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Learning occupants' indoor comfort temperature through a Bayesian inference approach for office buildings in United States

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ABSTRACT
A carefully chosen indoor comfort temperature as the thermostat set-point is the key to optimizing building energy use and occupants' comfort and well-being. ASHRAE Standard 55 or ISO Standard 7730 uses the PMV-PPD model or the adaptive comfort model that is based on small-sized or outdated sample data, which raises questions on whether and how ranges of occupant thermal comfort temperature should be revised using more recent larger-sized dataset. In this paper, a Bayesian inference approach has been used to derive new occupant comfort temperature ranges for U.S. office buildings using the ASHRAE Global Thermal Comfort Database. Bayesian inference can express uncertainty and incorporate prior knowledge. The comfort temperatures were found to be higher and less variable at cooling mode than at heating mode, and with significant overlapped variation ranges between the two modes. The comfort operative temperature of occupants varies between 21.9 and 25.4°C for the cooling mode with a median of 23.7°C, and between 20.5 and 24.9°C for the heating mode with a median of 22.7°C. These comfort temperature ranges are similar to the current ASHRAE standard 55 in the heating mode but 2-3°C lower in the cooling mode. The results of this study could be adopted as more realistic thermostat set-points in building design, operation, control optimization, energy performance analysis, and policymaking.

KEYWORDS
Thermal comfort; Bayesian inference; ASHRAE Thermal Comfort Database; Active learning; Temperature set-point; Office buildings

Nomenclature

Abbreviations

ASHRAE	The American Society of Heating, Refrigerating and Air-Conditioning Engineers
clo (I_{cl})	Clothing insulation
Eq.	Equation
h (g/g dry air)	Humidity
ISO	International Standard Organization
kWh	kilowatt hour
MCMC	Markov Chain Monte Carlo
met (met)	Metabolic rate
n	Number of observations
°C	Degree Celsius
PMV (1)	Predicted Mean Vote
PPD (%)	Predicted Percentage Dissatisfied
RH (%)	Relative humidity
sd	Standard deviation
Std. Err.	Standard Error

TA (1)	Thermal acceptability
TC (1)	Thermal comfort
TP (1)	Thermal preference
TS (1)	Thermal sensation
US	United States
v (m/s)	Air speed

Subscripts/superscripts

T_a (°C)	Air temperature
T_i (°C)	Temperature for the i^{th} observation
$T_{neutral}$ (°C)	Neutral temperature
$T_{observed}$ (°C)	Observed temperature
T_{out} (°C)	Outdoor temperature
T_r (°C)	Mean radiant temperature
$TS_{observed}$ (°C)	Observed thermal sensation
TS_i (°C)	Thermal sensation vote for the i^{th} observation

Greek symbols

β	(Estimated) coefficient
ε_i	Prediction error for the i^{th} observation
λ	Prior variance of the estimated coefficient
σ^2	Variance of the prediction error
$N(\mu, \Sigma)$	Normal distribution with a mean value of μ and standard deviation of Σ

1 Introduction

Buildings consume a large proportion of energy and emit a substantial amount of greenhouse gas to maintain a comfortable thermal environment [1], [2] for occupants' comfort, satisfaction [3], productivity [4], health [5] and well-being. The approaches to curtail building energy consumption while improving environmental quality not only include applying energy efficient technologies [6] and materials [7], enhancing building sensing, prediction [8], [9] and control [10], but also rely on a better understanding of occupants' behaviors and their true demands. A key research question to understand occupants' thermal demand is what is the suitable indoor temperature set-point that could satisfy occupants' comfort need at affordable energy consumption level [11]. The answer to this question is the basis for building design, performance simulation, cooling technology selection and operation [12], control optimization, prediction-based analysis and policymaking [13].

Up to date, thermal comfort standards and researchers have proposed two major frameworks to determine the proper temperature set-points: the PMV-PPD (Predicted Mean Vote – Predicted Percentage Dissatisfied) approach and the adaptive comfort approach.

1.1 PMV-PPD approach

The PMV-PPD approach was originally proposed by Fanger in 1970s [14]. The PMV-PPD approach is a physical-based heat-balance model, which develops the relation between the Predicted Mean Vote (PMV) with four environmental factors and two personal factors, as shown in Table 1. Then the mapping from PMV to the Predicted Percentage Dissatisfied (PPD) was identified from chamber experiments, rather than in real building environments. Last, by setting the objective for PMV and assuming the value of clothing insulation and metabolic rate for indoor occupants, the temperature set-point was found.

As the first paradigm of thermal comfort studies, the PMV-PPD approach was adopted in the US [15] and international [16] thermal environment standards for buildings. However, the accuracy of PMV-PPD model depends on the dedicated calibration of input parameters. Additionally, the complexity of the heat-balance model limits its applicability in practice. In addition to the air and radiant temperature, which we are interested in, there are four other parameters that need to be considered in the PMV-PPD model. Accordingly, the PMV-PPD model is unable to provide an explicitly recommended indoor temperature set-point, because the comfortable temperature range predicted by the PMV-PPD model depends on other factors such as humidity, air speed, metabolic rate and clothing insulation [15]. In other words, the building operator and controller might not know what the temperature set-point should be, as the humidity or air speed is usually not measured in real practice.

Additionally, even if the environmental parameters of air speed and humidity were measured, the uncertainty of the predicted suitable indoor temperature set-point is still high, since it is difficult to accurately estimate the clothing insulation and metabolic rate of inhabitants [17]. The most widely used way to estimate these two factors is the Table Lookup Method. However, Brager et al. found that the calculated clothing insulation value might differ by 20% if different sources of tables and algorithms were used [18]. Kingma and van Marken Lichtenbelt argued the metabolic rates listed in the current standard need to be recalibrated [19]. As a result, Ribeiro et al. claimed that the uncertainty of PMV calculation might be as large as 0.5 scale unit on the seven-point standard scale [20].

1.2 Adaptive comfort approach

The adaptive comfort approach was proposed by de Dear and Brager in late 1990s [21], and confirmed by Nicol and Humphreys [22] in the early 2000s. In contrast to the physical-based PMV-PPD approach, the adaptive comfort model was developed through data-driven approach from the ASHRAE Global Thermal Comfort Database I. The key idea behind the adaptive comfort model is occupants would actively adapt to the ambient through behavioral, physiological and psychological adjustment, and accordingly should not be considered as static as they are assumed in the PMV-PPD model. For instance, the clothing insulation might vary from time to time, as occupants would adjust their clothing to make themselves thermally comfortable [23]. The major mathematical assumption of the adaptive comfort model is the outdoor temperature should be a good proxy of the adaptive behaviors [22]. Based on this assumption, it is further assumed that the comfortable temperature is linearly related to the outdoor temperature[15]. A summary and comparison between the PMV-PPD and the adaptive comfort approach are presented in Table 1.

Compared with the PMV-PPD approach, the simplicity of adaptive comfort approach makes it popular among the building industry. However, the validity of the adaptive comfort model triggers concerns of the model oversimplification as most data supporting the model were from occupants in naturally ventilated buildings. Additionally, the assumption that 'indoor comfort temperature is a linear function of outdoor temperature' was challenged by researchers from time to time [24].

Table 1 Summary of two major approaches to determining the indoor temperature set-point

	PMV-PPD approach	Adaptive Comfort approach
Thermal metrics	Predicted Percentage Dissatisfied	Thermal Acceptable Rate
Influential factors	Indoor temperature T_{in} Air speed v Humility h Clothing insulation clo Metabolic rate met	Indoor temperature T_{in} Outdoor temperature T_{out}
Models	$PMV = f(T_a, T_r, v, h, clo, met)$ $PPD = g(PMV)$	$T_a = kT_{out} + b$
Objective	Predicted Percentage Dissatisfied less than 10%	Thermal Acceptable Rate above 80% or 90%
Advantages	• Heat balance model, clear physical implication	• Simple input, easy to use • Consider adaptive behavior
Disadvantages	• Model is complex, requiring six parameters as input. Some inputs are difficult to measure in practice. • The mapping between PMV and PPD was regressed from limited samples in a climate chamber rather than from real built environments.	• The assumption of linear relation between the comfort temperature and the outdoor temperature lacks theory support • The mapping between the comfort and outdoor temperature was regressed mainly from naturally ventilated buildings. Their use for mechanically cooled buildings need further justification.

1.3 Objectives

This study aims to derive and discuss the proper indoor temperature set-point for U.S. office buildings. The Bayesian-based data-driven approach would be used to address the limitations of the heat balance model and the adaptive comfort model. The key advantage of this method lies in its ability to deliver an explicit temperature set-point without compromising the model's capability to take into account personal characteristics and preferences.

This study focuses on the context of U.S. office buildings. According to the 2012 Commercial Building Energy Consumption Survey, office buildings have the largest building stocks of more than one million in the U.S. compared with other usage types of buildings, taking footage of 16 billion square feet (15 billion square meters) and consuming energy of 1.2 quadrillion Btu (352 billion kWh) per year [25]. A properly chosen temperature set-point would benefit the design and operation of U.S. office buildings in an energy-efficient way, which has a substantial effect on building energy conservation and greenhouse gas emission reduction in the U.S.

The remaining of this paper starts with an introduction to the methodology, including data, terminology, assumption, and Bayesian Inference method (Section 2). In Section 3, the results of applying Bayesian Inference to the ASHRAE Thermal Comfort Data are presented (Section 3.1), and compared with the existing standards (Section 3.2). Section 4 discusses this paper's contribution (Section 4.1) and limitations (Section 4.2). Conclusions are drawn in Section 5.

2 Methodology

2.1 Data

As a global effort to build up an open-source data platform, the ASHRAE Global Thermal Comfort Database II collected 81,846 sets of data combining both the objective indoor climatic observations and 'right-now-right-here' subjective evaluations [26]. The ASHRAE Global Thermal Comfort Database II was released in

2018. Along with the ASHRAE Thermal Comfort Database I [27], which was released in 1998 and collected 22,000 data points, a combined thermal comfort database containing 103,846 observations is now available. To achieve a larger sample size, the dataset combining Database I and II has been analyzed in this study, and would be referred to as ASHRAE Global Thermal Comfort Database in this paper.

In the ASHRAE Global Thermal Comfort Database, 45 attributes were measured and reported, covering information about the physical environment, subject's response, and the characteristics of the building and respondents. Thanks to the great efforts to clean and organize the data in a consistent format, the ASHRAE Global Thermal Comfort Database becomes a good resource to apply machine-learning techniques to study research questions on the building thermal environment and occupants' thermal comfort.

Focusing on the context of US office buildings, we filtered 11,600 data points from the original database with more than 103,000 measurements. These data were collected from 10 cities across the country, including Berkeley, San Francisco, Alameda, Philadelphia, San Ramon, Palo Alto, Texas[1], Walnut Creek, Grand Rapids, and Auburn.

2.2 Terminology

Before explaining the statistical methods used in this study, it is necessary and beneficial to clarify the terminology first. Thermal comfort study is basically about how occupants respond to the physical thermal environment. Therefore, there are two sets of temperature-related terminologies used in thermal comfort studies: one for the objective thermal environment, and the other for the subjective occupant response, as shown in Figure 1.

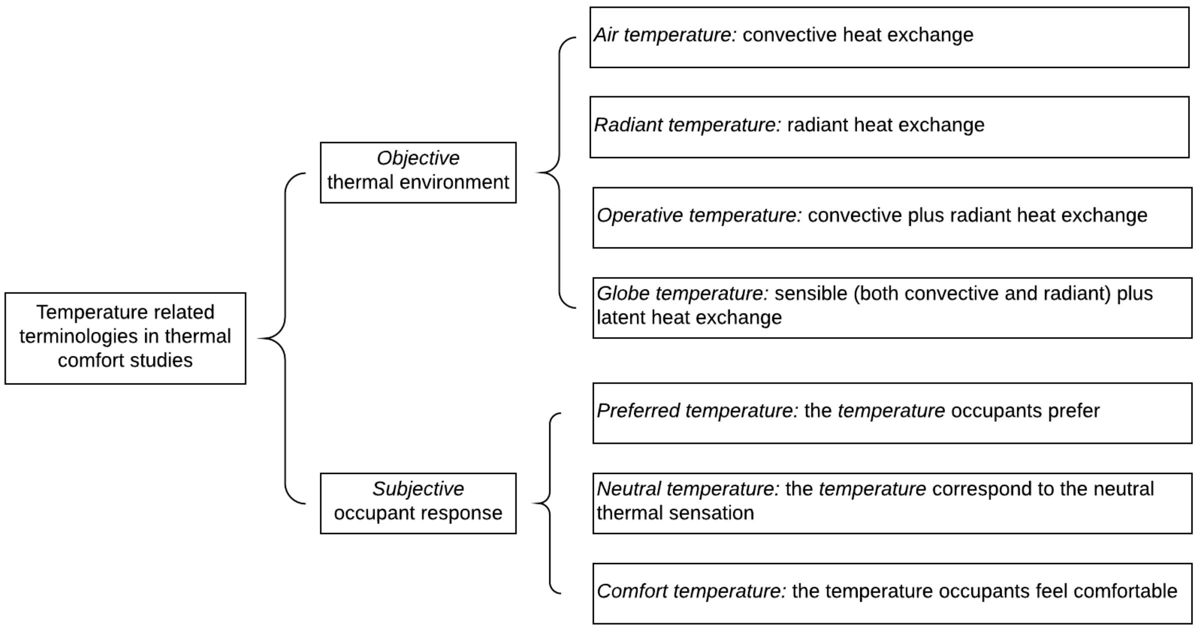


Figure 1: Temperature related terminologies in thermal comfort studies

Four metrics are widely used to characterize the objective indoor environmental conditions [15]. Air temperature is defined as the temperature of the air at a point [15]. The mean radiant temperature (MRT) is defined as the temperature of a uniform, black enclosure that exchanges the same amount of heat by radiation with the occupant as the actual surroundings [15]. Air temperature and mean radiant temperature characterize the heat exchange between human subjects and the ambient environment through convection and radiation process. Operative temperature is defined as the uniform temperature of an imaginary black enclosure, and the air within it, in which an occupant would exchange the same amount of heat by radiation plus convection as in the actual non-uniform environment [15]. Therefore, operative temperature considers the sensible heat exchange, including both the convection and radiation. Globe temperature, also referred to as the Wet-bulb Globe Temperature (WBGT), is a measure of heat stress, which takes both the sensible and latent heat

[1] The Database has not specified the data was collected from which city or cities in Texas.

exchange (through sweat evaporation) into account [15]. In this research, we considered the neutral air and operative temperatures, rather than the globe temperature for two reasons. First, the indoor air and operative temperature are most widely used in thermal comfort studies (as shown in Table 2) and building controls, and could be a direct input into building simulation tools such as EnergyPlus [28] for thermal loads calculation and energy performance simulation. Second, in office settings, the sweat evaporation would not vary too much since office buildings have a moderate and close-to-neutral thermal environment.

As for the measurement of subjective occupant thermal responses, there are three metrics widely used: the preferred, neutral, and comfort temperature. The preferred temperature is measured by allowing subjects to freely adjust the ambient temperature based on their preference, and then recording the average temperature during a given period of time. The neutral temperature is measured by regressing the temperature with thermal sensation, and then finding the temperature corresponding to neutral thermal sensation (Thermal Sensation equals to 0). The comfort temperature has a relatively ambiguous definition, corresponding to the temperature that makes occupants feel comfortable.

In ASHRAE Global Thermal Comfort Database, the air, radiant, operative and globe temperatures were recorded, as shown in Table 2. Contrarily, the preferred, neutral and comfort temperatures were not recorded, as these three subjective metrics could not be directly measured.

Table 2 Temperature metrics recorded in the ASHRAE Global Thermal Comfort Database

	Heat exchange considered	Missing data rate in ASHRAE Database	
		Whole database	U.S. offices
Air temperature	Convection	7.1%	0.1%
Radiant temperature	Radiation	52.0%	8.0%
Operative temperature	Convection and radiation	46.1%	3.9%
Globe temperature	Convection, radiation and latent	75.8%	7.9%

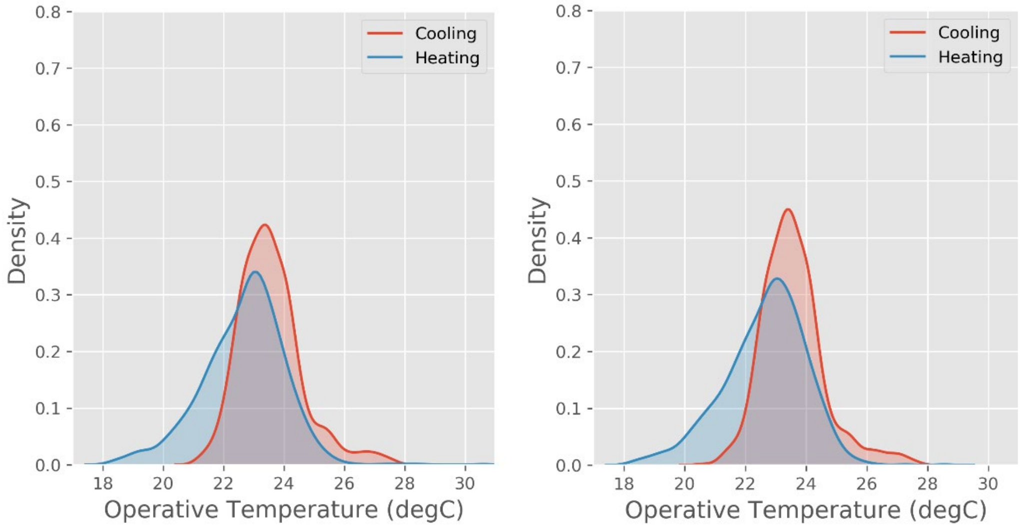
2.3 Assumption

2.3.1 Criteria to determine temperature set-point

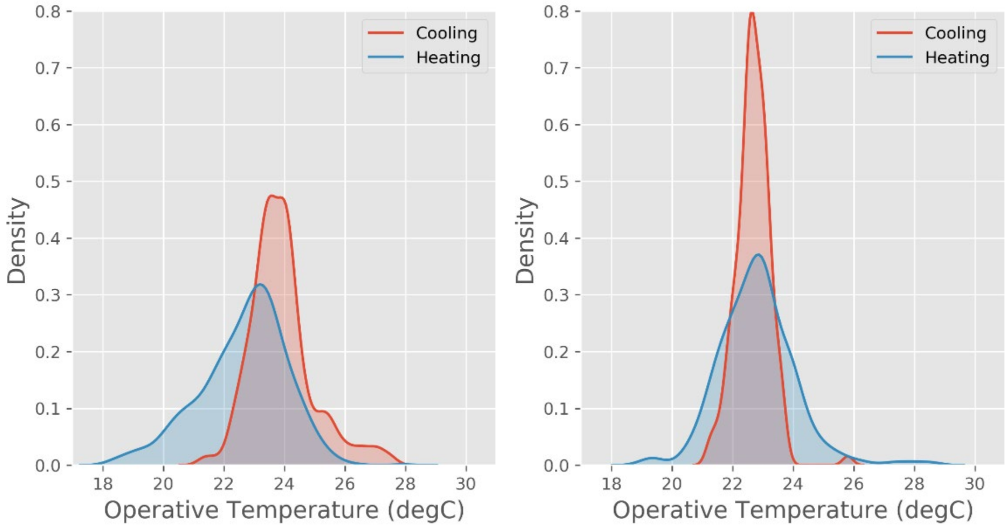
In order to select the proper temperature set-point, the first question needs to be clarified is which thermal metrics should be used to define occupants' thermal satisfaction. Four thermal metrics were recorded in the ASHRAE database: thermal sensation, thermal comfort, thermal acceptance and thermal preference. These four thermal metrics are designed for varying purposes [29], but they all could be used to set up the criteria to determine the temperature set-points, as shown in Table 3.

Table 3 subjective thermal metrics recorded in ASHRAE Global Thermal Comfort Database

	Scale in ASHRAE Database	Criteria to select temperature set-point	Missing rate in ASHRAE Database	
			Whole database	Data for US offices
Thermal sensation (TS)	-3 (cold) to +3 (hot)	-0.5 < TS < +0.5	2.9%	21.5%
Thermal comfort (TC)	1 (very uncomfortable) to 6 (very comfortable)	TC >= 4 (Slightly comfortable)	67.9%	30.1%
Thermal acceptability (TA)	0 (not acceptable), 1 (acceptable)	TA = 1	42.0%	47.7%
Thermal preference (TP)	cooler, no change, warmer	TP = no change	20.5%	43.2%



(a) -0.5 < Thermal sensation < +0.5 (b) Thermal comfort >= 4



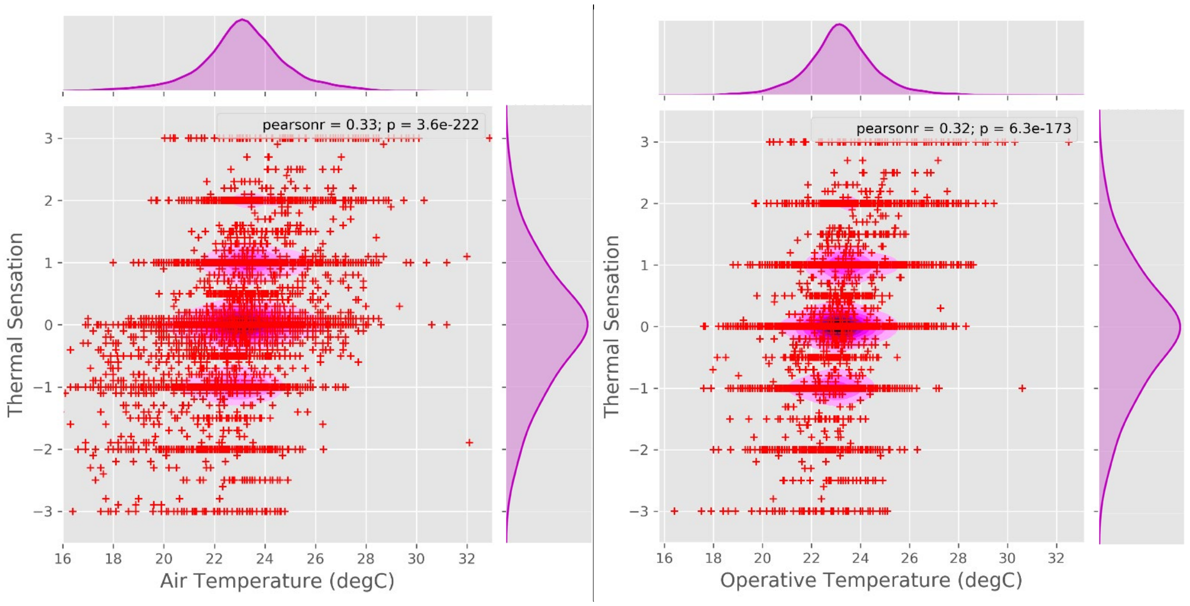
(c) Thermal acceptability = acceptable (d) Thermal preference = no change

Figure 2: Preferred/satisfied temperature distribution for different criteria

Figure 2 plots the distribution of the preferred temperature when different thermal metrics and criteria were adopted. The criteria of thermal sensation, thermal comfort and thermal acceptability give similar shapes of preferred temperature distribution; however, the criterion of *thermal preference equals to 'no change'* gives a more concentrated and less variant temperature range. If we choose 'thermal preference is no change' as our goal, the recommended temperature set-point range would be narrower than the range recommended from the other three metrics.

In this study, the first assumption is *'thermal sensation close to neutral'* would be used as the rule to determine temperature set-point for three reasons. First, the current ASHRAE [15] and ISO [16] standards adopted this rule to determine the comfortable temperature range. Second, the temperature distribution shape given by these metrics is similar to that given by thermal comfort and thermal acceptability. Third, the thermal sensation is the most widely used metrics in thermal comfort surveys and has the lowest missing rate in ASHRAE Database, as shown in Table 3.

Figure 3 plots the relation between the temperature and thermal sensation for US office buildings. A statistically significant correlation could be observed, with the temperature increasing, subjects' thermal sensation shifts towards the warm side. The distribution of the thermal sensation, air and operative temperature all passed the Shapiro-Wilk test with the p-value very close to one, indicating the samples of thermal sensation, air and operative temperature all follow the Gaussian distribution. One reason behind this close-to-normal distribution of the thermal sensation, air and operative temperature might be the large sample size of this dataset.



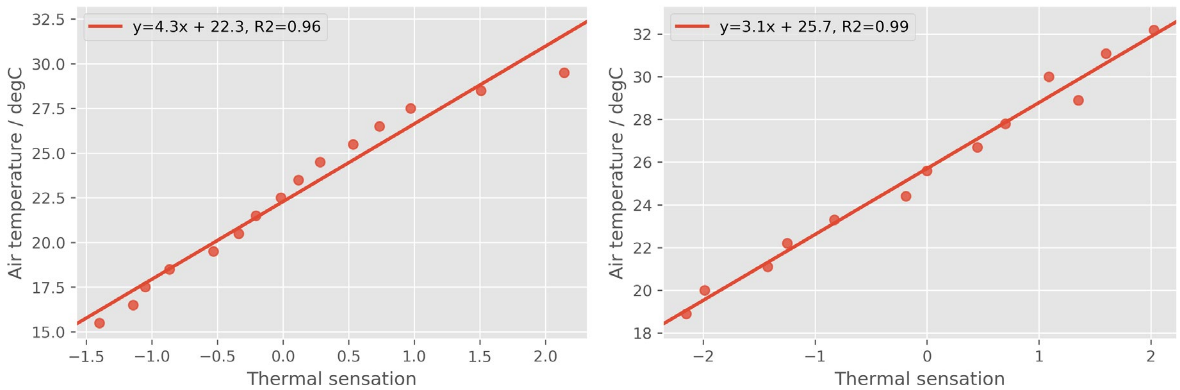
(a) Thermal sensation with air temperature (b) Thermal sensation with operative temperature

Figure 3: Data overview of observations for US office buildings

2.3.2 Linear relation between the thermal sensation and temperature

Another major assumption for this study is the thermal sensation and temperature are linearly correlated, as shown in Eq. 1. This assumption could be justified from the classical PMV model that thermal sensation is linearly correlated with PMV, while PMV is linearly correlated with the air temperature given other factors stay constant [14]. The linear relation between the temperature and thermal sensation was also applied in the existing studies [30], [31], [32], [33], [34], [35]. Lastly, this assumption was found to match well with both the ASHRAE Thermal Comfort Database and Fanger's pioneer experiment [14], as shown in Figure 4. It is worthwhile to point out that this linear relation might only hold in the moderate thermal environment. As the built environment would unlikely be either too hot or too cold, it is reasonable to expect this assumption holds in buildings.

$$T_i \sim \beta_0 + \beta_1 * TS_i + \varepsilon_i \qquad \text{Equation 1}$$



(a) ASHRAE Thermal Comfort Database (update) (b) Fanger's experiment (priori)

Figure 4: Linear relation between thermal sensation and temperature

2.4 Bayesian inference

2.4.1 Motivation

Linear regression is a useful and straightforward way to illustrate how the indoor temperature influences occupants' thermal sensation. However, linear regression could only inform us about the 'average' behavior of a group of people, and could not provide any insights about the inter-individual variabilities in thermal comfort needs. Additionally, univariate linear regression could not consider the adaptive behaviors that occupants might take in varying indoor environments. Therefore, linear regression might be too simple to determine the comfort temperature.

Bayesian Inference is the tool selected in this study to infer the temperature set-point for HVAC control for the following three reasons. First, Bayesian Inference can quantify the uncertainty or variability in the estimated model parameters. Under the context of this study, the Bayesian Inference provides a useful and powerful tool to quantify occupants' thermal adaptive behaviors and inter-individual variabilities in thermal comfort demands, both of which need to be taken into account in selecting comfort temperature. Additionally, Bayesian approach can easily account for hidden variables [36] such as metabolic rate, clothing, individualized preference [37], which are difficult to measure but important in thermal comfort studies. Thirdly, Bayesian Inference facilitates active learning, allowing the controller to update the set-point based on new observations. Bayesian approach is data efficient and flexible in this regard, as it could seamlessly combine new observations once they are available [36]. If no new observations are available, the prior distribution could be used to determine the thermostat set-point and to facilitate the control.

2.4.2 Literature review

Though Bayesian Inference has successful applications in the fields of education, science, medicine, engineering, it has not been extensively applied in the built environment field, which might be due to the relatively small sample size and relatively large computational resources it requires. In the thermal environment field, Lee et al. applied Bayesian Inference to predict an individual's thermal preference through a two-step approach. First, the occupants are clustered into different groups. Then, Bayesian Inference was applied to predict the thermal preference of each cluster based on environmental and behavioral parameters [38]. Bayesian approach has also been used to account for the modeling uncertainty associated with difficult-to-measure variables [37]. Langevin et al. applied Bayesian approach to predict thermal sensation, acceptability, and preference based on PMV value [39]. Aoki et al. applied Bayesian Network to analyze how local thermal comfort would influence whole body thermal comfort level [40]. In the visual environment area, Lindelöf used the Bayesian approach to estimate the visual discomfort probability as a function of the illuminance under the office settings [41]. Sadeghi et al. applied Bayesian classification and inference models to develop probability distributions of occupants' preference about the visual environment (prefer darker, brighter, or no change) [42]. Additionally, Sadeghi et al. developed a hierarchical Bayesian approach to model occupants' behavior and interactions with shading and lighting system in private offices [43].

2.4.3 Method

The Bayesian approach considers model parameters as random variables from some priori probability distributions, and then updates the prior distributions with measured data using Bayes Theorem [44]. To be more specific, the parameters to be identified in this study is the intercept (β_0) and slope (β_1) of Equation 1. The identified intercept β_0 is the inferred neutral temperature, as it is the temperature corresponding to the neutral thermal sensation.

Considering that the regression error is always unavoidable, we added a prediction error of ε_i to the linear regression, as shown in Eq.1. This prediction error might result from the variability of clothing insulation, metabolic rate, inter-individual difference on thermal demands, etc.

If we assume the prediction error follows the Gaussian distribution with a variance of σ^2 as Eq.2, then the relation between temperature and thermal sensation could be rewritten as Eq. 3.

$\varepsilon \sim N(0, \sigma^2)$ Equation 2

$T \sim N(X\beta, \sigma^2 I)$ Equation 3 (*likelihood distribution*)

$$X = \begin{bmatrix} 1 & TS_1 \\ \vdots & \vdots \\ 1 & TS_n \end{bmatrix}$$ Equation 4

Where T is an n dimension vector, and n is the number of observations. X is an n*2 matrix with the elements in the first column all equaling to 1, and the element in the second column equaling to the measured Thermal Sensation in each observation, as shown in Eq.4. β is a two-dimensional vector with the first element equal to the intercept term β_0 and the second element equal to the slope term β_1 in Eq.1. Eq. 3 quantifies the relation between temperature and thermal sensation if the coefficient vector β is given, and is also called the *likelihood distribution*.

In Bayesian linear regression, we also need to know the prior distribution of β. Assuming β follows the Gaussian distribution as Eq. 5, we need to find the prior value for β_0, β_1 and their variances. Eq. 5 is also called the *prior distribution*. To estimate the prior value of β_0 and β_1, we used the Fanger's laboratory data for the development of the PMV-PPD model. The raw data was recorded in Table 14 of [14], and Langevin et al. have reorganized it in Table 1 of [39]. As for the prior variances λ of β, we could not find any sources to estimate it, and therefore assume them to be 1.

$$\beta \sim N(\beta_{prior}, \lambda_{prior} I)$$ Equation 5 (*priori distribution*)

Given the *likelihood distribution* and the *prior distribution*, we could generate the *posterior distribution*, as shown in Eq. 6. What we need to do now is to use the observed pairs of (T, TS) to update the *prior distribution* of β (both the value and the variance). On the right side of the equation, $P(\beta)$ is the *priori distribution (Eq.5)*, $P(T|\beta, TS)$ is the *likelihood distribution (Eq.3)*; on the left side of the equation, $P(\beta|T, TS)$ is the *posterior distribution* based on the new observations of *(T, TS)*.

$$P(\beta|T, TS) = \frac{P(T|\beta, TS) * P(\beta)}{\int P(T|\beta, TS) * P(\beta) * d\beta}$$ Equation 6 (*update for the posterior distribution*)

Given the above assumptions and the observed pairs of (T, TS), the analytical distribution of β could be calculated with Eq. 7.

$$P(\beta|T, TS) = N(\mu, \Sigma)$$
$$\mu = (\lambda\sigma^2 I + X^T X)^{-1} X^T T$$
$$\Sigma = (\lambda I + \sigma^{-2} X^T X)^{-1}$$
Equation 7

After inferring the distribution of β with the data in ASHRAE Database, the next step is to calculate the distribution of neutral temperature by setting $TS = 0$ with Eq.8, where $P(\beta)$ is the *posterior distribution* of β calculated from Eq. 7 based on new observations of *(T, TS)*.

$$P(T_{neutral}|TS = 0) = \int P(T_{neutral}|\beta, TS = 0) * P(\beta) * d\beta$$ Equation 8

In addition to the analytical solution, we could use the Markov Chain Monte Carlo (MCMC) method to approximate the distribution of neutral temperature. There is a *Python* package called *PyMC3 Bayesian inference library* implementing the MCMC in *Python*.

3 Results

3.1 Inferred comfort temperature

Though the operative temperature could more comprehensively characterize the thermal environment of an indoor space since it considers the effect of longwave radiation from interior surfaces on occupants, the air temperature is actually more widely used in practical building controls. Because of this, we developed two models, one for operative temperature, and the other for air temperature. The estimated β and σ for Eq. 3 are presented in Table 4. Compared with the linear regression, which only estimates the value of parameters, the Bayesian approach estimates the variance of parameters as well.

Table 4: Inferred parameters

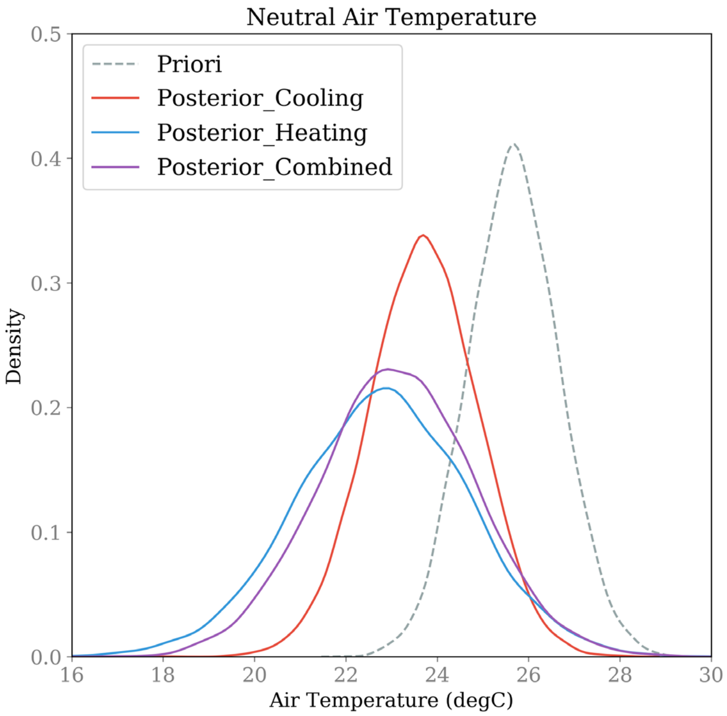
		β_0		β_1		σ	
		mean	sd	mean	sd	mean	sd
Operative temperature	Whole dataset	23.15	0.02	0.45	0.02	1.38	0.01
	Cooling only	23.61	0.04	0.25	0.03	1.09	0.02
	Heating only	22.69	0.04	0.30	0.04	1.36	0.03
Air temperature	Whole dataset	23.11	0.02	0.59	0.02	1.72	0.01
	Cooling only	23.72	0.03	0.27	0.03	1.19	0.02
	Heating only	22.81	0.05	0.29	0.05	1.87	0.04

With the estimated β and σ, we could infer the distributions of the neutral air and operative temperature in general, cooling, and heating conditions, which are presented in Figure 5. To facilitate the comparison, the priori distribution of neutral temperature deduced from Fanger's experiment [14] is presented as the dotted grey line in Figure 5. The inferred neutral temperature is 2.5°C lower than that calculated from Fanger's experiment [14], confirming the necessity of updating the model based on new observations.

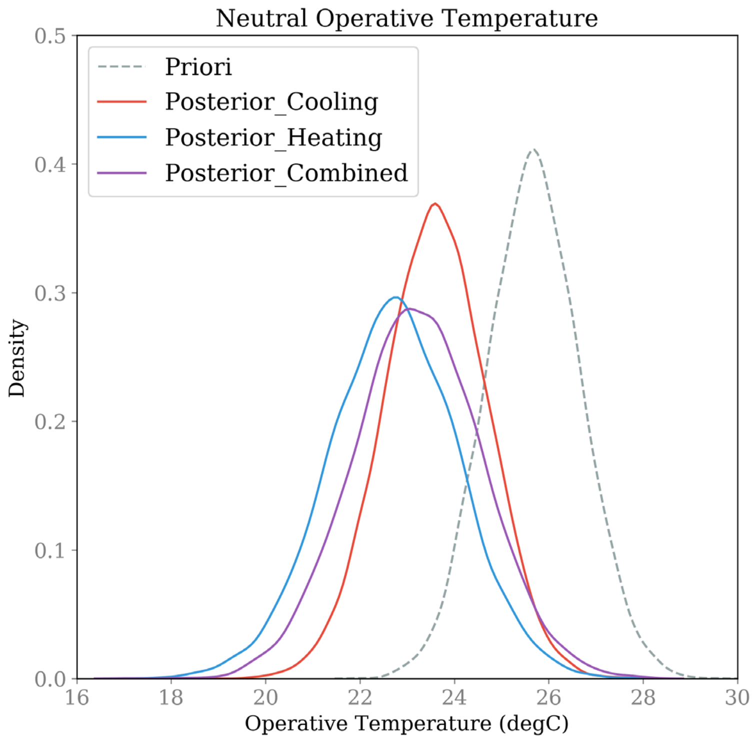
In addition to inferring the temperature set-point for the whole dataset (purple line), we differentiated cooling (red line) and heating (blue line) conditions to find the suitable set-point for each case. The reason to differentiate cooling and heating conditions is the preliminary linear regression found a significant difference between the *neutral temperature* of heating and cooling. This behavior is also predicted by the adaptive comfort theory [21]. However, we did not separate the dataset by other factors such as sex/gender, as preliminary linear regression and the existing studies [45] did not find a statistically significant difference in *neutral temperature* between males and females.

The neutral temperature in cooling conditions is on average 1°C higher and less variant than the neutral temperature in heating conditions. This is because, in cooling conditions, inhabitants tend to wear less and accordingly have less room to adjust their clothing. As for the comparison between air temperature and operative temperature, the mean value of the neutral air temperature (Figure 5a) and neutral operative temperature (Figure 5b) are close to each other; however the neutral operative temperature is less variant. This is because, to infer the neutral air temperature, the variable of radiation temperature is not included and need to be considered in the residual term and accordingly brings in extra uncertainties.

The third observation from figure 5 is that the variation of the posterior air and operative temperature is higher than that of the priori distribution. The reason is the posterior distribution is inferred from field measurements, while the priori distribution is deduced from Fanger's chamber experiment. The real building environment is more complex than the chamber environment in terms of occupants' clothing, activities, etc., and accordingly would result in more diversified neutral temperature.



(a) Inferred neutral air temperature



(b) Inferred neutral operative temperature

Figure 5: Priori (dotted gray line) and Posterior distribution under cooling (red), heating (blue) and cooling heating combined (purple) condition

Table 5 summarized the key statistics of the neutral air and operative temperature for the cooling, heating conditions, and the whole dataset. We chose the 5% and 95% of the estimate as the temperature set-point range, since if the indoor temperature is within the 5% and 95% range, there is no evidence to reject the null hypothesis that the inhabitants would feel thermally non-neutral given the 10% significance level. From the adaptive comfort perspective, the inhabitants exposed to this temperature range could adapt themselves to feel thermally neutral by adjusting their clothing, expectations, or taking other adaptive measures.

Table 5: Neutral temperatures (°C)

		mean	sd	5% estimate (Recommended lower boundary)	95% estimate (Recommended upper boundary)
Air temperature	Whole	23.11	1.72	20.37	25.95
	Cooling	23.72	1.19	21.83	25.61
	Heating	22.81	1.87	19.84	25.78
Operative temperature	Whole	23.15	1.38	20.96	25.34
	Cooling	23.62	1.09	21.89	25.35
	Heating	22.69	1.36	20.53	24.85

3.2 Comparison with the current ASHRAE Standard

Figure 6 and Table 6 compared the temperature set-point range derived by this study and the ranges recommended by ASHRAE Standard 55-2017 [15]. The data in the ASHRAE Database would recommend a lower cooling temperature set-point and a similar heating temperature set-point compared with the ASHRAE Standard 55-2017.

As discussed in the Introduction Section, to get an explicit temperature set-point, some assumptions need to be made on parameters such as the clothing insulation, Relative Humidity (RH) and the air velocity. However, there is no guarantee that every person would dress with exact 0.5 clo in a cooling environment and 1.0 clo in a heating environment as assumed in the ASHRAE Standard 55. Meanwhile, the Relative Humidity and air velocity are rarely controlled in practice. Therefore, in the Bayesian-based data-driven approach used in this paper, we do not need to make any assumptions about those parameters. The variability of those unsure parameters, such as clothing level, were considered in the variance of the estimated parameters, which makes sense in real life since the clothing level is a random variable for different subjects in the same ambient environment due to the individual difference [46].

Another way to interpret the comfort/neutral temperature range is that inhabitants exposed to the cooling temperature range of 21.9 to 25.4°C or the heating temperature range of 20.5 to 24.9°C could adapt themselves to be thermally neutral by taking 'reasonable' measures such as adjusting their clothing or using personal fans if available to increase local air velocity. Those adaptive measures are believed to be 'reasonable' because they were 'observed to be taken' by subjects in the ASHRAE Database to achieve thermal neutrality.

Table 6: Comparison with ASHRAE Standard 55-2017 (Operative temperature °C)

	Standard	Approach	Conditions	Lower limit	Upper limit
Cooling	ASHRAE 55-2017	PMV-PPD	0.5 clo, 50% RH, 0.1 m/s air velocity	23.9	26.8
		Adaptive Comfort	30°C outdoor temp, 90% acceptability	25.1	29.5
			30°C outdoor temp, 80% acceptability	23.3	30.6
	This study	Bayesian	None	21.9	25.4
Heating	ASHRAE 55-2017	PMV-PPD	1.0 clo, 40% RH, 0.1 m/s air speed	20.5	24.2
		Adaptive Comfort	10°C outdoor temp, 90% acceptability	18.6	23.3
			10°C outdoor temp, 80% acceptability	17.4	24.5
	This study	Bayesian	none	20.5	24.9

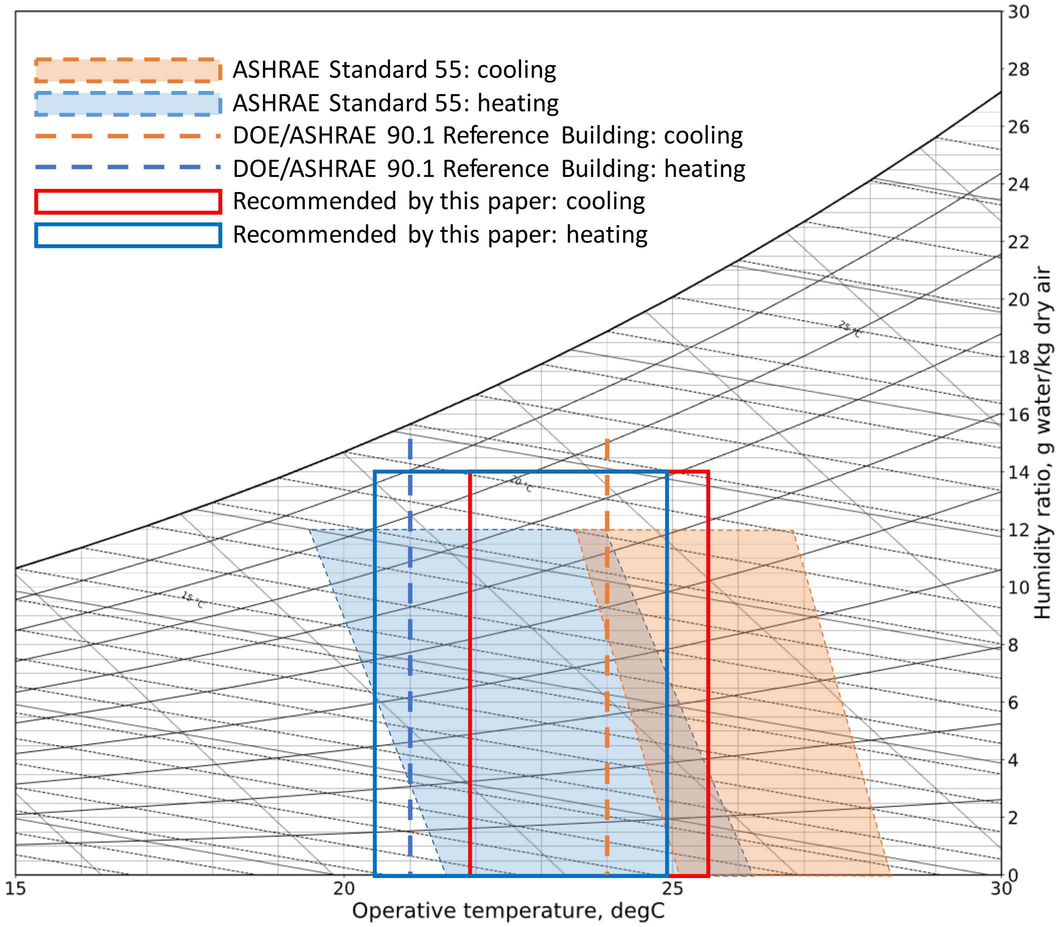


Figure 6: Inferred neutral operative temperatures: the ASHRAE Standard 55 considers the influence of humidity, while the DOE/ASHRAE 90.1 Reference building models and the set-point recommended in this paper do not considered the humidity

The data in the ASHRAE Database recommend a similar heating comfort temperature but a lower cooling comfort temperature compared with the ASHRAE Standard 55-2017. A lower cooling temperature means more energy usage and greenhouse emissions [47], [48]. Results from the data-driven approach reflect the reality but might not be the ideal scenario. The dress code in office settings that expects business suit fails to adapt to the varying outdoor temperature might be the root cause of the preferred lower comfort temperature and thus higher energy consumption in summer. To reduce electricity consumption, the Japanese government promotes a 'Super Cool Biz' campaign to encourage office workers to shed their suits, aiming to increase the temperature set-point in government offices to 27.5°C and reduce 15% of cooling energy consumption [49].

However, the comfort temperature range recommended by DOE/ASHRAE 90.1 Reference Building models and this paper only considers the influence of temperature, ignoring humidity. This simplification is made based on the assumption that office environments are usually not controlled to achieve a specific humidity set-point as long as the relative humidity ranges from 30% to 70%. It is acknowledged that although humidity has some effect on occupants' comfort, this effect would be insignificant if the humidity is within a reasonable, non-extreme range [50]. Furthermore, the effects of humidity on comfort are considered differently in the two mainstream thermal comfort frameworks: the PMV-PPD approach considers the humidity [14] while the Adaptive Comfort approach ignores it [21].

4 Discussion

This paper discussed the selection of temperature set-point for HVAC systems by applying Bayesian Inference on the recently released ASHRAE thermal comfort database. The proper selection of temperature set-point influences not only occupants' satisfaction [51], productivity [52], and health [53], but also the building energy consumption. Hoyt et al.'s simulation study found a widened temperature band can result in HVAC energy savings up to 70%, depending on the climate [54]. For instance, in temperate climates such as San Francisco, increasing the cooling set-point from 22 to 25°C could save 29% cooling energy, while reducing the heating set-point from 21 to 20°C could save 34% heating energy [54]. Steemers and Yun's regression study on the Residential Energy Consumption Survey (RECS) data found similar results in residential settings that heating energy would increase with higher heating temperature set-point [55]. Therefore, a careful and rational selection of HVAC set-point temperature is crucial to energy conservation, carbon emission reduction, and sustainable development.

4.1 Contribution

4.1.1 Smart thermal comfort management by active learning

Both the PMV-PPD and the Adaptive Comfort approaches aim to propose a universal thermal comfort model, to meet the thermal comfort demand for everyone. However, the research community gradually realized the existence and importance of inter-individual variability in terms of thermal comfort [46]. Different groups of people might desire different temperature set-points in their buildings. Recognizing the personalized thermal comfort behaviors and demands, the concept of occupant responsive building control and smart buildings has been proposed, which use occupants' feedback to manage a building's thermal environment [56]. For instance, Chen et al. collected occupants' thermal sensation to dynamically adjust the temperature set-point by applying the Extended Kalman Filter techniques [57], [58].

Another key concern in thermal comfort studies is about whether a relation (e.g., between temperature and thermal sensation) derived from a specific group of people could be generalized and applied to another. Someone would argue that the PMV-PPD model was developed from college-aged Danish subjects, which might not be suitable for people living in the U.S. or Asia; while the adaptive comfort theory was developed for naturally ventilated buildings, which might be unsuitable for air-conditioned buildings. Additionally, studies have shown that occupants' thermal demands might evolve over time [59]. Therefore, a self-adaptive approach that could learn from new data is needed to determine the comfort temperature.

The Bayesian approach provides us with a handy tool to deal with those concerns. The relations found in another group or a more general group of people, such as in this study derived from the ASHRAE Database, could serve as the prior distribution for a specific group of people in the target building. If no more data is observed, we have no reason or evidence to reject prior knowledge. However, once we have collected more data, as in the occupant responsive building controls, we could use new observations to update the prior distribution. If we keep collecting data and updating the model, the updated posterior distribution could always reflect the latest changes in occupant behaviors and thermal demands, which might vary as new users move in or with the shift of seasons. In other words, once new data are observed and used to train the model, the thermal comfort model would evolve through the Bayesian approach to update the recommended comfort temperature that is more capable of reflecting the thermal demands of current users. This evolving and updating behavior is also called active learning.

Therefore, for the implementation of occupant responsive building control, this study would be helpful in the following two ways:

- First, to provide a prior knowledge about the value and variation of the comfort temperature, which was derived from the largest thermal comfort database up-to-date, and could serve as a prior distribution for U.S. office buildings.
- Second, to demonstrate the use of the Bayesian approach to update the prior distribution of comfort temperatures with new observations collected from new studies or occupants in real buildings.

4.1.2 Inferring temperature set-point through a data-driven approach

In this study, we summarized the approach to infer the temperature set-point through two mainstream theories: the PMV-PPD model, and the adaptive comfort model. Then we proposed a data-driven approach to infer the suitable temperature set-point from the recently released ASHRAE Thermal Comfort Database, the largest database in thermal comfort field so far; and then compared the temperature set-point inferred from the ASHRAE database to those recommended by the existing standards based on the classical thermal comfort theory.

The data-driven approach provides a way to infer the temperature set-point that is closer to the status quo. The realistic temperature set-point could: first, facilitate more accurate building performance simulation, load prediction; and second, better inform the HVAC design, cooling technology selection, and policymaking.

Comparing with existing models, the data-driven Bayesian approach avoids the input of hard-to-measure parameters needed by the PMV-PPD model. Those hard-to-measure factors such as metabolic rate, clothing were considered by the variance of neutral temperature and inferred from the measured data, solving the over-simplification concern of the adaptive comfort model.

4.2 Limitations

A major limitation of this study is we only applied the Bayesian Inference method to study the comfort temperature of U.S. office buildings. Therefore, the results might not apply to other building types or other countries. As the existing studies have confirmed that the thermal demands vary by building types [60] and countries [61], due to different occupants behaviors and motivations. For instance, in residential buildings, occupants have greater control over the thermal environment than in office buildings, as they do not need to share thermostat or other controls with their coworkers [62]. The higher perceived control has a psychological effect [63] that might lead to a wider acceptable temperature range [32]. Additionally, occupants need to pay the utility bills for heating and cooling in residential but not in offices, which constitutes an economic motivation to accept a wider temperature range in residential buildings. Although the comfort temperature range calculated for the U.S. office buildings might be unsuitable for other building types in other countries, the Bayesian Inference method used in this study could apply to the data collected from those building types or countries.

Another limitation lies in the fact that Bayesian Inference method is more computational demanding than the existing approaches such as the adaptive comfort approach, which uses a linear function of outdoor temperature to infer the indoor comfort temperature. This is a trade-off between computational cost and inference accuracy, which widely exists in almost every field of data-driven approach. It is not necessary to update the comfort temperature on a real-time basis for each new observation. Instead, the inferred comfort temperature can be updated on a daily or even weekly basis for a group of new observations.

In this study, the recently released ASHRAE thermal comfort database is used. No further data quality control was done beyond ASHRAE's data requirements. The data and results are solid for two reasons. First, as a research funded by ASHRAE, the data collection process of the ASHRAE thermal comfort database is well documented and reliable. For instance, only data from peer-reviewed journals or conference articles were included in the database [26]. In this regard, the data in the ASHRAE database might have unavoidable uncertainties, but would be free from systematic biases. Secondly, the random measurement uncertainties could be mitigated with the increasing sample size. As the largest database in the field of thermal comfort, the ASHRAE database provides us a unique opportunity for applying Bayesian approach to infer the temperature set-point in real buildings through a data-driven approach.

5 Conclusions

This study applies the Bayesian Linear Regression on the data recorded in the ASHRAE Global Thermal Comfort Database to learn the indoor comfort temperature set-points for U.S. office buildings, which are between 21.9 and 25.4°C for cooling conditions and between 20.5 and 24.9°C for heating conditions. Compared with the simple linear regression, the Bayesian Inference is a useful way to quantify the uncertainty and variability of the estimated parameters, which is important in the context of inferring temperature set-point since the variability of estimated parameters reflects the occupants' thermal adaptive behaviors and inter-individual variabilities in thermal demands.

This study is helpful for the implementation of occupant responsive building control in two ways. First, we quantified the linear relation between temperature and thermal sensation by providing not only the mean value but also the estimated variance. Because the ASHRAE Database is general and contains the largest sample size up-to-date, the estimated values recorded in Table 4 of this paper could serve as a prior distribution for other target buildings. Second, we introduced the Bayesian Inference technique, which is a useful and powerful tool for active learning, enabling the update of the thermal comfort model with new observations, which could reflect the latest adaptive behaviors and thermal demands of current users.

Future studies can apply the Bayesian Inference to the ASHRAE Database for other regions/countries or other building types to explore differences in indoor comfort temperature set-points from the U.S. office buildings and to understand the influential factors that drive such differences.

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