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Analysis of Thermal Sensation: Evaluating Environmental and Subjective Factors, Using the ASHRAE Global Thermal Comfort Database II and SCATS Databases

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ABSTRACT

Although thermal comfort in buildings is a crucial component in determining occupant well-being and energy consumption, it is impacted by a complex interaction between subjective and physical factors. Recent studies on indoor environmental quality have cast doubt on conventional static models by demonstrating how a person's thermal perception can be greatly influenced by their cultural expectations, acclimatization, and personal background. So, the aim of this study is to define to what extent do individuals from different countries, with varying cultural backgrounds and habits, perceive indoor thermal environments differently, considering environmental and subjective parameters.

For this, the ASHRAE Global Thermal Comfort Database II and the SCATS database were used to identify potential patterns of thermal sensation and comfort perception across different countries. Data from office environments during the summer and winter was used. The environmental parameters considered to build the models were air temperature (ta), operative temperature (top), airspeed (vel) and relative humidity (rh) and the subjective parameters considered for the analysis were clothing insulation (clo) and metabolic rate (met).

To examine the relationship between thermal sensation and both environmental and personal factors, a cumulative link model for ordinal responses was applied. In addition, a cumulative link mixed model was used to account for potential unobserved heterogeneity at the study level, particularly important given that the data were drawn from multiple independent studies. In total, eight different models were tested to determine the most suitable one for predicting thermal sensation votes. Additionally, different thermal comfort scenarios recommended by the EN 16798 standard were evaluated to account for variations in thermal perception among users from different countries.

As a result, the most suitable model was the one that considers operative temperature, relative humidity, airspeed, metabolic rate, clothing insulation and country as predictors, where operative temperature and metabolic rate display strong positive associations with thermal sensation across both seasons, while airspeed shows significant negative effects, particularly in summer. Although relative humidity is also statistically significant, its influence on thermal sensation is weaker compared to other variables. Also, the shift in the influence of clothing insulation appears positively related to warmth in summer but negatively in winter.

A comparison between countries for regional differences in thermal sensation was carried out. The inclusion of country as a categorical predictor in the thermal sensation models reveals clear regional differences in how participants from various locations experience and report thermal environments. During summer and winter, thermal neutrality is the most frequently predicted response across most countries, indicating a general tendency toward comfort under average conditions.

These findings highlight the role of climate, building practices, and cultural norms in shaping thermal perception and underscore the limitations of static comfort standards when applied across diverse geographic contexts. This leads to variations among countries regarding the acceptability levels linked to standardized indoor conditions, showing the importance of air movement to make higher indoor temperatures more comfortable. However, the benefits of increased airspeed are influenced by users' climate adaptation, with moderate airflow improving comfort in most cases but excessive velocities reducing acceptability in some regions.

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1. Introduction

It is widely recognized that individuals spend approximately 90% of their time within indoor environments, where they are in continuous interaction with the surrounding conditions (Jara-Baeza et al., 2025). Consequently, ensuring an appropriate indoor environment becomes essential. Key factors such as indoor air quality (IAQ), lighting, acoustics, and thermal conditions are considered fundamental components in achieving optimal indoor environmental quality (IEQ). These parameters play a crucial role in influencing occupants' health, comfort, and productivity. For example, inadequate thermal conditions may contribute to discomfort and symptoms associated with Sick Building Syndrome (SBS), potentially affecting cognitive functions such as concentration and memory, and ultimately hindering performance. Therefore, the implementation of a well-designed and properly regulated thermal environment has the potential to enhance occupant well-being, efficiency, and comfort during indoor activities (Sharma et al., 2025).

Nevertheless, providing an acceptable indoor environment is not solely limited to maintaining appropriate indoor air quality or ensuring comfortable building conditions. Another critical aspect that must be considered is energy consumption. The growing impacts of climate change, the increasing levels of pollution, the global energy crisis, the depletion of natural resources, and the continued reliance on fossil fuels have intensified efforts to reduce energy consumption, particularly within the building sector (Almtuly et al., 2025). According to Elhami et al. (2025), based on projections from the World Bank and the International Energy Agency, the building sector ranks among the largest energy consumers worldwide, exerting considerable influence on climate change, primarily due to greenhouse gas (GHG) emissions generated throughout the building's lifecycle — from construction to operation and eventual decommissioning.

In this context, regional variations in energy consumption patterns within the building sector further emphasize its substantial role in overall energy demand. These patterns not only reflect climatic conditions and building technologies but also underline the impact of national policies, user behavior, and socio-economic factors. For instance, in Iran, the energy consumption of buildings is reported to be nearly three times higher than the global average, while in hot-arid regions buildings tend to consume approximately 75% of the country's total energy use (Almtuly et al., 2025). Similarly, the Energy Performance of Buildings Directive (EPBD, EU/2024/1275) reported in 2024 that approximately 40% of the total energy consumed within the European Union (EU) is attributed to buildings. Furthermore, over one-third of the EU's energy-related GHG emissions originate from the building sector, while approximately 75% of the existing building stock remains energy-inefficient. Notably, nearly 80% of the energy consumed in residential buildings across the EU is dedicated to heating, cooling, and hot water.

As highlighted by Almtuly et al. (2025), the demand for cooling systems is projected to continue rising, driven by factors such as population growth, increasing urbanization, and the need of individuals to improve their living standards. Consequently, various strategies and solutions are being explored with the aim of enhancing building performance, while simultaneously preserving indoor comfort conditions and maintaining satisfactory indoor air quality.

In this regard, recent literature has emphasized that thermal comfort is a complex phenomenon, influenced not only by environmental and physiological parameters but also by subjective factors related to individual background and previous experiences. As highlighted by Pistore and Pasut (2023), thermal comfort expectations are shaped by exposure to certain climates, cultural habits, and social practices, which directly influence how occupants perceive and adapt to thermal environments. This recognition challenges the universal applicability of traditional thermal comfort models and reinforces the need to consider occupant diversity in building design and operation.

To develop effective solutions, it is essential to first understand the complex interaction between building occupants and the indoor environment. Moreover, it is important to acknowledge the diversity of these interactions, as they vary across different contexts, users, and climates. Considering these variations, it is fundamental for the design of energy-efficient buildings whose performance and operation are not compromised by occupant discomfort or dissatisfaction (Pistore & Pasut, 2023).

Accordingly, the main objective of this research is to analyze the variation in thermal sensation among users from different countries, based on both environmental and physiological parameters, considering environmental variables such as air temperature, relative humidity, operative temperature, and airspeed, as well as physiological factors including metabolic rate and clothing insulation.

This analysis seeks to provide a deeper understanding of typical occupant behavior in response to thermal environments, considering both cultural and climatic differences. Based on this knowledge, it is possible to explore strategies for optimizing energy consumption by integrating occupant behavior and local climatic conditions into building operation practices.

Ultimately, this research seeks to promote an approach that goes beyond relying solely on technological solutions. Instead, it emphasizes the importance of understanding user behavior and perception to design and operate buildings that respond more effectively to occupants' real needs and expectations.

1.1Research Problematic

This study seeks to answer the following research question:

“To what extent do individuals from different countries, with varying cultural backgrounds and habits, perceive indoor thermal environments differently? Specifically, does the influence of established parameters—such as operative temperature, relative humidity, airspeed, clothing insulation, and metabolic rate—on thermal sensation vary across cultural contexts?”

By addressing this question, the research aims to provide a foundation for future energy-saving strategies that consider user behavior and local climatic conditions, moving beyond purely technological solutions towards a more user-centered approach to building design and operation.

1.2 Objective

The aim of this research is to analyze the variation of thermal sensation among occupants from different countries, using the country of residence as a proxy to indirectly explore user behavior, expectations and their perception of thermal environments during the seasons of summer and winter.

To investigate how environmental, physiological, and subjective parameters influence thermal sensation across different countries and climatic zones, ASHRAE Global Thermal Comfort Database II and the SCATS database were used. Through these databases, the research seeks to identify potential patterns of thermal sensation and comfort perception across different countries, contributing to a better understanding of occupant behavior in relation to thermal environments.

1.2.1. Specific Objectives

- To compare thermal sensation responses across countries by integrating field data from the ASHRAE and SCATS databases.
- To examine the relationship between thermal sensation and key environmental parameters, such as air temperature, relative humidity, operative temperature, and airspeed.
- To explore the influence of physiological parameters, including metabolic rate and clothing insulation, on occupants' thermal sensation.

2. Literature Review

2.1 Thermal Comfort Model

2.1.1 Thermal Comfort

According to ASHRAE/ANSI Standard 55 (2017), thermal comfort is defined as a "state of mind that expresses satisfaction with the thermal environment." This definition is rooted in physical principles, particularly those related to thermal conditions and overall well-being. However, accurately assessing thermal comfort presents a challenge due to its subjective nature. Given its complexity, it is essential to understand people's thermal perception and provide them with an indoor environment that is both suitable and meets their needs (Brager & de Dear, 2008; Zheng et al., 2025).

2.1.2 Thermal Sensation

Due to the complex and subjective nature of thermal comfort, it is nearly impossible to measure it directly. As a result, various indicators have been developed to evaluate individuals perceived thermal responses under different environmental conditions. In the field of environmental thermophysiology, thermal sensation is defined as an individual's subjective perception of temperature, reflecting how warm or cold they feel in a specific setting. This perception arises from the interaction between physiological responses and environmental variables. Thermal sensation is widely regarded as a standard parameter in thermal comfort research and is frequently used in experimental studies to assess and classify comfort levels (Velt & Daanen, 2017).

The concept of thermal sensation is commonly linked to the subjective thermal response used to evaluate the thermal condition of the human body. Given the inherent complexity of assessing this parameter, it becomes essential to apply accurate methods for its measurement and quantification. Subjective thermal sensation is typically evaluated using multi-point rating scales, known as Thermal Sensation Votes (TSV), which capture individuals' perceptions of thermal comfort (Zheng et al., 2025).

Various studies have proposed different scales to evaluate thermal sensation. In 1936, Thomas Bedford conducted one of the earliest investigations into thermal comfort and was the first to introduce a seven-point scale to assess thermal perception. Since then, alternative scales, including three-point, five-point, nine-point, and eleven-point scales, have been developed to capture subjective thermal responses with varying degrees of granularity. Despite the existence of multiple Thermal Sensation Vote scales, the ASHRAE seven-point scale remains the most widely used and standardized tool in thermal comfort research, serving as the primary reference in most related studies (Zheng et al., 2025).

Figure 2.1 illustrates the various types of Thermal Sensation Votes. As shown, increasing the number of voting scale points enhances the level of detail in the thermal sensation descriptors, making the distinctions between intermediate categories more explicit.

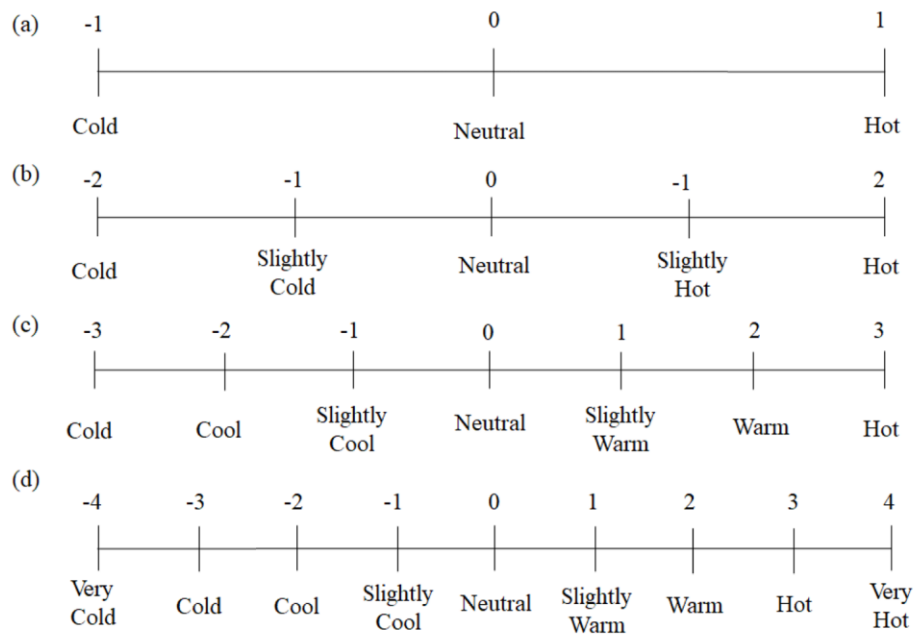

Figure 2.1 (a) three-point; (b) five-point; (c) seven-point; (d) nine-point voting scale (Zheng et al., 2025)

Numerous studies have been conducted to develop reliable indices for evaluating thermal sensation in indoor environments. Among the most widely recognized are the Predicted Mean Vote (PMV) and the Predicted Percentage of Dissatisfied (PPD). These indices provide a standardized, quantitative framework for assessing thermal comfort and identifying specific areas that may require environmental improvements (Evola et al., 2025).

2.1.3 Predicted Mean Vote (PMV)

The Predicted Mean Vote (PMV) model, developed by Fanger, is one of the most established and widely adopted methods for quantifying thermal comfort. It has been officially incorporated into several national and international standards, including ASHRAE 55, ISO 7730, and CEN 15251. Despite its broad acceptance, the applicability of the PMV model may vary depending on geographic and climatic conditions, which can limit its universal implementation (Zhang et al., 2019).

The PMV model is based on the human body's heat balance and considers six primary factors—four environmental (air temperature, radiant temperature, humidity, and air velocity) and two personal (metabolic rate and clothing insulation). It predicts the average thermal sensation of a large group of people on the ASHRAE seven-point thermal sensation scale, which ranges from –3 (cold) to +3 (hot) (Roni & Hariri, 2022).

2.1.4 Predicted Percentage Dissatisfied (PPD)

According to the ASHRAE/ANSI Standard 55 (2017), the Predicted Percentage of Dissatisfied (PPD) is a quantitative index that estimates the proportion of individuals likely to experience thermal discomfort—specifically, those who feel either too cold or too warm within a given indoor environment. This index reflects the percentage of occupants who are not thermally satisfied, often due to localized sources of discomfort. The primary contributors to such discomfort are typically unwanted cooling or heating effects on specific parts of the body (dos Reis et al., 2022).

Figure 2.2 presents the relationship between the Predicted Percentage of Dissatisfied (PPD) and the Predicted Mean Vote (PMV) indices, as established by ASHRAE (2017). According to this standard, an indoor environment is generally regarded as thermally acceptable when at least 80% of occupants report thermal satisfaction. This criterion corresponds to a PPD value lower than 20%, which is widely recognized and applied as a reference threshold for evaluating acceptable indoor thermal conditions.

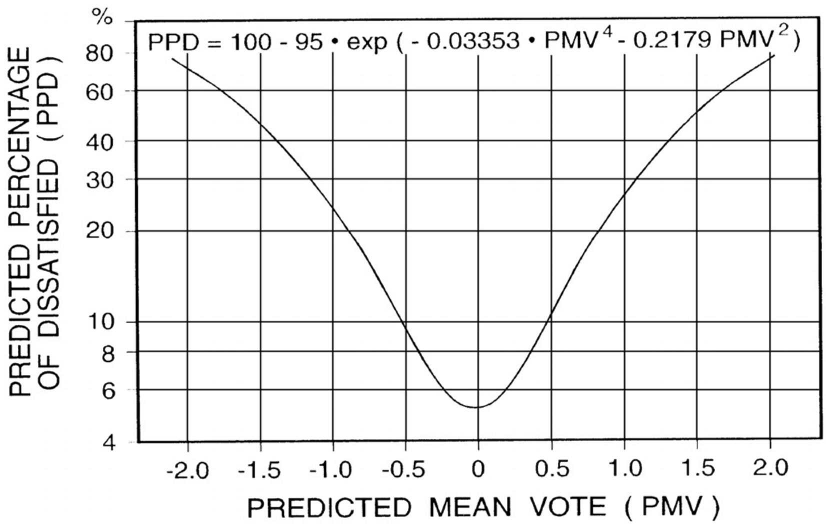

Figure 2.2 PPD as a function of PMV

Within the context of the PMV/PPD model, thermal neutrality is attained when the metabolic heat produced by the human body is effectively released, allowing for a stable thermal balance between the individual and their surrounding environment (Ibrahim et al, 2018).

The calculation of the PMV/PPD model is grounded in a combination of environmental and personal factors that significantly influence thermal comfort. According to ASHRAE (2017), six key variables under steady-state conditions determine whether an indoor thermal environment is acceptable. These include four environmental parameters—air temperature, air speed, relative humidity and operative temperature —and two personal factors: clothing insulation and metabolic rate. Together, these variables allow for a comprehensive evaluation of the heat exchange between the human body and its surroundings, forming the basis of the PMV and PPD indices used in thermal comfort assessments.

2.2 Parameters that Affect Thermal Comfort

The perception of thermal comfort experienced by an individual within a specific environment and at a particular moment results from the interaction of multiple factors, both physical and non-physical, in nature. These factors exert their influence based on their inherent characteristics, relative importance, and capacity to affect human thermal sensation.

2.2.1 Environmental Parameters

2.2.1.1 Air Temperature

Air temperature refers to the temperature of the environment surrounding an individual's body, and it is commonly measured in degrees Celsius (°C) or Fahrenheit (°F). Extensive research has established a significant relationship between thermal comfort and human performance, identifying air temperature as one of the most critical factors influencing thermal perception. This is largely due to the high sensitivity of the human body to fluctuations in ambient temperature. Variations in air temperature — whether in the form of increases or decreases — have been shown to directly affect both individual well-being and task performance (Roni & Hariri, 2022).

2.2.1.2 Air speed

Airspeed is defined as the rate of air movement at a specific point around a person, regardless of the air's direction, and is typically measured in meters per second (m/s) or feet per minute (ft/min). It significantly influences the convective heat exchange between the human body and the surrounding environment, thereby affecting overall heat loss. Depending on the indoor conditions, airspeed can contribute to either heating or cooling a space. Like temperature, airspeed plays a critical and fundamental role in thermal comfort, as humans are particularly sensitive to changes in airflow (Roni & Hariri, 2022).

As noted by Cengel and Ghajar (2015), low but steady air circulation is important for maintaining thermal comfort. Adequate airflow aids in displacing the warm, humid air surrounding the body and replacing it with cooler, drier air. For this process to be effective, the airflow must be strong enough to promote heat and moisture removal, yet gentle enough to avoid being perceptible. Excessive airspeed can lead to discomfort, thereby diminishing the overall thermal comfort experience. Table 2.1 presents the average subjective assessments of air velocity levels, as perceived by individuals under common, everyday environmental conditions.

Table 2.1 Average Perception of Air Velocity (Auliciems & Szokolay, 2007)

Air velocity (m/s)	**Occupant's subjective responses**
< 0.25	Unnoticed
0.25-0.50	Pleasant
0.50-1.00	Awareness of air movement
1.00-1.50	Draughty
> 1.50	Annoyingly draughty

2.2.1.3 Relative Humidity

Based on the thermodynamics definition the relative humidity is defined as the relation between the partial pressure of the vapor in the gas mixture and the partial pressure of the vapor in the gas mixture if the gas were saturated at the given temperature of the mixture (Himmelblau, 1997). In the context of thermal comfort, relative humidity refers to the air's capacity to retain moisture. This parameter directly influences the extent to which the human body can dissipate heat through evaporative processes, thereby affecting overall thermal regulation. Under high ambient temperatures, elevated relative humidity significantly hinders the body's capacity to regulate heat through evaporative cooling. Conversely, lower humidity levels enhance this thermoregulatory mechanism. The recommended range for indoor relative humidity typically spans from 30% to 70%, with a target value of approximately 50% regarded as optimal for maintaining thermal comfort (Cengel & Ghajar, 2015).

2.2.1.4 Operative Temperature

According to Auliciems and Szokolay (2007), operative temperature (Top) is an index that corresponds to the temperature of a uniform and isothermal black enclosure, which would produce identical convective and radiative heat exchanges between the human body and its surroundings as those occurring in an actual, thermally non-uniform space. Air temperature and radiant temperature are fundamental parameters that directly affect the operative temperature, as this variable represents the combined influence of both factors on human thermal perception. The operative temperature can be determined through the application of the following equation:

$$t_o = \frac{(h_c * t_a + h_r * t_r)}{(h_c + h_r)} \tag{1}$$

Where, t_o denotes the operative temperature, h_c and h_r correspond to the convective and radiative heat transfer coefficients, respectively, expressed in W/m^2K. In addition, t_a represents the air temperature, while t_r refers to the mean radiant temperature, both measured in degrees Celsius °C (Olesen et al, 2019).

2.2.2 Physiological Parameters

2.2.2.1 Metabolic Rate

According to ASHRAE/ANSI Standard 55 (2017), metabolic rate is defined as “the rate of transformation of chemical energy into heat and mechanical work by metabolic activities of an individual, per unit of skin surface area”. In scientific terms, a Metabolic Equivalent of Task (MET) is commonly characterized as the standard reference value for human energy expenditure, corresponding to the amount of energy utilized by an individual at rest in a thermoneutral setting. Metabolic rate is commonly expressed in terms of MET, with 1 MET corresponding to an energy expenditure of 58.2 W/m^2 (Fletcher et al., 2020).

According to international standards, several methodologies exist for estimating metabolic rate. One of the most widely applied approaches involves the systematic observation of an individual's physical activity, followed by the assignment of a corresponding reference MET value derived from established tabulated data (Fletcher et al., 2020). Although this observational method is widely applied in practice, it may be associated with a considerable degree of uncertainty, particularly when assessing higher levels of physical activity. Consequently, a more precise approach for determining metabolic rate involves the direct measurement of respiratory oxygen consumption, which provides a more accurate estimation of the body's energy expenditure (Cengel & Ghajar, 2015).

Moreover, extensive research has established that metabolic rate constitutes a fundamental parameter influencing human thermal comfort, particularly as it varies with the intensity and nature of physical activities such as sitting, writing, standing, walking, etc. An increase in the level of physical activity leads to a proportional rise in the metabolic rate. Consequently, even relatively small variations in the MET values associated with specific activities may result in substantial deviations in the assessment and prediction of thermal comfort conditions (Na et al, 2019).

Examples of metabolic rates corresponding to different physical activities are presented in Table 2.2, expressed in met units and per unit of body surface area.

Table 2.2 Metabolic Rate Values by Activity Type (ASHRAE, 2017)

Activity	**Metabolic Rate**	
	Met Units	**W/m^2**
Sleeping	0.7	40
Seated, quiet	1.0	60
Standing, relaxed	1.2	70
Walking about	1.7	100
Driving an automobile	1.0-2.0	60-115
Machine work - heavy	4.0	235

2.2.2.2 Clothing Insolation

Based on ASHRAE (2017), clothing insulation is defined as the thermal resistance offered by a complete clothing ensemble against the exchange of sensible heat between the human body and its external environment. This property reflects the garment system's ability to reduce heat loss or gain through conduction, convection, and radiation, and is conventionally quantified using the unit 'clo' as a standardized measure of insulation performance, where 1 clo is equivalent to 0.155 m^{2}K/W.

Clothing insulation can be assessed through a variety of methods. These include direct measurements performed in climate-controlled chambers, utilizing either thermal manikins or actively engaged human subjects to simulate real-world conditions. Nevertheless, a widely employed technique is the clo-checklist method, which involves the use of structured questionnaires to systematically catalog the individual garments worn by a subject, thereby enabling a standardized estimation of clothing insulation. Table 2.3 provides a compilation of representative clothing insulation values, illustrating a range of typical garment configurations (Wang et al, 2019).

Table 2.3 Clothing Insulation Values across Typical Garment Combinations (ASHRAE, 2017)

Garment Description	**I_{clo} (clo)**
Walking shorts, short-sleeve shirt	0.36
Trousers, short-sleeve shirt	0.57
Long-sleeve coveralls, T-shirt	0.72
Trousers, long-sleeve shirt, suit jacket	0.96
Knee-length skirt, long-sleeve shirt, half-slip, long-sleeve sweater	1.10
Insulated coveralls, long-sleeve thermal underwear tops and bottoms	1.37

Clothing insulation represents a fundamental factor in the regulation of human thermal comfort, offering individuals substantial adaptability in responding to varying thermal environments. Nevertheless, this variable is influenced by a range of environmental and situational factors, including social dress norms, variations in indoor and outdoor climatic conditions, and the characteristics of building ventilation systems. Within the framework of thermal adaptation strategies, clothing serves as a primary means by which occupants can achieve thermal neutrality. This concept, commonly referred to as neutral clothing, is defined as the optimal level of clothing insulation (clo value) that allows individuals to maintain a neutral thermal sensation without necessitating active intervention in the indoor environmental conditions. An illustrative representation of the concept of neutral clothing is provided in Figure 2.3 (Wang et al, 2019).

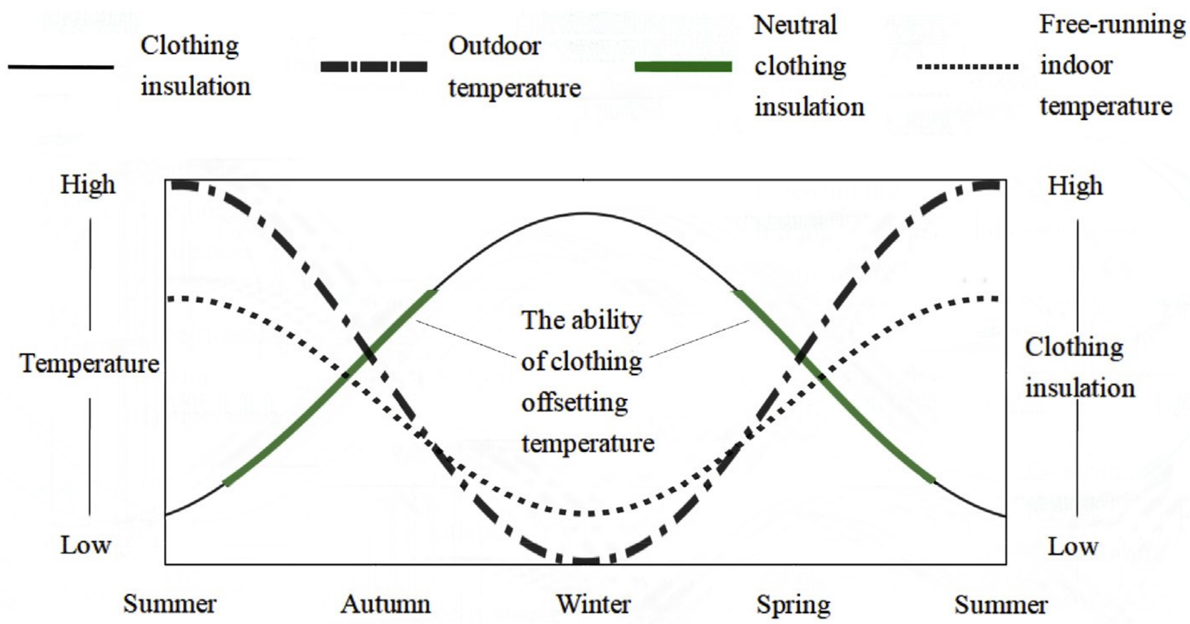

Figure 2.3 Neutral clothing diagram (Wang et al, 2019)

2.2.3 Subjective Parameters

Previous research has highlighted that human thermal comfort responses within indoor environments are influenced not only by physical or thermal parameters but also by a range of non-thermal factors. These factors, which include individual expectations, adaptation processes, thermal sensation, and subjective perception, play a significant role in shaping occupants' comfort experiences. However, such variables are not explicitly considered within the traditional Predicted Mean Vote (PMV) model, which primarily focuses on objective environmental and physiological parameters (Li et al., 2020).

In the context of thermal comfort research, subjective concepts have gained relevance in recent years, particularly in studies aiming to explain variations in comfort perception among users from different backgrounds. These concepts are fundamental to understand why occupants from different regions, despite being exposed to similar environmental conditions, may report different levels of thermal satisfaction. Consequently, these factors should be considered when analyzing user behavior and designing energy-efficient and occupant-centered buildings (Pistore & Pasut, 2023).

2.2.3.1 Adaptation

The concept of adaptation describes the process through which individuals adjust to their thermal environment over time. According to de Dear and Brager (1998), adaptation occurs through three primary mechanisms: (i) behavioral adaptation, involving conscious or unconscious actions such as adjusting clothing or modifying the use of HVAC systems; (ii) physiological adaptation, referring to biological changes like acclimatization to repeated thermal exposure; and (iii) psychological adaptation, which involves shifts in thermal perception or expectation based on past experience or contextual factors. Together, these adaptation processes allow individuals to tolerate a wider range of thermal conditions beyond those predicted by purely physical models.

2.2.3.2 Sensation

According to ASHRAE/ANSI Standard 55 (2017), sensation is defined as “a conscious subjective expression of an occupant’s thermal perception of the environment”. In the field of thermal comfort, sensation refers to the immediate experience resulting from the activation of thermal receptors in the skin and the body's response to environmental temperatures (Yan et al, 2024).

2.2.3.3 Perception

Corresponds to the psychological process through which individuals interpret and evaluate the thermal sensations they experience. This interpretation is subjective and can be influenced by various factors (Nikolopoulou & Steemers, 2003). Therefore, perception plays a key role in shaping how different people assess the same thermal conditions in diverse ways.

2.2.3.4 Expectation

According to Nikolopoulou and Steemers (2003), expectation can be understood as the anticipation or mental image that individuals develop regarding how their surrounding environment should feel, rather than how it is perceived at a given moment. In the context of thermal comfort, expectations influence how occupants evaluate indoor conditions, shaping their tolerance and satisfaction levels. These expectations do not arise in isolation but are shaped by multiple factors, such as previous thermal experiences, the characteristics and typology of the building, cultural practices, and the climatic context to which individuals are accustomed (Pistore & Pasut, 2023).

2.2.4 Ventilation

Ventilation plays a critical role in determining indoor environmental quality, particularly in the context of thermal comfort. To achieve a thermally comfortable indoor environment, the selection of ventilation strategies plays a critical role. Natural ventilation, such as opening or closing windows, allows fresh air to enter the space passively, whereas mechanical ventilation systems—employing devices like fans or heaters—actively regulate indoor air conditions.

Adequate ventilation contributes to thermal comfort by regulating indoor air temperature, removing excess heat, and facilitating evaporative cooling through increased air velocity. Air movement enhances convective and evaporative heat loss from the human body, thereby improving comfort levels in warm environments (Fanger, 1970).

2.2.4.1 Natural Ventilation (NV)

Natural ventilation relies on wind-driven forces to introduce fresh air into indoor spaces. As highlighted by Zhai et al. (2015), it stands out as one of the most effective strategies for minimizing cooling demands and lowering overall energy consumption in buildings. However, for the effective implementation of natural ventilation strategies, thoughtful design is essential. This requires accurate prediction of air movement patterns and thermal behavior within the space to ensure proper ventilation rates and maintain indoor comfort. Moreover, the adaptive comfort model suggests that occupants in naturally ventilated spaces have a greater tolerance for temperature variation, primarily due to their ability to control ventilation (Brager & de Dear, 2000).

2.2.4.2 Mechanical Ventilation (MV)

Mechanical ventilation systems are responsible for regulating indoor temperature, humidity, and airflow. Referred collectively as HVAC (Heating, Ventilation, and Air Conditioning), these systems play a critical role in delivering fresh outdoor air and distributing it evenly throughout interior spaces to maintain thermal comfort and air quality. However, the thermal response and overall efficiency are influenced by how effectively their control parameters are adjusted and managed (Cengel & Ghajar, 2015; Elhami et al, 2025).

3. Methodology

3.1 ASHRAE Global Thermal Comfort Database II

The data used in this study was obtained from the open-source ASHRAE Global Thermal Comfort Database II. This database comprises thermal comfort data collected from numerous field studies, with approximately 81,846 sets of indoor climatic observations. This dataset was developed through the direction of University of California at Berkeley´s Center for the Built Environment and University of Sydney´s Indoor Environmental Quality (IEQ) Laboratory.

This dataset includes background information, including the gender and age of occupants, as well as detailed building characteristics such as typology, operational mode, and geographic location. It also includes subjective comfort assessments, covering parameters such as thermal acceptability, thermal sensation, and thermal preference, among others. Additionally, the dataset provides instrumental thermal comfort measurements, including air temperature, relative humidity, operative temperature, air speed, etc. Furthermore, meteorological data such as outdoor temperature and humidity are included. This raw data has been collected over the past 20 years from various countries and climate zones worldwide.

This database is derived from field studies carried out across five continents, encompassing a diverse range of geographical regions and countries (23 in total). Based on Roni and Hariri (2022), shifts in seasons and dominant weather patterns significantly impact how individuals physiologically adapt, modify their behavior, and perceive indoor comfort. The database contains thermal comfort measurements categorized according to the Köppen climate classification, covering 16 climate types across all four seasons. The highest number of thermal comfort data is associated with the climatic zones of hot-summer Mediterranean, humid subtropical, hot-semi arid and tropical wet savanna. In terms of seasonal data, the highest quantity was collected during the summer and winter months. The distribution of records and climatic zones around the world is presented in Figure 3.1.

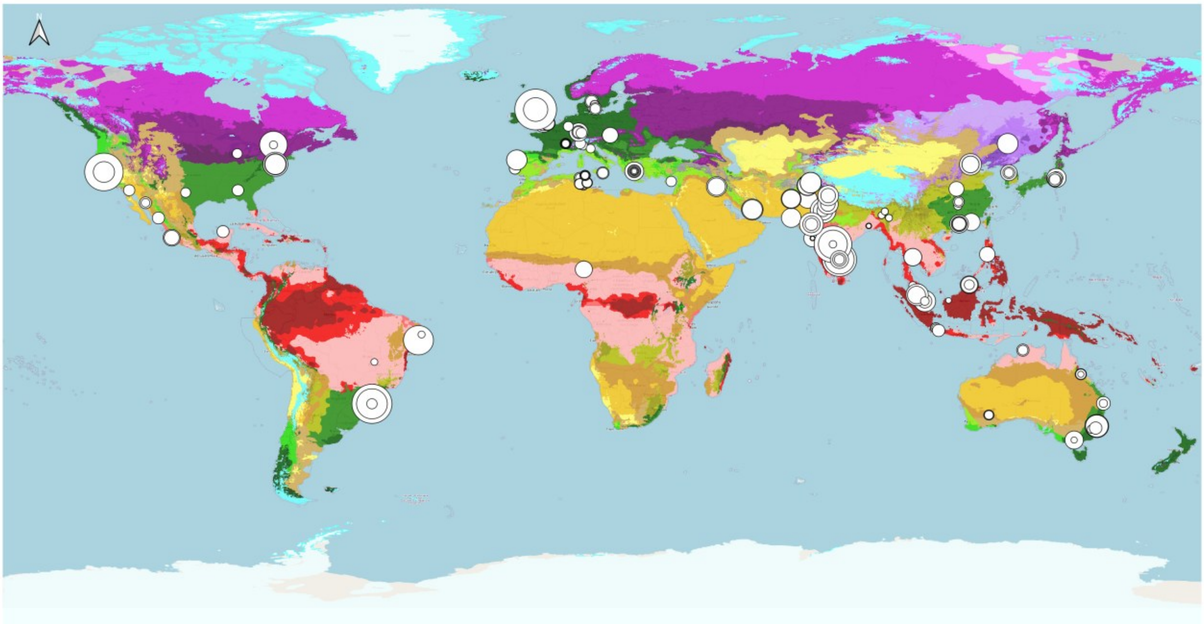

Figure 3.1 Geographical distribution of field studies in the ASHRAE Global Thermal Comfort Database II

3.1.1. Dataset Extracted for the analysis

For the scope of this work, the dataset was modified. The indoor environmental parameters extracted from the database were air temperature (ta, °C), relative humidity (rh, %), operative temperature (top, °C), air speed (vel, m/s), and the subjective parameters of the user included were clothing insulation (clo) and metabolic rate (met). These six factors were selected in accordance with the ASHRAE 55-2017 standard, which establishes that all six factors must be considered when determining thermal comfort conditions. Finally, in line with the study's objective, the Thermal Sensation parameter was included in the analysis, as it is typically associated with the subjective thermal response used to assess the thermal state of the human body (Zheng et al., 2025).

To clean the dataset, rows with missing values were removed. Subsequently, since the geographical information was stored in a separate metadata file, the parameters "country" and "city" were incorporated into the updated dataset using the "building id" as a reference.

To ensure data consistency, a comparison against relevant standards was conducted. The values for "met" and "clo" were typically calculated according to the ASHRAE 55 or ISO 7730 standards. After reviewing the data and identifying their sources and corresponding standards, the data from contributors for whom the standard used to calculate "clo" and "met" parameters was not specified were excluded, as their origin could not be determined. Additionally, data from authors whose original data could not be linked to any standard were also excluded, as no clear relationship with the standards could be established.

To further refine the analysis, the seasonal classification between summer and winter was determined based on astronomical criteria. This was achieved by examining the geographical coordinates (latitude and longitude) and the recorded time of year, as detailed in the metadata file. Establishing this distinction ensures that climate-related variables are properly contextualized within the seasonal framework.

For United Kingdom (UK), seasonal classification was based on the dates of measurement. Data collected during March and April were excluded, as these months fall within spring, a season not relevant to this study. Similarly, data from October, categorized as autumn, were also discarded. For transitional months at the boundary between summer and winter (May and September), temperature was used as a determining factor:

- Measurements with temperatures below 22°C were classified as winter conditions.
- Measurements with temperatures above 24°C were classified as summer conditions.

For Indonesia, all data were categorized as summer, given the consistently warm temperatures. In Indonesia, which has a tropical climate, the minimum temperature recorded during February and March 2015 (the period of data collection) was 20°C, with a maximum of 27°C and an average of 23°C. These conditions suggest the need for lighter clothing.

As established in the literature review, thermal sensation is commonly assessed using multi-point rating scales. The present database includes thermal sensation votes recorded on both five-point and seven-point scales. To ensure data consistency, the seven-point scale was chosen as the sole instrument for thermal sensation assessment due to two primary reasons. First, the dataset employing the five-point scale comprises 305 observations, whereas the seven-point scale dataset contains a substantially larger sample of 19,258 observations. This significant disparity in sample size could impact the robustness of statistical inferences. Second, the five-point scale data exhibited a limited range of responses. Specifically, no observations corresponded to the '-2' (very cold) category, and very few responses were recorded for the '+2' (very hot) category. This suggests a potential underutilization of the scale's full range and consequently, potentially less informative data distribution. Therefore, considering both the limited range of responses and the smaller dataset, the data obtained using the seven-point scale was selected for further analysis.

3.2. SCATS Database

The Smart Controls and Thermal Comfort (SCATS) database forms the empirical foundation for the adaptive comfort model introduced by Nicol and Humphreys in their 2002 work, Adaptive Thermal Comfort and Sustainable Thermal Standards for Buildings (Pistore et al., 2023). Developed between December 1997 and December 2000, the SCATS project was designed around the principles of adaptive comfort theory. Its primary goal was to explore strategies for reducing energy use in air-conditioned buildings and to promote the use of natural ventilation. To achieve this, the project focused on developing intelligent control systems capable of responding dynamically to indoor and outdoor environmental conditions, in line with the adaptive comfort approach (McCartney & Nicol, 2002).

3.2.1. Scats Database Integration

In the earlier analysis using the ASHRAE II database, although the dataset contained entries from various regions, the representation of Europe was largely limited to data from the UK. To strengthen the European dimension of the analysis and enable more balanced comparisons across regions, data from the SCATS database, as presented in Pistore et al. (2023), was incorporated. This addition brought in further observations from Europe and contributed to a broader and more diverse dataset overall.

To ensure consistency and quality before integration, the SCATS data underwent a thorough cleaning process. This included the removal of missing (NA) values and categorization of records based on seasonal periods. Specifically, the dataset was segmented as follows: winter (December–February), spring (March–May), summer (June–August), and fall (September–November). However, for the purpose of this analysis, only the data corresponding to summer and winter seasons were considered.

3.3. Data Collection and Preprocessing

The data used in this study were collected from office environments, as this was the most readily available and comprehensive dataset for evaluating thermal sensation. Given the influence of seasonal variation on indoor environmental factors and human thermal perception, separate models were developed for the summer and winter periods. This seasonal split allows for a more accurate representation of how individuals perceive thermal conditions in different climatic contexts. Thermal sensation responses can vary significantly between seasons due to changes in clothing insulation, outdoor temperatures, solar radiation, and the operation of HVAC systems.

A final round of data cleaning was performed to ensure the analysis reflects realistic indoor office conditions by applying filters to remove extreme or improbable values. Air temperature (ta) and operative temperature (top) were both limited to a range between 15°C and 35°C, which aligns with commonly observed thermal conditions in office environments. Clothing insulation (clo) was restricted to values between 0.3 and 4, as lower values may represent minimal clothing, not typical in offices. Metabolic rate (met) was filtered to include values between 0.8 and 2.5. These filters were implemented to improve data quality and focus the analysis on plausible scenarios of thermal comfort in office settings.

Subsequently, after applying these filters and categorizing the data by season—focusing exclusively on summer and winter—the final dataset was composed of 15,872 observations, with 10,501 corresponding to summer and 5,371 to winter.

3.4. Statistical Analysis

3.4.1. Cumulative Link Model (CLM) for Ordinal Responses

To analyze the thermal sensation votes, which were collected using a seven-point ordinal scale ranging from -3 (Cold) to +3 (Hot), a Cumulative Link Model (CLM) was employed. This type of regression model is particularly when the dependent variable is ordinal, that is, when the response categories have a natural ordering but the distances between categories are not necessarily equal (McNukty, 2021).

In the cumulative logit approach, the model estimates the cumulative probabilities of the response variable falling at or below a certain category, given the values of the explanatory variables. The model for our case of a seven-level ordinal response can be expressed as:

$$logit\big(P(Y \leq j)\big) = \log\left(\frac{P(Y\leq j)}{P(Y>j)}\right) = \alpha_j - \beta_1 x_1 - \cdots - \beta_k x_k \qquad for\ j = -3, \dots, +3 \tag{2}$$

Where:

- Y refers to the ordinal response variable (thermal sensation votes);
- j refers to each response category arbitrary coded in the set {-3, -2, -1, 0, 1, 2, 3};
- α_j represents the intercept associated with category j;

- $\beta_1, \beta_2, \ldots, \beta_k$, are the coefficientes for the predictor variables $x_1, x_2, \ldots, x_k$

A key assumption of the cumulative link model is the proportional odds assumption, which implies that the effect of each predictor on the odds of being in a higher versus a lower category of the response variable is constant across all thresholds (Hosmer et al., 2013). In other words, the coefficients of the predictors do not vary between the different cut-points of the dependent variable.

In the present study, the cumulative link model was applied to assess the relationship between thermal sensation and several environmental and personal parameters, namely air temperature, relative humidity, operative temperature, airspeed, metabolic rate, and clothing insulation. The use of the cumulative link model allowed for estimating the probability of a person reporting a given level of thermal sensation depending on the conditions of the indoor environment and the characteristics of the occupant.

3.4.1.1. Interpretation of Model Coefficients and Thresholds

In the cumulative link model, the estimated coefficients (β) of the predictor variables represent the effect of a one-unit increase in the corresponding variable on the log-odds of reporting a higher thermal sensation category. A positive coefficient ($\beta > 0$) indicates that as the predictor increases, the likelihood of a response in a higher thermal sensation category (e.g., feeling warmer) increases. Conversely, a negative coefficient ($\beta < 0$) implies that as the predictor increases, the probability of a response falling into a lower thermal sensation category (e.g., feeling cooler) increases.

It is important to note that, due to the structure of the model, the coefficients are interpreted in terms of their influence on the cumulative probability of being at or below a certain category of thermal sensation.

In addition to the predictor coefficients, the model estimates a set of thresholds (also referred to as cut-points or intercepts) that separate the adjacent categories of the ordinal response variable. These thresholds (α_j) are constants that reflect the baseline log-odds of being at or below category j when all predictor variables are equal to zero. In practical applications, the absolute values of these thresholds are less relevant than the differences between them, as they primarily help define the location of the response categories on the latent scale underlying thermal sensation. The combined effect of all predictors allows the model to estimate, for any given set of environmental and personal conditions, the probability of an occupant reporting each possible level of thermal sensation (Agresti, 2010; McNukty, 2021).

3.4.1.2. Mixed Effects Model

Since the thermal sensation data were collected from multiple studies, it was important to account for potential heterogeneity between them — such as variations in measurement protocols, participant characteristics, or contextual factors not explicitly included in the model. To address this, a mixed effects cumulative link model was employed, which extends the standard cumulative link model by incorporating both fixed and random effects (Hedeker, 2008). This modeling approach is particularly suitable for hierarchical or clustered data structures, as it allows for the estimation of population-level relationships while also accounting for variation across groups or clusters — in this case, different studies (Tutz & Hennevogl, 1996).

In the present study, fixed effects captured the influence of environmental and personal parameters on thermal sensation votes, as previously outlined, while random effects were used to model unobserved heterogeneity at the study level. This allowed the model to control inter-study variability and better isolate the effects of the predictors of interest. To account for unobserved heterogeneity across studies, a random intercept was added to the model presented in equation 2, resulting in the following formulation:

$$logit\big(P(Y_i \le j)\big) = \alpha_j - \beta_1 x_{1_i} - \cdots - \beta_k x_{k_i} - u_i \qquad (3)$$
$$for\ i = 1, \dots n \qquad j = -3, \dots, +2$$

Where:

- The terms Y_i, α_j, β_k and x_i were previously defined.
- u_i represents the random intercept for study i, accounting for unobserved heterogeneity between studies. It is assumed that $u_i \sim \mathcal{N}(0, \sigma_u^2)$, indicating that the study-specific random effects are assumed to be distributed as uncorrelated normal variables with mean zero and variance equal to σ_u^2 (Dunn, 2020).

3.4.2. Model Specification and Selection Criteria

Given that a small subset of Thermal Sensation Votes was recorded as continuous (non-integer) values—while the majority were already ordinal values in the set {-3, -2, -1, 0, 1, 2, 3} —the data were pre-processed to align with the ordinal requirements of the cumulative link model. Specifically, the continuous entries were transformed by rounding them up to the nearest integer using the ceiling function, to appropriately reflect their ordinal nature.

For the statistical analysis, the ordinal package (Christensen, 2023) in R (R Core Team, 2025) was employed to fit cumulative link models (CLMs) and cumulative link mixed models (CLMMs), which are suitable for modeling ordinal outcome variables while accounting for random effects. The clmm() function was applied to estimate a proportional odds model, integrating both fixed effects and a random intercept to account for study-level variability. This approach allowed for appropriate modeling of the ordinal nature of thermal sensation votes while controlling for unobserved heterogeneity across studies. Model estimates were obtained through Maximum Likelihood Estimation (MLE) and mixed models were fitted with the Laplace approximation and adaptive Gauss-Hermite quadrature (Dunn, 2020; Christensen, 2023).

To investigate the predictors influence on thermal sensation, the sjPlot package (Lüdecke, 2024) in R was employed. Specifically, the function generates a graphical representation of the model coefficients along with their associated confidence intervals in the form of a dot plot, commonly referred to as a forest plot (Lüdecke, 2024). This visualization technique, originally developed for the presentation of meta-analytic results, has become a widely accepted method for summarizing estimates derived from regression models.

A forest plot visually aligns the point estimates (in this case, odds ratios) and their confidence intervals for each predictor variable along a horizontal axis. A vertical reference line is included to represent the null hypothesis—typically at 1 when odds ratios are used—allowing for a straightforward interpretation of statistical significance. If the confidence interval for a given estimate crosses this reference line, the effect is considered not statistically significant at the specified confidence level. The logarithmic scale used in this context ensures that odds ratios less than one are symmetrically represented in relation to those greater than one, aiding in interpretability (Woodall, 2014). In the present analysis, the forest plot was applied to compare the relative effects of the predictors.

3.4.2.1. Meta-analysis

Meta-analysis is a statistical approach used to synthesize findings from multiple independent studies that investigate a common research question. Its primary advantage lies in its ability to provide more precise and robust estimates of effect sizes than those obtained from individual studies alone. Additionally, it enhances statistical power and enables the identification of overarching patterns, inconsistencies, or moderator effects across diverse datasets. A critical function of meta-analysis is to explore and quantify heterogeneity—differences in results or methodologies between studies—which can offer important insights into contextual or methodological influences on the observed outcomes (Haidich, 2010).

In this study, a meta-analytic perspective was adopted through the application of a cumulative link mixed model (CLMM). Individual-level data were compiled from various studies conducted in different countries, and study origin was included as a random effect in the model to account for between-study variability. This structure allowed for the evaluation of potential differences in thermal sensation votes attributable to the context or origin of the data. To support the interpretation of the model outputs, forest plots were generated using R, visualizing the study effect. These graphical representations, which are commonly used in meta-analytic frameworks, are presented and discussed in Section 4.

3.4.2.2. Model Comparison and Selection

To identify the most appropriate model for predicting thermal sensation votes, a list of six cumulative link models and two cumulative link mixed models were developed and compared. These models varied in their structure by including different combinations of fixed and random effects. Specifically, the models incorporated environmental parameters as fixed effects, and in some cases, the country of origin or study identifier to capture broader contextual influences. Given that the observations originated from multiple independent studies, certain models included a random intercept for study to account for inter-study variability. The Akaike Information Criterion (AIC) served as the primary metric for comparing model performance, with lower AIC values indicating a better fit. The corresponding AIC values for each model are reported in the results section.

Separate comparisons were conducted for the summer and winter subsets of the data to account for seasonal differences in thermal perception. A detailed overview of the models tested, and their corresponding formulas are presented in Table 3.1.

Table 3.1 Overview of Tested Model Structures

Model	Formula	Description
M0a	TSV ~ ta + top + rh + +vel + met + clo + (1 | study)	Initial model; excluded due to multicollinearity (ta and top)
		CLMM with study as random effects and ta as fixed effects.
M0b	TSV ~ ta + top + rh + +vel + met + clo	CLM includes ta and top without study as random effects.
M1	TSV ~ top + rh + +vel + met + clo + (1 | study)	CLMM with study as random effects
M2	TSV ~ top + rh + +vel + met + clo + country + (1 | study)	CLMM with study as random effects and including country as fixed effect
M3	TSV ~ top + rh + +vel + met + clo + study	CLM including study as fixed effects
M4	TSV ~ top + rh + +vel + met + clo + country	CLM including country as fixed effects
M5	TSV ~ top + rh + +vel + met + clo + study + country	CLM including study and country as fixed effects
M6	TSV ~ top + rh + +vel + met + clo + country + year	CLM including country and year as fixed effects

4. Results and Discussion

4.1. Effect of Inter-Study Variability

To assess the impact of various environmental and physiological factors on thermal sensation, the models presented in Table 3.1, M0a and M0b were fitted: a cumulative link mixed model and cumulative link model, respectively. The first model incorporates both fixed and random effects, accounting for individual variability and heterogeneity between the different studies. In contrast, the second model includes only fixed effects, providing insights into the relationship between each predictor and the outcome, assuming that the effects are constant across studies. Table 4.1 presents the estimates and p-values for each variable under both models.

Table 4.1 Statistical analysis of the covariates of M0a and M0b Models

Variable	M0a (Fixed and Random Effects)			M0b (Fixed Effects)		
	Estimate	p-value	Signif.	Estimate	p-value	Signif.
ta	0.26	1.56e-11	***	0.12	0.000908	***
rh	-0.01	< 2e-16	***	-0.01	< 2e-16	***
top	0.09	0.012	*	0.15	5.73e-05	***
vel	-1.45	< 2e-16	***	-1.93	< 2e-16	***
met	0.48	1.61e-14	***	0.32	1.36e-07	***
clo	0.47	1.48e-09	***	-0.33	3.64e-06	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

In comparison with the results in Table 4.1, p-values for most variables are consistent across both models, with both models showing strong statistical significance. Specifically, the variables air temperature (ta), relative humidity (rh), airspeed (vel), metabolic rate (met), and clothing insulation (clo) all have p-values less than 0.001 in both models, indicating a high level of significance. However, the operative temperature (top) has a higher p-value when accounting for random effects, suggesting that the inclusion of random effects reduces its statistical significance compared to the fixed-effects-only model.

Regarding the estimates, there are notable differences between the two models. For instance, the air temperature (ta) variable shows a larger estimate in the M0a model compared to the M0b model, indicating that when random effects are included, the relationship between air temperature and thermal sensation becomes stronger.

When comparing the estimates signs from the M0a and M0b models, a change in the sign of the coefficient for clothing insulation (clo) was observed: negative in the M0b and positive in the M0a. This difference can be attributed to the incorporation of random effects in the M0a model, which accounts for unobserved heterogeneity across studies. In the model M0b, the assumption of homogeneous effects across all observations may lead to biased estimates due to omitted variable bias, particularly when group-level variations (study-specific conditions) influence both the predictors and the outcome (Baetschmann et al., 2015).

By modeling the study as a random effect, the CLMM corrects this heterogeneity, revealing the within-study association between clothing insulation and thermal sensation more accurately. This phenomenon aligns with what is known as Simpson's Paradox, where a trend that appears in aggregated data reverses or disappears when examined within subgroups. In this case, while individual study data show a positive relationship between clothing insulation and thermal sensation, the aggregated model without random effects suggests the opposite direction. As highlighted by Beck (2018), such inconsistencies emphasize the importance of incorporating group-level effects in ordinal models to ensure valid inference.

To visually illustrate the variability across different studies, Figure 4.1 is presented, which displays the random effects (study-specific deviations) for each study. The plot shows the study-specific effects, along with the 95% confidence intervals, highlighting how each study's data deviates from the overall model. This visualization emphasizes the heterogeneity between studies and aligns with the prior analysis, which identified study-specific differences as a factor in explaining the variability in thermal sensation responses across studies.

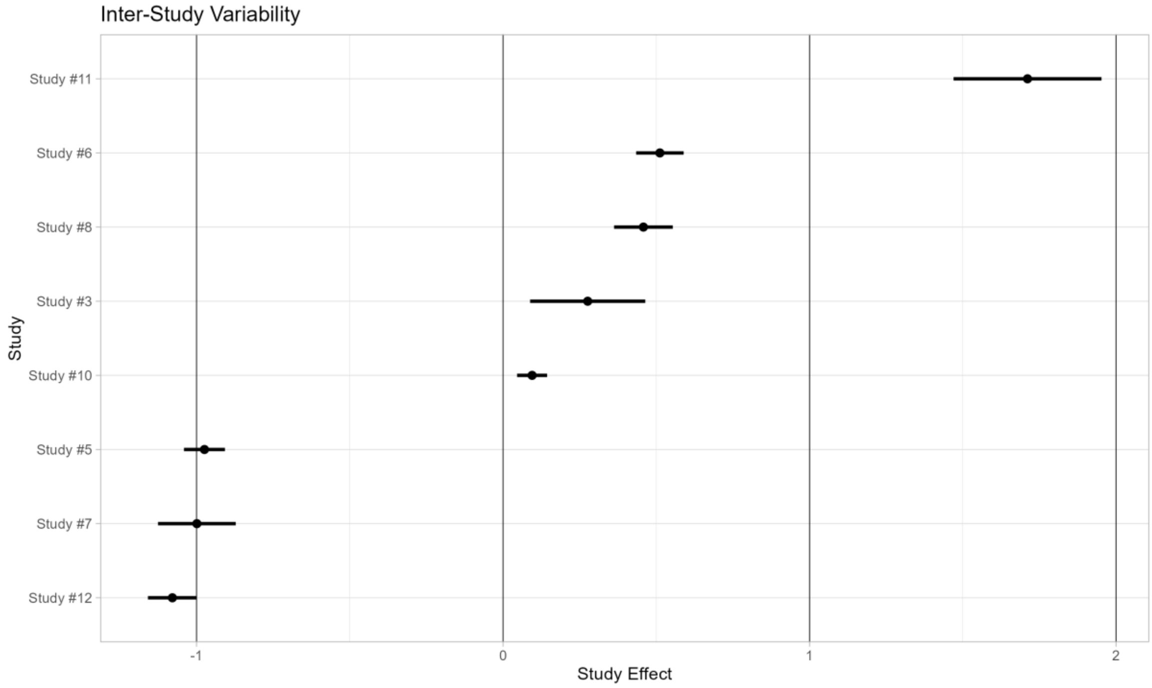

Figure 4.1 Heterogeneity of Study Effect Estimates at the 95% Confidence Level

Figure 4.1 illustrates the heterogeneity across the eight studies included in the ASHRAE dataset by presenting the estimated study-specific random effects from the cumulative link mixed model. Each study is represented by a point estimate and its corresponding 95% confidence interval. These random effects quantify the deviation of each study's baseline thermal sensation rating from the overall model intercept, after accounting for the fixed effects. Notably, the confidence intervals for all studies do not overlap zero, suggesting that the baseline thermal sensation ratings in each study differ significantly from the overall mean. However, the magnitude and direction of these deviations vary across studies. Positive estimates indicate studies where participants reported higher thermal sensation levels than predicted by the fixed effects alone, whereas negative estimates reflect lower-than-expected ratings. Study 11 exhibited a pronounced positive deviation, indicating a systematic tendency toward higher thermal sensation votes, while Studies 5, 7, and 12 showed substantial negative deviations, suggesting consistently lower ratings (Borenstein et al, 2009).

As a next step, a comparison was conducted between models M0a and M1 to address the effect of air temperature (ta) and operative temperature (top) in the model. While both variables were initially included in the earlier models due to their theoretical relevance, it became evident that top inherently accounts for the influence of ta, along with other thermal components. To evaluate whether including both predictors was redundant, M0a—which includes both ta and top—was compared with M1, which retains only top. This comparison aimed to assess whether top alone provided sufficient explanatory power without compromising model quality. The results of this comparison are presented in Table 4.2, and based on this evaluation, ta was removed from subsequent models to reduce redundancy and avoid inflated standard errors due to collinearity.

Table 4.2 Model Comparison: AIC (summer and winter)

Model	AIC (Summer)	AIC (Winter)
M0a (with ta and top)	27664.81	13244.36
M1 (with top only)	27606.05	13242.49

As presented in Table 4.2, the comparison between models M0a and M1 was carried out to evaluate the impact of air temperature (ta) and operative temperature (top). In M0a, both variables were included, while in M1, ta was excluded. The results show that excluding air temperature led to an improvement in model fit, with lower AIC values observed in both seasons. In the summer subset, the AIC decreased, indicating a notable gain in model performance. A similar, though smaller, difference was observed in winter. These reductions suggest that including both ta and top introduces redundancy, likely due to their strong correlation. As mentioned in section 1, air temperature directly influences operative temperature, which helps explain the overlapping contribution of these variables.

Removing ta not only simplified the model structure but also avoided potential issues related to inflated standard errors and unstable coefficient estimates. Based on these results, top was retained as the primary temperature-related predictor in all subsequent models.

4.2. Model Comparison and Selection

Having established operative temperature (top) as the primary temperature-related predictor, a broader model comparison was conducted to evaluate the performance of several cumulative link models using different combinations of fixed and random effects. The models varied in their inclusion of contextual variables such as country, study, and year, either as fixed effects or, where appropriate, random intercepts. Each model was fitted separately for summer and winter datasets to account for seasonal differences in thermal sensation. Model performance was assessed using the Akaike Information Criterion (AIC), with lower values indicating improved fit. Table 4.3 summarizes the AIC values for each model across both seasons.

Table 4.3 AIC Summary for CLMM Tested Models

Model	AIC (Summer)	AIC (Winter)
CLMM models		
M1	27664.81	1342.49
M2	27467.03	1349.42

As a first step in the analysis, models based on the cumulative link mixed model (CLMM) were compared. Model M1 includes study as a random effect, while model M2 adds country as a fixed effect alongside the random effect for study. The comparison between models M1 and M2 provides insight into the impact of including country as a fixed effect when modeling thermal sensation.

In the summer subset, M2 achieves a notably lower AIC value compared to M1, indicating a substantial improvement in model fit. A difference of nearly 198 points suggests that including country-level information greatly enhances the model's ability to explain variability in thermal sensation during warmer conditions. In contrast, the winter subset shows a slight increase in AIC when country is added. This minor difference suggests that including the country as a fixed effect in the winter model does not improve fitness and may introduce unnecessary complexity without meaningful gain.

In the initial phase of the analysis, study origin was modeled as a random effect to account for inter-study variability using cumulative link mixed models. However, due to the limited number of distinct studies in the dataset, the estimation of random effects became statistically unstable. Maximum Likelihood estimation tends to perform well with large sample sizes, but when the number of clusters is small, it can become unstable and may lead to convergence issues or overfitting. Given this limitation, and to maintain interpretability and model stability, study was treated as a fixed effect in the remaining models. This approach allowed for the consideration of potential differences between studies while avoiding the limitations associated with insufficient group-level replication.

After addressing the limitations related to modeling study as a random effect, the next set of models focused on comparing different combinations of fixed effects. These models included study, country, and year as predictors in various configurations to assess how contextual factors influence thermal sensation. The aim was to evaluate whether including these variables improved model performance and to determine the most effective structure for capturing variability across both summer and winter datasets. Table 4.4 presents the AIC values for each of the fixed-effect models considered.

Table 4.4 AIC Summary for CLM Tested Models

Model	AIC (Summer)	AIC (Winter)
CLM models		
M3	28929.07	13506.54
M4	27476.63	13332.82
M5	27477.44	13248.75
M6	27312.76	13058.25

As shown in Table 4.4, the lowest AIC values for both summer and winter are observed in model M6, which includes country and year as fixed effects. This suggests that, in terms of statistical fitness, M6 performs best among the tested CLM models. However, including the year as a predictor introduces practical issues. First, multicollinearity arises due to the overlapping between year and country, which complicates the interpretation of the individual effects. Second, the model produces NA coefficients for several year levels, indicating that some years lack sufficient data or variability to estimate reliable effects. This leads to non-estimable parameters and reduces the model's robustness. For these reasons, despite its lower AIC, model M6 may not be the most appropriate choice for further analysis.

A further comparison was conducted between models M3, M4, and M5 to evaluate whether including country, study, or both as fixed effects improve model fit. As shown in Table 4.4, the next lowest AIC value after M6 corresponds to model M5, which incorporates both country and study as predictors. This suggests that the combined inclusion of contextual variables enhances model performance. However, introducing both predictors simultaneously can lead to multicollinearity, particularly in cases where each study is uniquely associated with a specific country. When such overlap exists, one variable may absorb the variance explained by the other, resulting in inflated standard errors and reduced model interpretability. As Harrell (2015) points out, including highly correlated predictors, especially categorical ones with overlapping information, can distort regression estimates and complicate inference, even when overall model fit improves. Therefore, despite the AIC performance, model M5 may not be the most appropriate choice for further analysis due to the risk of multicollinearity and reduced interpretability.

Finally, a comparison was made between models M3 and M4. Model M3 includes study as a fixed effect, while model M4 incorporates country instead. As shown in Table 4.4, model M4 yields the lower AIC values in both seasonal subsets, indicating better overall model performance. Among these two, M4 stands out as the more suitable choice for further analysis. The model benefits from the consistently significant country-level effects observed in both summer and winter, reinforcing its explanatory strength. Notably, the AIC reduction is more pronounced in the summer dataset, suggesting that country-specific differences in thermal sensation responses may be more evident under warmer conditions. In contrast, during winter, these differences are still present but appear to have a slightly less dominant role. Based on these findings, model M4 was selected as the most appropriate structure for the following analysis.

4.3.Seasonal Differences in Thermal Sensation

The first set of results from model M4 focuses on the environmental and physiological variables included as fixed effects. These predictors were evaluated separately for the summer and winter datasets, and the corresponding estimates and significance levels are summarized in Table 4.5.

Table 4.5 Statistically significant variable of environmental and personal factors on thermal sensation

Covariates	**Summer season**			**Winter season**		
	Estimate	**p-value**	**Signif.**	**Estimate**	**p-value**	**Signif.**
top	0.47	< 2e-16	***	0.32	< 2e-16	***
rh	-0.01	2.88e-16	***	-0.01	1.28e-05	***
vel	-1.76	< 2e-16	***	-0.69	1.09e-02	*
met	0.49	5.64e-10	***	0.40	3.23e-04	***
clo	0.60	5.96e-07	***	-0.38	1.08e-03	**

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Only predictors with a p-value less than 0.05 are considered statistically significant. A positive estimated value indicates that an increase in the specific variable is associated with a warmer or less cold thermal sensation rating. Conversely, a negative value suggests an association with a cooler thermal sensation (Saugo et al, 2009).

In the summer season, operative temperature, metabolic rate and clothing insulation exhibit highly significant positive relationships with thermal sensation votes. The estimate for operative temperature and metabolic rate indicates that as these variables increase, individuals are more likely to report a warmer thermal sensation. This relationship is well supported by thermophysiological mechanisms. As operative temperature rises, the thermal gradient between the skin and the surrounding environment is reduced, thereby impairing the body's ability to dissipate heat (ASHRAE, 2017). Simultaneously, an increase in metabolic rate—due to physical activity—leads greater internal heat production (Fanger, 1970). When both factors are present at the same time, they place a greater thermal demand on the body, often going beyond what natural mechanisms like sweating and increased blood flow can handle to keep a stable internal temperature. As a result, people tend to feel warmer. This effect tends to be stronger during the summer months, when temperatures are already high and there may be fewer options left to adapt through clothing, activity level, or changes in the environment (Parsons, 2002).

Regarding clothing insulation, the analysis indicates that higher insulation levels during summer are associated with an increased thermal sensation, reflecting a perception of greater warmth. This finding aligns with the interpretation proposed by Pistore et al. (2023), who suggest that elevated clothing insulation in summer may result from occupants' behavioral responses aimed at achieving greater thermal comfort, potentially reflecting a desire for warmer conditions. Moreover, this behavior may represent a practical and accessible adaptive strategy, particularly in office settings where environmental modifications are limited, and clothing adjustments constitute one of the simplest means of personal thermal regulation.

Conversely, relative humidity and airspeed show highly significant negative relationships with thermal sensation. A higher relative humidity and increased airspeed are both associated with cooler thermal sensations in the summer season. This could be explained, because of the increased use of ventilation systems or fans, which often accompany rising temperatures and lead to enhanced convective and evaporative cooling.

During winter, airspeed emerged as a statistically significant predictor of thermal sensation, though its effect is smaller compared to the summer season. This may be due to generally lower airspeeds in winter, as natural ventilation and fan usage are minimized, leading to reduced perceptual variation in air movement. Additionally, clothing insulation had a significant negative effect in winter, indicating that higher insulation levels were associated with cooler thermal sensation votes. This likely reflects the common behavior of wearing more insulating clothing in colder months, which serves as a thermal buffer and may attenuate the perceptual influence of airspeed (Parsons, 2014).

Operative temperature and metabolic rate were both found to have positive and statistically significant associations with thermal sensation in the winter model, indicating that increases in either variable are linked to a heightened perception of warmth. Operative temperature, which integrates the effects of air temperature and mean radiant temperature, is a fundamental driver of thermal comfort, as it directly influences the heat exchange between the human body and the surrounding environment. An increase in operative temperature reduces the thermal gradient between the skin and the environment, thereby diminishing the body's ability to dissipate heat and resulting in a warmer thermal sensation (Fanger, 1970).

Similarly, the metabolic rate reflects the rate of internal heat generation due to physical activity. Higher levels of metabolic activity increase the body's endogenous heat production, which contributes to thermal load and elevates perceived warmth (Parsons, 2014). Even in winter conditions, when ambient temperatures are lower, elevated metabolic rates can significantly increase thermal sensation, particularly in individuals engaged in light-to-moderate physical activity.

In both seasonal models, the estimate for relative humidity is negative, indicating that higher humidity levels are associated with a lower likelihood of reporting a warmer thermal sensation. Although this result may initially seem counterintuitive, it reflects the complex nature of humidity's influence on thermal perception, as supported by recent literature. Watanabe et al. (2024) explain that the effect of relative humidity is context dependent. In warm and hot environments, elevated humidity hinders the evaporation of moisture from the skin, mucosa, and respiratory tract, which in turn limits the body's capacity for heat dissipation. This leads to increased skin wettedness and discomfort, particularly when combined with the friction caused by damp clothing. However, this form of discomfort may not always be perceived as "feeling hotter" but rather as clammy or stuffy, potentially prompting more neutral or slightly cooler thermal sensation votes in subjective assessments.

The negative estimates observed in both summer and winter further support the idea that relative humidity's role in thermal sensation is not only physiological but also shaped by psychological and contextual factors. Additionally, as mentioned by Djamila et al. (2014), air temperature and relative humidity are often closely linked, which makes it hard to tell how much each one affects thermal comfort on its own. In this case, that overlap is even more likely because operative temperature is already included in the model, and it partly reflects the influence of air temperature. So, the specific effect of humidity might be hidden or mixed in with other variables.

In winter, although ambient humidity is generally lower, increased indoor moisture due to reduced ventilation or artificial humidification can create sensations of air stagnation. These conditions may still lead to negative thermal impressions, reinforcing the observed inverse relationship between relative humidity and reported thermal sensation.

To visually support the statistical findings discussed above, Figure 4.2 presents the odds ratios and corresponding confidence intervals for the key predictors of thermal sensation during the summer and winter seasons. The figure complements Table 4.5 by illustrating the magnitude and direction of each variable's influence in a more intuitive format. Predictors positioned to the right of the reference line (odds ratio = 1) are associated with a warmer thermal sensation, while those to the left indicate a cooler perception.

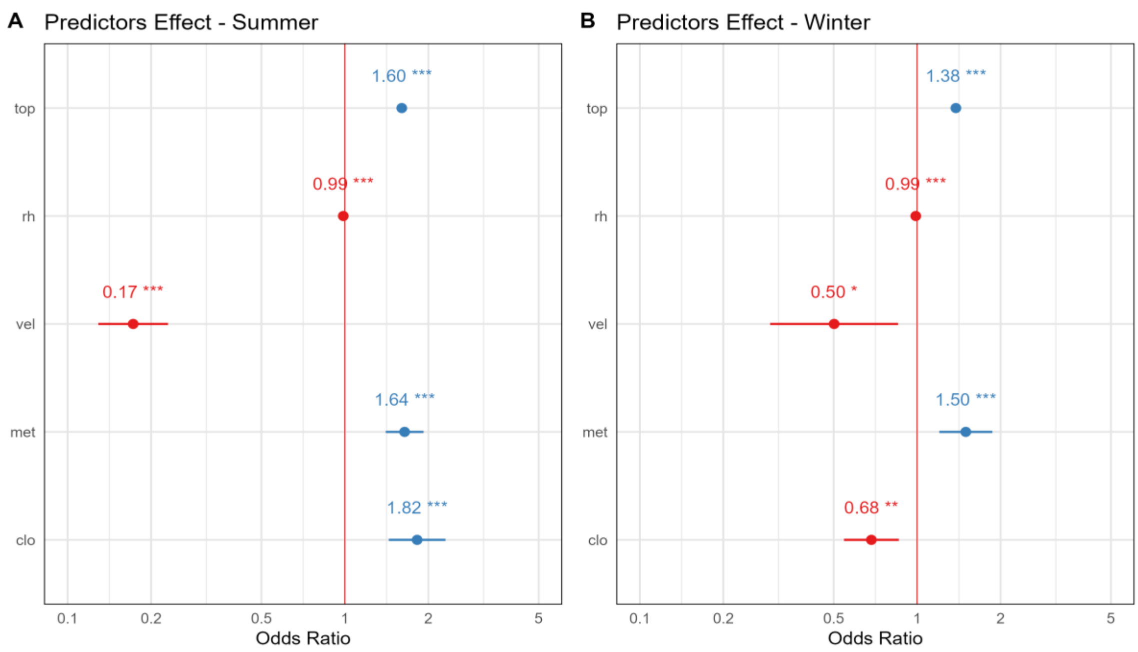

Figure 4.2 Effect of Environmental and Personal Predictors on Thermal Sensation Votes during summer (A) and winter (B) seasons

As shown in Figure 4.2, the graphical representation confirms the patterns discussed earlier, operative temperature and metabolic rate display strong positive associations with thermal sensation across both seasons, while airspeed shows significant negative effects, particularly in summer. Although relative humidity is also statistically significant, its odds ratio is very close to 1 in both seasons, suggesting that its influence on thermal sensation is weaker compared to other variables. The plot also highlights the shift in the influence of clothing insulation, which appears positively related to warmth in summer but negatively in winter.

4.4.Country Differences in Thermal Sensation

In addition to environmental and physiological factors, the country was included as a fixed effect to account for regional differences in thermal sensation. Table 4.6 presents the country-level estimates for both summer and winter. The reference category for the analysis is Australia, enabling a direct comparison between thermal responses in Australia and other countries during both seasons. Several countries show statistically significant deviations from the reference group, highlighting how cultural, climatic, or contextual factors may influence occupants' thermal responses. Notably, some countries included in the summer model do not appear in the winter model due to the absence of data for that season. For these cases, no coefficients could be estimated, and the respective entries are left blank in the table.

Table 4.6 Estimated country effects on thermal sensation votes

Covariates		**Summer season**			**Winter season**		
		Estimate	**p-value**	**Signif.**	**Estimate**	**p-value**	**Signif.**
Country	Canada	-1.18	< 2e-16	***	-0.57	2.90e-06	***
	France	-0.60	1.15e-02	*	0.28	9.86e-02	.
	Greece	-2.30	1.72e-13	***	-1.68	8.93e-04	***
	Indonesia	-1.54	< 2e-16	***	-	-	-
	Japan	-1.34	< 2e-16	***	-	-	-
	Malaysia	-1.74	< 2e-16	***	-	-	-
	Pakistan	-1.95	< 2e-16	***	-0.25	9.92e-03	**
	Portugal	-1.35	< 2e-16	***	0.25	1.97e-02	*
	Singapore	-1.06	< 2e-16	***	-	-	-
	Sweden	-0.60	3.70e-06	***	-0.41	2.40e-02	*
	UK	-0.56	7.52e-11	***	1.09	< 2e-16	***
	USA	0.47	5.90e-11	***	0.46	1.48e-10	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

The inclusion of country as a categorical predictor in the thermal sensation models reveals clear regional differences in how participants from various locations experience and report thermal environments. As can be observed in Table 4.6, among the analyzed countries during summer, all countries significantly differ from Australia. Most of the countries reported negative estimates suggesting that these countries experienced the same thermal conditions as cooler compared to Australians. This trend was especially pronounced for participants from warmer climates. For instance, people from Greece shows a large negative effect, suggesting a much lower tendency to describe conditions as “warm” or “hot” compared to Australians. The strong cool bias among Greek participants suggests a higher heat tolerance or a different expectation of warmth, suggesting that people from this region are more sensitive to warm conditions potentially due to long-term acclimatization to hot and humid climates (Lee et al, 2010).

A similar cool-shift in summer sensation was observed for other hot-climate countries in the dataset. Participants from Malaysia, Indonesia, Singapore, and Pakistan all had significantly negative TSV differentials relative to Australia, indicating they consistently felt cooler than Australians in the same environments. This widespread trend implies that individuals accustomed to high ambient temperatures do not perceive moderate warmth as uncomfortably hot as readily as Australians do.

Interestingly, even participants from some cooler-climate countries like Canada, the UK, and Sweden, reported slightly cooler sensations on average than Australians during summer. Preliminarily this may seem counterintuitive, as one might expect occupants from colder regions to feel warmer in a hot environment. However, this outcome likely reflects differences in comfort expectations and adaptive behavior. For instance, people from these countries often experience naturally ventilated or only modestly air-conditioned summers and may have adapted to occasional warmth through behavioral adjustments. They could thus be less inclined to label a given temperature as “too hot”, compared to Australians, who often expect cooler indoor temperatures because air-conditioning is common (Zander et al, 2023).

Notably, the USA was the only country to report significantly warmer TSV, indicating that under similar thermal conditions, people from the USA tended to feel warmer than Australians. This could be because the U.S. group had a lower heat tolerance or a greater propensity to perceive conditions as “warm/hot.” This situation could be due to a combination of cultural expectations, mechanical conditioning habits, and rigid thermal comfort standards. American buildings, particularly homes and offices, are typically equipped with centralized HVAC systems designed to maintain a narrow and fixed temperature range throughout the year (Outcault et al., 2016). U.S. occupants are accustomed to tightly controlled environments, which makes even slight deviations feel uncomfortable (Yang et al., 2014).

In contrast, winter results have more heterogeneous effects. Countries such as Canada, Greece, Pakistan and Sweden shows a significant negative effect compared with Australia. While Portugal, UK and the USA, present a positive significant effect compared to Australians, suggesting that at the same conditions in these countries, people tend to feel warmer. Notably, in Greece the individuals felt substantially colder than Australians in winter conditions, suggesting that at equivalent indoor temperatures, Greeks were more likely to report feeling on the "cool/cold" side, relative to Australians. This situation likely reflects its milder winters and cultural context regarding heating. Buildings in Mediterranean climates are often less insulated or lack central heating common in cooler countries, and occupants may be acclimated to feeling a bit cool in winter.

When considering Sweden and Canada, the negative effect during winter could suggest that the individuals still felt cooler than Australians, possibly due to cultural preferences for cooler indoor environments, greater physiological cold sensitivity despite heavy clothing or the widespread use of well-insulated, energy-efficient buildings in Nordic countries, which provide thermally stable indoor environments and consequently influence user perception (Wågø et al., 2016). This implies that even with sufficient heating, people from Nordic climates might maintain a sensation slightly on the cool side. This pattern may be attributed to long-term climatic or cultural adaptation to cold environments, which shapes both physiological responses and thermal comfort expectations.

Participants from Pakistan also reported more cold discomfort compared to Australians. Pakistan's diverse climate includes regions with cool winters, and indoor heating is not common; thus, Pakistani occupants could be experiencing colder indoor environments and subsequently feeling colder. In contrast, the UK and USA groups reported significantly warmer sensations in winter relative to Australia, meaning British and US occupants were less likely to feel cold under the same conditions. The largest positive winter effect for the UK, indicates a strong tendency for UK participants to feel warmer or more thermally satisfied at lower temperatures compared to Australians. In the UK, this trend may be attributed to the widespread use of well-regulated heating systems in office buildings. Liu et al. (2013) observed that one of the most common strategies for maintaining indoor comfort in UK offices is the use of centralized or localized heating units, which ensure consistently warm environments during colder months. Similarly, participants from the United States exhibited a positive winter TSV difference, indicating a greater tendency to feel warmer under the same indoor conditions compared to Australians. This may be attributed to the widespread use of indoor heating in the U.S., which maintains standard comfort temperatures and potentially reduces occupants' acclimatization to cooler environments.

Additionally, Portugal exhibited a mild positive coefficient in winter, indicating Portuguese respondents on average felt a bit warmer than Australians. Many Portuguese buildings, particularly older ones, are often underheated or rely on basic heating solutions, individuals have developed a cultural and behavioral adaptation to cooler indoor climates. As noted by Costa-Carrapiço et al. (2022), people living in regions such as Alentejo tend to perceive these conditions as comfortable or even warm. This perception likely stems from habituation and lower expectations of thermal comfort, resulting in a broader tolerance for cooler indoor environments. Although smaller in magnitude, the Portuguese case fits the broader pattern that countries with warmer winter norms or more heating tends to have occupants who feel warm at lower temperatures.

These findings align with the notion that the human body can adapt to a wide range of thermal conditions without requiring specific genetic traits. As noted by Schweiker et al. (2018), repeated exposure to cold can enhance the body's thermogenic capacity, enabling individuals to develop physiological adaptations that improve tolerance to lower temperatures. It is important to note that for some countries, data were only available for the summer season, which limits the ability to draw seasonal comparisons. Nevertheless, the overall pattern suggests that geographic, climatic, and potentially cultural differences play a meaningful role in shaping thermal sensation.

To complement these findings, Figure 4.3 and Figure 4.4 present the predicted probabilities of thermal sensation votes ranging from -3 (Cold) to +3 (Hot) across countries included in the analysis for summer and winter conditions, respectively. These predictions are generated by setting all other model predictors to their mean values, to standardize and compare crosscountry differences in thermal perception under average conditions. This visual summary makes it easier to compare the strength and direction of each country's effect.

These figures show the predicted probabilities of TSV for each country, along with their associated 95% prediction intervals. Each point represents the estimated probability of a specific TSV category, while the horizontal lines denote the range of uncertainty around these estimates. The length of these intervals reflects the degree of uncertainty; longer intervals suggest greater variability or less certainty in the prediction. This is especially noticeable for certain countries such as Greece, where the intervals tend to be wider across multiple TSV categories, indicating more variability in the predicted thermal responses.

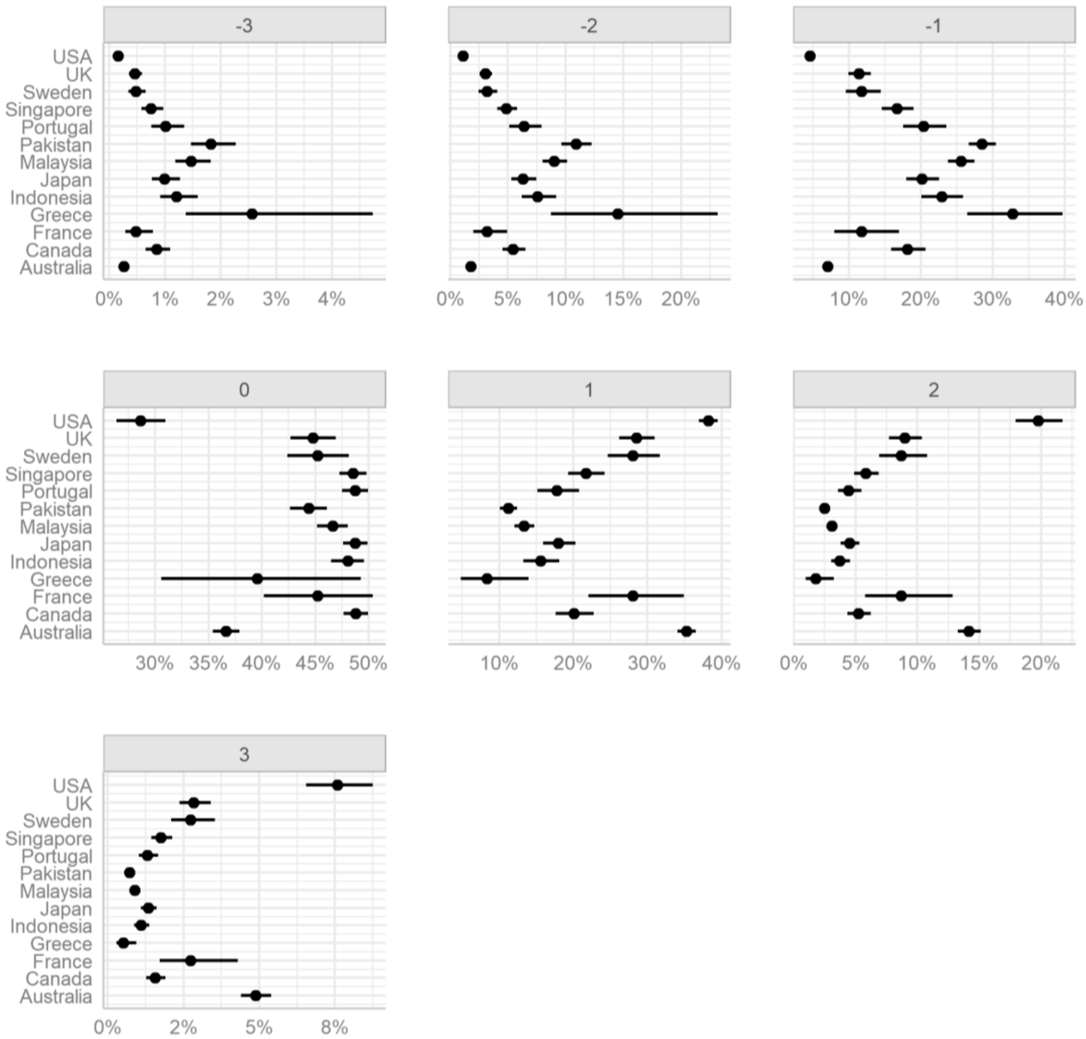

Figure 4.3 Predicted Probabilities of TSV per country during Summer

As is shown in Figure 4.3, there is a clear variability across countries. This supports the earlier findings regarding national differences in thermal perception. In the case of the United States, there is a high probability (approximately 40%) of individuals reporting a sensation of being slightly warm (TSV = +1), and about 20% are likely to report feeling warm (TSV = +2). In contrast, the probability of reporting thermal neutrality (TSV = 0) is relatively low at around 25%, especially when compared to other countries, where neutral sensations are more dominant. This pattern suggests that individuals in the U.S. may have a lower tolerance for heat or a greater tendency to perceive indoor environments as warm or hot, even under average summer conditions.

Thermal neutrality is the most frequently predicted response across most countries, indicating a general tendency toward comfort under average conditions. This is particularly evident in Singapore, Portugal, Japan, Indonesia, and Canada, where the probability of reporting a neutral sensation approach 45–50%. Such a strong central tendency suggests that individuals in these countries are more likely to perceive their environments as thermally comfortable during summer, at least when all other factors are held at average levels.

In Greece, while thermal neutrality remains the most likely response at approximately 45%, there is also a notably high probability of slightly cool (TSV = -1) sensations, reaching close to 30%, one of the highest among all countries. In contrast, warm sensations are comparatively less frequent. This suggests that, despite Greece's warm summer climate, occupants tend to perceive indoor environments as slightly cool, as it was discuss above. All these findings reinforce the idea that thermal comfort is shaped not only by external climate but also by local expectations, building practices, and adaptive behaviors. However, the broader intervals present for each TSV case may suggest that the thermal comfort responses were more diverse or inconsistent, leading to a less precise estimate.

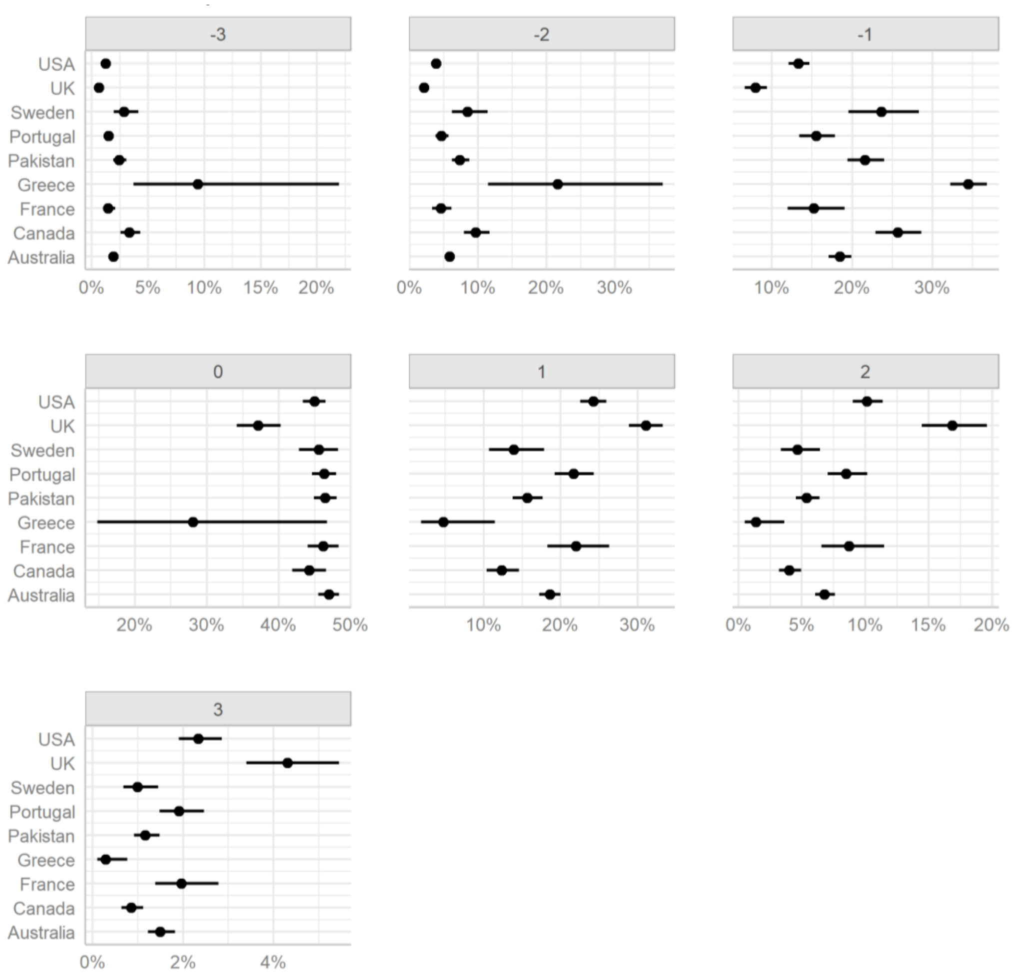

Figure 4.4 Predicted Probabilities of TSV per country during Winter

Figure 4.4 highlights notable contrasts in how people from different countries perceive thermal conditions under standardized winter scenarios. Thermal neutrality remains the dominant response in almost all countries, where the probability approaches 50%. This consistent preference suggests a general ability to maintain comfortable indoor conditions during the winter, likely through well-regulated heating systems or adaptive behaviors that stabilize perceived thermal comfort. Even in colder countries like Sweden and UK, neutrality remains the most common vote, which might reflect the prevalence of efficient heating technologies.

In Greece, the likelihood of cold sensations is significantly higher than in other countries. Suggesting that occupants in Greece often perceive indoor environments as underheated during winter. Interestingly, the probability of warm sensations is minimal. Overall, Greece's winter profile reflects a notable contrast: while not exposed to harsh winters, the population still reports a considerable degree of cold discomfort, pointing to potential gaps in thermal management and building performance during the heating season. However, the uncertainty intervals are particularly wide for TSV values of -3, -2, and 0, as noted in the summer results. Such broad intervals suggest that participants' responses were less uniform in these categories.

Moreover, to explore the variation in thermal sensation votes across different countries, Figure 4.5 illustrates the predicted probability distribution of TSV by season. The red curves indicate the distribution during summer, while the blue curves represent the distribution for winter. As previously noted, in some countries only summer data is available; therefore, only the red line appears in those respective plots.

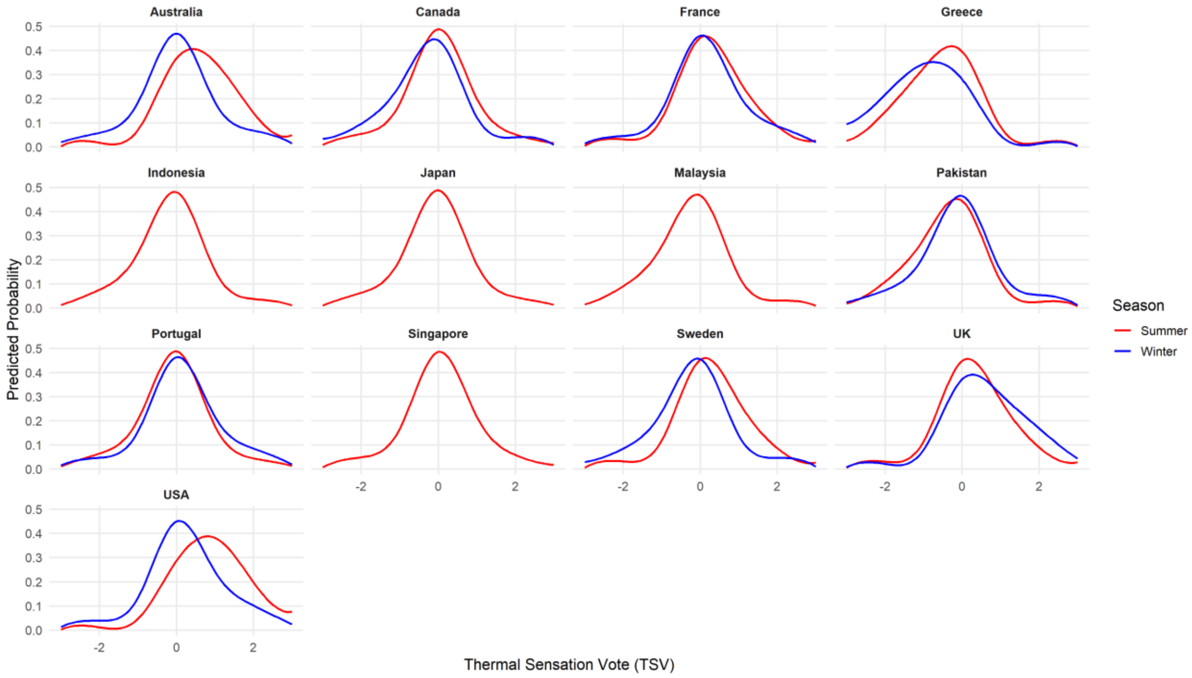

Figure 4.5 Season Predicted distributions for TSV by Country and Season

The distributions presented in Figure 4.5 reveal notable seasonal patterns in thermal sensation votes across countries. Generally, the curves are centered around a neutral TSV (approximately 0), with some variation in spread and skewness depending on the country and season. In most cases, the distributions for summer and winter show clear shifts, indicating differing thermal perceptions between seasons. As it can be observed, in countries such as Indonesia, Japan, Malaysia and Singapore, with data just for summer, in all this cases, the distributions follow a roughly normal shape centered near the neutral TSV value, suggesting that most thermal sensations reported indoors cluster around thermal neutrality.

Countries like France, Pakistan and Portugal, show less pronounced seasonal separation, where both distributions are relatively symmetric and close to neutral. This pattern likely results from a combination of factors that mitigate seasonal discomfort, possibly reflecting a psychological adaptation and adjusted comfort expectations over time, and relatively stable indoor thermal conditions, with most occupants experiencing neutral regardless of season.

In countries such as Canada and Sweden, the winter distributions are shifted to the left, indicating a trend toward cooler thermal sensation votes during colder months. This shift suggests that occupants tend to perceive conditions as slightly cool in winter, as was mentioned above, due to the cultural preferences for cooler indoor settings. On the other hand, Greece is noticeably shifted to the cooler end of the scale, suggesting that occupants tend to feel slightly cold indoors during the colder months. One likely explanation is climatic adaptation, as a country with a predominantly warm Mediterranean climate, buildings, behaviors, and even thermal expectations are often oriented toward coping with heat rather than cold.

In the case of the UK, the winter distribution is shifted to the right, indicating that individuals tend to perceive indoor environments as warm during the colder months. This observation aligns with the earlier discussion regarding the widespread presence of well-regulated heating systems in office buildings, which are generally effective in maintaining comfortable indoor temperatures despite low outdoor conditions.

During summer, both Australia and the USA exhibit a rightward shift in the thermal sensation distributions, suggesting that individuals often perceive indoor environments as warm. This trend likely reflects the sensitivity of occupants to elevated indoor temperatures, even if minor. As noted earlier, in both countries, there is a strong reliance on tightly controlled indoor climates, particularly in offices. This habituation to stable thermal conditions can reduce occupants' adaptability, making even modest increases in temperature feel noticeably uncomfortable.

For a better visualization of comparisons between countries during the summer season, Figure 4.6 presents the predicted probability distributions of Thermal Sensation Votes for each country. In each panel, the focal country is highlighted in red, while the distributions for all other countries are shown in gray.

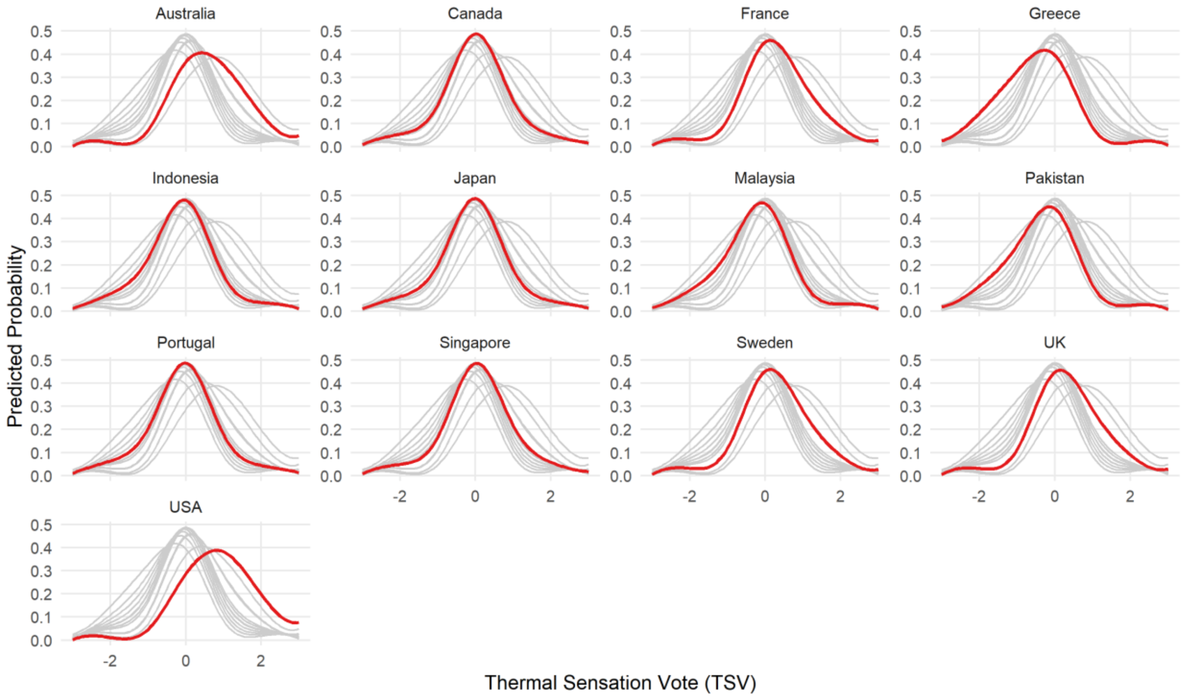

Figure 4.6 Highlighted Countries: TSV Probability Curves during Summer

Figure 4.6 illustrates the comparison between different scenarios, which highlights notable differences in how occupants perceive indoor thermal conditions across diverse climatic and cultural contexts.

The USA and Australia exhibit a left-skewed distribution, indicating a tendency for occupants to feel slightly warm indoors, which may reflect both the influence of external heat and reduced adaptability due to prolonged exposure to tightly controlled environments. In contrast, as was discussed above, Greece displays a broader and more right-skewed distribution, suggesting greater variability in indoor thermal experiences and a higher prevalence of cold sensations.

Moreover, this plot reinforces the observation made in Figure 4.3, where the probability of reporting a neutral TSV was approximately 50% in most cases. Figure 4.6 illustrates that the distribution of predicted TSV for most countries tends to follow a bell-shaped pattern, generally centered around the neutral point.

Furthermore, Figure 4.7 displays the predicted probability distributions of Thermal Sensation Votes during the winter season for all countries, enabling a more focused and comparative interpretation. In each panel, the focal country is highlighted in blue, while the distributions for all other countries are shown in gray.

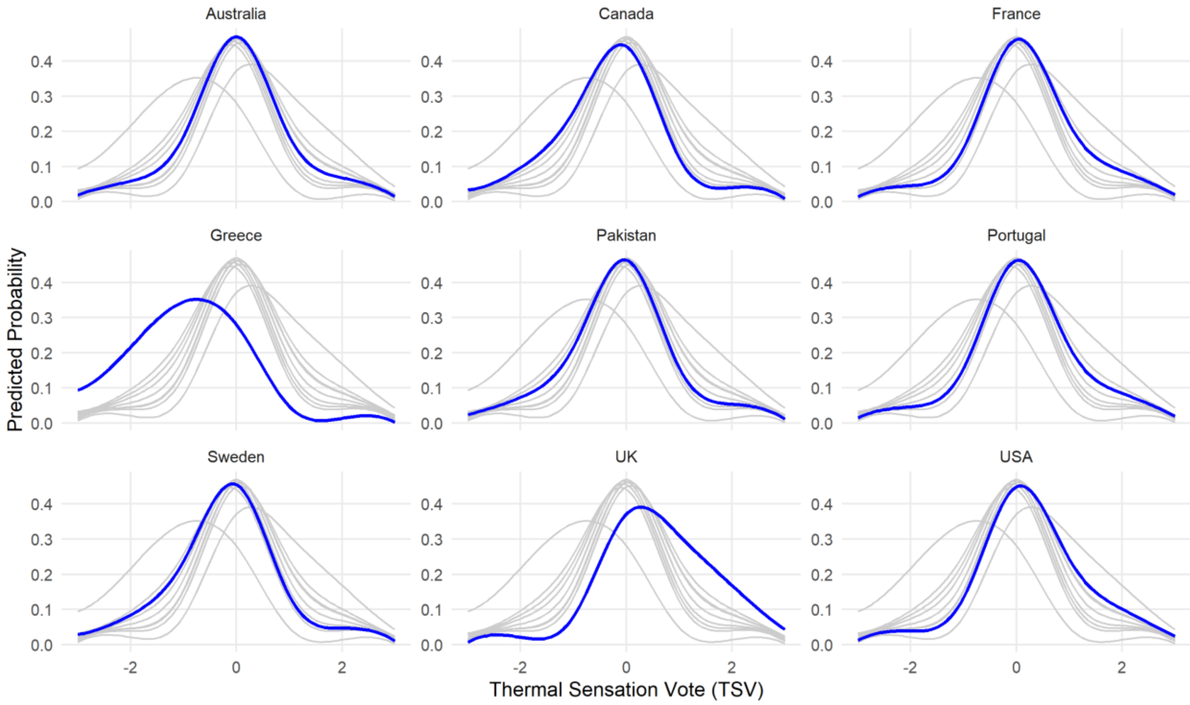

Figure 4.7 Highlighted Countries: TSV Probability Curves during Winter

Figure 4.7 presents the predicted probability distributions of TSV revealing clear contrasts in how occupants from these regions perceive indoor environments during colder months. The UK shows a distinct rightward shift, with the peak occurring just above the neutral point, suggesting that indoor spaces are generally perceived as warm. Similarly, as was analyzed in Figure 4.4, this emphasizes the shape and central tendency of each country's distribution, revealing that most follow a symmetric, bell-shaped curve centered around the neutral TSV.

In contrast, Greece displays a notably right-skewed distribution, where a noticeable proportion of occupants' report feeling cool, differing thermal comfort perceptions among respondents in those regions. These differences highlight how both climatic context and thermal adaptation shape comfort perception across regions, even when indoor environments aim for neutrality.

4.5. Ventilation Effect on Thermal Sensation

The variation in thermal sensation across different ventilation modes represents a key aspect of thermal sensation analysis. Distinguishing between naturally ventilated (NV), and other types of ventilation such as mixed-mode or mechanically ventilated buildings offers a clearer view of how different systems influence comfort. To explore this, the earlier analysis using the M4 model was repeated, this time splitting the data according to ventilation mode. The results of this analysis are presented in Table 4.7 for summer and Table 4.8 for winter.

Table 4.7 Estimated ventilation effects on thermal sensation during summer

Covariates		Natural Ventilation			Non-Natural Ventilation		
		Estimate	p-value	Signif.	Estimate	p-value	Signif.
top		0.39	< 2e-16	***	0.60	< 2e-16	***
rh		-9.70e-03	1.00e-06	***	-0.02	6.55e-13	***
vel		-1.20	2.03e-11	***	-2.33	3.22e-15	***
met		0.54	1.53e-07	***	0.51	8.09e-05	***
clo		2.13	< 2e-16	***	-0.40	9.42e-03	**
Country	Canada	-	-	-	-1.06	< 2e-16	***
	France	-0.23	0.55		-0.99	1.30e-03	**
	Greece	-1.75	9.74e-04	***	-3.12	2.37e-15	***
	Indonesia	-0.31	8.48e-02	.	-2.53	< 2e-16	***
	Japan	-1.07	4.18e-04	***	-1.48	< 2e-16	***
	Malaysia	9.99e-02	0.80		-1.53	< 2e-16	***
	Pakistan	-2.10	< 2e-16	***	-	-	-
	Portugal	-1.51	2.21e-15	***	-1.56	< 2e-16	***
	Singapore	-0.97	7.54e-11	***	-0.76	2.22e-09	***
	Sweden	-	-	-	-0.47	5.10e-04	***
	UK	-1.26	< 2e-16	***	-0.49	1.36e-03	**
	USA	-0.13	0.30		0.88	< 2e-16	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

At first sight, all the environmental and physiological parameters have a significant effect on thermal sensation in both natural and non-natural ventilation. Where operative temperature significantly increases thermal sensation, but its effect is stronger in non-NV buildings compared to NV ones. This suggests that occupants in air-conditioned spaces are more sensitive to temperature changes, potentially due to reduced adaptive opportunities. Similarly, airspeed consistently decreases thermal sensation in both environments, but with a noticeably greater effect in non-NV buildings, reinforcing the idea that mechanical airflow has a more pronounced impact in indoor settings. Relative humidity shows a cooling effect in both cases, slightly more so in non-NV spaces, likely due to interactions with HVAC systems. Metabolic rate has a positive effect in both ventilation modes, which means while increasing the activity rate individuals tend to feel warm, as was discussed in section 4.3.

An important finding when considering ventilation mode are the results obtained for clothing insulation, which in natural ventilated spaces, higher clothing levels lead to a marked increase in perceived warmth, which aligns with expectations in warmer, adaptive settings. However, in non-NV environments, the effect reverses slightly, possibly because occupants wear more insulating clothing to stay comfortable in air-conditioned conditions, which can reduce the sensation of warmth, which is an adaptive behavior considering that this parameter is under the people's control.

On the other hand, when comparing the ventilation effect for each country during summer, it shows that there is no statistically significant difference in countries like France, Indonesia, Malaysia and the USA comparing with the reference, Australia. This means that people from these countries tend to report similar thermal sensations as Australians. It is important to notice that all countries present a significant effect on the model of non-NV ventilation during summer. This result supports the idea that thermal comfort is not universal, even in controlled indoor conditions. Cultural, climatic, and behavioral differences persist and meaningfully affect how people experience the same thermal environment.

Notably, the negative estimates of Greece and Indonesia are higher in the model of non-NV, this could be interpreted that people from these countries feel significantly cooler relative to Australians in air-conditioned environments than they do in naturally ventilated ones.

As shown in Table 4.8 when natural ventilation is used in winter, most of the predictors are not significant, just operative temperature when considering the environmental and physiological parameters. The effect is stronger in non-NV, suggesting that in heated buildings, people perceive warmth more intensely per degree to increase than in naturally ventilated winter settings. In contrast, non-NV spaces show more predictable and significant influences, for temperature, humidity, airspeed, metabolic rate, and clothing, all of which behave as expected in heated environments.

Table 4.8 Estimated ventilation effects on thermal sensation during winter

Covariates		Natural Ventilation			Non-Natural Ventilation		
		Estimate	p-value	Signif.	Estimate	p-value	Signif.
top		0.23	< 2e-16	***	0.43	< 2e-16	***
rh		-3.29e-03	0.42		-0.02	6.26e-09	***
vel		-0.26	0.54		-0.87	1.59e-02	*
met		0.21	0.24		0.51	4.39e-04	***
clo		-0.30	0.12		-0.33	2.41e-02	*
Country	Canada	-	-	-	-0.78	1.03e-08	***
	France	0.44	0.25		0.41	8.92e-02	.
	Greece	-	-	-	-2.08	3.57e-05	***
	Indonesia	-	-	-	-	-	-
	Japan	-	-	-	-	-	-
	Malaysia	-	-	-	-	-	-
	Pakistan	-0.24	0.44		-	-	-
	Portugal	0.09	0.78		0.31	1.44e-02	*
	Singapore	-	-	-	-	-	-
	Sweden	-	-	-	-0.65	8.35e-04	***
	UK	1.23	1.40e-04	***	0.99	4.38e-12	***
	USA	0.72	2.27e-02	*	0.35	1.97e-05	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Moreover, country effects are stronger and more consistent in non-NV settings, suggesting that in more controlled indoor climates, cultural and climate-based expectations shape thermal comfort more noticeably. Country like Greece feel much cooler indoors than Australians, possibly due to differences in building design, heating system performance, or personal adaptation. Meanwhile, UK and USA occupants consistently report warmer sensations, which may reflect over-heating or different indoor comfort norms.

4.6. Acceptability rates for each country

With the model established, a final analysis was carried out to assess acceptability rates and explore how thermal sensation may vary under different indoor conditions. This evaluation was based on the design parameters outlined in EN 16798-2 standard (CEN, 2020). The specific environmental conditions used in each scenario are summarized in Table 4.9, which reflects the recommended threshold values for the four Indoor Environmental Quality (IEQ) categories defined in the standard.

Table 4.9 Scenarios for winter and summer based on the UNI EN 16798–2 standard (Pistore et al, 2023)

			MET	CLO	RH	Vair
Non-Natural Ventilation	**Scenario 1**	Winter	1.2	1	50%	<0.1 m/s
				top per IEQ		
			IV = 16°C	III = 18°C	II = 20°C	I = 21 °C
			MET	**CLO**	**RH**	**Vair**
	Scenario 2	Summer	1.2	0.5	50%	<0.1 m/s; 0.6 m/s; 0.9 m/s; 1.2 m/s
				top per IEQ		
			IV = 28°C	III = 27°C	II = 26°C	I = 25.5°C
			MET	**CLO**	**RH**	**Vair**
Natural Ventilation	**Scenario 3**	Winter	1.2	1	40%	<0.1 m/s
				top per IEQ		
			IV = 17-25°C	III = 18-25°C	II = 20-25°C	I = 21-25 °C
			MET	**CLO**	**RH**	**Vair**
	Scenario 4	Summer	1.2	0.5	60%	<0.1 m/s; 0.6 m/s; 0.9 m/s; 1.2 m/s
				top per IEQ		
			IV = 21-28°C	III = 22-27°C	II = 23-26°C	I = 23.5-25.5°C

Based on the parameters presented in Table 4.9, lists of plots are presented to illustrate the estimated probabilities of individuals reporting specific thermal sensations across the four Indoor Environmental Quality categories defined by the standard. These plots reflect different scenario conditions, different operative temperatures during winter, and both operative temperatures and varying airspeeds in summer. According to Pistore et al. (2023), the acceptability rate refers to the percentage of users who report thermal sensations within the range of slightly cool, neutral, and slightly warm. In the figures, this rate is visually differentiated by color, with green indicating values equal to or above 80%, in alignment with the threshold set by ASHRAE Standard 55 for acceptable indoor thermal environments.

Figures 4.8 and 4.9 present the acceptability rates for each country for each IEQ Category for summer and winter seasons respectively, for scenario 1 and 2, for non-Natural Ventilation.

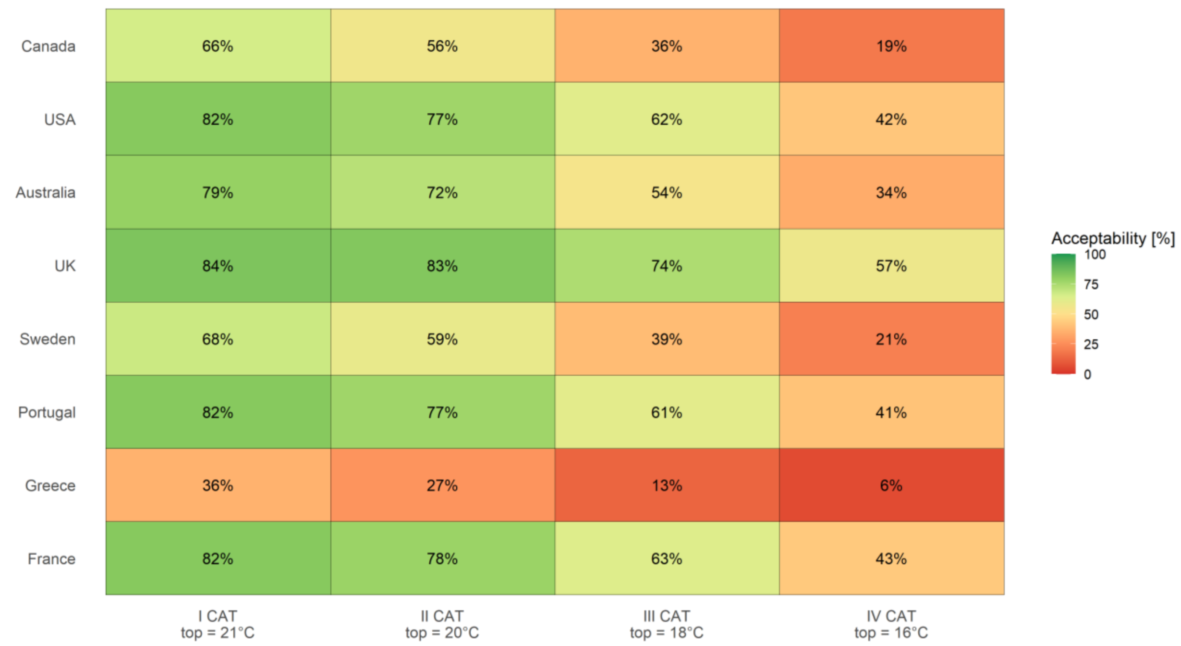

Figure 4.8 Acceptability rates for each country for each IEQ Category – Scenario 1 Winter

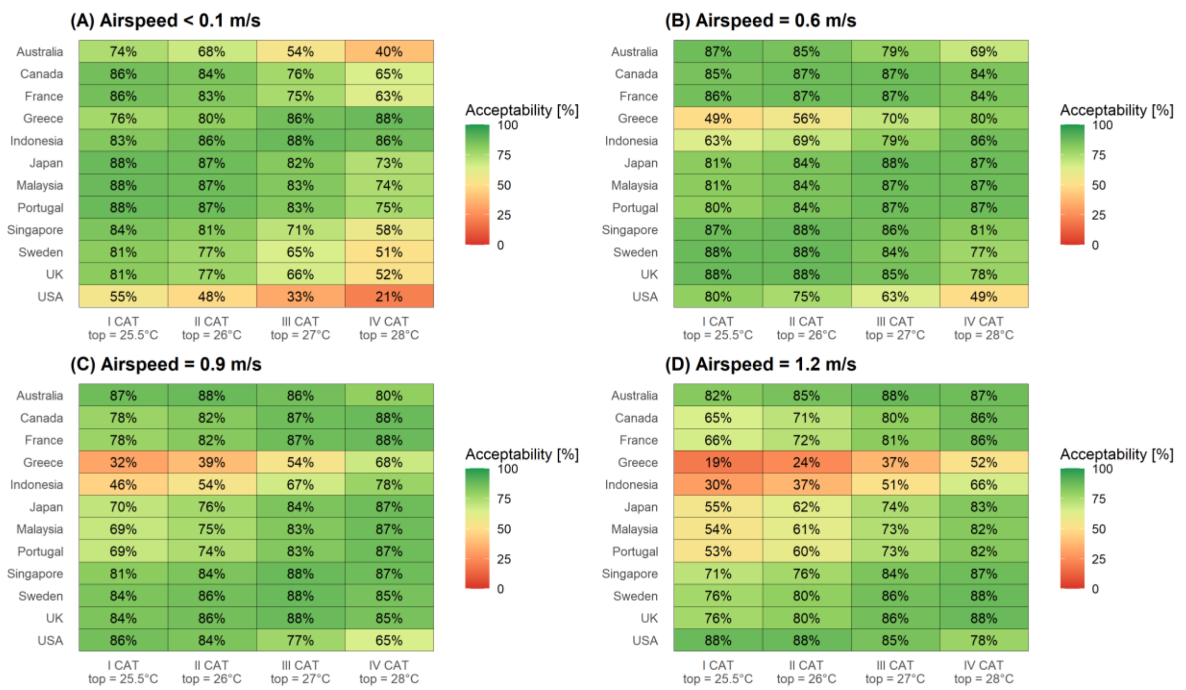

Figure 4.9 Acceptability rates for each country for each IEQ Category – Scenario 2 Summer

Figure 4.8 reinforces the earlier observation that individuals from Greece show the most distinct thermal responses during winter. Even under the most comfortable category (Category I), with an operative temperature of 21°C, Greek individuals tend to feel cool, resulting in an acceptability rate of just 36%. In contrast, users from other countries generally report more neutral sensations under the same conditions, with higher acceptability. The UK presents a particularly interesting case; acceptability remains high even through Category III, suggesting that individuals from the UK maintain a broader comfort tolerance and feel comfortable at lower operative temperatures. For the remaining countries, acceptability tends to remain relatively strong up to Category II. However, a decline occurs in Categories III and IV, indicating that lower indoor temperatures progressively reduce thermal satisfaction in those regions.

Figure 4.9 presents the acceptability rates across the four Indoor Environmental Quality (IEQ) categories under varying airspeeds during the summer season with non-Natural ventilation. As shown, air velocity has a clear impact on perceived thermal comfort. First, at an airspeed below 0.1 m/s, acceptability is notably lower in many countries, particularly under the IV Category, where rates drop. This suggests that in the absence of air movement, users experience considerable thermal discomfort at elevated operative temperatures.

Moderate increases in airspeed to 0.6 m/s and 0.9 m/s show mixed results. While countries such as the UK, Sweden, Singapore, France, Canada and Australia reach acceptability levels around or above 80%, others like Portugal, Malaysia, and Japan remain within 60–70%, particularly under Categories I and II. This implies that airspeed alone is not always sufficient to ensure thermal comfort, and its effect is moderated by users' climatic background, expectations, and possibly clothing or metabolic rates.

On the other hand, when considering Indonesia and Greece, when airspeed increases from 0.6 m/s to 0.9 m/s, acceptability declines under cooler operative temperatures (CAT I and II). This suggests that at moderate operative temperatures, additional air movement may induce a sensation of overcooling or discomfort. It is possible that subjects perceived the airflow as excessive relative to the actual thermal demand, leading to lower thermal satisfaction.

At the highest airspeed level of 1.2 m/s, as was noticed above, in some countries acceptability drops, particularly in CAT I and II. This drop suggests that excessive air movement may cause localized discomfort or be perceived negatively, especially when not controlled by the user. Overall, the results confirm that airspeed is a powerful adaptive mechanism for enhancing thermal comfort in warm conditions. However, the benefits of air movement are not uniform across all users or regions.

A similar analysis was carried out using data collected exclusively from occupants of naturally ventilated office buildings. Based on the parameters established in Table 4.9 for Natural Ventilation, Figure 4.10 and Figure 4.11 are presented for winter and summer respectively.

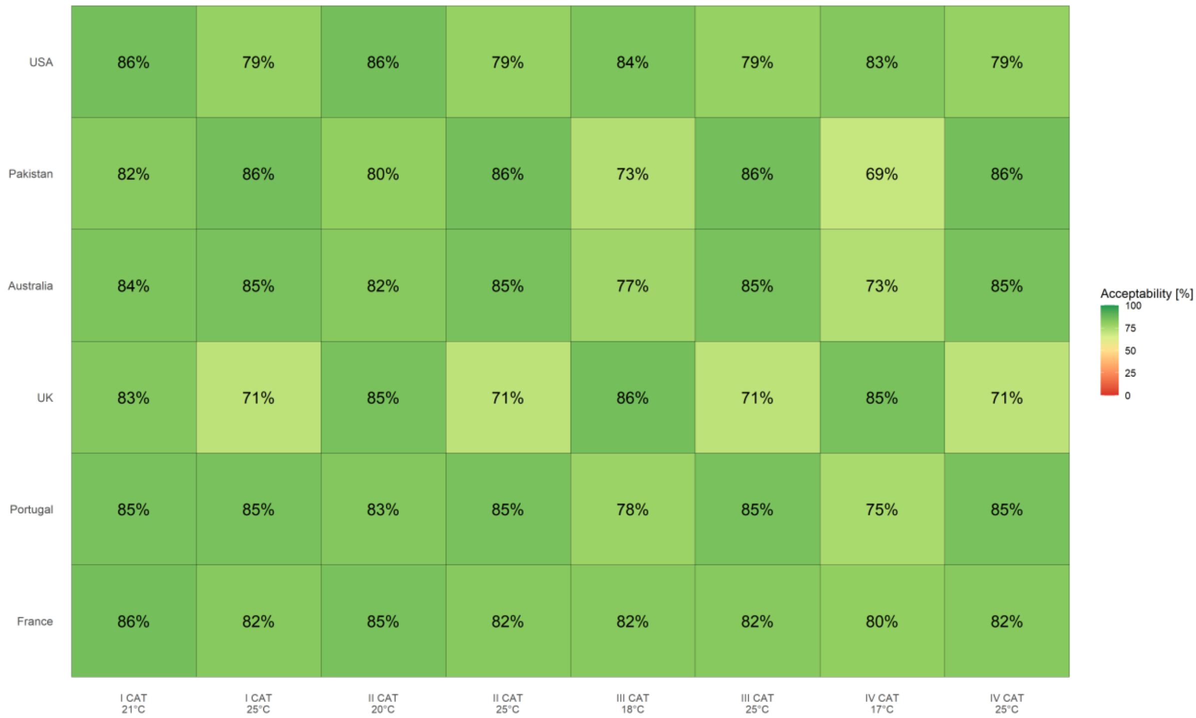

Figure 4.10 Acceptability rates for each country for each IEQ Category – Scenario 3 Winter

Figure 4.11 Acceptability rates for each country for each IEQ Category – Scenario 4 Summer

As shown in Figure 4.10, scenario 3 representing winter conditions in naturally ventilated buildings reveals consistently high acceptability rates across all evaluated countries and temperature categories. In most cases, thermal acceptability exceeded 80%, even within the broader operative temperature range of 17–25°C. This suggests that for these countries natural ventilation is sufficient for thermal comfort in winter. Users tend to report high comfort levels without mechanical heating across a wide range of temperatures, supporting the idea about the adaptive comfort model where occupants in NV buildings tolerate and adapt to broader temperature variations, even at lower operative temperatures, most users are comfortable, meaning that well-designed NV buildings can perform efficiently without compromising user satisfaction. The high levels of reported comfort suggest that in winter, NV strategies can provide satisfactory indoor environments while minimizing energy consumption.

In Figure 4.1, results from Scenario 4, simulating summer conditions in naturally ventilated buildings, reveal a more nuanced relationship between thermal acceptability and air movement. At low airspeed, many countries already show high acceptability under lower temperature categories. However, as operative temperature increases, acceptability declines.

Increasing the airspeed to 0.6 m/s generally improves acceptability, especially in higher categories, supporting the known cooling effect of air movement in warm environments. Nevertheless, as airspeed reaches 0.9 m/s and 1.2 m/s, the acceptability gains plateau or even reverse in some regions, where discomfort may be introduced due to excessive air motion or perceptual overcooling. Notably, tropical countries such as Singapore, Indonesia, and Malaysia maintain relatively high acceptability across all velocities and temperature categories, reflecting their populations' greater adaptive tolerance to warm conditions.

These findings align with adaptive comfort theory and reinforce the importance of air movement as a passive strategy in warm climates. However, they also highlight the need to calibrate air velocity carefully, as excessive airflow may reduce comfort, particularly when not matched with sufficient heat load or user expectations.

Conclusions

This study provides evidence-based examination of how both environmental conditions and human factors shape indoor thermal sensation. By analyzing over fifteen thousand occupant responses drawn from the ASHRAE Global Thermal Comfort Database II and the SCATS database, the research quantified the effects of key variables on thermal sensation and revealed notable seasonal and country-specific trends.

- There is an individual variability and heterogeneity between the different studies, due to the variations in measurement protocols, participant characteristics, or contextual factors, however due to the limited number of distinct studies in the dataset, the estimation of random effects became statistically unstable.
- In the summer season, operative temperature, metabolic rate and clothing insulation exhibit highly significant positive relationships with thermal sensation votes. Conversely, relative humidity and airspeed show highly significant negative relationships with thermal sensation.
- During winter, airspeed emerged as a statistically significant predictor of thermal sensation, though its effect is smaller compared to the summer season.
- Clothing insulation had a significant negative effect in winter, indicating that higher insulation levels were associated with cooler thermal sensation votes. Operative temperature and metabolic rate were both found to have positive and statistically significant associations with thermal sensation in the winter model, indicating that increases in either variable are linked to a heightened perception of warmth.
- In both seasonal models, the estimate for relative humidity is negative, indicating that higher humidity levels are associated with a lower likelihood of reporting a warmer thermal sensation. Reflecting the complex nature of humidity's influence on thermal perception.
- The inclusion of country as a categorical predictor in the thermal sensation models reveals clear regional differences in how participants from various locations experience and report thermal environments.
- During summer, thermal neutrality is the most frequently predicted response across most countries, indicating a general tendency toward comfort under average conditions.
- During the summer season, participants from Greece exhibited one of the highest probabilities of reporting slightly cool thermal sensations, reaching nearly 30%.

However, in both summer and winter, the length of the confidence intervals for Greece indicates greater uncertainty, suggesting that thermal sensation responses were more diverse or inconsistent compared to other countries.

- During winter, thermal neutrality remains the dominant response in almost all countries, where the probability approaches 50%, suggesting a general ability to maintain comfortable indoor conditions during this season.
- Occupants in air-conditioned spaces are more sensitive to temperature changes, potentially due to reduced adaptive opportunities.
- Airspeed decreases thermal sensation in both NV and non-NV environments, but with a noticeably greater effect in non-NV buildings, reinforcing the idea that mechanical airflow has a more pronounced impact in indoor settings
- While increased airspeed enhances thermal acceptability, its effectiveness depends on user background and climate adaptation. Moderate air velocities improve comfort for many, but excessive airflow may reduce acceptability in some regions, highlighting the need for context-specific strategies.

By emphasizing the significant context-dependence of thermal sensation, which is impacted by both seasonal climatic variations and regional or cultural customs, these empirical findings lend credence to the concepts of adaptive comfort theory. In essence, people from different climatological backgrounds see the same interior environment differently, and their comfort levels vary depending on local temperature conditions and social norms.

It is important to recognize that the methodology used in this study has some limitations. The source data variability is one drawback. Numerous separate field investigations, each with its own methodologies, participant samples, and climates, served as the basis for the comfort surveys. It is challenging to properly account for the heterogeneity introduced by the variety of contexts, despite efforts to standardize and clean up the combined dataset.

Another limitation is that the data only covers a limited number of countries and climate zones; countries of Latin America and Africa, for example, were either absent or underrepresented, which restricts the findings' potential to be applied globally.

Finally, the findings of this thesis have significant implications for the design and functioning of user-centered, energy-efficient buildings. Recommending a shift from a strict, one-size-fits-all mindset to a more flexible, adaptable approach for HVAC control systems and building standards. In the real world, engineers and architects can apply these ideas to create structures that encourage occupant adaptability by including localized control systems, operable windows, or fans that allow people to adjust their immediate surroundings. This can significantly reduce energy consumption for heating and cooling.

Nomenclature

ta = Air Temperature

rh = Relative Humidity

vel = Airspeed

top = Operative Temperature

met = Metabolic Rate

clo = Clothing Insulation

h_c = Convective heat transfer coefficient

h_r = Radiative heat transfer coefficient

Acronymous:

ASHRAE = American Society of Heating, Refrigerating and Air-Conditioning Engineers

CEN = European Committee for Standardization

CLM = Cumulative Link Model

CLMM = Cumulative Link Mixed Model

EU = European Union

GHG = Greenhouse gas

HVAC = Heating, Ventilation and Air Conditioning

IMD = Indian Meteorological Department

IAQ = Indoor Air Quality

IEQ = Indoor Environmental Quality

ISO = International Organization for Standardization

MLE = Maximum Likelihood Estimation

ML = Maximum Likelihood

MV = Mechanical Ventilation

NV = Natural Ventilation

PMV = Predicted Mean Vote

PPD = Predicted Percentage Dissatisfied

SBS = Sick Building Syndrome

SCATS = Smart Controls and Thermal Comfort

TSV = Thermal Sensation Votes

USA = United States of America

UK = United Kingdom

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A. APPENDIX

Table A.1 Statistical analysis of the covariates of M1 Model

Covariates	Summer season			Winter season		
	Estimate	p-value	Signif.	Estimate	p-value	Signif.
top	0.406163	< 2e-16	***	0.372905	< 2e-16	***
rh	-0.017884	< 2e-16	***	-0.005351	0.051924	.
vel	-1.670427	< 2e-16	***	-0.468538	0.147423	
met	0.544089	3.44e-10	***	0.495497	0.000315	***
clo	0.755287	5.09e-10	***	-0.498225	8.79e-05	**

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table A.2 Statistical analysis of the covariates of M2 Model

Covariates	Summer season			Winter season		
	Estimate	p-value	Signif.	Estimate	p-value	Signif.
top	0.459135	< 2e-16	***	0.372902	< 2e-16	***
rh	-0.013983	< 2e-16	***	-0.005853	0.027800	*
vel	-1.593135	< 2e-16	***	-0.470822	0.145499	
met	0.556004	1.66e-10	***	0.494592	0.000323	***
clo	0.752128	1.91e-09	***	-0.468869	0.000220	***
countrycanada	-0.658007	0.388		-0.619407	0.101387	
countryindonesia	0.262809	0.655		-	-	-
countryjapan	0.454413	0.437		-	-	-
countrymalaysia	0.005803	0.992		-	-	-
countrypakistan	-0.711255	0.305		-0.410629	0.269010	
countrysingapore	-0.924176	< 2e-16	***	-	-	-
countryuk	0.634573	0.356		1.345869	0.000472	***
countryusa	1.002495	0.187		0.277212	0.447792	

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table A.3 Statistical analysis of the covariates of M3 Model

Covariates	Summer season			Winter season		
	Estimate	p-value	Signif.	Estimate	p-value	Signif.
top	0.288762	< 2e-16	***	0.312440	< 2e-16	***
rh	-0.009886	6.05e-11	***	-0.004934	0.0327	*
vel	-1.964908	< 2e-16	***	-0.557317	0.0832	.
met	0.315262	0.000215	***	0.229694	0.0851	.
clo	-0.107385	0.355545		-0.975236	< 2e-16	***
study	-0.025111	0.000870	***	-0.083667	8.17e-09	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table A.4 Statistical analysis of the covariates of M4 Model

Covariates	Summer season			Winter season		
	Estimate	p-value	Signif.	Estimate	p-value	Signif.
top	0.459593	< 2e-16	***	0.327889	< 2e-16	***
rh	-0.012859	2.87e-15	***	-0.011728	1.32e-05	***
vel	-1.654948	< 2e-16	***	-0.478927	0.13653	
met	0.553879	1.92e-10	***	0.395469	0.00384	**
clo	0.658471	1.03e-07	***	-0.293722	0.01812	*
countrycanada	-1.180509	< 2e-16	***	-0.584483	2.13e-06	***
countryindonesia	-1.505959	< 2e-16	***	-	-	-
countryjapan	-1.315969	< 2e-16	***	-	-	-
countrymalaysia	-1.749099	< 2e-16	***	-	-	-
countrypakistan	-1.903436	< 2e-16	***	-0.279820	0.00478	**
countrysingapore	-1.026535	< 2e-16	***	-	-	-
countryuk	-0.527528	2.72e-06	***	1.540116	< 2e-16	***
countryusa	0.460957	1.47e-10	***	0.435714	1.24e-09	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table A.5 Statistical analysis of the covariates of M5 Model

Covariates	Summer season			Winter season		
	Estimate	**p-value**	**Signif.**	**Estimate**	**p-value**	**Signif.**
top	0.459183	< 2e-16	***	0.346534	< 2e-16	***
rh	-0.012753	5.35e-15	***	-0.007719	0.00474	**
vel	-1.665880	< 2e-16	***	-0.569022	0.07811	.
met	0.556353	1.62e-10	***	0.440864	0.00129	**
clo	0.655440	1.19e-07	***	-0.523665	3.67e-05	***
countrycanada	-1.126040	< 2e-16	***	-0.698950	1.77e-08	***
countryindonesia	-1.563802	< 2e-16	***	-	-	-
countryjapan	-1.374163	< 2e-16	***	-	-	-
countrymalaysia	-1.806885	< 2e-16	***	-	-	-
countrypakistan	-1.799648	< 2e-16	***	-0.802520	2.13e-12	***
countrysingapore	-1.041123	< 2e-16	***	-	-	-
countryuk	-0.431244	0.00257	**	1.994605	< 2e-16	***
countryusa	0.536740	8.34e-08	***	0.039086	0.63947	
study	0.022590	0.27677		-0.178637	< 2e-16	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table A.6 Statistical analysis of the covariates of M6 Model

Covariates	Summer season			Winter season		
	Estimate	p-value	Signif.	Estimate	p-value	Signif.
top	0.479315	< 2e-16	***	0.4099956	< 2e-16	***
rh	-0.009196	1.42e-07	***	-0.0001394	0.96349	
vel	-1.572995	< 2e-16	***	-0.6110015	0.06964	.
met	0.642175	3.36e-13	***	0.5129601	0.00026	***
clo	0.526225	3.53e-05	***	-0.7157726	3.93e-08	***
countrycanada	-0.969507	< 2e-16	***	-1.2197256	3.71e-11	***
countryindonesia	-1.385522	< 2e-16	***	-	-	-
countryjapan	-1.196947	< 2e-16	***	-	-	-
countrymalaysia	-1.614540	< 2e-16	***	-	-	-
countrypakistan	-1.274261	< 2e-16	***	-0.2164731	0.44734	
countrysingapore	-3.303486	1.46e-10	***	-	-	-
countryuk	-0.286522	0.02207	*	1.4207731	8.31e-07	***
countryusa	-1.473456	0.00605	**	-0.2566019	0.25148	
year1983	0.600325	5.29e-13	***	-	-	-
year1984	-0.067243	0.51957		-0.0985210	0.73330	
year1986	2.728325	2.15e-07	***	1.0122920	0.00132	**
year1987	2.120072	6.06e-05	***	1.5157005	2.59e-09	***
year1992	-	-	-	-0.2007935	0.10232	
year1993	-0.522201	3.11e-06	***	1.2007106	1.52e-05	***
year1994	NA	NA	NA	0.6797369	0.02194	*
year1995	-0.353063	0.04738	*	1.6605674	< 2e-16	***
year1996	-	-	-	0.9383875	8.83e-05	***
year1997	0.266928	0.08493	.	1.7933500	< 2e-16	***
year2009	0.373192	6.26e-05	***	1.1154785	< 2e-16	***
year2015	NA	NA	NA	-	-	-

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1