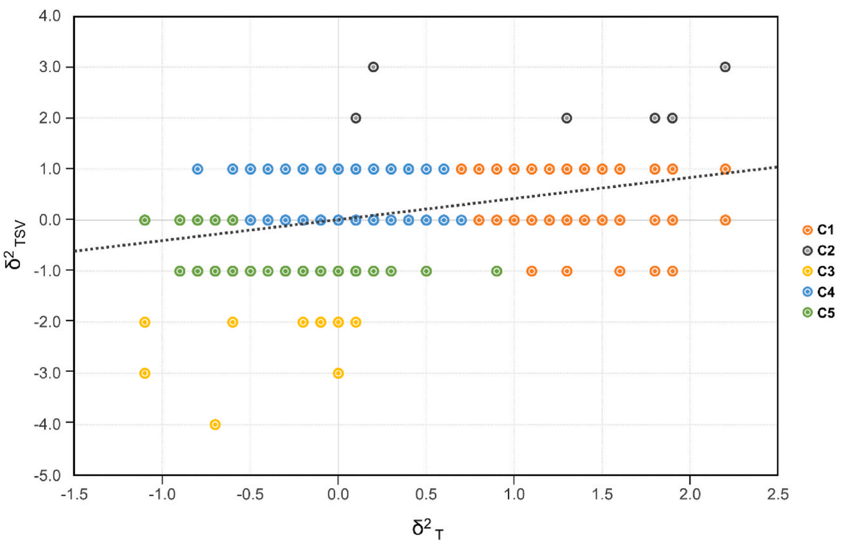



**Fig. 6.** Scatter plots for the five clusters. *Note:* $\delta^2_{TSV}$: Change in TSV (variance), $\delta^2_T$: Change in temperature (variance), C1: cluster 1, C2: cluster 2, C3: cluster 3, C4: cluster 4, C5: cluster 5.

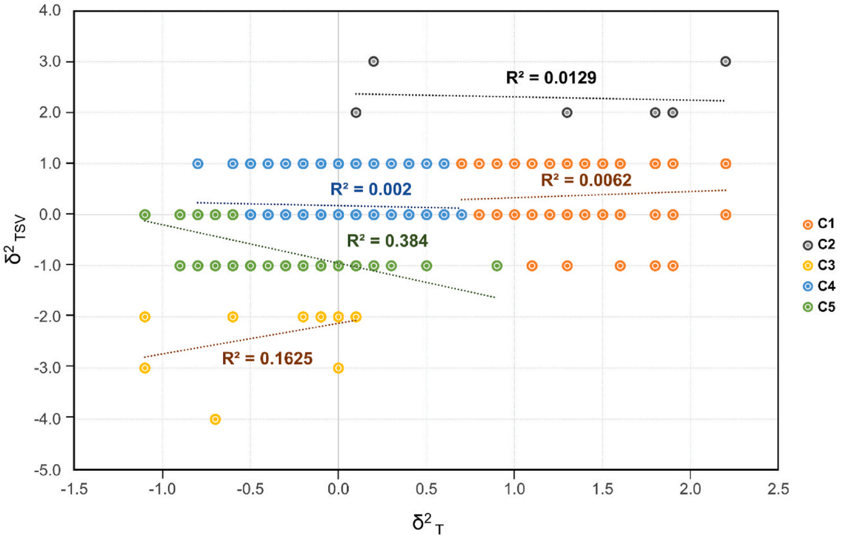



**Fig. 7.** Linear values of the five clusters. *Note*: $\delta^2_{TSV}$: Change in TSV (variance), $\delta^2_T$: Change in temperature (variance), C1: cluster 1, C2: cluster 2, C3: cluster 3, C4: cluster 4, C5: cluster 5.

A regression coefficient of 0.006 was obtained using the equation for C1 (i.e., y = 0.21 + 0.12 * x). A regression coefficient of 0.013 was obtained using the equation for C2 (i.e., y = −2.13 + 0.6 * x), 0.163 for C3 (y = −2.13 + 0.6 * x), 0.002 for C4 (y = 0.18–0.07 * x), and 0.384 for C5 (y = −0.95 – 0.75 * x). C4 had the smallest regression coefficient, whereas C5 had the largest regression coefficient among the five clusters.

Fig. 8 presents the TSV range for each cluster, which allows a visualization of the thermal sensations of the participants by color. Most participants in C1 had the sensation of Thermal Hot (T.H.), showing a "neutral" comfort. C2 was within the T.H. and comfortable range (T.H.-C); however, C2 participants did not feel varying degrees of comfort, judging from the broad distribution of the "comfortable" range. C3 showed a combination of T.C. and uncomfortable (T.C.-U), presumably because "uncomfortable" was inferred from the predominant "cold" response, as the experiment was conducted in winter [64]. C4 showed a mixed distribution of T.C.-C and T.H.-C combinations. C4 had the most neutral range, suggested that it was the cluster with the highest comfort level. C5 occupied the T. C. range, which was more similar to the "neutral" and "uncomfortable" ranges than the "comfortable" range.

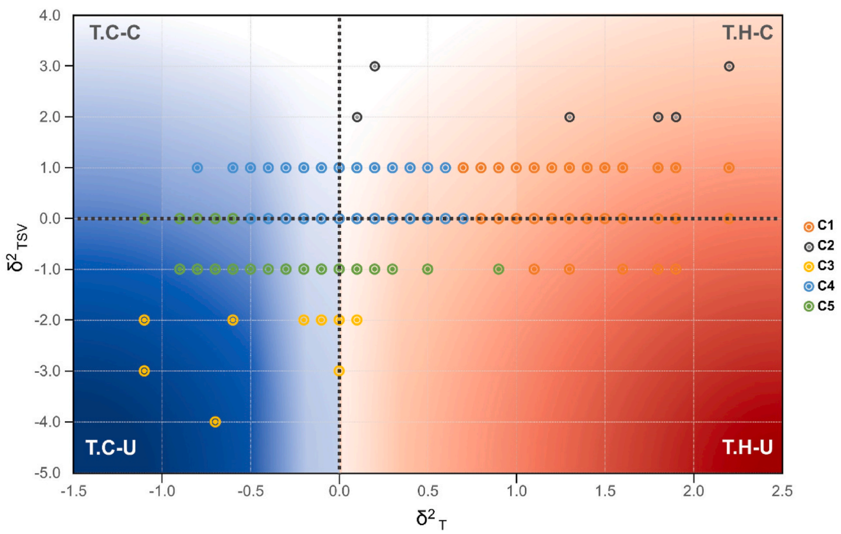



**Fig. 8.** TSV range for five cluster. *Note:* $\delta^2_{TSV}$: Change in TSV (variance), $\delta^2_T$: Change in temperature (variance), C1: cluster 1, C2: cluster 2, C3: cluster 3, C4: cluster 4, C5: cluster 5, T.C–C: Thermal Cool Comfort, T.H–C: Thermal Hot Comfort, T.C–U: Thermal Cool Uncomfortable, T.H–U: Thermal Hot Uncomfortable.

## 4. Discussion

### 4.1. Sensitivity analysis of each occupant cluster

The SA(sensitivity analysis) can be performed to evaluate the influence and importance that the input variables have on the output value and identify the important traits of the input-output interactions [65–67]. In a stepwise regression analysis, the relative importance of a variable on the output value can be evaluated using sensitivity indices, such as the importance of a variable in a specific model and the standardized rank regression coefficient (SRRC).

We evaluated the sensitivity as follows (Eq. (1)):

$$SA(SC) = \frac{\Delta OP \; / \; OP_{BC}}{\Delta IP \; / \; IP_{BC}}, \tag{1}$$

where $\Delta OP$ is change in output, $OP_{BC}$ is output of base case, $\Delta IP$ is change in input and $IP_{BC}$ is input of base case. In this study, SA is the sensitivity coefficient (SC) between the TSV and a thermal environmental factor, where the input variable value of $x$ is the change in the thermal environmental factor and the output value of $y$ is the change in the TSV. Table 3 lists the SA results for each variable and cluster. The input variables for the base case ($IP_{BC}$) were set as the environmental factors, excluding the temperature, viz. Temperature, RH, $CO_2$, PMV, and PPD, based on the thermal comfort value. The temperature was set at the standard temperature of the laboratory heating device (22 °C). The sensitivity magnitude to which the occupants responded to changes in the thermal environmental factors was analyzed, with all variables fixed. Five thermal environmental factors (i.e., the temperature, RH, $CO_2$, PMV, and PPD) were considered because previous studies have verified them as factors affecting the thermal comfort of the occupants. They were perceived by the five occupant clusters derived through k-means. An output value closer to 0 indicated that the corresponding variable had less of an influence on the output. In this study, the mean SRRC score was used as the reference value.

The analysis results are expressed as absolute values, with 0 as the reference (Table 3).

The analysis identified C2 ($SRRC_T = 5.874$) as the cluster with the highest sensitivity to the RH, $CO_2$, and PPD ($SRRC_H = -7.278$, $SRRC_{CO2} = -0.217$, and $SRRC_{PPD} = -3.995$, respectively), as well as temperature. In contrast, C4 exhibited the least sensitive responses to the temperature, RH, $CO_2$, and PMV ($SRRC_T = -0.052$, $SRRC_H = -0.039$, $SRRC_{CO2} = 0.005$, and $SRRC_{PMV} = 0.016$, respectively). C3 showed a high sensitivity of 10.0 for the PMV ($SRRC_{PMV}$), whereas C1 had the least sensitive response to the PPD.

As a result, C2, which was sensitive to four out of the five environmental factor input variables (thermal environmental factors), was classified as the “sensitive” group (level 5), and C3, which was sensitive to one factor, was classified as the “fairly sensitive” group (level 4). C4, which adapted to four environmental factors (i.e., values close to 0), was classified as the “insensitive” group (level 1), and C1, which responded to one factor, was classified as the “fairly insensitive” group (level 2). C5 was classified as the “neutral” group (level 3).

To verify the validity of results, ranges were set based on the reference values provided in previous studies [68,69] that used SA.

**Table 3**
Sensitivity analysis results for each variable and cluster.

| TSV Clustering | Input variables (x) | | | | | | | | | | Sensitivity group |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\delta^2_T$ | | $\delta^2_H$ | | $\delta^2_C$ | | $\delta^2_{PMV}$ | | $\delta^2_{PPD}$ | | |
| | $SRRC_T$ | $\sigma_T$ | $SRRC_H$ | $\sigma_H$ | $SRRC_{CO2}$ | $\sigma_{CO2}$ | $SRRC_{PMV}$ | $\sigma_{PMV}$ | $SRRC_{PPD}$ | $\sigma_{PPD}$ | |
| C1 | 0.285 | 0.455 | –0.468 | 3.272 | 0.017 | 0.061 | 1.546 | 2.676 | –0.049 | 0.274 | G2 |
| C2 | 5.874 | 8.074 | –7.278 | 7.204 | –0.217 | 0.310 | 5.357 | 3.845 | –3.995 | 5.992 | G5 |
| C3 | 4.892 | 10.967 | –0.949 | 16.062 | 0.058 | 0.181 | 10.000 | 13.540 | –2.499 | 6.210 | G4 |
| C4 | –0.052 | 2.569 | –0.039 | 1.861 | 0.005 | 0.080 | 0.016 | 2.822 | 0.063 | 1.506 | G1 |
| C5 | 0.600 | 4.255 | –0.440 | 3.375 | –0.019 | 0.428 | 2.159 | 4.482 | 0.298 | 2.933 | G3 |

*Note:* $\delta^2_T$: Change in temperature(variance), $\delta^2_H$: Change in humidity, $\delta^2_C$: Change in $CO_2$, $\delta^2_{PMV}$: Change in PMV, $\delta^2_{PPD}$: Change in PPD, SRRCy: Standard regression coefficient of y, $\sigma_y$:: Standard deviation of y.

-Sensitivity group: 1 = insensitive; 2 = rather insensitive; 3 = neutral; 4 = rather sensitive; and 5 = sensitive.
-Blue = minimum value; and red = maximum value of each input variable (ref. value = 0)

**Table 4**
Sensitivity analysis results with rearranged group ranking.

| TSV Clustering | Input variables (x) | | | | | | | | | | Sensitivity level |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\delta^2_T$ | | $\delta^2_H$ | | $\delta^2_C$ | | $\delta^2_{PMV}$ | | $\delta^2_{PPD}$ | | |
| | SRRC T | σ T | SRRC H | σ H | SRRC CO2 | σ CO2 | SRRC PMV | σ PMV | SRRC PPD | σ PPD | |
| C2 | **5.874** | **8.074** | **–7.278** | **7.204** | –0.217 | 0.310 | **5.357** | 3.845 | **–3.995** | **5.992** | L5 |
| C3 | 4.892 | **10.967** | –0.949 | **16.062** | 0.058 | 0.181 | **10.000** | **13.540** | –2.499 | 6.210 | L4 |
| C5 | 0.600 | 4.255 | –0.440 | 3.375 | –0.019 | 0.428 | 2.159 | 4.482 | 0.298 | 2.933 | L3 |
| C1 | 0.285 | 0.455 | –0.468 | 3.272 | 0.017 | 0.061 | 1.546 | 2.676 | **–0.049** | 0.274 | L2 |
| C4 | **–0.052** | 2.569 | **–0.039** | 1.861 | **0.005** | 0.080 | **0.016** | 2.822 | 0.063 | 1.506 | L1 |

*Note:* $\delta^2_T$: Change in temperature(variance), $\delta^2_H$: Change in humidity, $\delta^2_C$: Change in $CO_2$, $\delta^2_{PMV}$: Change in PMV, $\delta^2_{PPD}$: Change in PPD, SRRCy: Standard regression coefficient of y, $\sigma_y$: Standard deviation of y.

-Sensitivity group: 1 = insensitive; 2 = rather insensitive; 3 = neutral; 4 = rather sensitive; and 5 = sensitive.
-Blue = minimum value; and red = maximum value of each input variable (ref. value = 0)

Table 4 (i.e., sensitivity analysis results with rearranged group ranking) lists the results derived by applying the items described below.

1) Most important variable (shaded red). In general, this variable has a value of 0.4 or higher; all values of 0.4 or higher were defined as the most important variables.
2) Second most important variable (blue). In general, its value ranges from 0.1 to 0.2; values ranging from 0.39 to 0.1, below the cut-off value (0.4) of the most important variables, were defined as important variables.
3) Fairly important variable (green). A variable with a value of approximately 0.05; a value ranging from 0.09 to 0.05, below the cut-off value (0.1) of the important variables, was defined as a fairly important variable.
4) Irrelevant variable (yellow). A variable with a zero value; in this study, values ranging from 0.049 to 0, below the cut-off value (0.05) of fairly important variables, were defined as irrelevant variables.

The irrelevant variables were $CO_2$ and PPD in C1; RH, $CO_2$, and PMV in C4; and $CO_2$ in C5. C2 and C3 were as "sensitive" groups because they showed high sensitivity to all five input variables. Moreover, C2 and C3 were equally sensitive to the temperature, RH, PMV, and PPD, whereas C2 showed a more sensitive response (blue) to $CO_2$. Therefore, C2 was considered a more sensitive group than C3.

The most insensitive group was identified by examining the "irrelevant" variables. C4 showed the lowest sensitivity to the RH, $CO_2$, and PMV such that it was classified in the range of irrelevant variables C2 and C3 were rated as sensitive groups, yielding no irrelevant variables. C5 did not respond to one variable, whereas C1 did not respond to two variables. Therefore, C4, which did not respond to three variables, can be considered the most "insensitive" group.

Combining the results of the two analyses, identical results were obtained using both methods for the classification of the sensitivity group. However, more detailed results could be obtained with the application of the sensitivity reference value, as compared with using 0 as the reference value. In particular, the sensitivity reference value enabled the analysis of intergroup relationships by dividing the importance into three levels (most important, important, and fairly important), as well as analyzing the unrelated variables.

C2 was the "most sensitive group" (L5) among the five clusters. High values were derived from four out of the five variables, and the result was consistent with the "most important variable." However, the sensitive (C2) and fairly sensitive (C3) groups showed high standard deviations, whereas the other clusters showed standard deviations ranging from 0 to 5. Therefore, we must examine the cause (s) of the high standard deviations in these two sensitive groups. The thermal environment control indicators were therefore investigated by comprehensively analyzing the TSV and TCV values and thermal environmental factors.

### 4.2. Classification of control indicators

Using Table 5, the TSV, TCV, and thermal environment were comprehensively analyzed. C2 and C3 showed higher standard

**Table 5**
TSV, TCV, and thermal environment were comprehensively analyzed.

| | | | C1 | C2 | C3 | C4 | C5 |
|---|---|---|---|---|---|---|---|
| Occupant | TSV | mTSV | −0.116 | 0.143 | −2.385 | −0.443 | −0.780 |
| | | $\sigma_{TSV}$ | 1.138 | 0.900 | 1.044 | 1.249 | 1.194 |
| | TCV | mTCV | 5.326 | 4.143 | 3.769 | 5.242 | 5.076 |
| | | $\sigma_{TCV}$ | 1.250 | 0.900 | 0.927 | 1.289 | 1.311 |
| Thermal environment | Temperature | mT | 21.9 | 22.4 | 21.9 | 21.9 | 22.2 |
| | | $\sigma_T$ | 1.808 | 1.304 | 1.058 | 1.825 | 1.211 |
| | RH (Humidity) | mH | 19.0 | 20.2 | 21.4 | 20.3 | 19.2 |
| | | $\sigma_H$ | 2.260 | 2.552 | 2.416 | 3.204 | 2.703 |
| | $CO_2$ | $mCO_2$ | 735.5 | 766.0 | 779.6 | 772.7 | 760.5 |
| | | $\sigma_{CO2}$ | 102.424 | 129.014 | 150.084 | 136.593 | 101.854 |
| | PMV | mPMV | −0.4 | −0.3 | −0.4 | −0.3 | −0.2 |
| | | $\sigma_{PMV}$ | 0.415 | 0.352 | 0.263 | 0.426 | 0.290 |
| | PPD | mPPD | 11.7 | 9.3 | 9.1 | 11.0 | 8.1 |
| | | $\sigma_{PPD}$ | 10.562 | 7.886 | 5.936 | 12.327 | 5.823 |
| Sensitivity | $\delta_T^2$ | mT | 0.285 | 5.874 | 4.892 | −0.052 | 0.600 |
| | | $\sigma_T$ | 0.455 | 8.074 | 10.967 | 2.569 | 4.255 |
| | $\delta_H^2$ | mH | −0.468 | −7.278 | −0.949 | −0.039 | −0.440 |
| | | $\sigma_H$ | 3.272 | 7.204 | 16.062 | 1.861 | 3.375 |
| | $\delta_C^2$ | $mCO_2$ | 0.017 | −0.217 | 0.058 | 0.005 | −0.019 |
| | | $\sigma_{CO2}$ | 0.061 | 0.310 | 0.181 | 0.080 | 0.428 |
| | $\delta_{PMV}^2$ | mPMV | 1.546 | 5.357 | 10.000 | 0.016 | 2.159 |
| | | $\sigma_{PMV}$ | 2.676 | 3.845 | 13.540 | 2.822 | 4.482 |
| | $\delta_{PPD}^2$ | mPPD | −0.049 | −3.995 | −2.499 | 0.063 | 0.298 |
| | | $\sigma_{PPD}$ | 0.274 | 5.992 | 6.210 | 1.506 | 2.933 |
| Result | | | Rather insensitive | Sensitive | Rather sensitive | Insensitive | Neutral |

*Note:* mTSV: Mean thermal sensation vote, mTCV: Mean thermal sensation vote, $m_y$: Mean of y, $\sigma_y$: Standard deviation of y, $\delta_T^2$: Change in temperature (variance), $\delta_H^2$: Change in humidity, $\delta_C^2$: Change in $CO_2$, $\delta_{PMV}^2$: Change in PMV, $\delta_{PPD}^2$: Change in PPD.

deviations (>5) than the other clusters (0–5). As C2 and C3 are sensitive groups, the occupants in these clusters perceived changes in the thermal environment more sensitively than those in the other clusters, which also increased the magnitude of the variations, leading to larger standard deviations.

Differences were also observed among the sensitive groups. While C3 had a higher mean TSV than C2 (−2.385 vs. 0.143), C2 was more sensitive to the thermal environmental factors. Comparing their TSV and TCV values, C2 showed a "neutral" response in both the TSV and TCV, whereas C3 showed a "slightly cold" response for the TSV and "slightly uncomfortable" response for the TCV. Although the experiments were conducted in winter, C3 was particularly sensitive to cold conditions. Furthermore, though C2 and C3 perceived changes in the thermal environment, C2 occupants responded with more comfort while C3 occupants responded with less comfort depending on whether they accepted the change or not. Similar to C3, C5 showed a high sensitivity to the PMV; C3 responded to the temperature, PPD, and PMV, whereas C5 only responded to the PMV (sensitivity levels to the other factors were close to 0). C5, as the "neutral" sensitivity group, responded to a specific factor (PMV) compared with C3. Therefore, C3 requires control indicators considering the PMV (PPD), for which it showed high sensitivity, along with basic (temperature) control. Additionally, as this cluster perceived the changes faster than the other clusters, a positive effect may be obtained with a minimal change by applying an acclimation time [70,71] longer than the 10 min allocated in this study.

Of the five clusters, C1 and C4 were classified as insensitive. They had a negligible response to changes in the thermal environment (close to zero). Of these, C1 was a slightly insensitive group and responded to the PMV ($\delta_{PMV}^2 = 1.546$), though lower than the other clusters (C3($\delta_{PMV}^2$) = 10.000; C5($\delta_{PMV}^2$) = 2.159). C4 was an insensitive group, showing a "neutral" TSV and "fairly comfortable" TCV, where the C4 occupants were able to maintain a comfortable thermal environment with appropriate TCV and TSV values by adjusting only the current thermal environment.

The C2 and C4 occupants perceived thermal comfort, but showed distinct responses to the change in the thermal environment: sensitive for C2 and insensitive for C4. The occupants of both clusters had a high thermal adaptability [72–74] and could actively adapt to changes in the thermal environment. The only difference was that C2 could sensitively react and accept the changes in the thermal environment, whereas C4 occupants evaluated the current thermal environment as comfortable without perceiving the change. C4 was "insensitive" because its occupants were familiar with the current environment. Drawing on the results of Cao et al. [67], maintaining a high indoor temperature is associated not only with energy waste, but also with occupant discomfort. Energy-saving control criteria can be applied to C2, as well as an acclimation time longer than the HVAC control interval (10 min), applied in this study. As C2 can respond and rapidly adapt to changes, control indicators considering building energy can be applied to C2 more readily than to the other clusters. Additionally, a positive effect can be achieved in C4 according to results [75], where occupants accustomed to comfortable indoor thermal environments can better adapt to low-quality indoor environments.

### *4.3. Limitations and future research*

This study was conducted as a field study in an office building with a centrally controlled HVAC system. The number of participants was limited because the study site is an actual office. Large-scale experiments are therefore required to obtain statistically significant results. However, Chen [76] demonstrated that the experimental data collected from a small number of participants can provide significant energy savings without sacrificing thermal comfort by considering the occupant feedback in the control design. Additionally, similar to other questionnaire survey studies [76–78], this study aimed to derive the behavioral patterns of the occupants instead of monitoring their behavior. As this study was conducted in an office in an indoor thermal environment in winter, there were several limitations such as outdoor climatic factors, participants, and scheduling. However, significant effort was focused on collecting as much data as possible in the given environment. An extensive literature review was conducted to control the variables that may have appeared during the experiments [79].

As a result of the field experiment, there was a difference in indoor temperature of about 10° between morning and afternoon. The low outdoor temperature in the morning and the high outdoor temperature in the afternoon affected the indoor temperature difference. In particular, depending on the characteristics of curtain wall buildings, the increase in building temperature due to inflow of solar radiation appears to have a significant impact. Accordingly, in this study, prior research was referred to during the analysis, and occupant comfort was analyzed taking temperature differences into account.

Human behavior is complex and diverse, and may not be fully expressed in statistical models. However, a recent research trend [80, 81] has explored the repetitive behaviors of occupants interacting with indoor environments based on energy-control behavior. An alternative approach [82,83] attempts to save energy and improve the thermal comfort of the occupants in buildings by integrating into simulation tools the mechanisms of the interactions between occupant behavior when seeking thermal comfort and the thermal environmental factors of the building. The results of these efforts can be used as inputs for future energy model development or other application studies that require detailed occupancy data. This highlights the importance of grouping the complex perceptions of occupant thermal comfort into clusters with similar data.

## 5. Conclusions

In this study, we clustered occupants responding to the thermal environment of an office, performed SA to determine the sensitivity levels of each cluster to the thermal environmental factors, and proposed control measures based on our findings. Clustering was employed to support the reliability of the results derived from the variables used in this study. The TSVs and TCVs data collected from the occupants (participants) were clustered according to similar values. Finally, SA was performed on the resulting clusters and the thermal environment. The following conclusions were obtained in response to the research questions formulated to achieve the three objectives set in this study.

1) Although the TSV represents the subjective perceptions of the occupants, we found distinguishable similarities in their thermal sensation traits and grouped similar TSV values into five clusters that responded differently to the same thermal environment.
2) Each cluster showed different TSV and TCV patterns, which allowed us to classify the groups that had sensitive responses to the current thermal environment into those that accept changes in the environment and those that did not. For example, two groups had sensitive responses, but showed different traits based on which they were divided into a group that could accept changes in the thermal environment and a group that could not.
3) Different control indicators should be applied to the different groups. For example, a group with high thermal adaptability can contribute to building energy savings by raising the HVAC control standard. For a group with low thermal adaptability, the thermal comfort of the occupants and building energy efficiency can be concurrently improved by adjusting the set temperature and applying the control indicator based on the comfort standard of the thermal environmental factor to which the group had a sensitive response.

The thermal sensation traits of occupants play an important role in building energy consumption and can be used as an effective method for building energy management across numerous aspects. Therefore, integrating the physiological and behavioral data of the occupants into the HVAC control is important. A comfortable and stable indoor thermal environment must be implemented via comfort-based control.

The results of this study show that people have different levels of adaptability and sensitivity to a given thermal environment. Research on clustering various thermal behaviors and traits can serve as an important component of strategic control system development aimed at improving building energy efficiency and occupant thermal comfort. Furthermore, a proper understanding of the relationship between the thermal comfort of an occupant and the indoor thermal environment can lead to the development of new technologies for building systems with optimized energy use.

## Informed consent statement

Clear and Informed written consent was obtained from all donors involved in this study.

## Additional information

No additional information is available for this paper.

## CRediT authorship contribution statement

**Sungkyung Kim:** Writing – original draft, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Jihye Ryu:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **Won-Hwa Hong:** Writing – review & editing, Methodology.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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