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Data-Driven Modeling of Indoor Thermal Comfort for Smart Cooling Systems[#]

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ABSTRACT

This paper presents a systematic study of data-driven modeling of indoor thermal comfort for smart cooling systems, establishing an analytical framework encompassing three main aspects: data collection, modeling analysis, and control execution. The findings indicate that existing studies in data collection exhibit the characteristics of integrating multi-source data, combining objective and subjective data, and employing multi-technology collaborative collection. During the modeling and analysis phase, machine learning algorithms play a dominant role in indoor thermal comfort modeling, achieving higher predictive accuracy than the traditional Predicted Mean Vote model. These models can be divided into two categories: group and personal models, with the latter showing greater potential for personalized predictions. In terms of control execution, the primary strategies can be categorized into two types: model-based optimization control and adaptive control that integrates user feedback. Their effectiveness in improving comfort, reducing energy consumption, and dynamically responding to personalized needs and environmental changes has been preliminarily validated. Furthermore, this paper outlines critical challenges at different stages and systemic levels in this field and proposes directions for future research.

Keywords: thermal comfort, smart cooling system, energy consumption, data collection, machine learning, control execution

NONMENCLATURE

Abbreviations	
ANN	Artifact Neural Network
BP	Back-propagation Neural Network
BGRU	Bidirectional Gate Recurrent Unit
CC	Correlation Coefficient
CNN	Convolutional Neural Network
DT	Decision Tree
DNN	Deep Neural Network
EC	Energy Consumption
EL	Ensemble Learning
ELM	Extreme Learning Machine
ETC	Extra Tree Classifier
FNN	Feedforward Neural Network
GB	Gradient Boosting
GM	Group Model
HVAC	Heating, Ventilation, Air Conditioning
IoT	Internet of Things
IBWO	Improved Beluga Whale Optimization
KNN	K-Nearest Neighbors
L	Linear Regression
LR	Logistic Regression
LDA	Linear Discriminant Analysis
LSTM	Long Short-Term Memory
ML	Machine Learning
MBE	Mean Bias Error
MSE	Mean Squared Error
MAPE	Mean Absolute Percentage Error
NA	Not Available
NB	Naive Bayes
OOB	Out-of-Bag Score
PM	Personal Model
PMV	Predicted Mean Vote
R	Regression Value
R^2	Coefficient of Determination
RF	Random Forest
RL	Reinforcement Learning
RR	Ridge Regression
ROC	Receiver Operator Characteristic
RMSE	Root Mean Squared Error
ST	Skin Temperature
SCN	Stochastic Configuration Network

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SVM	Support Vector Machine
SVR	Support Vector Regression
TCV	Thermal Comfort Vote
TPV	Thermal Preference Vote
TSV	Thermal Sensation Vote
VAF	Variance Accounted For
WLS	Weighted Least Squares
Symbols	
s	Plural

1. INTRODUCTION

Building energy consumption constitutes a significant share of national energy use, with Heating, Ventilation, and Air Conditioning (HVAC) systems accounting for approximately 40%–50% of total building energy use [1]. Especially in regions with hot climates or high cooling demands, the cooling system becomes the crucial energy consumer during summer and transitional seasons. At the same time, people today spend nearly 90% of their time indoors, making indoor thermal comfort an important factor influencing human health and daily life [2]. However, traditional thermal comfort models, such as the Predicted Mean Vote (PMV), often fail to accurately represent actual human thermal perception, partly because they overlook individual differences. In recent years, thermal comfort modeling has entered a data-driven phase [3]. The introduction of artificial intelligence, big data, and other advanced techniques has markedly improved the predictive accuracy of models, providing critical technical support for smart cooling systems to better satisfy occupants' thermal comfort requirements while reducing cooling energy consumption.

A review of existing literature reveals that most prior surveys have focused on only one aspect of the field. For instance, Čulić et al. analyzed data types and collection methods for modeling personal thermal comfort [4]. Qavidel Fard et al. focused on machine learning (ML) [5]. Han et al. surveyed reinforcement learning (RL)-based comfort control systems for indoor environments [6]. However, a systematic review that integrates the three dimensions, i.e. data, models, and control, is still lacking. This review systematically examines recent advances in data-driven modeling of indoor thermal comfort for smart cooling systems. The analysis is structured around three core aspects: data collection, modeling analysis, and control execution. It summarizes data sources, types, and collection methods; compares sample size, algorithm selection, performance metrics, outputs, model types, and performance across different studies; and synthesizes system control strategies. Finally, the paper identifies current research challenges, summarizes major findings, and offers insights for developing more accurate, personalized, and energy-efficient smart cooling systems.

2. METHODOLOGY

2.1 Review method

A systematic literature search was conducted across two databases: ScienceDirect and IEEE Xplore. Keywords included "indoor thermal comfort", "indoor thermal comfort model", "smart cooling" and "intelligent HVAC". The search scope was limited to papers published from 2015 to 2025. Initially, thousands of articles were retrieved. Subsequently, the retrieved papers were screened to include studies focusing on indoor thermal comfort, indoor thermal comfort models, and smart cooling systems, while excluding those related to outdoor environments, naturally ventilated buildings, heating, localized cooling, and materials to maintain focus on indoor cooling environments and thermal comfort in air-conditioned buildings. Additionally, non-English publications and purely theoretical models were excluded unless they offered unique research perspectives. Ultimately, 42 papers were selected for future review.

2.2 Analytical framework

To systematically review recent advances in data-driven modeling of indoor thermal comfort for smart cooling systems, this paper constructs an analytical framework around three core aspects: data collection, modeling analysis, and control execution, as illustrated in Fig. 1. The system first uses multi-technology methods that integrate multi-dimensional data from multiple sources. It then develops thermal comfort models using data-driven approaches, transforming multi-dimensional information into actionable comfort metrics. Finally, it regulates the operation of the cooling system through control strategies. The subsequent sections will elaborate on this framework in detail.

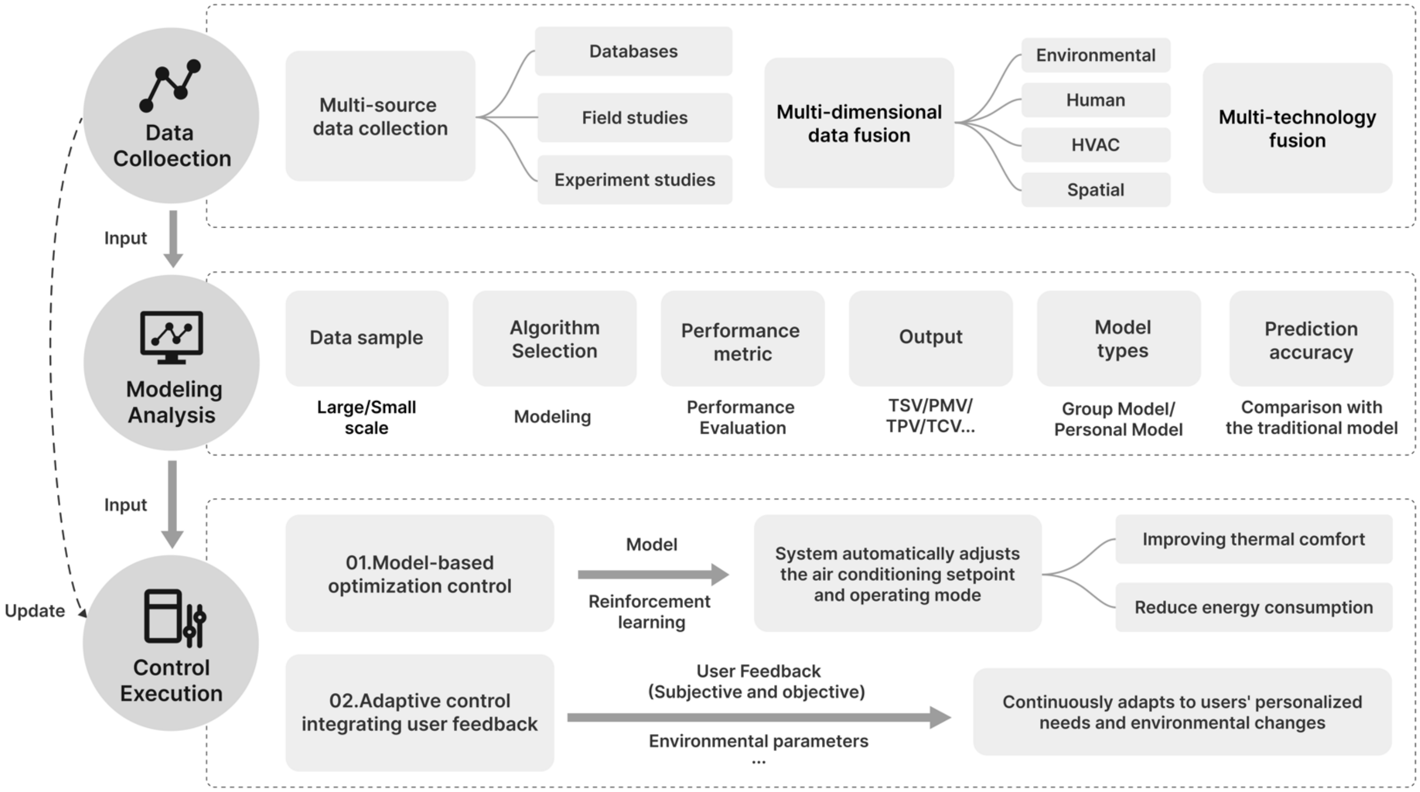

Fig. 1 Analytical framework diagram

3. DATA COLLECTION

This section outlines the data collection phase of the reviewed papers, including data sources, types, and collection methods.

3.1 Data sources

Among the reviewed literature, 12 studies used existing databases. Ten of these sourced their data from two major public databases: the ASHRAE RP-884 [7], [8], [9] and the ASHRAE Global Thermal Comfort Database II [10]. The use of these databases is due to their large scale and diverse data types and to their field research origins, which better represent thermal comfort conditions in real-world environments. The remaining two studies, [11] and [12], used datasets that were specifically collected for their respective research projects.

In addition, 30 studies in this review collected data through field measurements [13], [14], [15] or controlled-chamber experiments in which parameters could be artificially regulated [11], [16], [17].

3.2 Data types

The data collected in this study can be categorized into four main types: environmental, human, HVAC-related, and spatial. Among these, environmental and human data were the most common. Environmental data typically includes the environmental parameters from the PMV model, such as air temperature, relative humidity, air velocity, and mean radiant temperature. Some studies additionally considered outdoor environmental parameters [7], [10]. Human data mainly includes physiological parameters, personal information, and subjective feedback, while behavioral data were collected in only three studies [13], [16], [18]. Most of the reviewed studies demonstrated multi-dimensional data fusion, with only one paper [19] focusing solely on human data.

Research involving spatial and HVAC operational parameters remains limited. Only one study [14] investigated spatial characteristics, and one paper [8] recorded air-conditioning operating modes.

3.3 Data collection methods

Existing research often employs a multi-technology fusion technique to collect multi-dimensional data, using devices like environmental sensors [11], [13], [17], weather stations [11], [13], [16], infrared devices [11], [15], [20], [21], [22], wearable devices [11], [13], [17], and cameras [16], [23], [24]. With the rapid development of the Internet of Things (IoT), these devices can be further integrated as sensing nodes into an IoT architecture. This fusion enables device interconnection and data interoperability, allowing systems to support more diverse, real-time, and multi-source data.

4. MODELING ANALYSIS

Among the reviewed papers, only one study [20] used solely traditional mathematical methods for modeling. The remaining 41 studies all used ML methods for modeling. This section will analyze six main aspects: data profile, algorithm selection, performance metrics, outputs, model types and comparison with the traditional models. Detailed data are shown in Table 1.

Table 1. Comparison of ML models in the reviewed papers

Paper	Sample size	Algorithm(s)	Performance metric(s)	Outputs(s)	Model type(s)
[7]	NA	ELM, SCN, RF, SVR	RMSE	PMV	GM
[8]	9470	SVM, ANN	RMSE, MAE, CC	7-point TSV	GM
[9]	5576	KNN, SVM, ANN	Recall, Confusion Matrix	TSV	GM
[10]	17814	RF, KNN	Accuracy, Specificity, ROC Precision, Recall, F1-score, Confusion matrix	3 and 7-point TSV, TPV	GM
[11]	NA	LSTM	RMSE	TSV, TPV, TCV	PM
[12]	NA	RF, SVM, KNN, AdaBoost	MSE, ROC, F1-score	3-point TPV, 2-point TPV	PM
[13]	368	RF	MSE, RMSE, MAE, R^2, Accuracy, Recall, Precision, F1-score	7-point TSV, TSV	GM
[14]	756	DT, SVM, ANN, RF, NB, KNN	Accuracy, MAE, RMSE	TSV, TPV, TCV	GM
[15]	470	WLS, ANN	Accuracy, the Cohen's Kappa Coefficient, ROC	3-point TPV	PM
[16]	10838	BGRU	Accuracy	3-point TPV	PM
[17]	3600	RF, BP, CNN	Precision, Recall, F1-score	7-point TSV	GM
[18]	NA	NB, DT, SVM, ANN	Accuracy	temperature	PM
[19]	NA	KNN, RF, LR, NB	Accuracy, ROC, Precision, Recall	TSV	PM
[21]	5357	RF-IBWO-BP-LSTM	RMSE, MAE, MBE, R^2, Recall Accuracy, F1-score	ST, TSV	PM
[22]	210	ANN, NB, KNN, SVM, LR, DT, RF	Accuracy, MAE	7-point TSV	PM
[23]	7400	KNN	Accuracy	3-point TSV	PM
[24]	1944	GB	Accuracy, Recall, Precision, F1-score	7-point TSV, 7-point EC	GM
[25]	36	KNN	Accuracy	5-point TSV	GM
[26]	540	DT, SVM, KNN, RF, NN	Accuracy, F1-score, ROC	7-point TSV	PM
[27]	2371	ANN	Precision, Recall, F1-score	5-point TCV	PM
[28]	700	RF	Accuracy, Sensitivity, Precision	2-point TCV	GM
[29]	4 subjects	L, SVM, ANN	MAE, Accuracy	TSV	PM
[30]	700	SVM, ELM	Accuracy, MSE, Recall, Precision	2-point TCV	GM
[31]	NA	SVM, RF, EL, KNN, ANN	Accuracy, Recall, F1-score, ROC, Precision, Confusion Matrix	3-point TSV	GM
[32]	over 500	ANN	R^2	TSV	GM
[33]	1199	SVM	Accuracy	TSV	PM
[34]	11164	Deep FNN	MSE	PMV	GM
[35]	20000	RF	Accuracy	metabolic rate	GM
[36]	NA	LSTM	MAE, MSE	PMV	GM

[37]	24312	ANN, SVR, RF, RF & SVR	MAE, RMSE, R^2, F-test	7-point TSV	GM
[38]	NA	SVM, RF, KNN, ANN	Accuracy, F1-score	3-point TCV	PM
[39]	3004	ANN	R, RMSE, VAF, Accuracy	PMV, 7-point TSV	GM
[40]	NA	SVM	/	thermal comfort zone	GM
[41]	NA	SVM, ANN, LR, LDA, KNN, DT	Accuracy	3-point TCV	GM
[42]	1955	SVM	Accuracy	7-point TSV	PM
[43]	2371	KNN, DT, ANN, SVM, NB	Precision, Recall, F1-score	5-point TCV	PM
[44]	3888	SVM, RF, AdaBoost	Accuracy	3-point TSV	PM
[45]	1429	LR, DT, SVM, KNN, RF, GB	Precision, Recall, F1-score	3-point TSV	GM
[46]	NA	CNN	Accuracy	7-point TSV, 7-point TCV	GM, PM
[47]	NA	SVM, RF, ETC, ANN, CNN, LSTM	Accuracy, MAE, MAPE	2-point TCV, TSV	GM
[48]	573	RF	Accuracy, OOB, Diversity, Calculating Time	7-point TSV	GM

4.1 Data sample

As shown in Table 1, the sample sizes of these 41 studies ranged from 36 [25] to 24312 [37]. Large-sample modeling is known to improve a model's generalization performance. However, it entails high data cleaning costs and substantial computational requirements. In contrast, small-sample modeling has shorter training cycles, which facilitates diverse debugging strategies, yet it often results in suboptimal model performance.

4.2 Algorithm selection

Among the 41 studies reviewed, the most frequently used ML algorithms are Support Vector Machines (SVM), Random Forests (RF), Artificial Neural Networks (ANN), K-Nearest Neighbors (KNN), and Decision Trees (DT). Among these, SVM, RF, and ANN are the most commonly applied, which aligns with the findings reported by Qavidel Fard et al. [5].

In addition to using a single algorithm or multiple algorithms for independent modeling, some studies have adopted hybrid modeling strategies. For example, Yang et al. combined mathematical and ML models to improve stability on small, unbalanced datasets by leveraging their strengths [26]. Similarly, Liu et al. showed that hybrid models constructed by integrating multiple algorithms achieve higher prediction accuracy than single models [21].

4.3 Performance metrics

Through statistical analysis of the reviewed papers, this study identifies several commonly used evaluation metrics, primarily including accuracy, root mean square error (RMSE), precision, recall, F1-score, and mean squared error (MSE). Among these metrics, accuracy was the most widely adopted, with 65.85% of the studies using it as the primary indicator for evaluating overall model performance.

4.4 Outputs

Thermal comfort models typically output either continuous thermal response values or categorical labels. As summarized in the literature reviewed, the primary outputs include the Thermal Sensation Vote (TSV), Predicted Mean Vote (PMV), Thermal Preference Vote (TPV), and Thermal Comfort Vote (TCV).

TSV characterizes the thermal sensation of subjects. For quantitative analysis, most studies used a discrete scale as their output. The 7-point TSV, ranging from -3 (Cold) to 3 (Hot), was the most common, appearing in 12 of the reviewed papers. TPV reflects subjects' preferences for thermal environments, while TCV is used to evaluate thermal comfort states. Additionally, some studies continued to use PMV as an output, maintaining the application of classical thermal comfort theory.

4.5 Model types

Approximately 58.54% of the studies focused on developing group models (GMs), suitable for predicting thermal comfort in uniform environments. Other studies focused almost entirely on developing personal models (PMs), which emphasize individual differences and more accurately reflect personal thermal perception.

Only one study [46] developed both model types concurrently. Its validation results indicated that the group-oriented model had lower predictive accuracy for thermal sensation and comfort. The PM, in contrast, which was developed using multiple experimental data points from a single subject, demonstrated exceptional performance. This finding highlights the significant individual variability in thermal sensation and comfort.

4.6 Comparison with the traditional model

Among the reviewed papers, ML-based models showed significantly higher predictive accuracy than the PMV model, achieving an overall accuracy of only 34% [49]. For example, Haghirad et al. achieved accuracies of 72.40% for thermal preference and 60.40% for the 7-point TSV using a RF model [10]. Similarly, Upasani et al. achieved accuracy rates of 72.00% for regression and 89.00% for classification models by integrating multi-source data from both environmental and physiological sources [13].

5. CONTROL EXECUTION

This section reviews the control executive phase of the system. Among the literature reviewed, nine studies built upon thermal comfort models to further investigate control executive strategies, aiming to validate the system's practical effectiveness. These studies can be broadly categorized into two types: model-based optimization control and adaptive control integrating user feedback.

5.1 Model-based optimization control

A total of five of the reviewed studies [9], [11], [24], [29], [34] used model-based optimization for system execution. The core idea is to use thermal comfort models as the primary basis for decision-making, enabling active adjustment of air conditioning setpoints and operating modes to achieve specified comfort or energy consumption goals. RL, which learns optimal decisions through trial and error in dynamic environments, is now widely applied to complex control tasks [50]. For instance, Lu et al. integrated a thermal comfort model with a Q-learning-based RL temperature controller to achieve the autonomous optimization of the temperature setpoint [9]. This approach enabled the system to automatically adjust from any initial temperature state to a defined comfortable temperature range.

5.2 Adaptive control integrating user feedback

Four studies [18], [23], [32], [33] implemented adaptive control strategies that incorporate user feedback. These systems collect user status information across multiple channels and use it as input for control decisions, establishing a closed-loop mechanism that includes perception, decision-making, execution, and updating [51]. Beyond collecting subjective feedback from users through human-machine interfaces and mobile applications, these systems can also continuously monitor physiological parameters using wearable devices. By integrating this data with environmental readings, the systems continually train and update thermal comfort models, enabling dynamic adaptation to individual user preferences and changing conditions. For example, Lai and Yao developed a smart management system that enables users to enter activity levels and other parameters through a human-machine interface [33]. This system updated its model with real-time sensor data and employed optimization algorithms to dynamically adjust air conditioning operations to meet user requirements. Finally, operational information was feeding back to the user through the interface, completing the closed loop.

6. DISCUSSION

6.1 Current challenges

Each of the three aspects faces distinct challenges. During data collection, issues include privacy concerns and disruption to subjects' normal activities. Moreover, parameters such as clothing insulation and metabolic rate are often oversimplified as fixed values or neglected, undermining model accuracy [45], [48]. In the modeling phase, limitations in data scale, collection duration, and diversity make it difficult to fully validate the models' long-term stability and effectiveness across different populations, climates, and building types. Furthermore, GMs often compromise individual thermal comfort due to averaging effects [32]. Additionally, research on control execution is limited, with most studies remaining theoretical, which slows the transition to practical application.

At the system level, time delays occur throughout the entire closed-loop process, from data collection and model computation to the final control execution, which can adversely affect real-time control performance. Additionally, it is particularly difficult to effectively balance the accuracy of model predictions while simultaneously ensuring the robustness of the control strategies applied.

6.2 Prospects for future work

Future research should focus on four levels: at the data collection level, it is necessary to develop more precise and low-interference dynamic parameter collection techniques to enhance data quality and model accuracy. In modeling, localized studies across different climates, building types, populations, and HVAC systems are needed to address the limitations of this paper regarding heating, building classifications, and demographic segmentation. In terms of regarding control level, more practical research on the execution of system control in real-world indoor environments is needed to ensure a balance among comfort, energy efficiency, and user experience. Finally, at the system level, closed-loop control performance must be optimized by balancing model accuracy and control robustness.

7. CONCLUSIONS

This paper provides a systematic review of the literature on data-driven modeling of indoor thermal comfort for smart cooling systems. The main conclusions are as follows:

Data collection features multi-source collection and integration, combining both objective and subjective data, and employing multi-technology collaborative collection.

Among the reviewed papers, ML is the primary modeling method, with SVM, RF, and ANN being the most commonly used algorithms. Accuracy is the most widely applied performance metric. Although numerous GMs have been developed, research on personalized modeling should be strengthened, given the high individual variability in thermal sensation. Moreover, ML models demonstrate higher predictive accuracy than the PMV model.

Finally, current research on the control execution of smart cooling systems can be broadly categorized into two main types: model-based optimization control and adaptive control that integrates user feedback. The potential to improve thermal comfort and reduce system energy consumption has been preliminarily validated.

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REFERENCE

[1] Y. Yang, G. Hu, C. J. Spanos. Stochastic Optimal Control of HVAC System for Energy-Efficient Buildings. IEEE Trans Control Syst Technol. 2022;30(1):376–83.

[2] Klepeis NE, Nelson WC, Ott WR, Robinson JP, Tsang AM, Switzer P, et al. The National Human Activity Pattern Survey (NHAPS): a resource for assessing exposure to environmental pollutants. J Expo Sci Environ Epidemiol. 2001;11(3):231–52.

[3] Zhao Q, Lian Z, Lai D. Thermal comfort models and their developments: A review. Energy Built Environ. 2021;2(1):21–33.

[4] Čulić A, Nižetić S, Šolić P, Perković T, Čongradac V. Smart monitoring technologies for personal thermal comfort: A review. J Clean Prod. 2021;312:127685.

[5] Qavidel Fard Z, Zomorodian ZS, Korsavi SS. Application of machine learning in thermal comfort studies: A review of methods, performance and challenges. Energy Build. 2022;256:111771.

[6] Han M, May R, Zhang X, Wang X, Pan S, Yan D, et al. A review of reinforcement learning methodologies for controlling occupant comfort in buildings. Sustain Cities Soc. 2019;51:101748.

[7] Feng X, Zainudin EB, Wong HW, Tseng KJ. A hybrid ensemble learning approach for indoor thermal comfort predictions utilizing the ASHRAE RP-884 database. Energy Build. 2023;290:113083.

[8] Zhou X, Xu L, Zhang J, Niu B, Luo M, Zhou G, et al. Data-driven thermal comfort model via support vector machine algorithms: Insights from ASHRAE RP-884 database. Energy Build. 2020;211:109795.

[9] Lu S, Wang W, Lin C, Hameen EC. Data-driven simulation of a thermal comfort-based temperature set-point control with ASHRAE RP884. Build Environ. 2019;156:137–46.

[10] Haghirad M, Heidari S, Hosseini H. Advancing personal thermal comfort prediction: A data-driven framework integrating environmental and occupant dynamics using machine learning. Build Environ. 2024;262:111799.

[11] Abdulraheem A, Lee S, Jung IY. Dynamic personalized thermal comfort Model:Integrating temporal dynamics and environmental variability with individual preferences. J Build Eng. 2025;102:111938.

[12] Fattahi M, Sharbatdar M. Machine-learning-based personal thermal comfort modeling for heat recovery using environmental parameters. Sustain Energy Technol Assess. 2023;57:103294.

[13] Upasani N, Guerra-Santin O, Mohammadi M. Developing building-specific, occupant-centric thermal

comfort models: A methodological approach. J Build Eng. 2024;95:110281.

[14] Alam N, Zaki SA, Ahmad SA, Singh MK, Azizan A, Othman N. Machine learning approach for predicting personal thermal comfort in air conditioning offices in Malaysia. Build Environ. 2024;266:112083.

[15] Arakawa Martins L, Soebarto V, Williamson T. Performance evaluation of personal thermal comfort models for older people based on skin temperature, health perception, behavioural and environmental variables. J Build Eng. 2022;51:104357.

[16] Xu M, Han Y, Liu Q, Zhao L. Action-based personalized dynamic thermal demand prediction with video cameras. Build Environ. 2022;223:109457.

[17] Ren J, Zhang R, Cao X, Kong X. Experimental study on the physiological parameters of occupants under different temperatures and prediction of their thermal comfort using machine learning algorithms. J Build Eng. 2024;84:108676.

[18] Peng Y, Nagy Z, Schlüter A. Temperature-preference learning with neural networks for occupant-centric building indoor climate controls. Build Environ. 2019;154:296–308.

[19] G. Cosoli, S. A. Mansi, M. Arnesano. Combined use of wearable devices and Machine Learning for the measurement of thermal sensation in indoor environments. In: 2022 IEEE International Workshop on Metrology for Living Environment (MetroLivEn). 2022. p. 1–6.

[20] Wu T, Li W, Jiang C, Sun X, Zhang J. Prediction and real-time correction method of human thermal sensation based on comprehensive characterization of multi-source data. J Build Eng. 2025;112:113760.

[21] Liu G, Luo X, Yu J, Sun Y, Zhang B. Prediction model for personalized thermal comfort of indoor office workers based on non-skin contact wearable device. Build Environ. 2025;272:112686.

[22] L. Yu, S. Chen, S. Qin, Y. Liu. Deep meta-learning for personal thermal comfort modeling in office buildings. In: 2022 China Automation Congress (CAC). 2022. p. 3988–93.

[23] Xiong L, Yao Y. Study on an adaptive thermal comfort model with K-nearest-neighbors (KNN) algorithm. Build Environ. 2021;202:108026.

[24] Haifeng L, (Cynthia) Hou H, Gou Z. User-centric approach to optimizing thermal comfort in university classrooms: Utilizing computer vision and Q-XGBoost reinforcement learning. Energy Build. 2024;323:114808.

[25] F. Hani Mohamed Salleh, M. binti Saripuddin. Monitoring Thermal Comfort Level of Commercial Buildings' Occupants in a Hot-Humid Climate Country Using K-nearest Neighbors Model. In: 2020 5th International Conference on Power and Renewable Energy (ICPRE). 2020. p. 209–15.

[26] Yang C, Zhang R, Kanayama H, Sato D, Taniguchi K, Matsui N, et al. Hybrid personalized thermal comfort model based on wrist skin temperature. Build Environ. 2025;268:112321.

[27] Haruehansapong K, Kliangkhlao M, Yeranee K, Sahoh B. Personal thermal comfort prediction using multi-physiological sensors: The design and development of deep neural network models based on individual preferences. Build Environ. 2023;245:110940.

[28] Chaudhuri T, Zhai D, Soh YC, Li H, Xie L. Random forest based thermal comfort prediction from gender-specific physiological parameters using wearable sensing technology. Energy Build. 2018;166:391–406.

[29] Lim SH, Kim TG, Yeom DJ, Yoon SG. Robust deep reinforcement learning for personalized HVAC system. Energy Build. 2024;319:114551.

[30] Chaudhuri T, Zhai D, Soh YC, Li H, Xie L. Thermal comfort prediction using normalized skin temperature in a uniform built environment. Energy Build. 2018;159:426–40.

[31] Li X, Xu J, Zhang J, Tian T, Xu R, Gao Y, et al. Using SHAP and Machine Learning for Dynamic Thermal Comfort Estimation during temperature ramp conditions with infrared camera. Build Environ. 2025;275:112824.

[32] Deng Z, Chen Q. Development and validation of a smart HVAC control system for multi-occupant offices by using occupants' physiological signals from wristband. Energy Build. 2020;214:109872.

[33] Jiang L, Yao R. Modelling personal thermal sensations using C-Support Vector Classification (C-SVC) algorithm. Build Environ. 2016;99:98–106.

[34] G. Gao, J. Li, Y. Wen. DeepComfort: Energy-Efficient Thermal Comfort Control in Buildings Via Reinforcement Learning. IEEE Internet Things J. 2020;7(9):8472–84.

[35] H. Luo, Z. Xu, J. Wu, H. Tavakkoli, Z. Ke, Izhar, et al. Accuracy Enhancement of Micro-PMV Sensor System for Human Thermal Comfort Measurements through Machine Learning. In: 2023 IEEE 16th International Conference on Nano/Molecular Medicine & Engineering (NANOMED). 2023. p. 137–40.

[36] V. Cipollone, N. Morresi, S. Serroni, S. Casaccia, M. Giovanardi, A. Pracucci, et al. AI-Based Methodology for Thermal Comfort Measurement: Application of a Simplified Comfort Model on a Real-Life Case Study. In: 2024 IEEE International Workshop on Metrology for Living Environment (MetroLivEnv). 2024. p. 286–91.

[37] Y. Liu, C. Cui, J. Xue, J. Xue. Data-driven Thermal Comfort Prediction Analysis. In: 2023 IEEE 18th

Conference on Industrial Electronics and Applications (ICIEA). 2023. p. 1879–84.

[38] J. Zhan, W. He. Evaluation and prediction of elderly thermal comfort at varying ambient temperatures based on electroencephalogram signals and machine learning. In: 2022 15th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI). 2022. p. 1–5.

[39] A. O. Ojo, O. M. Oluwafemi. Evaluation of Thermal Comfort in a Multi-Occupancy Office using Polak-Ribiére Conjugate Gradient Neuro-Algorithm. In: 2022 IEEE Nigeria 4th International Conference on Disruptive Technologies for Sustainable Development (NIGERCON). 2022. p. 1–5.

[40] Y. Su, Y. Zhou, Z. Xu, J. Wu, Y. Liu, Y. Guo, et al. Group Comfort Models: Predicting Indoor Group Thermal Comfort by Learning Preferences of Multiple Occupants. In: 2020 IEEE 16th International Conference on Automation Science and Engineering (CASE). 2020. p. 1325–30.

[41] T. Chaudhuri, Y. C. Soh, H. Li, L. Xie. Machine learning based prediction of thermal comfort in buildings of equatorial Singapore. In: 2017 IEEE International Conference on Smart Grid and Smart Cities (ICSGSC). 2017. p. 72–7.

[42] M. Javed, N. Li, S. Li. Personalized thermal comfort modeling based on Support Vector Classification. In: 2017 36th Chinese Control Conference (CCC). 2017. p. 10446–51.

[43] B. Sahoh, P. Chaithong, F. Heembu, K. Yeranee, Y. Punsawad. Physiological Signals-Driven Personal Thermal Comfort System Based on Environmental Intervention. IEEE Access. 2023;11:142903–15.

[44] A. A. Farhan, K. Pattipati, B. Wang, P. Luh. Predicting individual thermal comfort using machine learning algorithms. In: 2015 IEEE International Conference on Automation Science and Engineering (CASE). 2015. p. 708–13.

[45] P. Skaloumpakas, E. Sarmas, Z. Mylona, A. Cavadenti, F. Santori, V. Marinakis. Predicting Thermal Comfort in Buildings With Machine Learning and Occupant Feedback. In: 2023 IEEE International Workshop on Metrology for Living Environment (MetroLivEnv). 2023. p. 34–9.

[46] B. Deng, Y. Yang, J. Wang, X. Huang, S. Hu, T. Gao, et al. Prediction on Thermal Sensation and Thermal Comfort from Multi-Dimensional Environmental and Physiological Characteristics. In: 2023 42nd Chinese Control Conference (CCC). 2023. p. 8527–31.

[47] N. Morresi, S. Casaccia, M. Sorcinelli, M. Arnesano, A. Uriarte, J. I. Torrens-Galdiz, et al. Sensing Physiological and Environmental Quantities to Measure Human Thermal Comfort Through Machine Learning Techniques. IEEE Sens J. 2021;21(10):12322–37.

[48] H. Zhang, X. Yang, R. Tu, J. Huang, Y. Li. Thermal Comfort Modeling of Office Buildings Based on Improved Random Forest Algorithm. In: 2022 IEEE 11th Data Driven Control and Learning Systems Conference (DDCLS). 2022. p. 1369–76.

[49] Cheung T, Schiavon S, Parkinson T, Li P, Brager G. Analysis of the accuracy on PMV – PPD model using the ASHRAE Global Thermal Comfort Database II. Build Environ. 2019;153:205–17.

[50] T. Wei, Yanzhi Wang, Q. Zhu. Deep reinforcement learning for building HVAC control. In: 2017 54th ACM/EDAC/IEEE Design Automation Conference (DAC). 2017. p. 1–6.

[51] Moreno MV, Zamora MA, Skarmeta AF. User-centric smart buildings for energy sustainable smart cities. Trans Emerg Telecommun Technol. 2014;25(1):41–55.