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Application of Machine Learning in Thermal Comfort Studies: A Review of Methods, Performance and Challenges

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Abstract

This paper provides a systematic review on the application of Machine Learning (ML) in thermal comfort studies to highlight the latest methods and findings and provide an agenda for future studies. Reviewed studies were investigated to highlight ML applications, parameters, methods, performance and challenges. The results show that 62% of reviewed studies focused on developing group-based comfort models, while 35% focused on personal comfort models (PCMs) which account for individual differences and present high prediction accuracy. ML models could outperform PMV and adaptive models with up to 35.9% and 31% higher accuracy and PCMs could outperform PMV models with up to 74% higher accuracy. Applying ML-based control schemas reduced thermal comfort-related energy consumption in buildings up to 58.5%, while improving indoor quality up to 90% and reducing CO_2 levels up to 24%. Using physiological parameters improved the prediction accuracy of PCMs up to 97%. Future studies are recommended to further investigate PCMs, determine the optimum sample size and consider both fitting and error metrics for model evaluation. This study introduces data collection, thermal comfort indices, time scale, sample size, feature selection, model selection, and real world application as the remaining challenges in the application of ML in thermal comfort studies.

[1] Corresponding Author

Keywords: Thermal comfort; Machine learning; Group-based models; Personal comfort models; Performance; Prediction Accuracy

Nomenclature

List of abbreviations			
Term	**Explanation**	**Term**	**Explanation**
Ab	AdaBoost	ML	Machine Learning
AC	Air-conditioned	MPC	Model Predictive Control
AE	Average Error	MRT	Mean Radiant Temperature
AI	Artificial Intelligence	MSE	Mean Squared Error
ANN	Artificial Neural Network	NB	Naive Bayes
AUC (ROC)	Area Under the Receiver Operating Characteristics	NV	Naturally Ventilated
BM	Bayesian Method	PCM	Personal Comfort Model
BNN	Bayesian Neural Network	PCS	Personal Comfort System
CNN	Convolutional Neural Networks	PET	Physiological Equivalent Temperature
DT	Decision Tree	PMV	Predicted Mean Vote
DL	Deep Learning	PPD	Predicted Percentage Dissatisfied
ELM	Extreme Learning Machine	PSO	Particle Swarm Optimization
ENL	Ensemble Learning	r	Correlation Coefficient
ET*	Effective Temperature	R	Regression Method
FLS	Fuzzy Logic System	R^2	Coefficient of Determination
FOM	Firefly Optimization Method	RF	Random Forest
GA	Gaussian Method	RL	Reinforcement Learning
GNB	Gaussian Naïve Bayes	RMSE	Root Mean Square Error
GP	Genetic Programming	RNN	Recurrent Neural Network
HVAC	Heating, Ventilation, and Air Conditioning	ROC	Receiver Operating Characteristics
IAQ	Indoor Air Quality	SET	Standard Effective Temperature
IEQ	Indoor Environment Quality	SSE	Sum of Squares for Residuals
IoT	Internet of Things	SVM	Support Vector Machine
KNN	K-Nearest Neighbors	TBM	Tree-based Method
LDA	Linear Discriminant Analysis	TCV	Thermal Comfort Vote
LoR	Logistic Regression	TPV	Thermal Preference Vote
LVQ	Learning Vector Quantization	TSV	Thermal Sensation Vote
MAE	Mean Absolute Error		

1. **Introduction**

1.1 Research Background

People spend more than 80% of their time in indoor spaces [1], which highlights the importance of Indoor Environmental Quality (IEQ), especially during the COVID-19 lockdown and longer indoor stays. Thermal comfort as one of the essential elements of IEQ is defined as "the condition of mind expressing satisfaction with the thermal environment" [2]. To investigate thermal comfort, the two main approaches of Predicted Mean Vote-Percentage of Dissatisfied (PMV-PPD) and the adaptive approach have been implemented for a long time.

The Fanger's PMV-PPD model, which stems from a set of experiments in controlled climate chambers is based on thermal equilibrium equations between human body and its environment. According to Fanger, the human thermal sensation can be determined by four environmental factors (air temperature, relative humidity, mean radiant temperature and air velocity) plus two personal ones (cloth insulation and metabolic rate) [3]. This model has been used by many researchers during the last fifty years and has been reviewed in many studies [4–6]. Based on the literature, several studies [7–12] have recognized the validity of PMV-PPD model, whether implicitly or explicitly. However, many studies [13–19] have mentioned the poor prediction power of this model. Cheung et al. [17] analyzed the accuracy of the PMV–PPD model using ASHRAE Global Thermal Comfort Database II. They reported that the accuracy of this model in predicting observed thermal sensations was only 34%. The PMV-PPD model is proven to be reliable in uniform controlled steady conditions. However, real building conditions are usually dynamic and non-uniform [18]. Therefore, a major problem with PMV-PPD model is its lack of accurate prediction in different contexts, especially in field studies and under uncontrolled conditions. It has been found that the tolerance band of PMV index can be higher than 1.0 unit for people exposed to the same environment [19]. Moreover, the PMV index applies to healthy adults and not to children, older or disabled individuals. Furthermore, measuring/calculating several factors, such as mean radiant temperature, cloth insulation and metabolic rate is difficult, which increases the complexity of the model.

On the other hand, thermal adaptive method relates occupants' thermal sensations to outdoor air temperature by a linear regression equation. Thus, the main adaptive models are "black-boxes" based on a statistical analysis of field data [20]. The adaptive method originates from this assumption that a human being is active in his/her thermal environment and plays a role in adjusting the environmental conditions. It accounts for physiological, behavioral and psychological adaptation, although only at an aggregation level [21]. Due to adopting this method in different locations and under various conditions, wider acceptable indoor temperature ranges based on adaptive models have been included in international and national standards and this approach towards thermal comfort is regarded as a significant contributor in achieving low energy building design and operation [22].

However reducing all the effective parameters to only one parameter (outdoor air temperature), may cause over-simplification and neglecting the complexities of human thermal perception. Moreover, the predictive equation is derived from data, meaning that an equation for data in one context might not work in another [23].

Furthermore, both models are designed for predicting the average thermal state of a group and do not work for the assessment of individuals' thermal conditions. Moreover, input parameters for both models are fixed, which makes it difficult to analyze the effects of other potential parameters on thermal perception.

During the last decade, with the development of computer science and especially Artificial Intelligence (AI), this knowledge has been adopted in different fields, such as buildings and thermal comfort. "AI" can subtly be defined as the ability of computers to develop intelligent qualities, similar to those of humans, and consequently perform tasks that could previously be performed by humans alone [24]. Machine Learning (ML), which is a subset of AI can solve non-linear complex problems with big dimensions. In comparison with regression methods, ML has a much stronger performance in determining non-linear non-standard relations between independent and dependent variables [25].

ML thermal comfort models can find the relationships between occupants' thermal feedback and the affecting variables by themselves and without explicit knowledge of the physical effects of each factor (self-learning ability). Besides, these models can correct or adjust such comfort relationships by themselves, when applying to different contexts (self-correction ability) [26]. In comparison with PMV and adaptive models, ML models make it possible for the analyst to test different combinations of inputs and find the most effective parameter(s). Furthermore, ML can be adopted for both average-based models and Personal Comfort Models (PCMs).

1.2 Literature Review

Due to the advantages of this new approach, the increasing application of ML in thermal comfort and building energy efficiency studies does not seem to be surprising. Aiming at addressing the current gaps involved in applying machine learning models to building energy efficiency, the review paper by Wang, et al. [27] identified several issues, such as non-uniform and divergent research objects, diverse ML algorithms, limited data collection techniques and resources, data structure non uniformity, technology-oriented research paradigms, inadequate model adaptability, and lack of user confidence [27]. Similarly, reviewing the latest ML applications in thermal comfort studies can assist the researchers to identify the main gaps and potential future study areas. Reviewing the study contexts and ML models clarifies which contexts and models require more investigation. For example, Luo et al. [28] compared the performance of different ML algorithms and suggested that factors such as building type, building operation mode, and climate conditions were not among the top factors. However, these factors can affect occupants' thermal perception and require more investigation. Another related area that can be studied is the application of ML models in Personal Comfort Models (PCMs) and Personal Comfort Systems (PCSs). For example, Shan et al. [29] mentioned that an individual has its unique thermoregulation mode and thermal stress response, so it is necessary to establish PCMs for independent analyzes and predictions. Ngarambe et al. [24] reviewed 37 papers between 2005-2019 to investigate AI-based thermal comfort predictive models, the energy implications of AI-based thermal comfort controls, ML methods and algorithms for thermal comfort modelling, PMV models and PCMs. Their conclusion suggested that tuning, model optimization techniques, deployment of comfort models in building control systems and quantifying the benefits of AI-based comfort control systems should be further studied [24]. However, they mostly focused on air temperature and relative humidity and overlooked other parameters. Previous review papers, such as [24], [30–33] (Table 1) suggest that ML methods were mostly focused on introducing algorithms and the overall process without emphasizing essential issues, such as determination of sample size, time scale, target parameter, validation methods and performance metrics. Thus, there still is a need for a more comprehensive and detailed review of ML applications in thermal comfort studies.

Table 1. Summary of recent review papers.

Paper	Year	Number of Reviewed Papers	Years of Reviewed Papers	Objective(s)	Recommendations
[24]	2020	37	2005-2019	- Focusing on thermal comfort predictive models and their deployment in building control systems; - Discussing research gaps and potential future research directions.	Gaps and future research directions: - Lack of AI-based modeling in residential buildings and non-waking occupants; - Lack of sufficient amount of data in datasets; - High dependency on "supervised learning" methods; - Lack of generalization, transparency, and deterministic conclusions; - Tuning, parameters, and model optimization techniques; - Deployment of comfort models in building control systems; - Quantifying the benefits of AI-based comfort control systems.
[30]	2021	45	2005-2019	- Reviewing the analytical models and identifying the corresponding input variables; - Discussing application in models based on Artificial Neural Network (ANN) and Reinforcement Learning (RL).	Research gaps: - Lack of spatial configuration of buildings, such as room dimension, ceiling height, and total surface area to adjust control system or to incorporate into modeling; - Overlooking the linked effects of air temperature, air velocity, surface temperature, and mean radiant temperature; - Not investigating the prevalence of indoor air pollutants.
[31]	2020	105	2010-2020	- Summarizing recent occupant-centric thermal comfort practices following a framework with three themes: sensing, predicting, and controlling.	Challenges of occupant centric thermal comfort solutions: - Sensing technology; - Predicting model; - Controlling strategy.

[32]	2020	NA	NA	- Describing the fundamentals of an intelligent entity (rational agent) and components of its problem-solving process (i.e., search algorithms, logic inference, and machine learning); - Discussing the current application of intelligent personal thermal comfort systems in buildings; - Describing future directions for enabling the application of fully automated systems to provide comfort more efficiently.	Future directions: - A need for improvements in intelligent system methods to autonomously address the dynamic personal thermal comfort preferences of occupants in buildings. - A need for more complex control algorithms, so the intelligent system is better equipped to manage the equally complex data inputs from all personal thermal comfort profiles in the occupied space and deliver a suitable thermal environment.
[33]	2019	33	1997-2018	- Providing a comprehensive review of RL being implemented for occupant comfort control; - Analyzing the application of RL for comfort control in multi-agent environments; - Highlighting the potential of RL as a sustainable forerunner for occupant centric building operation in the evolving smart city.	Major challenges and Research gaps: - Lack of studies including comfort factors such as indoor air quality and lighting in comparison to thermal comfort; - Lack of incorporating occupancy patterns and/or occupant feedback into the control loop which are crucial for occupant-centric building operation;

1.3 Aim and Objectives

This paper aims to highlight the application of ML to thermal comfort studies and identify its related methods, performance and challenges by reviewing the most recent research studies in this area. More specifically, the objectives of the study are:

- Introducing the main applications of ML models in thermal comfort studies.
- Investigating ML practices in thermal comfort studies with a focus on sample sizes, tools, algorithms, generalization test methods and performance metrics.
- Specifying the main input and output parameters of ML models.
- Examining the performance of ML models in comparison with conventional models and their impact on the indoor thermal environment.
- Highlighting the main challenges of ML models in thermal comfort studies to provide an agenda for future studies.

2. Selection of Studies

Reviewed studies were selected from 2016-2021 for two main reasons; first, this study aims to highlight the most recent applications, methods, tools and findings in this area; second, the number of studies addressing thermal comfort using ML models has increased exponentially since 2016 [31]. The process of selecting papers is illustrated in Fig. 1. Firstly, two sets of keywords were provided, for thermal comfort and machine learning. Secondly, 15 combinations of thermal comfort and machine learning related terms (such as thermal comfort/machine learning, thermal comfort/artificial intelligence, thermal comfort/data-driven, Heating, Ventilation, and Air Conditioning (HVAC) control/machine learning, HVAC control/artificial intelligence, and HVAC control/data-driven) were searched on “Google Scholar”, “Science Direct”, “Research Gate”, and “Scopus” online databases. Using the sorted by relevance mode, 246 of the most relevant search results published from 2016 to 2021 were listed. Thirdly, titles, keywords, and abstracts of the listed papers were reviewed. Here, 137 papers that had addressed only thermal comfort or machine learning issues were eliminated, leaving a total of 109 papers. Finally, papers that met all the below criteria were included in the review:

- Being written in English;
- Being directly related to both thermal comfort and machine learning/artifical intelligence;

- Having clarified the main comfort analysis approach, whether group-based models or PCMs.
- Having clarified the source of data, whether it is existing data (such as ASHRAE databases) or specifically measured (field/climate chamber) or generated data (from simulation);
- Having provided a clear description of the methodology, in terms of data collection, input and target parameters, and algorithm(s);
- Being published by building physics-related journals (such as Building and Environment, Energy & Buildings, Renewable and Sustainable Energy Reviews) or conferences (such as IEEE International Conference on Automation Science and Engineering, IEEE International Conference on Smart Grid and Smart Cities, and Windsor Conference).

As a result, a total number of 60 papers published from 2016 to 2021 were selected for the review to conduct an in-depth study. Fig. 2 illustrates a word cloud of titles and keywords of the selected papers.

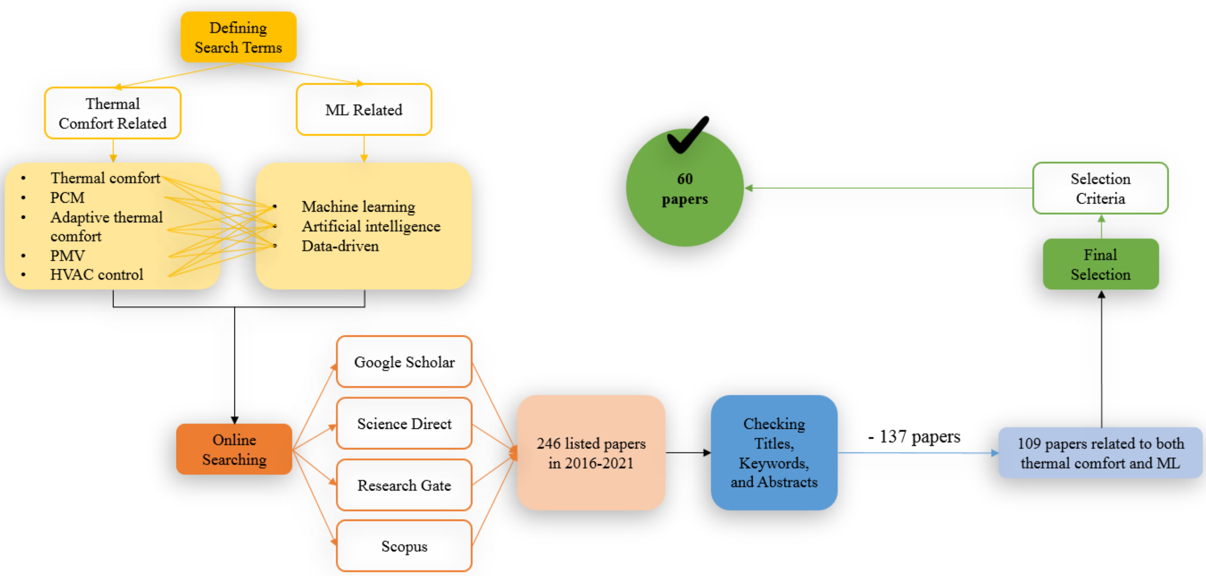

Fig. 1. The process of selecting studies.

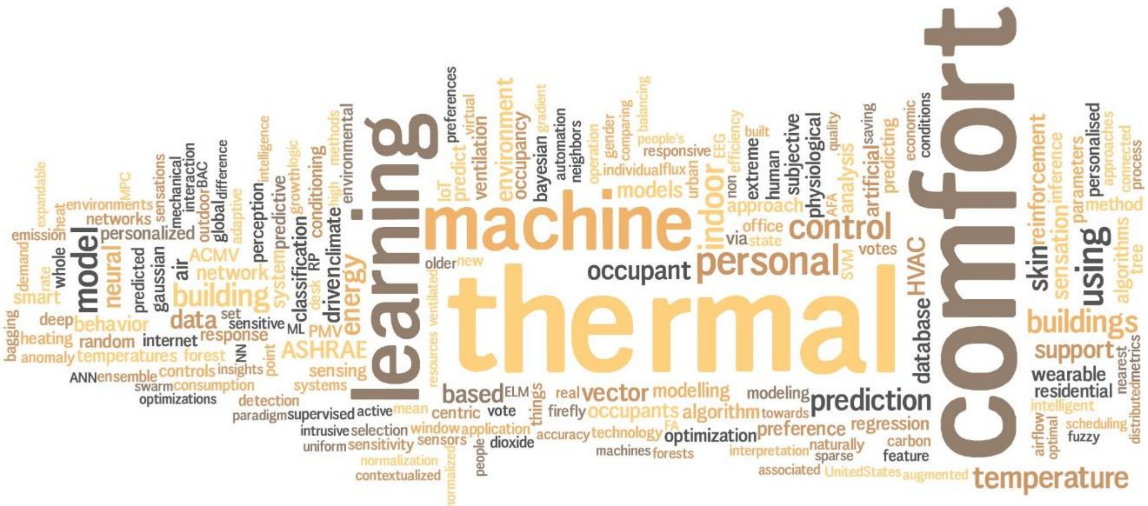

Fig. 2. A word cloud (with a maximum of 200 words) of titles and keywords of the reviewed papers.

3. An Overview of Reviewed studies

Reviewed studies are investigated in terms of their context and data to provide a more comprehensive overview of their frequency and distribution.

Fig. 3 illustrates the number of reviewed studies in each year which shows a generally increasing trend. The reason for the drop in 2021 can be related to the time of the last online search on August 5th 2021.

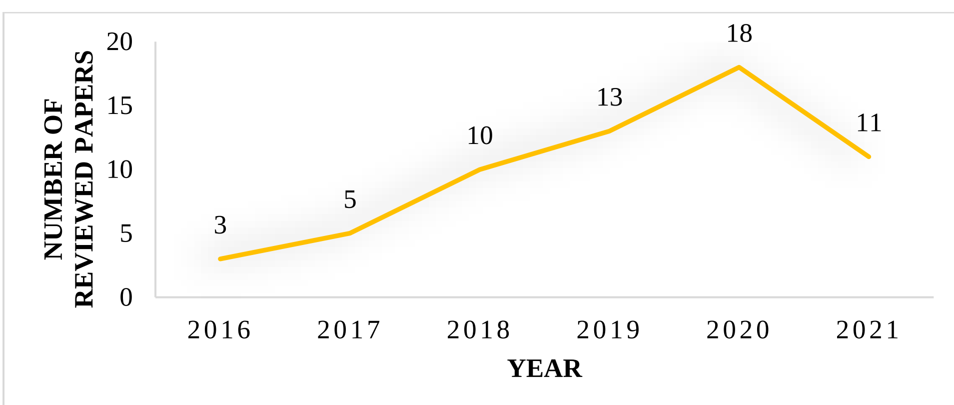

Fig. 3. The distribution of the selected papers from 2016 to 2021.

3.1 Study Context

The reviewed papers were classified based on their investigated seasons, regions, building types and operation modes. Since ASHRAE datasets were collected from various regions worldwide and during various seasons, papers using these databases covered various contexts, except reference

[34] for the Mediterranean and subtropical climate, reference [35] in Singapore and reference [36] in North America.

Seven papers ([18], [25], [37], [38], [39], [40], [41]) studied all seasons and one paper [42] mentioned that a period of 10 months was investigated. On the other hand, some studies ([30], [43], [44], [45], [39], [46], [47], [48], [49], [50]) did not clarify their studied seasons. Kim et al. [51] presented an overall framework for occupant-centric environmental control that could explain the reason for not mentioning the season(s). Sajjadian et al. [52] also introduced a framework and did not mention their studied seasons. Fig. 4 shows the frequencies of investigated seasons among the reviewed papers. It can be observed that summer or cooling season was the most studied time of year. Future studies are recommended to focus on other seasons, especially winter, which could require noticeable heating demands in cold climates.

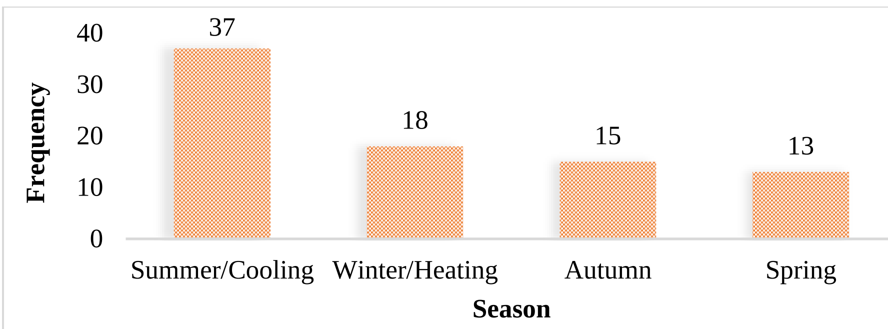

Fig. 4. The frequency of the determined investigated seasons.

Fig. 5 illustrates the distribution of the investigated locations, based on ASHRAE global database I and II [53], ASHRAE RP-884 [54] and other reviewed papers. After excluding studies that did not define their investigated regions or used ASHRAE databases, it was observed that far eastern areas (mostly Singapore and China) accounted for around 51% of the studied regions. Therefore, the reason for summer being the most studied season is the fact that most of the studies were conducted in hot and humid climate zones with high cooling demands. The next frequently studied regions were European countries (mostly Italy), followed by North America/USA, which accounted for around 25% and 20% of the investigated regions, respectively. On the other hand, although regions, such as Russia, Southern America, Africa and the Middle East can be exposed to severe climatic conditions, Fig. 5 shows a lack of studies on these areas, which is recommended to be addressed in future studies.

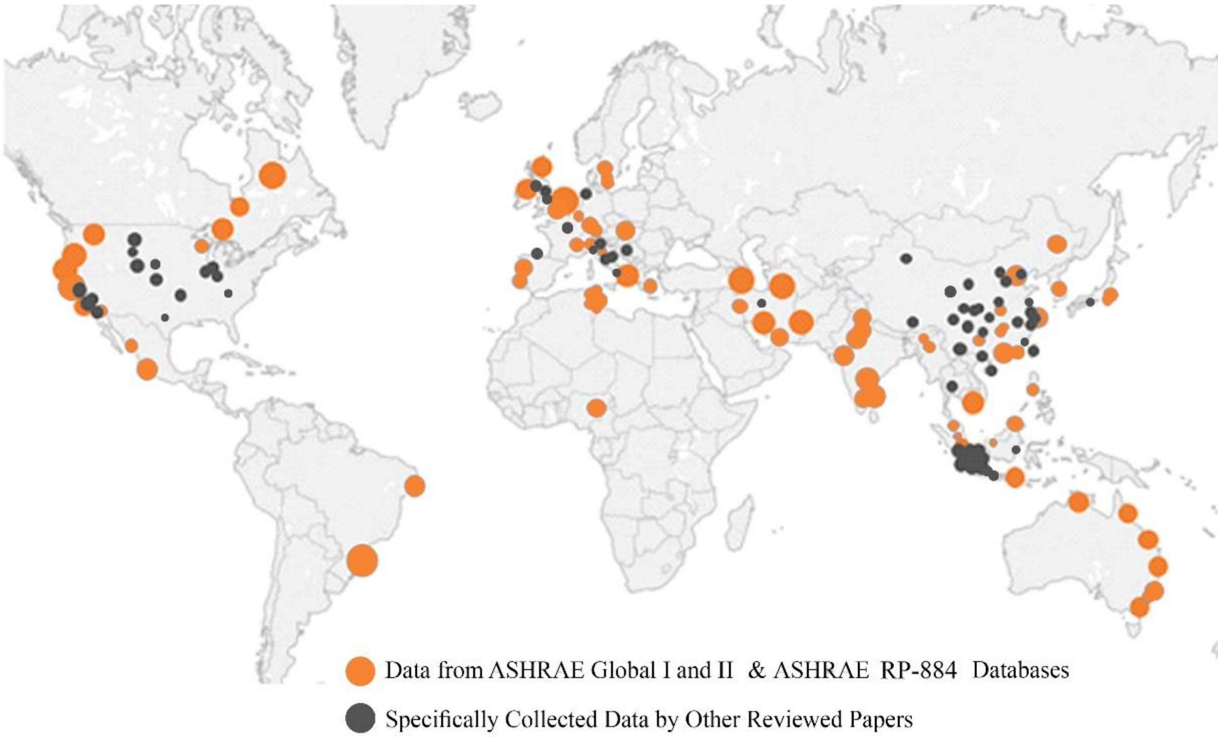

Fig. 5. The distribution of investigated regions on the world map.

To identify the most frequent building type, the study has eliminated studies on outdoor areas ([55–58]), one paper that studied all working and living spaces through the day [40], and papers that used ASHRAE databases with various building types ([26], [28], [59], [60], [34], [61], [62], [63], [35]). Results suggest that offices were the most investigated buildings, accounting for about 54% of the studied cases, followed by residentials (including dormitories, care-homes, houses and apartments), educational spaces, and lecture theatres, which accounted for around 27%, 14%, and 4% of the cases, respectively. Since thermal conditions can affect learning abilities and students' performance, further studies are recommended to focus on educational contexts. Another building type that can be focused on for future studies is hospitals and medical centres. Providing thermal comfort in hospitals can be a real challenge due to the variety of activities and different thermal sensations of patients, personnel and visitors. Moreover, the thermal quality of open public spaces can influence residents' outdoor life [57], therefore, another potential area for future studies is outdoor thermal comfort.

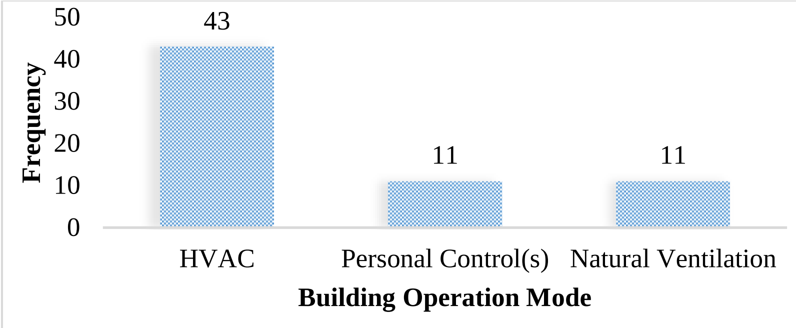

Fig. 6. The frequency of the operation modes of the investigated buildings.

As illustrated in Fig. 6, the most investigated building operation mode was HVAC, with around 66% of the specified cases. In some cases ([51], [37], [64], [41], [42], [65]) HVAC systems came along with control options such as desk fans, thermostats or other PCSs, which allowed occupants to adjust their environment and improve their thermal conditions. In some other cases (such as [66], [67]), the main heating/cooling/ventilation strategy was using PCSs. This review suggests that naturally ventilated buildings need further investigating to provide adequate fresh air through well-designed openings, especially with the outburst of COVID-19.

3.2 Data Collection

There are some publicly accessible thermal comfort datasets, such as ASHRAE global thermal comfort database II, the scales project, Langevin Longitudinal dataset, ERA5-Heat, and Winter Thermal Comfort and health for the elderly that can be used, which contain 107584, 8226, 678621, not mentioned, and 424 records, respectively [68]. Therefore, some studies used existing data from ASHRAE databases ([26], [28], [59], [60], [34], [61], [62], [63], [35]) while others collected data for their specific studies. Another noticeable point is the use of new technologies and online methods for data collection, which was adopted by several studies, such as [51], [37], [38], [67], [45]. With the development of sensors and Internet of Things (IoT), this strategy can be the subject of more in-depth investigations. However, some studies ([69], [70], [59], [58]) used simulation approach to generate data for their models. A detailed description of the collected input and output parameters is presented in section 4.3.

4. Machine Learning in Thermal Comfort Studies

This section provides an overview of the reviewed papers, in terms of ML process, applications, input and output parameters, algorithms and assessment methods, performance and challenges.

4.1 Machine Learning Process in Thermal Comfort Studies

Main practices of ML, namely, classification, regression, clustering, dimension reduction and learning in context have been adopted in the field of building performance [71]. As illustrated in Fig. 7, these practices are conducted by the means of three main methods including Supervised Learning, Unsupervised Learning, and Reinforcement Learning.

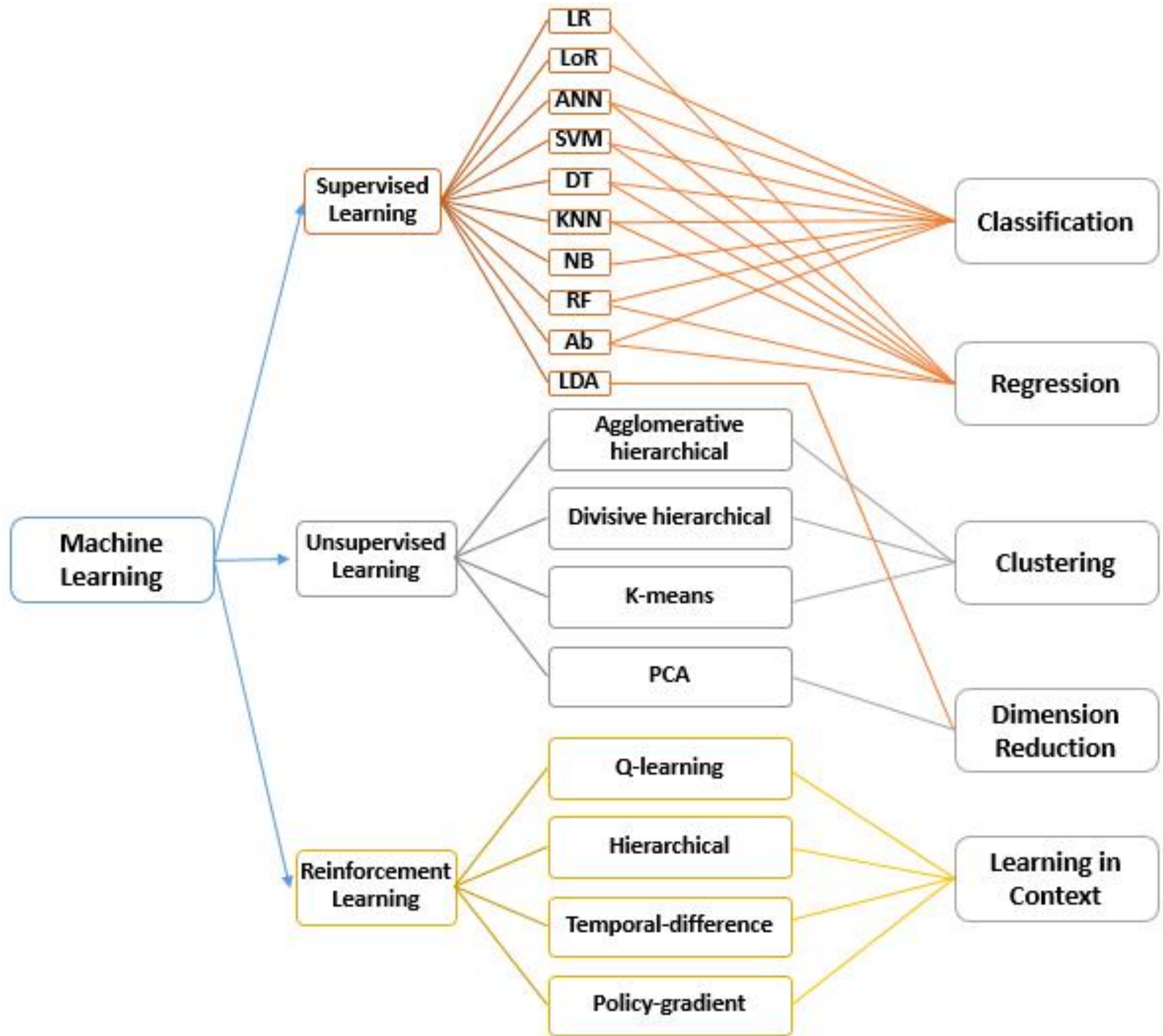

Fig. 7. ML methods and algorithms.

In general, the main process in thermal comfort studies that use ML models consists of 4 phases (Fig. 8):

1. ***Problem Identification Phase:*** The first step of any scientific study is to determine research questions and objectives. In this phase, thermal comfort researchers state their prediction problem and describe whether they intend to build average-based models or PCMs.

Furthermore, thermal perception indices (prediction target) and potential predicting parameters (predictors) are determined, mostly due to the existing literature.

2. ***Experimentation Phase:***

- *Data Collection:* Researchers can collect data from several sources, such as weather stations, environmental sensors, occupant questionnaires, operation of building systems, and contexts. Since ML models are data-driven methods and comfort data is multi-source, it is important to guarantee data quality. Improving sensing technology, developing multi-source data fusion methods, and optimizing data governance strategies are effective ways of solving data quality and collection problems [27].
- *Data Preparation:* When more than one data file is available, the process of merging data or data integration is conducted. Data cleansing, handling missing values, smoothing noisy data, identifying and removing outliers and resolving inconsistencies are also conducted if necessary. Moreover, data reduction including the reduction of datasets or/and dimension reduction (feature conditioning) can be done to improve the performance of models.
- *Splitting Data:* Dataset is divided into train and test subsets. The training set is used to develop models while the test set is used to estimate the predictive performance and generalization ability of the initially developed models.
- *Model Construction:* Linear Regression (LR), Logistic Regression (LoR), Artificial Neural Network (ANN), Support Vector Machine (SVM), Decision Tree (DT), K-Nearest Neighbors (KNN), Naive Bayes (NB) and Ensemble Learning algorithms, such as Random Forest (RF) and AdaBoost (Ab) are some examples of ML models that can be developed by the means of the training dataset. For each model, hyperparameters are tuned and the best performing combination of the hyperparameters is selected.
- *Model Validation:* After training a model, validation is conducted to test generalization ability of the model. Good generalization performance of a trained model indicates that the model is not over-fitted to the specific training dataset and can be applied for other datasets as well. There is a variety of performance metrics, such as r, R^2, accuracy, MAE, MSE, RMSE, and AUC (ROC) that researchers can use to evaluate ML models.

3. ***Model Selection Phase:*** By comparing the performance of ML models, the best performing one(s) are selected. However, another issue to consider is their time and computational cost. A proper trade-off between the performance of a model and its cost makes it an efficient model.

4. ***Application Phase:*** ML models are applied to actual buildings to provide building occupants with thermal comfort. A ML-based Model Predictive Control (MPC) system can be implemented to control the air-conditioning and mechanical ventilation systems [72]. However, there are some considerations in this area. These schemes require data collection, transformation and storage technologies. The speed of data collection and transfer should be high to make MPC systems able to respond to occupants' thermal requirements as soon as possible. Moreover, since these schemes should be able to handle big data, they require sufficient data storage space. Another issue is to monitor occupants with the least intrusion in their daily activities, which requires non-intrusive devices for data collection. In addition, repeatedly asking occupants about their thermal perception may distract them from their normal activities. It may even cause tedium and reduce the accuracy of responses. Thus, the time scale should be assigned in a way that provides a good prediction performance with the least number of repetitions. Furthermore, the performance of ML models in predicting different thermal perception metrics (such as TSV and TPV) should be compared and evaluated to identify the best describing metric as the target parameter.

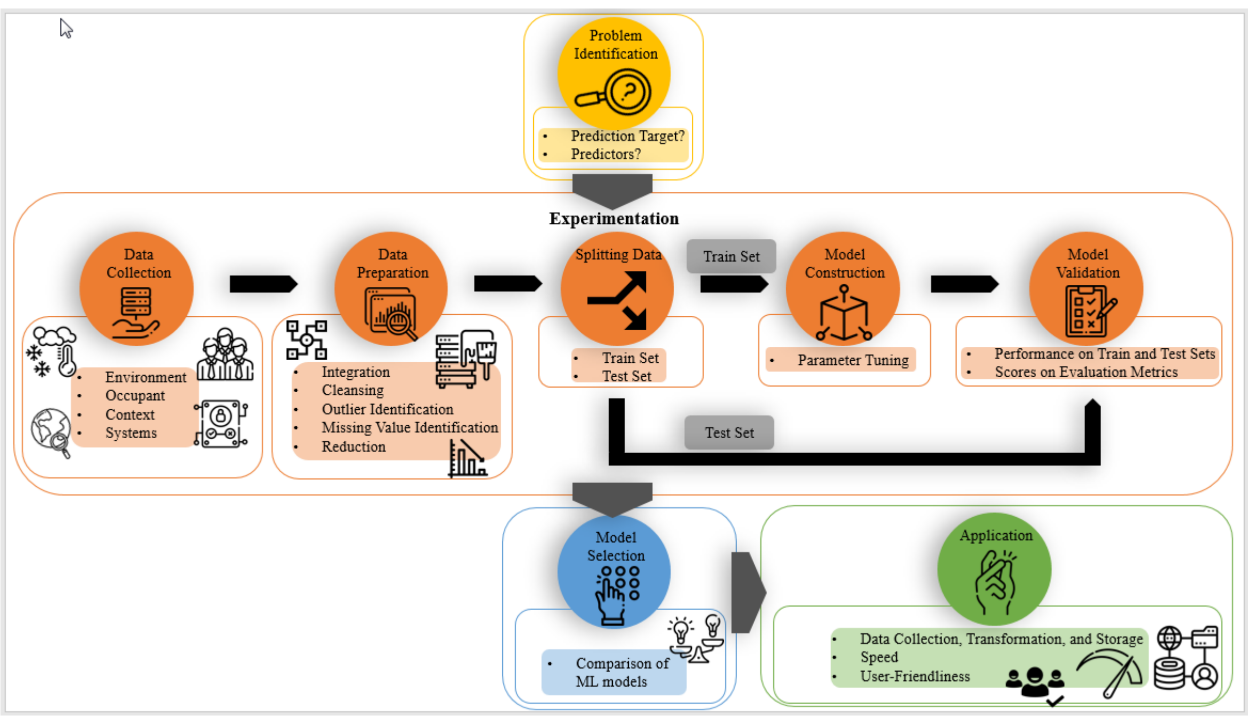

Fig. 8. ML process in thermal comfort studies.

4.2 ML Application

The main study features of the reviewed papers are categorized into six groups (Table 2).

Group-based models and PCMs: Table 2 shows that around 62% of studies focused on developing comfort models for a group of people, while 35% focused on PCMs. However, both group-based and PCMs were developed and compared in the study by Alsaleem, et al. [43], with the results showing PCMs have higher accuracies compared to group-based models.

Comparison of ML models: A fundamental step in using ML is model selection, therefore, 26 papers (such as [28], [29], [51]) addressed this issue and compared the performance of ML algorithms. Section 4.4 provides a review of ML models.

Optimized control of HVAC systems: To build a model for thermal comfort prediction, its application in the real world should be noticed as well. Thus, 13 papers (such as [44], [69], [73]) addressed this issue in terms of efficient control of HVAC systems, which can optimize energy consumption and improve the thermal environment. For example, Azuatalam et al. [69] used reinforcement learning with simulated data for PMV prediction in commercial spaces to develop a whole-building HVAC control and demand response model. Valladares et al. [70] aimed to optimize energy associated with thermal comfort and indoor air control via a deep reinforcement learning algorithm. Wang and Hong [59] applied reinforcement learning besides some supervised learning algorithms to predict the neutral operative temperature and neutral air temperature. Sajjadian et al. [52] adopted Fuzzy logic to predict the lower and upper bounds of the comfort zone in office spaces in an educational building.

Occupants' behavior: An essential factor that affects both thermal comfort and energy consumption is occupants' behavior. Considering that individuals' behavior is complex, ML algorithms are beneficial due to their ability to deal with complex problems. Therefore, 13 papers (such as [37], [64], [66]) focused on monitoring or predicting occupants' behavior. For example, Han et al. [74] adopted reinforcement learning for predicting occupants' window opening/closing behavior in office spaces in China. In another study, Lee and Ham [75] monitored occupants' behavior and studied the influence of activity-based metabolic rate on predicting personal thermal comfort using a wearable device and environmental sensors.

Feature selection: Using ML algorithms strongly depends on input features, therefore, around 23% of the papers (such as [70], [76], [77]) explained their sensitivity analysis or feature selection process.

Outdoor spaces: The use of ML in thermal comfort studies was not limited to indoor spaces. For example, Mladenović et al. [55] applied SVM and ANN algorithms to estimate thermal comfort, CO_2 emission and economic growth in an open urban space in Serbia and used Physiological Equivalent Temperature (PET) as the thermal comfort metric. In another study, Liu et al. [56] used local skin temperatures and SVM to predict TSV in urban outdoor areas. Kariminia et al. [57] took a systematic ML approach to analyze visitors' thermal comfort via predicting TSV, PMV, PET and Mean Radiant Temperature (MRT) in a public urban space in Iran. Eslamirad et al. [58] applied supervised machine learning to offer algorithms that help to identify the optimum morphology of green sidewalks to provide a higher outdoor thermal comfort and decrease errors in results.

Studying thermal comfort in relationship with other comfort aspects can provide a more comprehensive viewpoint. Thus, Pigliautile et al. [78] aimed at producing a multi-purpose comfort perception schema, i.e. considering thermal, visual, acoustic, and air quality comfort spheres under dynamic environmental conditions.

Table 2. The overall schema of the reviewed papers.

Paper	Developing models for a group	Developing personal models	Comparison of ML models	Aiming at optimized control of HVAC systems	Focusing on/ predicting occupants' behavior	Performing a sensitivity analysis/feature selection
[18]	●					
[25]	●					
[26]	●					
[28]	●		●			
[29]		●	●			
[43]	●	●	●	●		●
[51]		●	●			
[44]	●			●		
[69]	●			●		
[73]	●			●		
[70]	●			●		●
[59]	●					
[52]	●				●	
[37]	●		●		●	
[64]		●	●		●	
[66]		●	●		●	
[74]		●		●	●	
[75]		●	●		●	●
[76]	●		●	●		●
[77]	●					●
[55]	●		●			
[56]	●					

[57]	●		●			
[58]	●					
[78]	●		●			
[38]		●				
[60]	●					
[79]	●		●			
[34]	●					
[61]	●					
[67]		●	●			
[45]	●					
[39]		●				
[80]	●					
[36]	●					
[40]		●	●			
[81]		●	●			
[41]	●		●		●	
[82]	●		●			
[42]		●			●	
[83]	●					
[65]		●	●		●	
[84]		●	●	●		
[62]		●	●			●
[46]		●				●
[85]	●			●		
[47]		●				●
[86]		●	●			●

[48]				●	●	
[87]	●					●
[88]	●			●		
[89]		●		●		
[90]	●					●
[91]	●					●
[63]	●				●	●
[92]	●		●			
[93]		●	●			●
[49]	●			●	●	
[50]		●	●	●	●	
[35]	●		●			

4.3 Input and Output Parameters

According to Fig. 9, input parameters are classified into 14 main categories. It should be noted that for papers with multiple objectives, the input parameters were counted for each objective, separately, resulting in the total frequency of one of the variables (indoor environment) being more than 60 (the total number of papers). Moreover, the column "Focusing on/ predicting occupants' behaviour" covers various occupant behaviors, such as window opening/closing behavior, activity level, occupancy status, and thermal controls like adjusting set-points or fans. Table 3 also shows inputs and predicted outputs that were used by the reviewed papers.

- Indoor environmental parameters, personal/demographic parameters (clothing and metabolism), outdoor environmental and physiological parameters were the most frequently used input parameters among the reviewed papers due to their explicit relations with occupants' thermal conditions. Behavioral parameters can affect both thermal conditions and building energy consumption, however, they are less studied. There is only one paper considering occupants' behavior with regards to controls and optimization of HVAC systems [50]. This can be explained by the subjective and complex nature of behavioral factors, however, ML models with the ability to learn non-linear and complex relations can facilitate this issue, which can be the focus of future studies.
- The review suggests that indoor environmental parameters were used more than outdoor environmental ones. Considering that outdoor weather conditions can also impact people's expectations of the thermal environment according to the adaptive approach, future ML studies are recommended to conduct feature selection to identify the more important environmental variables (indoor or outdoor) in predicting occupants' thermal comfort.
- With the advent of the Internet of Things (IoT) and new technologies, using physiological parameters is increasing among studies, as they can directly capture occupants' body responses to thermal conditions, especially in developing PCMs. However, collecting physiological parameters usually requires sensors to be attached to occupants' skin, which may cause disturbance for people. Thus, employing new lightweight sensors with the least intrusion can be an interesting research area.
- Spatial and architectural parameters were only included in 2 papers ([58], [85]), one of which considered outdoor spatial parameters (density, height, and plan type) in conjunction with vegetation type and weather conditions to predict PMV in green sidewalks [58] and the other

one generated different design options to assess indoor thermal comfort using mechanical and natural ventilation [85]. Analyzing the effects of architectural parameters on thermal comfort can assist building designers to design spaces with enhanced indoor thermal environments, which can be the focus of future studies.

- Since thermal comfort is a complex concept with many known and unknown affecting parameters, investigating its relationship with other comfort aspects, such as visual, acoustical comfort, and indoor air quality (IAQ) can provide a more comprehensive viewpoint. Therefore, six papers ([25], [69], [67], [47], [86]) considered lighting/visual parameters, one of which [89] also considered noise/acoustical ones as inputs. However, due to a lack of research in this area, future studies are recommended to further investigate these parameters.
- TSV was the most frequently used output (target) parameter among the reviewed papers (around 48%). TPV, another metric that can be adopted as a proxy for occupants' thermal perception was included in around 12% of the reviewed studies. For example, Ma et al. [63] used TSV in conjunction with environmental and demographic parameters to predict TPV. The importance of TPV is in its direct relationship with the potential control actions that occupants might take to adjust their thermal condition. For example, 'TPV = want cooler' is probably associated with adaptive actions, such as turning on fans or increasing fan speed, opening window(s) or lowering the heating set-point. These actions are related to energy consumption and air quality, therefore, researchers are encouraged to focus on the importance of TPVs as well as TSVs in future studies.
- To quantify the subjective quality of thermal comfort and evaluate the performance thermal comfort models by mathematical metrics, thermal comfort responses (such as TSV and TPV) need to be redefined as ordinal numbers. Therefore, TSV responses are often defined as -3= feeling too cold, -2= feeling cold, -1= feeling slightly cold, 0= feeling neutral, 1= feeling slightly war, 2= feeling warm, and 3= feeling hot. Similarly, other thermal comfort metrics such as TPV responses are often defined as -2= preferring a cooler temperature, -1= preferring a slightly cooler temperature, 0= preferring no change in temperature, 1= preferring a slightly warmer temperature, 2= preferring a warmer temperature.

	Developing models for a group	Developing personal models	Aiming at optimized control of HVAC systems	Focusing on/ predicting occupants' behavior	Total
Outdoor Environment	18	7	3	6	34
Indoor Environment	29	19	10	9	67
Personal/Demographic	25	11	6	5	47
Contextual	10	5	1	3	19
Behavioral	4	6	1	6	17
Physiological	10	12	3	1	26
Lighting/Visual	2	4	2		8
Time Measure	10	5	2	5	22
CO_2 Concentration	9	2	4	1	16
Occupancy Status	5	1	3	2	11
Spatial/Architectural	2				2
Noise/Acoustical		1	1		2
Expressed State	2		2	2	6
Vegetation	1				1

Fig. 9. Heat map of the frequencies of used input parameters in relation with the main objectives of the reviewed papers.

Table 3. The input and output parameters of the reviewed papers.

Paper	**[OE]**	**[IE]**	**[PD]**	**[CON]**	**[B]**	**[P]**	**[L]**	**[TM]**	**[CC]**	**[OS]**	**[S]**	**[N]**	**[ES]**	**[V]**	**Outputs(s)**
[18]	●	●	●	●	●										TSV, TCV
[25]		●	●	●		●	●	●	●						TSV
[26]	●	●	●	●											TSV
[28]	●	●	●	●											3 and 7-point TSV
[29]						●									TSV
[43]		●	●			●									3-point TSV, Control action
[51]	●	●	●	●	●	●		●							TSV, TA, TPV
[44]						●									Thermal state (derived from TSV)
[69]		●	●	●			●		●	●					PMV
[73]	●	●						●		●					Temperature, Humidity (RH)
[70]	●	●							●						Temperature
[59]		●	●												Temperature
[52]			●					●							Temperature
[37]	●	●	●												TSV, Occupants' Behavior
[64]	●	●		●	●										TPV
[66]		●			●	●		●							TSV, TCV
[74]	●	●		●	●										Occupants' behavior
[75]		●	●			●									TSV

[76]		●	●											Energy Consumption, Temperature, Air Velocity, PMV
[77]		●	●											PMV
[55]	●		●						●					PET, CO_2 Emission, Gross Domestic Product (GDP)
[56]						●								TSV
[57]	●		●	●										TSV, MRT, PMV, PET
[58]	●										●		●	PMV
[78]						●		●						TSV
[38]		●	●											TSV
[60]	●	●	●	●				●	●					TSV, TCV, TPV, TA
[79]	●	●	●	●	●									TSV, ET*, SET, PMV
[34]	●	●	●											TSV
[61]	●	●	●	●				●	●					TSV
[67]		●				●	●							TSV
[45]	●	●												Thermal State Index (TSI), Optimal Air Temperature (OAT)
[39]	●	●						●	●	●				Temperature
[80]						●								Thermal Demand (TD)
[36]		●	●											TPV
[40]						●								TPV
[81]		●	●											TPV
[41]								●		●				Occupancy

[82]		●			●	●			●					TSV
[42]	●	●		●	●			●						TSV
[83]						●								Thermal State (TS), Discomfort (DC), Comfort (C)
[65]	●	●						●	●	●				Occupants’ behavior
[84]		●	●			●								TSV
[62]	●	●	●	●					●					3-point TSV
[46]		●				●								TPV
[85]		●	●								●			PMV, PPD
[47]		●	●			●	●							Thermal Perception
[86]	●	●	●			●	●		●					TSV
[48]		●	●											Occupants’ behavior (activity), Temperature
[87]		●	●											PMV
[88]	●	●							●	●			●	Control action
[89]		●	●				●		●			●		PMV
[90]	●	●	●	●										Thermal Comfort
[91]		●	●			●		●						TSV
[63]	●	●	●		●								●	TPV
[92]		●	●					●						PMV
[93]		●				●								TSV
[49]		●				●								TSV
[50]		●	●		●									Thermal Perception, Occupants’ behavior
[35]	●	●	●											3-point TSV

[OE]: Outdoor Environment; [IE]: Indoor Environment; [P/D]: Personal/Demographic; [CON]: Contextual [B]: Behavioral; [P]: Physiological; [L]: Lighting/Visual; [TM]: Time Measure; [CC]: CO_2 Concentration; [OS]: Occupancy Status; [S]: Spatial/Architectural; [TA]: Thermal Acceptance; [N]: Noise/Acoustical; [ET]: Expressed State; [V]: Vegetation.

4.4 Methods and Tools

This sub-section presents a comparison of sample sizes, tools, algorithms, generalization test methods and performance metrics of the reviewed papers. It should be noted that for papers with multiple objectives, the used algorithms were counted for each objective of these papers.

	Developing models for a group	**Developing personal models**	**Aiming at optimized control of HVAC systems**	**Focusing on/ predicting occupants' behavior**	**Total**
ANN	18	8	5	4	35
SVM	15	16	3	4	38
R	7	10	2	3	22
TBM	7	13	1	2	23
BM	6	5	1		12
ENL	11	13	2	5	31
KNN	7	7	1	1	16
RL/DL	6	2	6	3	17
GA	1	1		1	3
M	1			1	2
ELM	2		1		3
LDA	3	3			6
FOM	1		1		2
FLS	1		1	1	3
GP	2	1		1	4
LVQ		1		1	2
BNN	1			1	2
PSO			1		1
Kernel		1			1

Fig. 10. Heat map of the frequencies of used algorithms in relation with the main objectives of the reviewed papers.

- Samples contain various input parameters, such as environmental, demographic, contextual, behavioral, and physiological ones which can affect the output parameter (occupants' thermal response). According to Table 4, in some studies, such as [52], and [57], each subject's thermal response was captured once (the number of responses was equal to the number of subjects). On the other hand, in several other studies, such as [29], [64], and [75], each subject's response was captured several times (the number of responses was higher than the number of subjects). Thus, finding the appropriate proportion of responses to the number of respondents seems to be an important subject for sample size. Furthermore, Table 4 shows that there was a large variation among the papers in terms of sample sizes, ranging from 54 [43] to 192,021 [65].

The sample size is the number of collected samples or the number of rows in a data file. Since all ML methods are data-driven techniques, they strongly rely on data. Very small sample sizes may result in weak generalization performance of models and very large sample sizes may increase processing and convergence time, especially when working with time-consuming algorithms, such as SVM. Thus, determining the optimum sample size seems to be an important subject to be further studied.

- The most frequently used tools for building ML models were Matlab, Python and R, which were mentioned in around 25%, 23% and 13% of the papers, respectively. This might be related to their strong statistical analysis power and their user-friendly environments. Furthermore, Python provides various libraries that facilitate the coding process. The overview of the most frequent tools for ML development helps researchers in tool selection for their future studies.
- In addition to tools for building ML models, some studies ([69], [70], [59], [58], [67], [86]) adopted simulation instead of field or climate chamber measurements to generate data. The main challenge in this approach is that simulation requires determining many detailed inputs and calibration with real conditions.
- As illustrated in Fig. 10, the most frequently used algorithms among the reviewed papers were SVM, ANN and Ensemble Learning (mainly RF), followed by Tree-Based models and Regression methods (mainly LoR). Fathi et al. [94] also reported SVM, ANN and Ensemble Learning as the most frequently used algorithms. ANN model has robustness, which can effectively solve non-linear and complex problems. Besides, through adjusting the weights between different elements, ANN model can adapt to different cases [95]. SVMs can be trained with few numbers of data samples. Another advantage of SVM over other ML models is the uniqueness and global optimality of the generated solution, as it does not require non-linear optimization with the risk of sucking in a local minimum limit [96]. Finally, RF is a form of ensemble learning, which aggregates small and weak models into strong and large models. Therefore, even if a few of the sub-classifiers perform poorly, other classifiers can fix the gap, which leads to a better generalization [24].
- Providing thermal comfort plays a major role in building energy consumption, therefore, optimization can be used to reduce energy consumption without compromising occupants' thermal comfort. Optimization algorithms (such as Firefly Algorithms, GP, and PSO) are recommended to be further investigated.

- The most adopted generalization test method was 10-fold cross-validation, followed by splitting the dataset into 80% training and 20% testing subsets and 5-fold cross-validation. Another strategy, as in reference [28], is to change the K value for cross-validation (in this case, in the range of 5 to 100) and choose the best value for K.
- To have a good generalization, an appropriate trade-off between fitting model for data in hand and preventing overfitting should be observed. In other words, the model should obtain higher fitting measures and lower error measures. According to Table 4, the most frequently used metrics for performance evaluation were accuracy, R^2, RMSE, MSE, and r, which appeared in 50%, 23%, 20%, 18%, and 15% of the papers, respectively. R^2 and r show how much the built models can explain the patterns of data. Moreover, accuracy, MSE and RMSE can be used to see how accurate the model is in predicting output values for train or/and test datasets. This study recommends future studies to consider both fitting and error metrics for model evaluation.

Table 4. The algorithms and assessment methods of the reviewed papers.

Paper	Sample size	Tool/software	Algorithm(s)	Generalization test method	Performance metric(s)
[18]	5,512	Matlab	SVM, ANN	80% of dataset for train and 20% for test	MSE, MAE, r, R^2
[25]	1040 (field study) and 413 (lab study)	NA	ENL	NA	r, R^2, Accuracy
[26]	20,954	Weka	ANN, SVM	10-fold cross-validation	RMSE, MAE, r
[28]	81,968	Python (Scikit) , R	TBM, R, SVM, ANN, ENL, BM, KNN	20-fold cross-validation	MSE, R^2
[29]	450 (3 subjects)	NA	ANN	10-fold cross-validation	MSE, MAE
[43]	286 (54/91/143 for 3 subjects)	Python	TBM, ENL, SVM, PSO	Cross validation (random parts of the data for learning and evaluation)	Accuracy
[51]	NA	NA	R, TBM, BM, Kernel algorithms	NA	R^2, RMSE, ROC
[44]	700 (20 subjects: 10 male, 10 female)	R, OriginPro, Matlab	SVM, ELM	50% of dataset for train and 50% for test, 10-fold Cross validation for tuning parameters	MSE, Accuracy
[69]	NA	EnergyPlus (predicting energy consumption after application of RL control)	RL	NA	Reward
[73]	NA	Matlab	ANN	70% of dataset for train, 15% for validation and 15% for test	MAE, R^2

[70]	NA (10 years)	EnergyPlus, SketchUp Make and Open Studio (for simulation), BCVTB (for co-simulation), Python	RL	Results of 10 years for train, results of 10th year for test	Reward
[59]	870	OpenStudio, EnergyPlus (for energy analysis), Matlab	ANN, R, TBM, SVM, ENL, RL	365 data points (a year) for training and the remainder for test. Training set size varied from 5 % to 80 % of the available dataset, in increments of 5%.	RMSE (half of) MSE
[52]	100 (100 subjects)	Matlab	FLS	NA	RMSE
[37]	8,404 (4,939 (10 offices) and 3,465 (10 apartment/houses))	Matlab	5 ANN algorithms	NA	MAE, R^2
[64]	4,743 (38 subjects)	R	TBM, GP, ENL, SVM, R	150 times 2-fold cross- validation	AUC (ROC)
[66]	448 (2 female subjects)	Matlab	SVM, ENL	10-fold cross-validation	AUC (ROC)
[74]	NA (1 subject)	Python	RL, RNN	For RNN: 70% of dataset for train and 30% for test	RMSE for RNN and Reward for Q-learning and SARSA
[75]	63-115 per person (10 subjects), 953 in total	NA	KNN, ENL, SVM, LVQ	10-fold cross-validation	Accuracy, Cohen’s kappa

[76]	NA	Matlab	ELM, ANN, FOM	80% of dataset for train and 20% for test	MSE
[77]	More than 98,000 (training), about 20,000 (validation), 20,000 (test)	Matlab	ANN	For ANN development: 70% of dataset for train, 15% for validation and 15% for test	MSE, r, mean difference, relative and absolute error
[55]	NA	NA	SVM, ANN, GP	NA	RMSE, R^2, r
[56]	1,116 (26 subjects)	NA	SVM	80% of dataset for train and 20% for test	Accuracy, R^2, Spearman's rank correlation, P-value
[57]	454 (454 subjects, 191 winter/ 263 summer)	NA	ANN, GP, ELM	NA	RMSE, r, R^2
[58]	2,268 (randomly selected from 8000 models)	ENVI-Met (for data generation), Python	R	Various percentages of test set, cross-validation	MSE, Accuracy
[78]	1,360 and 1128 (for winter and summer, respectively 29 subjects)	NA	LDA, KNN, TBM, BM, SVM, ENL	5-fold cross-validation	Accuracy, r, R^2
[38]	1,199 (20 subjects)	LIBSVM library	SVM	5-fold cross-validation	Accuracy
[60]	16,795	NA	R, SVM	10-fold cross-validation	R^2, r
[79]	813 (813 subjects: (467 in NV and 346 in AC buildings))	Weka	ENL, ANN, SVM	10-fold cross-validation	MAE, RMSE, R^2, r
[34]	5576	NA	KNN, SVM, ANN	90% of dataset for train and 10% for test	Confusion Matrix

[61]	11,000	NA	KNN, GA	NA	Accuracy, True Positive Rate (TPR), True Negative Rate (TNR)
[67]	NA (8 subjects)	Grasshopper	KNN, TBM, BM, SVM	10-fold cross-validation	Accuracy for test samples
[45]	800 (thermal comfort prediction model) and 1,155 (energy consumption prediction model)	Matlab	ANN	NA	MSE, Accuracy
[39]	NA	Matlab	ANN, SVM, TBM, ENL	5-fold cross-validation	NA
[80]	969 (11 subjects, first experiment) and 59 (second experiment)	Matlab	SVM	NA	Accuracy
[36]	900 (generated for verification) and 1,712 (observation)	Python	BM	Randomly clustering 9 individuals into 3 clusters and attributing 900 data rows to them	(Clustering Problem)
[40]	3,848 (14 subjects)	'CARET' Package under R	R, ANN, SVM, KNN, BM, TBM, ENL	5-fold cross-validation	AUC (ROC), Cohen's kappa
[81]	648	Python	SVM, ENL	5-fold cross-validation	Accuracy, Precision, Recall
[41]	NA	Matlab	R, ENL, M, RNN	NA	Accuracy

[82]	400 to 500 (22 subjects)	Matlab	LDA, BM, KNN	50% of dataset for train and 50% for test	Accuracy
[42]	NA (7-10 subjects in 2 offices)	NA	GA	Cross-validation	Accuracy, RMSE
[83]	700 (20 subjects: 10 male, 10 female)	R	ENL	80% of dataset for train and 20% for test	P-value
[65]	192,021 (6 subjects)	R	TBM, ENL	60% of dataset for train, 20% for validation and 20% for test	Accuracy, MSE, RMSE
[84]	1,305 (50 subjects: 34 male, 16 female)	SPSS, R	R, BM, ANN, SVM, TBM, ENL	80% of dataset for train and 20% for test	Accuracy
[62]	12,829	Python	TBM, KNN, R, ENL, DL	80% of dataset for train and 20% for test	Confusion Matrix, Precision, Recall, F-Score
[46]	NA (19 males and 13 females)	NA	RF, SVM, R	50% of dataset for train and 50% for test, 10-fold cross-validation	Accuracy, F-Score
[85]	15,936	NA	DL/RL	A separate 664 data samples as test set, 10-fold cross-validation	Accuracy, AE, APE
[47]	22,575 (12 females and 13 males)	R Programming (for correlation analysis), Python	LDA, R, TBM, ENL, SVM	60% of dataset for train and 40% for test, 10-fold cross-validation	Accuracy
[86]	15,456, (8 subjects) for first model and 9,022 after feature selection	Grasshopper (for parametric model), Python	R, KNN, TBM, BM, SVM	80% of dataset for train and 20% for test, 10-fold cross-validation	Accuracy
[48]	NA	NA	DL, CNN	NA	RMSE
[87]	784	NA	ANN	100% of dataset for train and 100% for test	RMSE, R^2

[88]	NA (up to 72 subjects)	NA	DL	NA	Reward
[89]	Varying for 34 subjects	NA	KNN	N (100, 500, 1000 samples) for train and 0.15*N for test, N (100, 500, 1000 samples) for train and 6400-N for test	Accuracy
[90]	10,794	Python	ENL	70% of dataset for train and 30% for test	Accuracy, MSE
[91]	964 (13 subjects (443 for men, 522 for women))	Matlab	ANN	80% of dataset for train and 20% for test	Accuracy
[63]	78,113	Python	BNN	5-fold cross-validation	Accuracy, F-Score, AUC (ROC), Adjusted rand index (ARI)
[92]	172,800 (10 subjects)	TensorFlow	DL, R, TBM, BM	75% of dataset for train and 25% for test	Time complexity, Accuracy, Precision, Recall
[93]	NA (10-13 subjects)	Python	SVM, ENL, TBM, ANN, CNN	Leave one subject out (LOSO), 10-fold cross-validation	Accuracy, MAPE, MAE
[49]	1,200 (20 students and 10 staff)	Python	BM, KNN, TBM, SVM, ENL, ANN, RL	10-fold cross-validation	MAE, Normalized Reward (for RL)
[50]	NA	NA	R, SVM, ANN	NA	Accuracy
[35]	818 (235 subjects in 12 air-conditioned offices, 583 subjects in 4 naturally ventilated residentials)	NA	SVM, ANN, R, LDA, KNN, TBM	70% of dataset for train and 30% for test, 70% of dataset for train and 15% for validation and 15% for test (for ANN)	Accuracy

[NA]: Not Mentioned Specifically; [ANN]: Artificial Neural Network; [SVM]: Support Vector Machine; [R]: Regression Method; [TBM]: Tree-Based Method; [BM]: Bayesian Method; [ENL]: Ensemble Learning; [GA]: Gaussian Method; [M]: Markov Model; [RNN]: Recurrent Neural Network; [ELM]: Extreme Learning Machine; [KNN]: K-Nearest Neighbors; [LDA]: Linear Discriminant Analysis; [RL]: Reinforcement

Learning; [DL]: Deep Learning; [FOM]: Firefly Optimization Method; [FLS]: Fuzzy Logic System; [GP]: Genetic Programming; [CNN]: Convolutional Neural Networks; [LVQ]: Learning Vector Quantization; [BNN]: Bayesian Neural Network; [PSO]: Particle Swarm Optimization

4.5 Performance of ML Models

This section provides an overview of the performance of ML and PCMs in comparison with conventional methods, their impact on indoor environmental quality and energy consumption and their performance in relation to physiological parameters.

ML models and conventional methods: Results from many reviewed papers indicate that ML models perform better than conventional methods ([18], [22], [23],[33], [71], [51], [44], [73], [76], [70], [59], [64], [74], [55], [56], [38], [34], [39], [63], [49], [35]). For example, the results of a study by Chai et al. [18] showed that ML, especially the ANN model was effective in predicting TCV and TSV in naturally ventilated residential buildings in China. ML models also outperformed PMV and modified PMV models (aPMV, and ePMV) in predicting thermal sensation votes. Similarly, Chaudhuri et al. [35] implemented several classification algorithms for building a thermal comfort model with data from ASHRAE RP-884 (only from Singapore). Their results showed that ML approach achieved prediction accuracies of 73.14-81.2%, outperforming the traditional Fanger's PMV model with accuracies of only 41.68-65.5%. The proposed approach also outperformed modified PMV models (ePMV and aPMV), which attained accuracies of 61.75% and 35.51%, respectively. Zhou et al. [26] applied SVM to the ASHRAE RP-884 thermal comfort database. Compared to the PMV model, the new model's sum of squares for residuals (SSE) was reduced by 96.4% and the fitting degree increased by 83.7%. Ma et al. [63] applied BNN algorithm to build a predictive model for occupant thermal preference using the ASHRAE Global Thermal Comfort Database II. Their results revealed that BNN model (with cross-validated mean accuracy = 0.693) outperformed PMV and adaptive model with accuracies equal to 0.334 and 0.383, respectively. Hu et al. [49] compared the prediction performance of several ML algorithms with PMV, with the results showing that black-box methods (SVM, RF, and ANN) achieved better performance than the PMV model. Moreover, in an outdoor context, Kariminia et al. [57] developed an ELM to forecast thermal comfort of visitors in an open area in Iran and compared it with two other algorithms (i.e., GP and ANN). The ELM results had higher accuracy than GP and ANN with a very high coefficient of determination (0.9354) and performed better in predicting real thermal sensation votes than predicting PMV and especially PET values [57].

The performance of ML models is also investigated in studies with more sensitive occupants. For example, Wang et al. [25] developed two data-driven models (from a field study and a lab study) using RF to predict older people's thermal sensation. Their field study model, which was developed with 4 environmental and 2 human-related inputs produced an overall accuracy of 56.6% (24.9% higher than that of the PMV). Their lab study model, which was built with 5 local skin temperatures demonstrated an overall accuracy of 76.7%. Brik et al. [92] focused on various types of disability: physical, learning, intellectual, and neurological disabilities and built DL, LoR, DT, and GNB to predict PMV for this group. Their model showed an accuracy of 94% and precision and recall of 98% and 97%, respectively.

PCMs and conventional methods: Besides papers that addressed average-based models, the results from some other papers demonstrated the good performance of PCMs. PCMs take an individual person as the unit of analysis rather than populations or groups of people and use direct feedback from individuals and relevant data to train a model [51]. Shan et al. [29] showed that the prediction accuracy of a PCM was much higher than that of the PMV model when applied to individuals. Guenther and Sawodny [42] collected user feedback in daily working routines and developed a personalized comfort prediction model. Their results showed a 74% higher individual prediction accuracy compared to the standard PMV calculation. Similarly, the work conducted by Kim et al. [64] revealed that PCMs produced median accuracy up to 0.73, improving the predictions of PMV and adaptive modes with a median accuracy of 0.51. In another study, Liu et al. [40] developed PCMs using lab grade wearable sensors in normal daily activities. The developed PCMs with long-term tracking of physiological and environmental data resulted in a median prediction power of 78% accuracy and 79% AUC, which was significantly greater than conventional PMV and adaptive model [40]. Rehman et al. [62] developed a PCM for air-conditioned buildings from ASHRAE RP-884 database with an accuracy of 85% in predicting thermal sensation votes. Lee and Ham [75] used wearable sensors and ML to continuously monitor and analyze individual physiological signals, activity-based metabolic rates and environmental parameters to develop a robust data-driven personalized model in consideration of human activity variations. In another study, a KNN-based thermal comfort model was developed to establish a personalized adaptive thermal comfort environment [89]. The test results of this work manifested that the accuracy of the KNN model with 1000 sets of training data could reach up to 88.31%. Alsaleem et al. [43] evaluated various supervised ML algorithms to produce accurate PCMs for 3 individuals. They also built a general model, the accuracy of which was less than the PCMs with accuracies up to 88%. By bringing more personal interest and data, personalised models may help researchers to better understand the internal links of personal factors, such as psychology, physiology and behavioural ones [50]. Thus, this almost new paradigm has become one of the promising research trends in thermal comfort studies.

ML methods, indoor thermal conditions and energy consumption: Since one of the main goals for analyzing thermal perception is to adjust indoor thermal conditions, some studies trained and evaluated ML methods for this purpose. For example, Peng et al. [39] used ML to present a control strategy with learning capabilities to make cooling systems adapt to occupant temperature preferences under dynamic contexts comprising of indoor and outdoor conditions as well as occupant behavior. Their results showed that the active learning-based control reduced the need for occupant interventions in adjusting room temperatures to fit their preferences. Furthermore, a 4-25% reduction was reported in cooling energy demand. Valladares [70] proposed a deep reinforcement learning algorithm to maintain thermal comfort and air quality within optimal levels while consuming the least amount of energy from air-conditioning units and ventilation fans. Their proposed agent had 10% lower CO_2 levels than the current control system while consuming about 4–5% less energy. In another study [73] with the similar purpose of optimization, a Model Predicitve Control (MPC) system with an adaptive ML-based model for building automation and control applications was proposed, which reduced 58.5% of cooling thermal energy consumption in an office and 36.7% of cooling electricity consumption in a lecture theatre, as compared to their respective original controls [73]. Yu et al. [88] also developed a control algorithm for optimization of energy consumption of air-conditioning and exhaust fans through Deep Q-Learning. Their results showed that the deep learning agent offered energy saving up to 43% when compared with the air-conditioning with a fixed temperature of 25°C. On average, the energy-saving with this agent was about 19%, yet the corresponding CO_2 level was reduced by about 24% with the presence of agent control. Lu et al. [34] conducted a data-driven simulation of comfort-based temperature set-point control system with tabular Q-learning. Their results revealed that the best recall of the statistical thermal comfort model was 49.3%, which outperformed that of PMV being 43%. Furthermore, with the implementation of reinforcement learning controller, the thermal comfort-based controller could control the set-point to the optimal state with any start state after a certain number of episodes for training. Similarly, Han et al. [74] proposed a reinforcement learning method for the advanced control of window opening and closing to optimize its time point. Their results demonstrated that the RL control strategy improved thermal and indoor air quality by more than 90% when compared with the actual historically observed occupant data.

ML performance and physiological parameters: The performance of ML models can be impacted by input parameters, which are assumed to affect the output parameter. According to table 3, some studies used outdoor/indoor environmental and basic personal parameters. However, thermoregulation is the result of complex mechanisms that are modulated by mutual interactions between the sympathetic nervous system and the parasympathetic nervous system [93], which indicates the importance of physiological parameters. Thus, some recent studies have focused on physiological parameters. As an example, Chaudhuri et al. [44] presented a model, which used skin temperature of the area between the wrist and the fingers on the dorsal side of the hand, the gradient of skin temperature, body surface area and clothing insulation to evaluate thermal state. Their results showed that the model based on normalized skin features accurately predicted 87% of thermal states. In a similar study, the possibility to predict human thermal state from physiological parameters (hand skin temperature, hand skin conductance, pulse rate, blood oxygen saturation, and blood pressure) was investigated by using RF [83]. The results from this study manifested that physiological features exhibited the potential to indicate thermal state. Dai et al. [80] also used skin temperatures as the only input to an intelligent control model based on SVM. Their results demonstrated that using a single skin temperature correctly predicted 80% of thermal demands and using combined skin temperatures from different body segments could improve the model to over 90% accuracy. In addition to individual and environmental parameters, Du et al. [84] used skin temperature of nine different body parts to identify the main impacting factors for a localized airflow system and predict a cooling performance based on ML, with the results showing a prediction performance up to 83.99%. Jung et al. [46] investigated the performance of personal thermal comfort inference using classification algorithms. Their results indicated that when air temperature was used as the sole feature, a median accuracy of 42.6% was observed across all the models, which was drastically improved up to 97% when adding heat exchange rate as another feature. The results of another study revealed that physiological quantities could be used to estimate TSV with mean MAE and MAPE values that reached up to 1.4 and 24%, respectively [93]. Moreover, Liu et al. [56] developed a SVM model to predict the cool discomfort, comfort, and warm discomfort in outdoor environments using local skin temperatures and thermal load as inputs. Their results showed that when using single local skin temperature as input, the skin temperature of exposed body parts exhibited the highest prediction accuracy (66%–70%). The review by Vellei, et al. has suggested that skin temperature represents the most important physiological variable affecting thermal perception in the indoor built environment, with 70% of the reviewed studies having measured skin temperature and 39% of them having monitored the body core temperature as physiological parameters [97]. As wearable sensors such as multiparametric chest belts, smartwatches and smart bands need to represent a good trade-off between accuracy, intrusiveness and user acceptance [93], this review recommends future studies focus more on wearable sensors, their comfort and user acceptance to improve the performance of ML models.

Table 5 shows the performance of ML models in mathematical formats to make the comparison of their performance with other models possible. Table 5 suggests that ML models could outperform PMV models with up to 35.9% higher accuracy and even adaptive methods with up to 31% higher accuracy [63]. On the other hand, PCMs could outperform PMV models with up to 74% higher accuracy [42]. Applying ML-based control schemas reduced thermal comfort-related energy consumption in buildings up to 58.5% [73], while improving indoor quality up to 90% [74] and reducing CO_2 levels up to 24% [88]. Moreover, using physiological parameters improved the prediction accuracy of PCMs up to 97% [46].

Table 5. Performance of ML models.

	Study	Performance
ML models and conventional methods	[18]	$R^2_{ANN} = 0.799 + R^2_{PMV}$ or R^2_{ePMV}
		$R^2_{ANN} = 0.833 + R^2_{aPMV}$
		$R^2_{SVM} = 0.524 + R^2_{PMV}$ or R^2_{ePMV}
		$R^2_{ANN} = 0.558 + R^2_{aPMV}$
	[35]	Accuracy $_{ML}$ = 15.7-31.46% + Accuracy $_{PMV}$
		Accuracy $_{ML}$ = 11.39-19.45% + Accuracy $_{ePMV}$
		Accuracy $_{ML}$ = 37.63-45.69 % + Accuracy $_{aPMV}$
	[26]	SSE $_{SVM}$ = SSE $_{PMV}$ – 96.4%
		Fitting degree $_{SVM}$ = 83.7% + Fitting degree $_{PMV}$
	[63]	**CV mean accuracy $_{BNN}$ = 35.9% + CV mean accuracy $_{PMV}$**
		CV mean accuracy $_{BNN}$ = 31% + CV mean accuracy $_{Adaptive}$
	[49]	Performance $_{\text{intelligent thermal comfort neural network}}$ = 13.1-17.8% + Performance $_{PMV}$
	[57]	Accuracy $_{ELM}$ = 93.54% > Accuracy $_{\text{GP or ANN}}$
	[25]	(Field study) Accuracy $_{RF}$ = 24.9% + Accuracy $_{PMV}$
		(Lab study) Accuracy $_{RF}$ = 76.7%
	[92]	Accuracy $_{ML}$ = 94% , Precision $_{ML}$ = and 98% and Recall = 97%.
	[29]	Mean accuracy $_{PCM}$ = 89.2% >> Accuracy $_{PMV}$

PCMs and conventional methods		Mean MAE $_{PCM}$ = 0.16 and Mean MSE $_{PCM}$ = 0.06
	[42]	**Accuracy $_{PCM}$ = 74% + Accuracy $_{PMV}$**
	[64]	Accuracy $_{PCM}$ = 22% + Accuracy $_{PMV\ or\ Adaptive}$
	[40]	Median Cohen's kappa $_{PCM}$ = 74%, Median accuracy $_{PCM}$ = 78% and Median AUC $_{PCM}$ = 79% >> Cohen's kappa, Accuracy and AUC $_{PMV\ or\ Adaptive}$
	[62]	Accuracy $_{PCM}$ = 85%
	[89]	Accuracy $_{PCM}$ = 88.31%
	[43]	Accuracy $_{PCM}$ = 88% > Accuracy $_{General\ model}$
ML methods, indoor thermal conditions and energy consumption	[39]	Occupant interventions $_{Active\ learning\text{-}based\ control}$ < Occupant interventions $_{Current\ control}$ Cooling energy demand $_{Active\ learning\text{-}based\ control}$ = Cooling energy demand $_{Current\ control}$ – 4-25%
	[70]	CO_2 level $_{RL\ control}$ = CO_2 level $_{Current\ control}$ – 10% Energy consumption $_{RL\ control}$ = Energy consumption $_{Current\ control}$ – 4-5%
	[73]	**(Office) Cooling thermal energy consumption $_{ML\ control}$ = Cooling thermal energy consumption $_{Current\ control}$ – 58.5%** (Lecture theatre) Cooling electricity consumption $_{ML\ control}$ = Cooling electricity consumption $_{Current\ control}$ – 36.7%
	[88]	Energy consumption $_{RL\ control}$ = Energy consumption $_{Current\ control}$ – 19% (On average) **CO_2 level $_{RL\ control}$ = CO_2 level $_{Current\ control}$ – 24%**
	[34]	Recall $_{RL}$ = 6.3% + Recall $_{PMV}$ Set-point= Optimal state
	[74]	Thermal and indoor air quality $_{RL}$ = 90% + Thermal and indoor air quality $_{Current\ state}$
ML performance and physiological parameters	[44]	Accuracy $_{ML\ with\ normalized\ skin\ features}$ = 87%
	[83]	(Males) Accuracy $_{RF\ with\ physiological\ parameters}$ = 92.86% (Females) Accuracy $_{RF\ with\ physiological\ parameters}$ = 94.29%
	[80]	Accuracy $_{SVM\ with\ a\ single\ skin\ temperature}$ = 80% Accuracy $_{SVM\ with\ combined\ skin\ temperatures}$ ≥ 90%
	[84]	Accuracy $_{ML\ with\ skin\ temperatures}$ ≤ 83.99%
	[46]	**Median accuracy $_{ML\ with\ air\ temperature\ and\ heat\ exchange\ rate}$ = 97% = 54.4% + Median accuracy $_{ML\ with\ air\ temperature}$**
	[93]	MAE $_{ML\ with\ physiological\ parameters}$ ≤ 1.4 MAPE $_{ML\ with\ physiological\ parameters}$ ≤ 24%
	[56]	Accuracy $_{ML\ with\ skin\ temperatures\ of\ exposed\ body\ parts}$ = 66-70%
***Description:**		

Example 1: "$R^2_{ANN} = 0.799 + R^2_{PMV}$ or R^2_{Epmv}" means R^2 value of ANN is equal to R^2 value of PMV or ePMV models plus 0.799
Example 2: "Accuracy $_{ELM}$ = 93.54% > Accuracy $_{GP\ or\ ANN}$" means Accuracy of ELM is equal to 93.54% which is higher than accuracy of GP or ANN

4.6 Challenges of ML Models

In a recent review study, Khalil et al. [68] concluded that ML model selection, data privacy and security, and Federated Learning are the major challenges in the field of thermal comfort IoT data analytics. More comprehensively, the present review introduces some challenges relating to the process of all ML applications in thermal comfort studies.

- **Data collection:** There are 3 main approaches for data collection. Data can be collected through field studies, which indicate occupants' real conditions. However, controlling or measuring all of the potential affecting parameters can be a real challenge in this approach. In contrast, it is more feasible to control or limit affecting parameters in climate chambers. However, they do not represent naturally ventilated spaces and real-life conditions. On the other hand, the third approach (data generation) is to use data from simulated conditions, instead of real ones. For example, Eslamirad et al. [58] used ENVI-Met simulation to generate 8,000 samples to evaluate thermal comfort conditions in green sidewalks, from which 2,268 samples were selected for training their ML model to predict PMV values. However, simulation requires determining several input features, which are in many cases based on premises and can increase the risk of the performance gap between the model and real conditions. Moreover, simulating a large number of various options can be time-consuming. To mitigate the gap, the study by Xiong and Yao [89] has used combinations of simulated and field data. In this study, they collected real environmental parameters by the means of an artificial intelligent environmental controller. However, instead of real TSV, simulation was used to calculate PMV values which were considered as the output parameter (thermal perception indices). Thus, future studies are recommended to systematically compare data collection approaches due to study objectives, implementation challenges and solutions.
- **Thermal comfort indices:** A basic issue in thermal comfort study, is selecting a thermal perception metric. TSV has been the most used metric, however, TPV can be more associated with occupants' actions and consequently, energy consumption. Thus, future studies are

recommended to investigate both of these metrics, their relationships with input parameters and with each other.

- **Occupants' Responses:** In the case of supervised learning, occupants' responses (output values) are used as ground truth data. Once a ML algorithm is trained, its' prediction is compared with the real reported thermal responses in terms of evaluation metrics. When the prediction of an algorithm is close to the real occupants' responses, its performance is better. Time scale of asking occupants' thermal conditions is an important issue to prevent intrusion and tedium, while providing enough data to train ML models. As a solution to this matter, during a climate chamber study, Morresi et al. [93] asked the participants to express their TSV whenever there was a change in it, instead of collecting TSV with a specific frequency. However, the main limitation of this solution is that in real life, responders may forget to report their thermal perception. Thus, there seems to be a lack of knowledge in time scaling area, which is recommended to be further investigated.
- **Sample size:** To build a model with good generalization performance with proper processing and convergence time, determining the optimum sample size is another challenge, which is recommended to be the focus of future studies to bridge the gap in this area.
- **Feature selection:** Another consideration is selecting the right input parameters (conducting feature conditioning), which is important to prevent wasting time and energy on collecting inessential parameters and to less disturb occupants'. Therefore, many of the reviewed studies emphasized feature selection, since the optimization of input parameters not only increases the model accuracy but also makes the evaluation process easier. Future studies are recommended to consider contextual, psychological and architectural parameters as well to provide a more comprehensive feature selection process.
- **Model selection:** Since ML provides a range of various algorithms to work with, it's essential to choose proper ones in line with the objectives of the study. White-box models (such as NB, KNN, DT) generate an explicit expression that relates the environmental parameters with comfort levels, hence, one of their main advantages is that they are interpretable. However, comfort level is subjective and depends on many factors, which may not be learned by white-box these models. Different from the white-box methods, which rely crucially on the feature selection process, the black-box approaches can automatically learn the inherent coupling among different features [49]. Thus, some of the high qualified models for handling complex

problems are black-box models, such as SVM, ANN and ensemble learning methods, however, these models are not easily interpretable. In addition, they may be time-consuming, which can be a challenge for real ML applications in buildings. Therefore, researchers can adopt and evaluate ML models, in terms of their predictive performance, their complexities to work with, and their time and computational cost.

- **Real world application:** It is important to address both thermal comfort and energy consumption simultaneously to control energy consumption without compromising thermal comfort. As thermal comfort is a complex subject and interacts with many factors, further studies are recommended to investigate its interaction with other comfort aspects and energy consumption.

5. Conclusion

The use of ML models is growing in many scientific fields, such as thermal comfort studies due to their capabilities to handle complex and non-linear problems. To provide an insight into the role of ML techniques in recent thermal comfort investigations, 60 papers, published from 2016 to 2021 were systematically reviewed. The review was classified into several sub-sections: overall schema, data collection, study context, parameters, methods, challenges of ML models and their application. The main conclusions are summarized as below:

- Most of the reviewed studies (62%) focused on developing group-based comfort models, while 35% focused on PCMs. Since PCMs account for individual differences and present high prediction performances, they are recommended to be further studied.
- The most used tools for building ML were Matlab, Python and R due to their strong statistical analysis power and their user-friendly environments, which can assist researchers in tool selection.
- The most frequently used algorithms among the reviewed papers were SVM, ANN and Ensemble Learning (mainly RF), followed by Tree-Based models and Regression methods (mainly LoR) due to their abilities to handle complex problems.
- The most frequently used metrics for performance evaluation were accuracy, R^2, RMSE, MSE, and r, which appeared in 50%, 23%, 20%, 18%, and 15% of the papers, respectively. Future studies are recommended to consider both fitting and error metrics for model evaluation.
- ML models could outperform PMV and adaptive models with up to 35.9% and 31% higher accuracy and PCMs could outperform PMV models with up to 74% higher accuracy. Applying

ML-based control schemas reduced thermal comfort-related energy consumption in buildings up to 58.5%, while improving indoor quality up to 90% and reducing CO_2 levels up to 24%. Moreover, using physiological parameters improved the prediction accuracy of PCMs up to 97%.

6. Future Studies

To suggest research gaps in this area, major recommendations for future studies are summarized as below:

- Study contexts were reviewed in terms of regions, seasons, building types, and building operation modes. The review over regions suggests that regions, such as Russia, Southern America, Africa and the Middle East are less investigated and need to be further investigated. Due to the high frequency of previous studies in summer, future studies are recommended to investigate other seasons, especially winter due to its heating demand. The review over building types indicates that further studies need to focus on educational buildings and hospitals. As the most investigated building operation mode was HVAC, future studies are recommended to further investigate naturally ventilated buildings.
- Future studies are recommended to investigate the impacts of architectural and spatial features on thermal comfort, which can help architects and building designers in creating more comfortable and energy-efficient buildings. Moreover, future studies are recommended to further investigate the application of ML in outdoor thermal comfort studies.
- Physiological parameters directly indicate thermal conditions and their measurement with wearable sensors needs to represent a good trade-off between accuracy, intrusiveness and user acceptance. Therefore, it is interesting to investigate how wearable sensors can be developed in future research studies and industry to provide a high level of accuracy without disturbing users.
- In terms of ML algorithms, since optimization can be used to reduce energy consumption without compromising occupants' thermal comfort, algorithms such as Firefly algorithms, GP, and PSO are recommended to be further investigated.

7. References

[1] R. Zhao, S. Sun, R. Ding, Conditioning strategies of indoor thermal environment in warm climates, in:

Energy and Buildings, Elsevier, 2004: pp. 1281–1286. https://doi.org/10.1016/j.enbuild.2003.07.002.

[2] ASHRAE, ASHRAE Standard 55:1992 Thermal environmental conditions for human occupancy, ASHRAE Standard ; 55-1992. 19 (1992) 17.

[3] P.O. Fanger, Thermal comfort. Analysis and applications in environmental engineering., Copenhagen: Danish Technical Press, 1970.

[4] K. Karyono, B.M. Abdullah, A.J. Cotgrave, A. Bras, The adaptive thermal comfort review from the 1920s, the present, and the future, Developments in the Built Environment. 4 (2020) 100032. https://doi.org/10.1016/j.dibe.2020.100032.

[5] Q. Zhao, Z. Lian, D. Lai, Thermal comfort models and their developments: A review, Energy and Built Environment. 2 (2021) 21–33. https://doi.org/10.1016/j.enbenv.2020.05.007.

[6] M. Tahsildoost, Z.S. Zomorodian, Indoor environment quality assessment in classrooms: An integrated approach, Journal of Building Physics. 42 (2018) 336–362. https://doi.org/10.1177/1744259118759687.

[7] P.O. Fanger, FUNDAMENTALS OF THERMAL COMFORT, in: Advances In Solar Energy Technology, Elsevier, 1988: pp. 3056–3061. https://doi.org/10.1016/b978-0-08-034315-0.50562-0.

[8] J. Toftum, A.S. Jørgensen, P.O. Fanger, Upper limits of air humidity for preventing warm respiratory discomfort, Energy and Buildings. 28 (1998) 15–23. https://doi.org/10.1016/S0378-7788(97)00018-2.

[9] P. Ole Fanger, J. Toftum, Extension of the PMV model to non-air-conditioned buildings in warm climates, in: Energy and Buildings, Elsevier, 2002: pp. 533–536. https://doi.org/10.1016/S0378-7788(02)00003-8.

[10] N. Sirhan, S. Golan, Efficient PMV computation for public environments with transient populations, Energy and Buildings. (2020) 110523. https://doi.org/10.1016/j.enbuild.2020.110523.

[11] J. Wu, X. Li, Y. Lin, Y. Yan, J. Tu, A PMV-based HVAC control strategy for office rooms subjected to solar radiation, Building and Environment. 177 (2020) 106863. https://doi.org/10.1016/j.buildenv.2020.106863.

[12] A.A.W. Hawila, A. Merabtine, M. Chemkhi, R. Bennacer, N. Troussier, An analysis of the impact of PMV-based thermal comfort control during heating period: A case study of highly glazed room, Journal of Building Engineering. 20 (2018) 353–366. https://doi.org/10.1016/j.jobe.2018.08.010.

[13] P. Li, T. Parkinson, S. Schiavon, T.M. Froese, R. de Dear, A. Rysanek, S. Staub-French, Improved long-term thermal comfort indices for continuous monitoring, Energy and Buildings. 224 (2020) 110270. https://doi.org/10.1016/j.enbuild.2020.110270.

[14] H. Ikeda, T. Nakaya, A. Nakagawa, M. Yoshihiro, An investigation of indoor thermal environment in semi-cold region in Japan – Validity of thermal predictive indices in Nagano during the summer season, Journal of Building Engineering. (2020) 101897. https://doi.org/10.1016/j.jobe.2020.101897.

[15] D. Enescu, A review of thermal comfort models and indicators for indoor environments, Renewable and Sustainable Energy Reviews. 79 (2017) 1353–1379. https://doi.org/10.1016/j.rser.2017.05.175.

[16] H. Yun, I. Nam, J. Kim, J. Yang, K. Lee, J. Sohn, A field study of thermal comfort for kindergarten children in korea: An assessment of existing models and preferences of children, Building and Environment. 75 (2014) 182–189. https://doi.org/10.1016/j.buildenv.2014.02.003.

[17] T. Cheung, S. Schiavon, T. Parkinson, P. Li, G. Brager, Analysis of the accuracy on PMV – PPD model using the ASHRAE Global Thermal Comfort Database II, Building and Environment. 153 (2019) 205–217. https://doi.org/10.1016/j.buildenv.2019.01.055.

[18] Q. Chai, H. Wang, Y. Zhai, L. Yang, Using machine learning algorithms to predict occupants' thermal comfort in naturally ventilated residential buildings, Energy and Buildings. 217 (2020) 109937. https://doi.org/10.1016/j.enbuild.2020.109937.

[19] S.K. Sansaniwal, J. Mathur, S. Mathur, Review of practices for human thermal comfort in buildings: present and future perspectives, International Journal of Ambient Energy. (2020). https://doi.org/10.1080/01430750.2020.1725629.

[20] R. de Dear, J. Xiong, J. Kim, B. Cao, A review of adaptive thermal comfort research since 1998, Energy and Buildings. 214 (2020) 109893. https://doi.org/10.1016/j.enbuild.2020.109893.

[21] J. Malik, R. Bardhan, P. Banerji, Rethinking indoor thermal comfort in the era of rebound and pre-bound effect for the developing world: A systematic review, Indoor Air. 30 (2020) 377–395. https://doi.org/10.1111/ina.12664.

[22] R.T. Hellwig, D. Teli, M. Schweiker, J.H. Choi, M.C.J. Lee, R. Mora, R. Rawal, Z. Wang, F. Al-Atrash, A framework for adopting adaptive thermal comfort principles in design and operation of buildings, Energy and Buildings. 205 (2019) 109476. https://doi.org/10.1016/j.enbuild.2019.109476.

[23] M.A. Ortiz, S.R. Kurvers, P.M. Bluyssen, A review of comfort, health, and energy use: Understanding daily energy use and wellbeing for the development of a new approach to study comfort, Energy and Buildings. 152 (2017) 323–335. https://doi.org/10.1016/j.enbuild.2017.07.060.

[24] J. Ngarambe, G.Y. Yun, M. Santamouris, The use of artificial intelligence (AI) methods in the prediction of thermal comfort in buildings: energy implications of AI-based thermal comfort controls, Energy and Buildings. 211 (2020) 109807. https://doi.org/10.1016/j.enbuild.2020.109807.

[25] Z. Wang, H. Yu, M. Luo, Z. Wang, H. Zhang, Y. Jiao, Predicting older people's thermal sensation in building environment through a machine learning approach: Modelling, interpretation, and application, Building and Environment. 161 (2019) 106231. https://doi.org/10.1016/j.buildenv.2019.106231.

[26] X. Zhou, L. Xu, J. Zhang, B. Niu, M. Luo, G. Zhou, X. Zhang, Data-driven thermal comfort model via support vector machine algorithms: Insights from ASHRAE RP-884 database, Energy and Buildings. 211 (2020) 109795. https://doi.org/10.1016/j.enbuild.2020.109795.

[27] Z. Wang, J. Liu, Y. Zhang, H. Yuan, R. Zhang, R.S. Srinivasan, Practical issues in implementing machine-learning models for building energy efficiency: Moving beyond obstacles, Renewable and Sustainable Energy Reviews. 143 (2021). https://doi.org/10.1016/j.rser.2021.110929.

[28] M. Luo, J. Xie, Y. Yan, Z. Ke, P. Yu, Z. Wang, J. Zhang, Comparing machine learning algorithms in predicting thermal sensation using ASHRAE Comfort Database II, Energy and Buildings. 210 (2020) 109776. https://doi.org/10.1016/j.enbuild.2020.109776.

[29] C. Shan, J. Hu, J. Wu, A. Zhang, G. Ding, L.X. Xu, Towards non-intrusive and high accuracy prediction of personal thermal comfort using a few sensitive physiological parameters, Energy and Buildings. 207 (2020)

109594. https://doi.org/10.1016/j.enbuild.2019.109594.
[30] N. Ma, D. Aviv, H. Guo, W.W. Braham, Measuring the right factors: A review of variables and models for thermal comfort and indoor air quality, Renewable and Sustainable Energy Reviews. 135 (2021) 110436. https://doi.org/10.1016/j.rser.2020.110436.
[31] J. Xie, H. Li, C. Li, J. Zhang, M. Luo, Review on occupant-centric thermal comfort sensing, predicting, and controlling, Energy and Buildings. 226 (2020) 110392. https://doi.org/10.1016/j.enbuild.2020.110392.
[32] A. Ghahramani, P. Galicia, D. Lehrer, Z. Varghese, Z. Wang, Y. Pandit, Artificial Intelligence for Efficient Thermal Comfort Systems: Requirements, Current Applications and Future Directions, Frontiers in Built Environment. 6 (2020). https://doi.org/10.3389/fbuil.2020.00049.
[33] M. Han, R. May, X. Zhang, X. Wang, S. Pan, D. Yan, Y. Jin, L. Xu, A review of reinforcement learning methodologies for controlling occupant comfort in buildings, Sustainable Cities and Society. 51 (2019) 101748. https://doi.org/10.1016/j.scs.2019.101748.
[34] S. Lu, W. Wang, C. Lin, E.C. Hameen, Data-driven simulation of a thermal comfort-based temperature set-point control with ASHRAE RP884, Building and Environment. 156 (2019) 137–146. https://doi.org/10.1016/j.buildenv.2019.03.010.
[35] 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, Institute of Electrical and Electronics Engineers Inc., 2017: pp. 72–77. https://doi.org/10.1109/ICSGSC.2017.8038552.
[36] S. Lee, I. Bilionis, P. Karava, A. Tzempelikos, A Bayesian approach for probabilistic classification and inference of occupant thermal preferences in office buildings, Building and Environment. 118 (2017) 323–343. https://doi.org/10.1016/j.buildenv.2017.03.009.
[37] Z. Deng, Q. Chen, Artificial neural network models using thermal sensations and occupants' behavior for predicting thermal comfort, Energy and Buildings. 174 (2018) 587–602. https://doi.org/10.1016/j.enbuild.2018.06.060.
[38] L. Jiang, R. Yao, Modelling personal thermal sensations using C-Support Vector Classification (C-SVC) algorithm, Building and Environment. 99 (2016) 98–106. https://doi.org/10.1016/j.buildenv.2016.01.022.
[39] Y. Peng, Z. Nagy, A. Schlüter, Temperature-preference learning with neural networks for occupant-centric building indoor climate controls, Building and Environment. 154 (2019) 296–308. https://doi.org/10.1016/j.buildenv.2019.01.036.
[40] S. Liu, S. Schiavon, H.P. Das, M. Jin, C.J. Spanos, Personal thermal comfort models with wearable sensors, Building and Environment. 162 (2019) 106281. https://doi.org/10.1016/j.buildenv.2019.106281.
[41] B. Huchuk, S. Sanner, W. O'Brien, Comparison of machine learning models for occupancy prediction in residential buildings using connected thermostat data, Building and Environment. 160 (2019) 106177. https://doi.org/10.1016/j.buildenv.2019.106177.
[42] J. Guenther, O. Sawodny, Feature selection and Gaussian Process regression for personalized thermal comfort prediction, Building and Environment. 148 (2019) 448–458.

https://doi.org/10.1016/j.buildenv.2018.11.019.

[43] F. Alsaleem, M.K. Tesfay, M. Rafaie, K. Sinkar, D. Besarla, P. Arunasalam, An IoT Framework for Modeling and Controlling Thermal Comfort in Buildings, Frontiers in Built Environment. 6 (2020) 1–14. https://doi.org/10.3389/fbuil.2020.00087.

[44] T. Chaudhuri, D. Zhai, Y.C. Soh, H. Li, L. Xie, Thermal comfort prediction using normalized skin temperature in a uniform built environment, Energy and Buildings. 159 (2018) 426–440. https://doi.org/10.1016/j.enbuild.2017.10.098.

[45] T. Chaudhuri, Y.C. Soh, H. Li, L. Xie, A feedforward neural network based indoor-climate control framework for thermal comfort and energy saving in buildings, Applied Energy. 248 (2019) 44–53. https://doi.org/10.1016/j.apenergy.2019.04.065.

[46] W. Jung, F. Jazizadeh, T.E. Diller, Heat flux sensing for machine-learning-based personal thermal comfort modeling, Sensors (Switzerland). 19 (2019). https://doi.org/10.3390/s19173691.

[47] F. Salamone, A. Bellazzi, L. Belussi, G. Damato, L. Danza, F. Dell'aquila, M. Ghellere, V. Megale, I. Meroni, W. Vitaletti, Evaluation of the visual stimuli on personal thermal comfort perception in real and virtual environments using machine learning approaches, Sensors (Switzerland). 20 (2020). https://doi.org/10.3390/s20061627.

[48] M. Al-Faris, J. Chiverton, D. Ndzi, A.I. Ahmed, Vision based dynamic thermal comfort control using fuzzy logic and deep learning, Applied Sciences (Switzerland). 11 (2021) 1–17. https://doi.org/10.3390/app11104626.

[49] W. Hu, Y. Wen, K. Guan, G. Jin, K.J. Tseng, iTCM : Towards Learning-Based Thermal Comfort Modeling via Pervasive Sensing for Smart Buildings, IEEE Internet of Things Journal. PP (2018) 1. https://doi.org/10.1109/JIOT.2018.2861831.

[50] Y. Zhao, K. Carter, F. Wang, O. Uduku, D. Murray-Rust, Self-learning framework for personalised thermal comfort model, Proceedings of 10th Windsor Conference: Rethinking Comfort. (2018) 923–934.

[51] J. Kim, S. Schiavon, G. Brager, Personal comfort models – A new paradigm in thermal comfort for occupant-centric environmental control, Building and Environment. 132 (2018) 114–124. https://doi.org/10.1016/j.buildenv.2018.01.023.

[52] S.M. Sajjadian, M. Jafari, D. Pekaslan, An Expandable, Contextualized and Data-Driven Indoor Thermal Comfort Model, Energy and Built Environment. 1 (2020) 385–392. https://doi.org/10.1016/j.enbenv.2020.04.005.

[53] V. Földváry Ličina, T. Cheung, H. Zhang, R. de Dear, T. Parkinson, E. Arens, C. Chun, S. Schiavon, M. Luo, G. Brager, P. Li, S. Kaam, M.A. Adebamowo, M.M. Andamon, F. Babich, C. Bouden, H. Bukovianska, C. Candido, B. Cao, S. Carlucci, D.K.W. Cheong, J.H. Choi, M. Cook, P. Cropper, M. Deuble, S. Heidari, M. Indraganti, Q. Jin, H. Kim, J. Kim, K. Konis, M.K. Singh, A. Kwok, R. Lamberts, D. Loveday, J. Langevin, S. Manu, C. Moosmann, F. Nicol, R. Ooka, N.A. Oseland, L. Pagliano, D. Petráš, R. Rawal, R. Romero, H.B. Rijal, C. Sekhar, M. Schweiker, F. Tartarini, S. ichi Tanabe, K.W. Tham, D. Teli, J. Toftum, L. Toledo, K. Tsuzuki, R. De Vecchi, A. Wagner, Z. Wang, H. Wallbaum, L. Webb, L. Yang, Y.

Zhu, Y. Zhai, Y. Zhang, X. Zhou, Development of the ASHRAE Global Thermal Comfort Database II, Building and Environment. 142 (2018) 502–512. https://doi.org/10.1016/j.buildenv.2018.06.022.

[54] (PDF) Developing an Adaptive Model of Thermal Comfort and Preference - Final Report on RP-884., (n.d.).

[55] I. Mladenović, S. Sokolov-Mladenović, M. Milovančević, D. Marković, N. Simeunović, Management and estimation of thermal comfort, carbon dioxide emission and economic growth by support vector machine, Renewable and Sustainable Energy Reviews. 64 (2016) 466–476. https://doi.org/10.1016/j.rser.2016.06.034.

[56] K. Liu, T. Nie, W. Liu, Y. Liu, D. Lai, A machine learning approach to predict outdoor thermal comfort using local skin temperatures, Sustainable Cities and Society. 59 (2020) 102216. https://doi.org/10.1016/j.scs.2020.102216.

[57] S. Kariminia, S. Shamshirband, S. Motamedi, R. Hashim, C. Roy, A systematic extreme learning machine approach to analyze visitors' thermal comfort at a public urban space, Renewable and Sustainable Energy Reviews. 58 (2016) 751–760. https://doi.org/10.1016/j.rser.2015.12.321.

[58] N. Eslamirad, S. Malekpour Kolbadinejad, M. Mahdavinejad, M. Mehranrad, Thermal comfort prediction by applying supervised machine learning in green sidewalks of Tehran, Smart and Sustainable Built Environment. 9 (2020) 361–374. https://doi.org/10.1108/SASBE-03-2019-0028.

[59] Z. Wang, T. Hong, Learning occupants' indoor comfort temperature through a Bayesian inference approach for office buildings in United States, Renewable and Sustainable Energy Reviews. 119 (2020) 109593. https://doi.org/10.1016/j.rser.2019.109593.

[60] Z. Wang, J. Wang, Y. He, Y. Liu, B. Lin, T. Hong, Dimension analysis of subjective thermal comfort metrics based on ASHRAE Global Thermal Comfort Database using machine learning, Journal of Building Engineering. 29 (2020) 101120. https://doi.org/10.1016/j.jobe.2019.101120.

[61] Z. Wang, T. Parkinson, P. Li, B. Lin, T. Hong, The Squeaky wheel: Machine learning for anomaly detection in subjective thermal comfort votes, Building and Environment. 151 (2019) 219–227. https://doi.org/10.1016/j.buildenv.2019.01.050.

[62] S.U. Rehman, A.R. Javed, M.U. Khan, M. Nazar Awan, A. Farukh, A. Hussien, PersonalisedComfort: a personalised thermal comfort model to predict thermal sensation votes for smart building residents, Enterprise Information Systems. 00 (2020) 1–23. https://doi.org/10.1080/17517575.2020.1852316.

[63] N. Ma, L. Chen, J. Hu, P. Perdikaris, W.W. Braham, Adaptive behavior and different thermal experiences of real people : A Bayesian neural network approach to thermal preference prediction and classification, Building and Environment. 198 (2021) 107875. https://doi.org/10.1016/j.buildenv.2021.107875.

[64] J. Kim, Y. Zhou, S. Schiavon, P. Raftery, G. Brager, Personal comfort models: Predicting individuals' thermal preference using occupant heating and cooling behavior and machine learning, Building and Environment. 129 (2018) 96–106. https://doi.org/10.1016/j.buildenv.2017.12.011.

[65] S.S. Shetty, D.C. Hoang, M. Gupta, S.K. Panda, Learning desk fan usage preferences for personalised thermal comfort in shared offices using tree-based methods, Building and Environment. 149 (2019) 546–560. https://doi.org/10.1016/j.buildenv.2018.12.040.

[66] K. Katić, R. Li, W. Zeiler, Machine learning algorithms applied to a prediction of personal overall thermal

comfort using skin temperatures and occupants’ heating behavior, Applied Ergonomics. 85 (2020) 103078. https://doi.org/10.1016/j.apergo.2020.103078.

[67] F. Salamone, L. Belussi, C. Currò, L. Danza, M. Ghellere, G. Guazzi, B. Lenzi, V. Megale, I. Meroni, Application of IoT and Machine Learning techniques for the assessment of thermal comfort perception., Energy Procedia. 148 (2018) 798–805. https://doi.org/10.1016/j.egypro.2018.08.130.

[68] M. Khalil, M. Esseghir, L. Merghem-Boulahia, Applying IoT and Data Analytics to Thermal Comfort: A Review, Studies in Computational Intelligence. 971 (2021) 171–198. https://doi.org/10.1007/978-3-030-72065-0_10.

[69] D. Azuatalam, W.-L. Lee, F. de Nijs, A. Liebman, Reinforcement learning for whole-building HVAC control and demand response, Energy and AI. 2 (2020) 100020. https://doi.org/10.1016/j.egyai.2020.100020.

[70] W. Valladares, M. Galindo, J. Gutiérrez, W.C. Wu, K.K. Liao, J.C. Liao, K.C. Lu, C.C. Wang, Energy optimization associated with thermal comfort and indoor air control via a deep reinforcement learning algorithm, Building and Environment. 155 (2019) 105–117. https://doi.org/10.1016/j.buildenv.2019.03.038.

[71] M. Ayoub, A review on machine learning algorithms to predict daylighting inside buildings, Solar Energy. 202 (2020) 249–275. https://doi.org/10.1016/j.solener.2020.03.104.

[72] Y. Long, S. Liu, L. Xie, K.H. Johansson, A scenario-based distributed stochastic MPC for building temperature regulation, in: IEEE International Conference on Automation Science and Engineering, IEEE Computer Society, 2014: pp. 1091–1096. https://doi.org/10.1109/CoASE.2014.6899461.

[73] S. Yang, M.P. Wan, W. Chen, B.F. Ng, S. Dubey, Model predictive control with adaptive machine-learning-based model for building energy efficiency and comfort optimization, Applied Energy. 271 (2020) 115147. https://doi.org/10.1016/j.apenergy.2020.115147.

[74] M. Han, R. May, X. Zhang, X. Wang, S. Pan, Y. Da, Y. Jin, A novel reinforcement learning method for improving occupant comfort via window opening and closing, Sustainable Cities and Society. 61 (2020) 102247. https://doi.org/10.1016/j.scs.2020.102247.

[75] J. Lee, Y. Ham, Physiological sensing-driven personal thermal comfort modelling in consideration of human activity variations, Building Research and Information. 49 (2021) 512–524. https://doi.org/10.1080/09613218.2020.1840328.

[76] D. Zhai, Y.C. Soh, Balancing indoor thermal comfort and energy consumption of ACMV systems via sparse swarm algorithms in optimizations, Energy and Buildings. 149 (2017) 1–15. https://doi.org/10.1016/j.enbuild.2017.05.019.

[77] D. Palladino, I. Nardi, C. Buratti, Artificial Neural Network for the Thermal Comfort Index Prediction: Development of a New Simplified Algorithm, Energies. 13 (2020) 1–27.

[78] I. Pigliautile, S. Casaccia, N. Morresi, M. Arnesano, A.L. Pisello, G.M. Revel, Assessing occupants’ personal attributes in relation to human perception of environmental comfort: Measurement procedure and data analysis, Building and Environment. 177 (2020) 106901. https://doi.org/10.1016/j.buildenv.2020.106901.

[79] Z. Wu, N. Li, J. Peng, H. Cui, P. Liu, H. Li, X. Li, Using an ensemble machine learning methodology-Bagging to predict occupants' thermal comfort in buildings, Elsevier B.V., 2018. https://doi.org/10.1016/j.enbuild.2018.05.031.

[80] C. Dai, H. Zhang, E. Arens, Z. Lian, Machine learning approaches to predict thermal demands using skin temperatures: Steady-state conditions, Building and Environment. 114 (2017) 1–10. https://doi.org/10.1016/j.buildenv.2016.12.005.

[81] A.C. Cosma, R. Simha, Machine learning method for real-time non-invasive prediction of individual thermal preference in transient conditions, Building and Environment. 148 (2019) 372–383. https://doi.org/10.1016/j.buildenv.2018.11.017.

[82] X. Shan, E.H. Yang, Supervised machine learning of thermal comfort under different indoor temperatures using EEG measurements, Energy and Buildings. 225 (2020) 110305. https://doi.org/10.1016/j.enbuild.2020.110305.

[83] T. Chaudhuri, D. Zhai, Y.C. Soh, H. Li, L. Xie, Random forest based thermal comfort prediction from gender-specific physiological parameters using wearable sensing technology, Energy and Buildings. 166 (2018) 391–406. https://doi.org/10.1016/j.enbuild.2018.02.035.

[84] C. Du, B. Li, H. Liu, Y. Ji, R. Yao, W. Yu, Quantification of personal thermal comfort with localized airflow system based on sensitivity analysis and classification tree model, Energy and Buildings. 194 (2019) 1–11. https://doi.org/10.1016/j.enbuild.2019.04.010.

[85] V.J.L. Gan, H. Luo, Y. Tan, M. Deng, H.L. Kwok, Bim and data-driven predictive analysis of optimum thermal comfort for indoor environment, Sensors. 21 (2021). https://doi.org/10.3390/s21134401.

[86] F. Salamone, L. Belussi, C. Currò, L. Danza, M. Ghellere, G. Guazzi, B. Lenzi, V. Megale, I. Meroni, Integrated method for personal thermal comfort assessment and optimization through users' feedback, IoT and machine learning: A case study, Sensors (Switzerland). 18 (2018). https://doi.org/10.3390/s18051602.

[87] H.A. Dyvia1, C. Arif, Analysis of thermal comfort with predicted mean vote (PMV) index using artificial neural network, IOP Conference Series: Earth and Environmental Science. 622 (2021). https://doi.org/10.1088/1755-1315/622/1/012019.

[88] K.H. Yu, Y.A. Chen, E. Jaimes, W.C. Wu, K.K. Liao, J.C. Liao, K.C. Lu, W.J. Sheu, C.C. Wang, Optimization of thermal comfort, indoor quality, and energy-saving in campus classroom through deep Q learning, Case Studies in Thermal Engineering. 24 (2021) 100842. https://doi.org/10.1016/j.csite.2021.100842.

[89] L. Xiong, Y. Yao, Study on an adaptive thermal comfort model with K-nearest-neighbors (KNN) algorithm, Building and Environment. 202 (2021) 108026. https://doi.org/10.1016/j.buildenv.2021.108026.

[90] O.E. Taylor, P.S. Ezekiel, V.T. Emmah, Smart System for Thermal Comfort Prediction on Residential Buildings Using Data-Driven Model with Random Forest Classifier, 5 (2021).

[91] J. Zhang, H. Liu, Y. Wu, S. Zhou, M. Liu, Neural network-based thermal comfort prediction for the elderly, E3S Web of Conferences. 237 (2021) 02022. https://doi.org/10.1051/e3sconf/202123702022.

[92] B. Brik, M. Esseghir, L. Merghem-Boulahia, H. Snoussi, An IoT-based deep learning approach to analyse

indoor thermal comfort of disabled people, Building and Environment. 203 (2021) 108056. https://doi.org/10.1016/j.buildenv.2021.108056.

[93] N. Morresi, S. Casaccia, M. Sorcinelli, M. Arnesano, A. Uriarte, J.I. Torrens-Galdiz, G.M. Revel, Sensing physiological and environmental quantities to measure human thermal comfort through machine learning techniques, IEEE Sensors Journal. 21 (2021) 12322–12337. https://doi.org/10.1109/JSEN.2021.3064707.

[94] S. Fathi, R. Srinivasan, A. Fenner, S. Fathi, Machine learning applications in urban building energy performance forecasting: A systematic review, Renewable and Sustainable Energy Reviews. 133 (2020) 110287. https://doi.org/10.1016/j.rser.2020.110287.

[95] Z. Liu, D. Wu, Y. Liu, Z. Han, L. Lun, J. Gao, G. Jin, G. Cao, Accuracy analyses and model comparison of machine learning adopted in building energy consumption prediction, Energy Exploration & Exploitation. 37 (2019) 1426–1451. https://doi.org/10.1177/0144598718822400.

[96] S. Seyedzadeh, F.P. Rahimian, I. Glesk, M. Roper, Machine learning for estimation of building energy consumption and performance: a review, Visualization in Engineering. 6 (2018). https://doi.org/10.1186/s40327-018-0064-7.

[97] M. Vellei, R. de Dear, C. Inard, O. Jay, Dynamic thermal perception: A review and agenda for future experimental research, Building and Environment. 205 (2021) 108269. https://doi.org/10.1016/j.buildenv.2021.108269.