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Review

A Review of Different Methodologies to Study Occupant Comfort and Energy Consumption

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Abstract: The goal of this work is to give a full review of how machine learning (ML) is used in thermal comfort studies, highlight the most recent techniques and findings, and lay out a plan for future research. Most of the researchers focus on developing models related to thermal comfort prediction. However, only a few works look at the current state of adaptive thermal comfort studies and the ways in which it could save energy. This study showed that using ML control schemas to make buildings more comfortable in terms of temperature could cut energy by more than 27%. Finally, this paper identifies the remaining difficulties in using ML in thermal comfort investigations, including data collection, thermal comfort indices, sample size, feature selection, model selection, and real-world application.

Keywords: thermal comfort; thermal sensation; machine learning; energy saving

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1. Introduction

Energy usage in buildings is on the rise, and this is a primary global concern. HVAC (heating, ventilation, and air-conditioning) systems use a significant amount of energy, approximately 40% of the total building energy. Therefore, buildings have the potential to reduce their energy use by 20–30% while still utilizing existing building components [1].

Furthermore, most of the population spends 90% of their time indoors [2]. As a result, determining thermal comfort is critical [3]. A person's satisfaction with assessing their internal temperature environment refers to their thermal comfort [4]. It expresses how satisfied one is with the temperature. Thermal comfort is directly related to air temperature, radiant temperature, relative humidity, air speed, metabolic rate, and clothing insulation [5]. Therefore, any changes in these factors may affect how comfortable people feel in their bodies [6]. People can work more effectively when they are thermally at ease. This definition indicates that comfort comprises different mental factors and is affected by many physiological, physical, and other processes [7].

Previous occupant-centered control technologies optimized an HVAC schedule with occupant behavior, such as occupant presence and movement, occupancy patterns, and energy consumption patterns. For instance, a study proposed occupancy schedule-based HVAC scheduling to set appropriate indoor temperatures during unoccupied hours [8]. Another study developed an indoor environment control methodology that recognizes occupant activities, which could improve HVAC system energy efficiency [9]. Accordingly, creating more intelligent and effective HVAC system control strategies is essential to reduce building energy consumption while maintaining indoor thermal comfort. Thus, reducing the amount of energy used in buildings can reduce the overall energy consumed and the environmental problems that come with it. The occupant comfort model helps achieve a part of the goal, which lets buildings use the predicted occupant comfort value as the control standard for heating and cooling. This methodology saves energy and makes buildings more comfortable for the people who live or work there.

Personal comfort models have been made using different methods, such as input variables and feature selection. Even though there is no doubt that the field has grown, it still needs a more thorough and critical analysis of the similarities and differences between the different parts of predictive modeling. In addition, it is primary to identifying approaches for boosting energy productivity while maintaining comfort levels.

1.1. Previous Literature Reviews

Owing to the rise in studies on predicting thermal comfort, there is a need for a complete and critical analysis of all the approaches in this field. The review articles on occupant thermal comfort are summarized in Table 1. Despite the high quality of these studies, there is still a need for a review paper that focuses on different methodologies to study occupant comfort and energy consumption. On the one hand, some of these articles focused on a single aspect. For instance, the literature investigation showed that researchers focused on different issues, adopting diverse models and indices to investigate thermal comfort in classrooms for children only [10,11]. In addition, a review highlights studies related to hospitals [12]. Furthermore, an article discusses passive solar systems with a focus on African countries [13]. As a result, these review papers provided a general overview of previously published articles in this field, with little emphasis on identifying the strengths and limitations of the methodologies for all aspects. Furthermore, some papers were published three years ago, and a relatively large number of research papers have been published in this field since then and these need to be reviewed [14–17]. This growing trend emphasizes the importance of a current review article that explores the most recent methods.

Table 1. Comparison of previous literature reviews.

	Year	Years of Reviewed Papers	Focus
[14]	2020	2005–2019	Investigating the use of artificial intelligence (AI) in optimizing indoor thermal comfort systems: examining the necessary requirements, current uses, and potential advancements.
[15]	2020	2010–2020	A study of occupant-focused thermal comfort sensing, prediction, and control techniques.
[16]	2020	2005–2019	An analysis of the impact of AI on thermal comfort and energy consumption in buildings: a review of current practices and future possibilities.
[17]	2020	1968–2020	A review of thermal comfort in hospital settings.
[10]	2021	1969–2020	Innovations in thermal comfort for educational facilities: current challenges and prospects for the future.
[12]	2021	2007–2020	A study of thermal comfort and energy efficiency in public hospitals in tropical climates: a review of natural ventilation methods.
[11]	2022	1972–2021	An examination of ML techniques for improving thermal comfort in primary schools: current challenges and future directions.
[13]	2022	1970–2022	A study of the impact of passive solar systems on thermal comfort in Africa.

1.2. Novelty, Aim, and Objectives

This paper intends to highlight the application of ML to thermal comfort studies and identify its dataset, features, related methods, performance, and challenges by reviewing the most recent research studies in this area. The study's specific goals are as follows:

- The main categories of ML models in thermal comfort studies are introduced;
- Investigating ML practices in thermal comfort studies, focusing on sample sizes, tools, algorithms, and performance metrics;
- Identifying the features of ML models;
- Examining the performance of ML models compared to traditional models;
- Summarizing studies regarding energy consumption;
- Discussion of ML models in thermal comfort studies to provide a road map for future research.

This review summarizes articles about thermal comfort models and energy use, focusing on recent work. First, Section 2 focuses on the methodology of existing research in the field. Afterward, Section 3 explores datasets, feature selection, and methodologies for ML models for predicting thermal comfort. Then, in Section 4, there is a summary of current research that applies to energy consumption. Finally, before concluding in Section 6, an overview is provided in Section 5, along with challenges and recommendations for future research.

2. Methodology

With the help of the well-known database Scopus, a bibliometric analysis was performed to keep track of research in thermal comfort analytics. The following query was entered into Scopus: "thermal AND comfort AND energy AND consumption". The Scopus collection has 1377 publications from 2010 to 2022, while review papers were excluded.

Only recent papers were studied in the following sections.

2.1. Year of Publication

The articles related to thermal comfort and energy consumption are first grouped by the year they were published. Recent research trends in thermal comfort and energy use can be seen. According to Figure 1, the number of publications that have been searched for has increased significantly since 2010, ranging from 15 in 2010 to 255 in 2022. In general, people are starting to give more attention to the quality of the environment inside their homes because the economy is overgrowing, and people are becoming more concerned about their health and well-being.

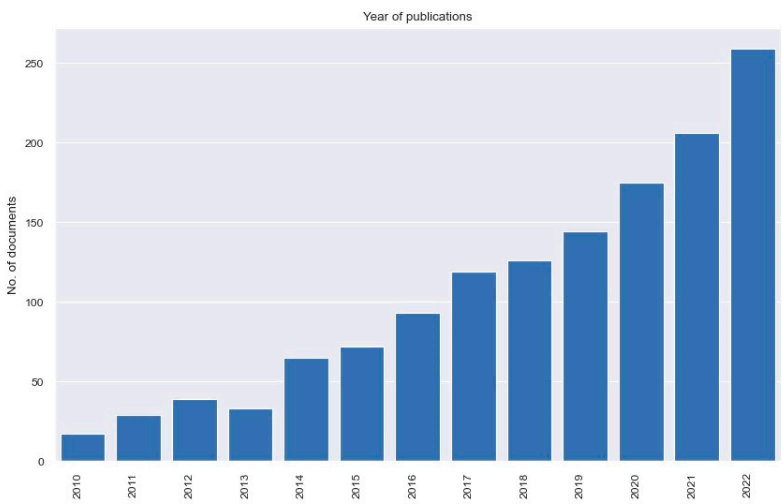

Figure 1. The number of published papers related to thermal comfort and energy consumption during the years 2010 to 2022.

2.2. Journal of Publication

As shown in Figure 2, the fifteen relevant journals are rated and summarized based on the number of papers published. It is clear that "*Energy and Buildings*", which has the most published articles, comes in first, followed by "*Building and Environment*", which has approximately 110 articles. In addition, "*Applied Energy*" has approximately 90 articles, and "*Energies*" has more than 75 articles, etc. Most of the time, the first top ten journals are the best places to find necessary information because they are closely related to the topic of this study. This can further represent society's concern for indoor environmental quality.

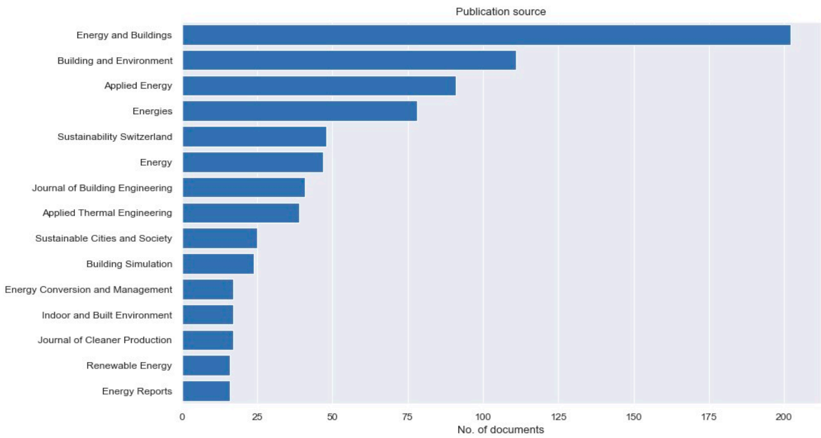

Figure 2. The number of published papers by journal titles.

3. Personal Thermal Comfort Prediction

3.1. Thermal Comfort Datasets

Most research data are either self-collected or derived from publicly available datasets. ASHRAE Global Thermal Comfort Database II is the most common public database used [18–21]. It is an open-source database with about 81,846 complete sets of objective indoor climate observations and subjective "right-here, right-now" ratings by the people who live or work in the building [22]. Another public database used is the Scales Project, which was made from surveys in 21 diverse languages on the thermal perception scales. Surveys were performed in 57 cities in 30 different countries and 8225 participants filled out questionnaires [23]. After cleaning the datasets, nearly half of the publications have sizes that are below 1000 data points. The study that had 286 data points is the smallest dataset [24]. The study that had 172,800 data points had the most extensive dataset [19]. As shown in Table 2, there is a different range of subject ages. Some research focuses on the elderly, while others have an average age between 20 and 35. As a consequence, depending on the need, gender might be an essential feature to be included in the input parameters of the model.

The number of people who participated in the studies ranged from 3 to 55. More than half of the studies included up to 20 individuals. For the self-collected data, the most prolonged duration was between 2006 and 2016, which was performed by filling out questionnaires [25]. One hundred fifty minutes is the shortest duration that the data were collected. This can be partly explained by the limitations in the processes of thermal comfort data collection, such as long monitoring intervals or relatively intrusive data collection tools and people less willing to participate in such scenarios.

A large number of data are required for the ML model. Furthermore, datasets are required to develop more robust prediction models with no technical bias, such as overfitting. These are two of the biggest problems with developing thermal comfort models. The proposed method of research uses the augmented dataset to generate synthetic labels based on occupant heating and cooling behavior and develop personal comfort models for each occupant. The article suggests using cluster analysis to find groups of people with similar comfort levels to solve this problem. It was accomplished so that the distance between them could be measured and grouped based on their preferences. A small number of clusters were discovered using data from a field study with 37 subjects. Each cluster had one or more participants corresponding to the same thermal preferences. Then, a group comfort model was trained using data from individuals in each cluster. Various ensemble learning methods were used to combine these pre-trained group comfort models [26]. An alternative study used the ensemble transfer learning (TL) method to overcome the poor generalization performance that resulted from insufficient datasets for each targeted subject [27]. Another paper proposed a hybrid deep-transfer learning-based thermal comfort model, which is a transfer learning-based convolutional neural network with long short-term memory (TL CNN-LSTM). It overcomes the challenges associated with modeling data inadequacy and class imbalance [20].

Table 2. Comparison of previous research on thermal comfort datasets.

	Data Source	Number of Samples	Number of Subjects	Duration	Age
[25]	Self-collected data	5081	-	Between 2006 and 2016	From 10 to 85 years with a mean of 35.5
[28]	ASHRAE Global Thermal Comfort Database II	31,057	-	Between 1979 and 2018	-
[18]	ASHRAE Global Thermal Comfort Database II	15,357	-	Between 1979 and 2018	From 16 to 95 years
[29]	Self-collected data	23,271	7	22 November to 7 December	Average age of 28.71 years
[27]	Self-collected data	5870	3	18 days	Approximately 30
[30]	Self-collected data	751	32	150 min	16 young: 23.6 ± 0.8, 16 elderly: 64.0 ± 4.9.
[20]	ASHRAE, SCALES Project, Self-collected data	ASHRAE: 20,340; SCALES Project: 2091, Self-collected data: 2063	-	-	<20, 21–30, 31–40, and 40+
[21]	Self-collected data	1000	34	From 22 July to 15 August in 2020; from 6 January to 19 March in 2021	-
[24]	Self-collected data	286	3	-	-
[31]	Self-collected data	-	11	9 months and two weeks	Between 66 and 85
[32]	Self-collected data	-	30	-	Female: 27.3 ± 3.7, Male: 29.3 ± 2.4
[33]	Self-collected data	942	55	-	Between 18 and 30 years old
[34]	Self-collected data	-	20	-	Between 21 and 39
[26]	Researcher study	4743	37	12 weeks	-
[19]	Self-collected data	172,800	10	6 months	25 years old

3.2. Prediction of Thermal Comfort Model Based on ML

3.2.1. Predicted Mean Vote (PMV)

PMV, a famous thermal comfort model based on heat balance equations, is frequently used to determine the thermal satisfaction within a group of people. PMV was proposed in 1970 by Fanger, a Danish professor [35]. Human comfort is divided into a 7-point thermal sensation scale by the PMV index: −3, −2, −1, 0, +1, +2, +3: "cold", "cool", "slightly cool", "neutral", "slightly warm", "warm", and "hot" [36]. Additionally, the PPD (predicted percentage of dissatisfied), produced as a function of the PMV index, quantifies the proportion of thermally dissatisfied individuals in an environment. The ideal indoor temperature is established when PPD is less than 10%, which leads to an energy-use PMV index between −0.5 and 0.5 [37]. The first research on occupant comfort was done using the PMV-PPD model. Probability analysis was used to measure the relationship between PMV and PPD. The essential parts of this model are two groups of variables that affect both the environment and the occupants. It considers six factors in total. Environmental factors include air temperature, mean radiant temperature, relative humidity, and air speed. Occupant factors include metabolic rate and clothing insulation [35]. On the other hand, such a study does have some limitations. Its main goal is to determine the average comfort level for a large group without considering individual differences. This could be more effective in predicting people's comfort levels in particular buildings, such as a home office. In recent years, cultural, social, and personal factors have also affected thermal comfort [4]. This suggests that thermal comfort has more to do with a person's feelings than with a particular set of objects. In addition, ML algorithms reduce prediction error by at least 25% compared to the PMV method, achieving a maximum accuracy of approximately 70% on a 7-value scale and more than 85% on a 3-value scale [38].

3.2.2. ML Methods

As illustrated in Figure 3, there are three types of learning techniques. Their descriptions are listed below.

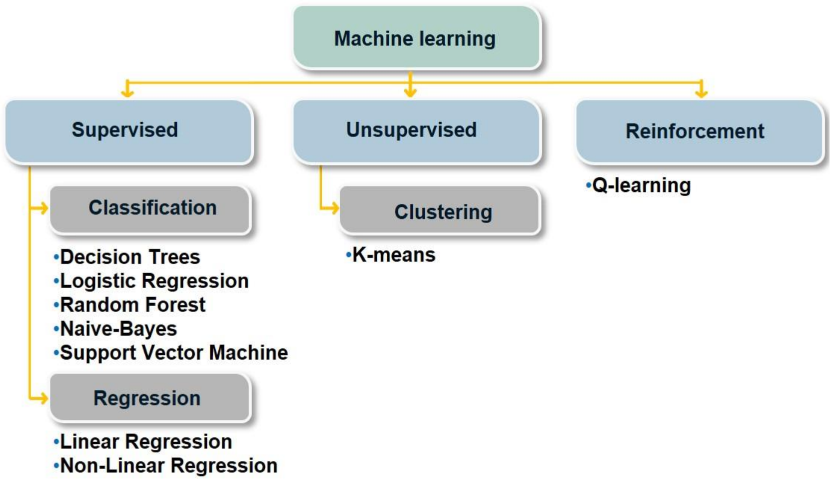

Figure 3. Types of ML.

- Supervised learning is a type of ML in which the data given to the machine are already labeled. The initial dataset is divided into two parts: training data and test data. The test dataset is used to assess the machine's efficiency and accuracy following training. As a result, supervised learning can be divided into two major learning tasks: regression and classification.
- Unsupervised learning is used to group the dataset into clusters when the records data are not well labeled and the number of output classes is unknown.
- Reinforcement learning (RL) is unsupervised learning in which the system must learn the desired outcome. Unlike supervised and unsupervised learning, RL does not seek to discover categories, reconstruct the system model, or uncover hidden structures. RL, on the other hand, seeks to make decisions and find the best solution possible given the inputs. It is composed of decision-making agents that can be single or multiple. The learner agent interacts with the environment, earning rewards and incurring penalties due to the agent's actions. The agent in a closed-loop system strives to maximize the

benefits. If the system's decision is correct, a reward is given; otherwise, the system is penalized.

3.2.3. Features Selection

Concerning the model input features used in the studies, research consistently investigates potential individual differences affecting thermal comfort. As shown in Figure 4, the input features are simply classified into two categories: human and environmental. Consequently, thermal comfort was predicted using environmental features such as air temperature, relative humidity, mean radiant temperature, and air velocity. Furthermore, outdoor environmental parameters such as temperature and humidity were considered, as they have physiological effects on individual thermal perception. Each individual perceives the same environment differently because the thermal sensation is a subjective response to the thermal environment. As a result, for thermal comfort modeling, personal parameters such as clothing insulation, age, gender, and metabolic rate were taken into account. On the other hand, personal factors could be explored further using physiological sensing, especially given the rapid advances in wearable sensor technologies that are currently available. Human factors such as skin temperature, blood pressure, blood glucose, salivary cortisol, and heart rate were the parameters receiving the most focus.

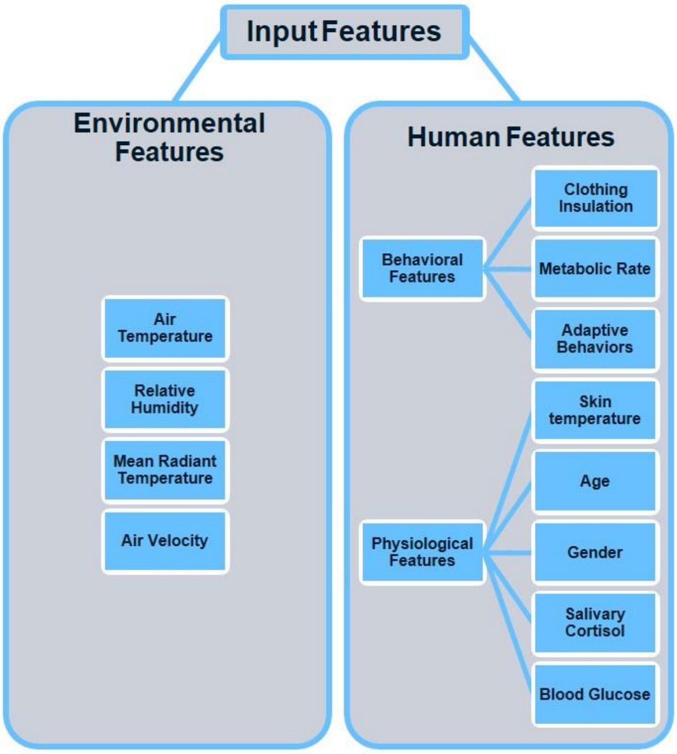

Figure 4. Input features for thermal comfort prediction models.

The model is more accurate in choosing the most critical factors and removing the unnecessary and irrelevant ones since it improves the algorithms' prediction results. The feature importance of each variable was calculated in [18] by using the random forest (RF) and gradient boosting decision tree (GBDT) algorithms to identify the key parameters that influence individual thermal comfort. Deep neural networks (DNN) and one-dimensional convolutional neural network (1D CNN) are two widely used deep learning algorithms for low-dimensional feature extraction, which were used by the authors of [27]. The Boruta method of RF was first used in [30]. Then, to reduce the number of interactive predictors even further, they used K-nearest neighbor (KNN) to filter the initial features based on their contributions to improve the model's overall accuracy. In [34], the authors proposed gradient boosting (GB) to generate each feature's importance. Some studies extracted features by examining the impact of different feature set combinations on the performance of the thermal comfort model and selecting the best one [20,24].

3.2.4. Comparison of ML Models

Researchers are using ML algorithms to make prediction models for the PMV index. ML algorithms have recently been used to solve complex non-linear problems because they learn independently and find the best solutions quickly. The PMV model is often used to measure thermal comfort because it is based on many laboratory tests that do not account for individual comfort [35] and, in some cases, do not make everyone satisfied with the result [39]. Consequently, most of the literature ignores data from individual occupants. It uses the ML method to predict thermal comfort, but it needs to consider all occupants. Thus, there is less diversity among the occupants. The people who lived there were modeled as an "average group," which is more of a statistical idea than an actual person. It is important to remember that occupant comfort varies depending on age, gender, background, and other personal traits. So, data from individual occupant comfort surveys are used to make personal comfort models, which is why "personal comfort" is becoming more popular. In addition, according to the research results, the customized thermal sensation vote (TSV) model may have a 58.1% higher accuracy than the generalist model [29]. The studies that have been performed on the human comfort model mentioned above are summarized in Table 3 along with the input variables used, the comfort scales, the evaluation metrics, and the results for each algorithm.

Table 3. Comparison of previous research on prediction of individual comfort model based on ML.

	Features Used	Comfort Scale	Evaluation Metrics	Algorithms + Results
[27]	Blood Volume Pulse; Heart Rate; Electrodermal Activity; Skin Temperature; Indoor Temperature; Indoor Relative humidity.	3-point scale (Cool/Neutral/Warm)	Accuracy	SVM:95%; RF:93%.
[29]	Indoor Air Temperature; Indoor Relative Humidity; Clothing Insulation; Heart Rate.	7-point scale (Cold/Cool/Slightly Cool/Neutral/Slightly Warm/Warm/Hot)	Accuracy	GB: 88.2%; RF: 88.0%; ANN: 85.0%; DT: 84.4%; SVM: 51.2%.
[30]	Air Temperature Ramp Direction; Air Temperature; Infrared Forehead; Hand Temperatures; Age; Gender.	3-point scale (Cool/Normal/Warm)	Accuracy	KNN: 83.6%; RF: 73.0%; BT: 72.6%; SVM: 72.2%.
[24]	Indoor Temperature; Metabolic Rate; Heart Rate; Galvanic Skin Resistance; Skin Temperature.	3-point scale (Cool/Normal/Warm)	Accuracy	DT: 65.50%; GBDT: 65.60%; RF: 69.94%; SVM: 81.87%.
[19]	Indoor Ambient Temperature; Indoor Relative Humidity; Indoor Air Velocity; Mean Radiant Temperature; Clothing Level; Metabolic Rate; Time; Disability Type.	7-point scale (Cold/Cool/Slightly Cool/Neutral/Slightly Warm/Warm/Hot)	Accuracy	LRC: 55.5%; NBC: 49%; ANC: 94%; DTC: 46%.

Table 3. *Cont.*

	Features Used	Comfort Scale	Evaluation Metrics	Algorithms + Results
[25]	Outdoor Air Temperature; Outdoor Relative Humidity; Indoor Air Temperature; Indoor Relative Humidity; Air Velocity; Mean Radiant Temperature; Clothing Insulation; Metabolic Rate; Climate; Adaptive Control Measures.	7-point scale (Cold/Cool/Slightly Cool/Neutral/Slightly Warm/Warm/Hot)	Pearson's r	ANNs: 0.6984; SVM: 0.6780; PMV: 0.6387; aPMV: 0.6360; ePMV: 0.6387.
[28]	Outdoor Monthly Air Temperature; Indoor Air Temperature; Indoor Globe Temperature; Indoor Relative Humidity; Air Velocity; Standards Effective Temperature; Clothing Insulation; Metabolic Rate.	7-point scale (Cold/Cool/Slightly Cool/Neutral/Slightly Warm/Warm/Hot)	Accuracy	DNN: 78.01%; CNN: 77.21%; RF: 74.85%; SVC: 30.7%; DT: 61.91%; GB: 42.1%; K-Neighbors: 67.14%; PMV: 36%.
[18]	Indoor Air Temperature; Indoor Relative Humidity; Air Velocity; Clothing Insulation; Metabolic Rate; Height; Weight; Age; Gender.	3-point scale (Cooler /No Change/Warmer)	F1	DCF: 0.7447; RF: 0.7659; GBDT: 0.7356; XGBoost: 0.7408; DT: 0.6987; NB: 0.7200; LR: 0.7236; KNN: 0.7179; DNN: 0.6981; SVM: 0.7335.
[20]	Outdoor Air Temperature; Outdoor Relative Humidity; Indoor Air Temperature; Indoor Relative Humidity; Mean Radiant Temperature; Clothing Insulation; Metabolic Rate; Age; Gender.	5-point scale (Cold/Cool/Comfort/ Warm/Hot)	Accuracy	PMV-PPD: 52%; LSTM: 61%.
[21]	Indoor Air Temperature; Indoor Relative Humidity; Indoor Air Velocity; Mean Radiant Temperature; Clothing Insulation; Metabolic Rate; Time Stamp.	7-point scale (Cold/Cool/Slightly Cool/Neutral/Slightly Warm/Warm/Hot)	Accuracy	KNN: 88.31%.
[31]	Air Temperature Ramp Direction; Air Temperature; Infrared Forehead; Hand Temperatures; Age; Gender.	3-point scale (Cooler/ No Change/Warmer)	Accuracy	ANN: 66.72%.
[32]	Electrodermal Activity; Heart Rate; Blood Pressure; Blood Glucose; Salivary Cortisol; Skin Temperature.	3-point scale (Cold/ Comfort/Hot)	Accuracy	RF: 67.0%; GBM: 63.4%; ANN: 60.8%.

Table 3. *Cont.*

	Features Used	Comfort Scale	Evaluation Metrics	Algorithms + Results
[33]	Air Temperature; Relative Humidity; Facial Skin Temperature.	3-point scale (Cool/ Neutral/Warm)	Accuracy	KNN: 83.6%; ANN: 79.9%; SVM: 79.9%.
[34]	Air Temperature; Radian Mean Temperature; Carbon Dioxide Level; Relative Humidity; Heart Rate; Human Skin Temperature.	3-point scale (Cool/ Neutral/Warm)	Accuracy	GBM: 80.4%.
[26]	Room Air Flow; Room Heating–Cooling Setpoint; Room Temperature; Room Damper Position; Room Heating Output; Outdoor Air Temperature; Outdoor Air Temperature; Relative Humidity.	3-point scale (Cool/ No Change/Warm)	Accuracy	DNN: 63.53%; RF: 63.70%; LSTM: 70.41%.

During field tests, it was found that PMV predictions could be better, especially in buildings with natural ventilation. The authors of [25] gathered data from naturally ventilated residential structures in 14 Chinese cities. The ML model was fed information about the environment, individual parameters, types of climate, and adaptive control strategies. The expected squared difference between the parameter's predicted value and real values is referred to as the mean square error (MSE). The mean of the absolute difference between the expected value and the actual value is represented by the term mean absolute error (MAE). The anticipated performance of ML was validated using MSE and MAE. The predicted model's accuracy increases with decreasing MSE or MAE values. Thus, artificial neuron network (ANN) models predicted TSV with MSE 0.8179 and MAE values 0.7058 of less value than traditional thermal-balance-based models PMV, predicted mean votes with expectancy factor (ePMV), and adaptive predicted mean vote (aPMV). Unfortunately, the data were collected more during the summer, leading to more data being needed during the winter. The authors of [28] suggested using the DNN model after being tuned using the Bayesian technique, which predicted the thermal sensation of occupants with 78% accuracy. DNN outperformed convolutional neural network (CNN) by 77.21%, RF by 74.85%, support vector classification (SVC) by 30.7%, decision tree (DT) by 61.91%, GB by 42.1%, K-neighbors by 67.14%, and PMV by 36%. The accuracy is formed from the confusion matrix based on the number of predictions of thermal sensation classes. The formula below represents the calculation of the accuracy where TN stands for true negative and FN stands for false negative. Additionally, TP is for true positive as the number of positive samples predicted as positive samples, and FP is for false positive as the number of negative samples expected as positive samples. In other words, accuracy (1) is the number of outputs correctly classified divided by the total number of samples:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Four ensembles and six ML models predicted thermal preference performance. The outcomes of traditional ML had F1 values of 0.6987 for DT, 0.7200 for naive Bayes (NB), 0.7200 for logistic regression (LR), 0.7236 for KNN, 0.6981 for DNN, and 0.7335 for support vector machine (SVM). In addition, the four ensemble models showed that F1 values were 0.7447 for deep cascade forest (DCF), 0.7659 for RF, 0.7356 for GBDT, and 0.7408 for extreme gradient boosting (XGBoost). Using the Comfort Database, the ensemble learning models were better at predicting temperature preferences than the traditional models. The Comfort

Database was divided by season and type of building, and each dataset was used to train the model in turn. This showed how much the different environmental factors affected the predictions. For instance, the average weighted F1-score of DCF in the classroom was 0.8475, significantly higher than 0.7016 before division. DCF and RF were the best at predicting how people are satisfied by their temperatures compared to the other eight models [18]. To assess the performance of the prediction, the following metrics were chosen: precision, recall, F1-score, and weighted F1-score, where F1i is the F1-score of X in class i, and K is the total number of classes. Precision (2) is a valuable metric for highly unbalanced classes. It measures the proportion of accurately predicted classes to all other predictions for that class. Recall (3), like precision, is the ratio of correctly predicted classes to all other classes that do not belong to that class. It is also a good metric to use when the classes are imbalanced. The F1 score (4) is the harmonic average of precision and recall. It is used to choose between accuracy and recall, and it can lead to a tradeoff between the number of false positives and negatives a model has. The last one is the weighted F1-score (5), which is the sum of class F1-scores weighted by the class proportion. The following equations are used to define the four metrics:

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1\text{-}score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{4}$$

$$Weighted\ F1\text{-}score = \frac{1}{k} \sum_{i=1}^{k} \beta i \cdot F1_i \tag{5}$$

An analysis of [29] revealed that the personalized TSV prediction model using GB performed best, and that ensemble learning techniques such as random forest and GB integrate predictions from numerous decision trees, decreasing the chance of overfitting, thereby increasing accuracy. For instance, GB had 88.21% and RF had 87.97% accuracy. In [21], the authors proposed that the best option for creating an adaptive thermal comfort model is KNN because of its high classification efficiency and accuracy. The test results showed that the KNN model could fulfill practical demands and have an accuracy rate of up to 88.31% using 1000 training datasets. However, it needs a large number of data for training. Another study outlines an IoT strategy for effectively modeling and managing indoor comfort. A technique for gaining access to and using a wearable device to collect data to construct a personal thermal comfort model was provided during the model phase. Moreover, the effectiveness of several ML methods for modeling individual comfort was examined. With an accuracy of 81.87%, the results showed that the SVM algorithm performed the best. The accuracy of the other ML algorithms was 80.44% for GBDT, 65.50% for RF, and 81.87% for SVM [24].

Most of the research addresses the problem, which is the need for more data. Thus, in [27], a pre-trained model was made with the datasets and a combination of deep learning and ML methods. The ensemble TL approach was used to overcome the weak generalization performance that appeared when the dataset of each targeted subject was insufficient and was based on the pre-trained model. Additionally, it was found that the ensemble TL worked well for the application when fewer and less balanced datasets were used in the target domains. The TL, SVM, and RF models were developed to predict individual human comfort. The findings demonstrated that the proposed SVM model's accuracy was 95%. Furthermore, the authors of [26] proposed a method to identify individuals with similar comfort sensations by using clusters to circumvent the need for more data on an individual, which leads to low prediction accuracy. Then, they created a group of comfort models for each collection. Finally, those models were combined using ensemble methods, which resulted in a general thermal comfort model to predict the comfort of a new individual. LSTM is the algorithm that had the highest accuracy, with an average precision of 70.41%, compared to DNN and RF, which had 63.53% and 63.70%, respectively. A stacked ensemble and a mixture of experts were used as ensemble methods to combine the group models. In addition, they attain an average accuracy of 71.0% and 49.1% when six hours of training data are available, which is much higher than the LSTM-based personal comfort model with 42.5%. Moreover, for effective thermal comfort modeling that uses the spatiotemporal relations in the thermal comfort data, TL CNN-LSTM is proposed by the authors of [20]. The findings indicated that LSTM had a 56% accuracy rate with limited data in target buildings.

Some studies concentrate on developing personal comfort models to forecast the thermal needs of the elderly. For instance, the authors of [31] investigated the creation of an ANN model with an accuracy of 66.72%, an average Cohen's kappa of 50.08%, and an average area under the receiver operating characteristic curve (AUC) of 0.77. Compared to generalized approaches, this shows that individualized models, utilizing both environmental and personal characteristics, perform better at making predictions. In addition, half of the [30] study's participants were elderly, while the other half were young, taking both age groups into account. SVM, DT, KNN, discriminant analysis, and ensemble methods were some of the commonly used ML algorithms that were used to examine two different types of input data. The first type was the professional setting with ten predictors that included multiple personal features and high-accuracy skin temperatures (0.15 °C). The second type was the practice setting with five predictors that were easier to obtain and had infrared skin temperatures. Results showed that the accuracy of KNN was the highest, with a value of 83.6% for the professional setting.

Some researchers added new factors related to skin temperature that affected the thermal comfort prediction. Consequently, the study in [34] investigated the use of physiological data from human facial skin temperature. The human comfort model was created with help from the GB technique. According to the findings, the GB algorithm has an accuracy rate of 80.4%. In [33], the authors recommended using infrared pictures to monitor local skin temperature. LR, SVM, ANN, and RF were among the ML algorithms used in the proposed strategy. According to the findings, LR and RF had accuracy rates of 79.4%. Additionally, ANN and SVM had accuracy rates of 79.9%. Recently, wearable sensors for cortisol and blood glucose monitoring have been created, and the idea of including additional bio-signal elements has been suggested. Therefore, the research of [32] considered blood glucose and salivary cortisol when developing an enhanced thermal comfort prediction model, and its predictive abilities were compared to those of conventional models. The proposed ANN model's accuracy was 73.4%.

All previous models did not take into account disabilities. The authors of [19] developed a DNN model that achieved an accuracy of 94% due to the fact that people without disabilities and those with learning and neurological disabilities have different thermal sensations. People with disabilities may have difficulty expressing their thermal comfort. For cold and cool; slightly cool and warm; slightly cool and cold; and hot and slightly warm situations, these variances mainly exist between the PMVs.

4. Energy Consumption

Most of the previous research studies' future works aim to include their model in the design of learning-based HVAC management techniques. According to the International Energy Agency (IEA), peak electrical energy consumption in countries with low HVAC adoption will rise by about 45 percent by 2050 [40]. This high consumption raises questions about the equipment's control and energy efficiency. Therefore, this study strikes a balance between the two fundamental objectives of thermal comfort and energy savings. Furthermore, the aim is to explore how much additional energy can be saved while maintaining occupant comfort. Described below are papers that include the amount of energy saving while providing thermal comfort.

As for [29], the customized TSV prediction model successfully transmitted the temperature at which the predicted TSV fulfills 0 to the HVAC system. It predicted the TSV at each temperature based on its received data. The average value of all subjects was compared between the setpoint control, manual control, and the blockchain IoT temperature control system. The average energy usage for the manual control and blockchain IoT was 341.9 Wh and 249.4 Wh, respectively. Consequently, the suggested BIoT temperature management system demonstrated 33% of thermal comfort dissatisfaction reduction and consumed 27% less energy than the manual control.

The tradeoff between thermal comfort and energy consumption is resolved by the multi-objective optimization model in [41]. Four operating variables that have a major impact on thermal comfort and energy consumption are chosen as decision variables. The multi-objective whale optimization technique is then linked with ANN to optimize the decision variables. Sensitivity analysis was used to look at how decision variables varied. The experiment results demonstrate that the suggested ANN for thermal comfort and energy consumption performs well, with goodness-of-fit values of 98.83% and 98.25%, respectively. In comparison to the reference operation, the optimization model decreases energy consumption by 16.51% and increases thermal comfort by 49.06%.

The authors of [42] used a groundbreaking, side-by-side experimental methodology to measure the effectiveness of occupancy-based control in commercial buildings. Heating, ventilation, and air conditioning were included in the occupancy detection systems. Their detection precision and impact on energy conservation and thermal comfort were examined. With more than an 80% satisfaction rate, it was discovered that occupancy-based regulation could maintain good thermal comfort and perceived indoor air quality. Although the occupancy sensor's accuracy and the exterior environment's state affected the daily energy saving, the weekly averaged energy-saving ranged from 17 to 24%.

In [43], the authors presented two energy management controllers, the swarm optimization fuzzy Mamdani (SOFM) and swarm optimization fuzzy Sugeno (SOFS), for scheduling and controlling electric loads in a residential building with ten apartments. The building was assumed to have a single-family setup. The electric loads considered in this study were divided into two types: daily-used appliances and seasonally used appliances (air-conditioning systems). Two demand-side management strategies were used to manage both loads: load shifting and load curtailment. First, the load scheduling technique (binary particle swarm optimization) was applied to schedule the daily electric loads. On the other hand, the load curtailment strategy (fuzzy logic) was used to manage the load well for electric loads that are only used during certain times of the year. The input parameters for daily used electric loads were the number of appliances, time slots, power rating, length of the operation time, and utility price. In the case of seasonally used electric loads, the input parameters considered were initialized setpoints, user occupancy, price ratings, and indoor and outdoor temperatures. The output parameters considered for both types of loads were energy consumption, cost, peak-to-average ratio, and energy efficiency. SOFM outperformed existing and unscheduled approaches by up to 45% and 48% in terms of minimizing energy consumption and cost reduction.

A further study in [44] presents an intelligent energy management and energy consumption optimization model for residential homes that incorporate the comfort level of the occupants. The proposed system uses sensors and the IoT to control home appliances intelligently, considering both environmental parameters and the effects of environment-driven consumer body dynamics on energy consumption. A hybrid energy management system (EMS) was modeled, designed, and analyzed that incorporated environmental perturbations and consumer body biological shifts, such as blood flows in the skin, fat, muscle, and core layers. The system was designed to reduce energy consumption and costs while maintaining comfort. The results show that the proposed system can reduce energy consumption and energy costs in different environmental conditions, such as cold, mild, hot, and normal conditions.

An alternative study reported in [45] proposed an improved bat algorithm (BA) with exponential inertia weight for the optimization of indoor comfort level and energy consumption in smart homes. The algorithm aimed to find the optimal set of appliances that control temperature, illumination, and air quality in order to maximize comfort and minimize energy usage. The study found that the BA with exponential inertia weight performed significantly better than other variants of the algorithm and previous works using different optimization algorithms. The proposed algorithm can be incorporated into a smart home system to provide occupants with optimum comfort and energy consumption. However, future studies with more enormous datasets and actual validation in smart home demonstration laboratories are recommended.

Additionally, the authors of [46] developed a framework for predicting and optimizing indoor air quality (IAQ), thermal comfort, and energy consumption in HVAC systems. The study used a database of limited ventilation parameters obtained through computational fluid dynamics (CFD) simulation to establish relationships between ventilation parameters, spatial parameters, a heat source, and ventilation performance. The proposed framework uses a hybrid prediction model that combines the extreme learning machine (ELM) model with the grey wolf optimizer (GWO) algorithm to predict thermal comfort level and indoor air quality. Results show that the prediction accuracy of PMV and CO_2 can be improved by up to 25.46% and 23.03%, respectively. In addition, the study found that seating arrangement directly affects the indoor environment, and the proportion of different optimization objectives can be set depending on the situation. Overall, the proposed framework provides accurate prediction results for other locations under other ventilation conditions and can improve buildings' energy efficiency and indoor air quality. Additionally, the study shows that 14.34% of energy savings are achieved in the example used.

In [47], the authors compared the performance of occupancy-based model predictive control (MPC) to that of reactive control. Ground-truth occupancy data were collected using applications installed on users' phones and regular surveys completed by occupants. Prediction and control horizons for MPC were selected as 24 h and 1 h, respectively. Finally, they used a particle swarm optimization algorithm in a weighted optimization algorithm to find the temperature that optimized PMV and energy use. According to the results, MPC reduced energy consumption by up to 13.3%.

In [48], a multi-objective genetic algorithm was used to cut down on both system energy use and MissTime. First, their study used a Markov model and historical occupancy data from a single office to predict how offices would be used. Then, they used EnergyPlus to determine how well the proposed algorithm worked and found that, compared to a scheduled control, it improved thermal comfort by 50% and cut energy use by 2%. On the other hand, MissTime does not consider the difference between the actual room temperature and the temperature that is wanted in the optimization problem.

The proposed approaches in previous work were evaluated in terms of energy savings and thermal comfort, ignoring other performance indicators such as economics and peak-shifting criteria. To fill this void, the authors of [49] investigated the peak-shifting capability of zonal reactive thermostats in residential buildings. They found that, when compared to an always-on thermostat, these thermostats reduced peak demand and energy consumption by up to 34.7% and 38.7%, respectively.

Moreover, a research study in [50] performed a financial analysis to assess the economic benefits of reactive control. Always-on and programmable thermostats were used as starting points. They constructed a probability function using the American Time Use Survey [51] to include occupancy patterns in the development of the control strategy. They used random numbers between 0 and 1 to create occupancy profiles, which were then compared to the probability of occupancy in each time interval. They demonstrated that the reactive strategy saved 20% of the energy and had a payback period of less than a year.

5. Challenges and Recommendation for Future Work

Based on the literature review results, the use of ML to predict thermal comfort has grown significantly in recent years. According to the discussion of the preceding studies, the performance of the personal comfort model based on ML is outstanding. This proves the great potential of human comfort models based on ML. This study evaluated personal thermal comfort model prediction performance using various metrics. Even though some of the reviewed studies compared the accuracy of their predictions, it required a long time to compare the results of the different models from different studies because the thermal comfort scales were different. The standards define a seven-point thermal sensation rating scale used in some studies [52]. Others modified or developed new thermal sensation rating scales for various modeling purposes. A standard rating scale, like the standardized seven-point scale, should be used in future work on personal thermal comfort to make it easier and fairer to compare performance.

Most previous studies on analyzing feature importance focused on performance improvement due to different feature combinations, allowing the identification of the most helpful feature sets. Nevertheless, the other studies reviewed should have discussed the relative importance of the features. The interpretability of relative feature importance levels may aid in identifying major features influencing an individual's or specific model's prediction accuracy. Moreover, it is also possible to do feature interaction analyses to determine how different features affect thermal sensations compared to each other. In summary, future modeling of personal thermal comfort should include similarity calculations and the selection of similar cases, sensitivity to feature selections, and relative importance levels of selected features. This would show the importance of future personal thermal comfort studies that examine more individual or specific features.

It is important to have HVAC control systems that use less energy and make people feel more comfortable because the temperature affects productivity. Therefore, thermal comfort modeling is crucial for HVAC control and energy optimization. ML thermal comfort models have recently become more popular than Fanger's PMV models because they are more accurate and easier to use. On the other hand, the requirement for complete labeled thermal comfort data from the occupants presents a significant modeling challenge. Consequently, advanced models that maintain comfort while minimizing energy consumption have a bright future. Individual occupant diversity should be considered, and future models could include precise comfort measures as well as responses gathered via thermal-based data collection methods such as cameras and thermal comfort applications. Furthermore, gathering datasets of indoor environmental and individual features is sometimes unrealistic and challenging in terms of both collection time and cost. For this reason, future work must consider ML to solve this specific issue.

According to the vast majority of studies conducted on HVAC systems discussed in Section 4, certain aspects of the research might call for further investigation. These include energy consumption prediction models for various subsystems and demand management, which considers new methods based on accurate data to control the energy bill while still providing adequate comfort for the occupants. In addition, research into new ML methods and models of occupant behavior could have significant impact if carried out in the future.

6. Conclusions

In smart buildings, the thermal comfort for the people who live there and the energy consumption savings are the most interesting topics. IoT technology allows for the management and operation of smart buildings, increasing thermal comfort and energy efficiency. To control the innovative building environment, a thermal comfort model is used to find the best setpoint that gives the desired level of comfort while using less energy overall. Thermal comfort is difficult to define because it depends on the features of people and indoor environments. Collecting data on specific attributes and the indoor environment can also be challenging. More research is required to determine how varying degrees of feature quantity, type, and accuracy affect ML algorithm performance and the creation of the most reliable ML algorithms. Different aspects should be involved while building a model. Challenging tasks should be taken into consideration: extract the specific and required features, develop a pre-trained model based on extensive data using a public open-source dataset, build an IoT architecture system to collect time-series data, resolve the time consumption for training the model for each individual, and overcome the lack of a dataset. Moreover, the ML of the comfort models must be used to create future HVAC management strategies and investigate how much additional energy may be saved while maintaining occupant comfort and keeping the energy bill low.

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