IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received July 8, 2019, accepted August 13, 2019, date of publication August 26, 2019, date of current version September 6, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2937320

Human Comfort in Indoor Environment: A Review on Assessment Criteria, Data Collection and Data Analysis Methods

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This work was supported in part by the Delta Electronics Inc., and in part by the National Research Foundation (NRF) Singapore under the Corp Lab@University Scheme.

ABSTRACT Occupants' comfort perception about the indoor environment is closely linked to their health, wellbeing and productivity. Improvement of comfort level in office buildings has significant positive impacts on both employers and employees. Human comfort in indoor environment usually can be assessed in four aspects: thermal comfort, visual comfort, acoustic comfort and respiratory comfort. In this paper, we present a literature review on the previous research contributions towards studying various aspects of human comfort with a special focus on the respective assessment criteria, data collection methods and data analysis approaches employed by former studies. Previous review work has covered the fundamental concepts associated with human comfort. However, their studies mainly focus on thermal comfort and there is limited work that covers other aspects of comfort. Moreover, few of them discuss how the data is obtained, how to extract useful information from the data and how the data is analyzed. To fill up this gap, this paper conducts the survey from the data-driven point of view. Through the survey, we find that sensor technology has been widely used in the data collection for various types of comfort, while so far the machine learning approaches are mainly applied in the area of thermal comfort study. Finally, some potential future research areas are proposed based on the current status of the research work. The established knowledge in this paper would provide useful insights for engineers or researchers who embark on their research in this area.

INDEX TERMS Human comfort, thermal comfort, assessment criteria, data analysis method, sensor technology, machine learning.

I. INTRODUCTION

The health and wellbeing of employees is of a great concern to business. According to statistics, about 90% of the overall business operating cost is spent on staff cost including medical benefit paid for employee [1]. Therefore, promoting health and wellbeing at work not only contributes to employees' active engagement and improved productivity, but also leads to remarkable savings in operating cost for employers [2]. For these reasons, one of the requirements for green office building is to provide an acceptable indoor environmental quality (IEQ) in view that it has significant impact on occupant satisfaction, health, and productivity [3]–[8]. Poor IEQ may lead to increased medical cost resulted from the building-related health issues and has adverse effects on employees' work performance, whereas good IEQ demonstrates positive effect on the business in terms of improved recruitment, lower turnover rate and increased productivity [9].

Indoor environmental quality has direct link to indoor human comfort which is commonly assessed from four aspects namely thermal, visual, acoustic and respiratory comfort. The four types of human comfort and their respective dependent environmental factors are depicted in Fig. 1. A more detailed description is given as follows.

The associate editor coordinating the review of this article and approving it for publication was Kemal Polat.

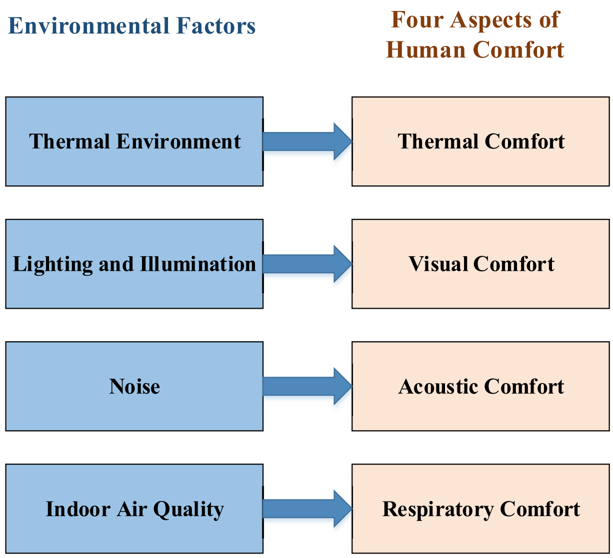

FIGURE 1. Relationship between environmental factors and human comfort in indoor environment.

- **Thermal Comfort** is used to describe "a condition of mind that expresses satisfaction with the thermal environment in which it is located" according to ISO Standard 7730 (1994) and ASHARE Standard 55 (2010) [10], [11]. ASHRAE is a professional association which makes thermal comfort standards and guidelines. Among different types of comfort, building occupants rank thermal comfort to be more important compared with visual, acoustic and respiratory comfort. It is reported having greater influence on an occupant's overall satisfaction with IEQ [12]. Another reason why thermal comfort is considered particularly important is the fact that the operation of HVAC (heating, ventilating and air conditioning) systems in buildings is mainly driven by thermal comfort. In developed countries, HVAC systems typically consume 50% of building energy use [13]. The above-mentioned reasons explain why thermal comfort has drawn more research interest and extensive research work has been conducted in this area.
- **Visual Comfort** is used to describe "the state of mind that expresses satisfaction with the visual environment" [14]. A good visual comfort ensures that people have sufficient light for the activities or tasks they are engaged in without exposing the eyes to a higher light level than which it can adapt to [10]. Either over-lighting or under-lighting will cause human visual discomfort.
- **Acoustic Comfort** refers to "the capacity to protect occupants from noise and offer an acoustic environment suitable for the purpose the building is designed for" [15], [16]. Acoustic comfort in buildings is an essential factor for ensuring the wellbeing of building occupants and better work performance.
- **Respiratory Comfort** is closely associated with indoor air quality (IAQ) which depends on three factors including the amount of pollutants, ventilation rate in the building and the duration of the pollutants being trapped within the space [17]. Indoor air quality considers the following parameters: temperature, humidity, carbon dioxide, PM2.5, ozone, formaldehyde, volatile organic chemicals, carbon monoxide etc [18]. The effects of exposure to poor indoor air quality on human respiratory symptoms and diseases have been studied which provides evidence to support the link [19], [20].

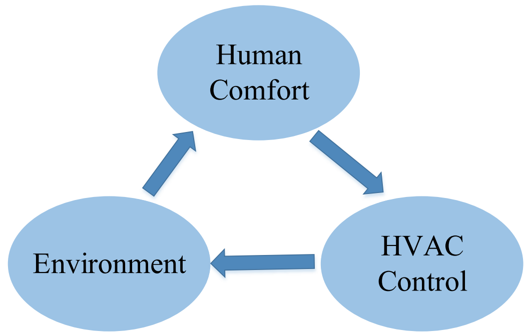

FIGURE 2. Human comfort driven control system for smart building.

To find the correlation between various environmental parameters and human comfort, researchers need to collect the human comfort perception data while taking environmental measurements concurrently. Data analytics tools can be applied to identify the relationship between these two datasets, with environmental data as input and human comfort perception as output. If a suitable model is identified to represent such relationship, the model could be used for online prediction of human comfort based on the input environmental data. Subsequently, the prediction outcome can serve as the basis to control the building HVAC systems in order to improve human comfort. HVAC control systems enable the building to provide a specified level of temperature, humidity, ventilation rate and air quality with the aim to achieve optimization of thermal comfort and energy consumption [21]–[25]. In such a manner, the three components - environment, human and HVAC control work together as a closed-loop control system that contributes to a smart building as illustrated in Fig. 2.

Recent advancements in sensor technology and data analytics have been driving the research forward on studying the relationship between environmental parameters and human comfort. Advances in sensor technology have enabled large-scale data collection in a wide spectrum of applications including indoor human behaviour studies [26]. Sensing devices are typically employed for collecting measurements that provide information about occupant comfort perception, user activity, indoor conditions and appliance consumption etc [27], [28]. The review work presented in [26] lists the common sensors that are used for collecting data related to user behaviour.

On the other hand, the integration of machine learning algorithms with automatic control systems in commercial and residential buildings proves the concept of "smart buildings" with the aim to save energy, ensure security or improve occupants' comfort [29]. As an application example in indoor human behaviour study, data-driven models have been developed for the estimation of building occupancy which can assist in emergency response flow and supporting decision making mechanism [30], [31]. Another example is a recommendation system proposed in [29] to demonstrate the use of machine learning techniques for intelligent building lighting controls that are capable of meeting the needs of both individual visual comfort and energy efficiency of the building.

In the context underlined above, the objective of this paper is to present a literature survey on the previous studies conducted on human comfort analysis in indoor environment with a main focus on the data collection methods and data analytics approaches that have been employed by different research groups. This paper describes the research contributions driven by technology advances in terms of sensor and data analytics, in the hope of providing some insights for researchers or engineers who embark on their research in this area.

So far, most available literature reviews mainly focus on thermal comfort and there is limited review work that covers other aspects of comfort. In terms of content, previous review work has addressed the fundamental concepts associated with human comfort or the framework of study. However, few of them discuss how the data is collected and how the data is analyzed. The main contributions of our paper are as follows.

- We survey the research contributions from the data-driven point of view. More focus of our work is given to review the data collection methods and data analytics approaches being employed.
- The summarized knowledge in this survey would act as a good starting point for the researchers working in this area and facilitate them to organize their thoughts so as to devise their own research methods.
- Previous work mainly focuses on thermal comfort and there is limited review work that covers other types of comfort. We cover both thermal comfort and other types of comfort. The review of the previous studies may assist researchers in generating new ideas to solve the existing problems in this field.

The next sections of this paper are organized according to the four types of comfort: Thermal, Visual, Acoustic and Respiratory. Within each section, the following aspects are discussed: criteria for indoor occupant comfort and relevant comfort indicators, data collection methods and data analysis approaches utilized for deriving the human comfort model (if any). In the conclusion section, we also propose a few potential areas that future comfort-related research may consider exploring and extending in.

Specifically, the rest of the paper is organized as follows. Section II presents thermal comfort. Section III introduces visual comfort. Acoustic comfort is described in Section IV. Section V presents respiratory comfort. General validation methods for machine learning based comfort models are described in Section VI. The discussion about the previous studies on human comfort is presented in Section VII. Section VIII concludes the paper and proposes our future work.

II. THERMAL COMFORT

To assess the performance of a building system, the occupants' thermal comfort has been one of the major criteria in the evaluation [32]. It's partly because thermal comfort can serve as the basis for designing intelligent HVAC (heating, ventilation and air conditioning) control systems. In order to realize thermal comfort control, first of all, indices need to be established to relate occupants' comfort to the surrounding physical parameters of the indoor environment [33]. A comprehensive review on indoor thermal comfort models and indicators was presented in [34].

A. CRITERIA FOR THERMAL COMFORT AND THERMAL COMFORT INDICATORS

Thermal comfort is mainly related to environmental factors and human factors. According to the literature, two major different models can be adopted to measure thermal comfort, namely the PMV/PPD model and the adaptive model [15], [35]. The classical PMV model considers six main factors which directly affect thermal comfort. These factors are grouped into environmental factors (mean radiant temperature, air temperature, relative humidity and air speed) and personal factors (clothing insulation and metabolic rate) [36]. The PMV/PPD model is applicable for the buildings equipped with air conditioning and ventilation systems, whereas the adaptive model is more suitable for the naturally conditioned buildings without mechanical systems [37]. The details of the commonly adopted thermal comfort indices are summarized as follows.

1) PREDICTED MEAN VOTE (PMV)

The Predicted Mean Vote (PMV) model [38] was developed based on the heat balance between the human body and the environment. The model was derived by using heat balance principles, and the data was collected from chamber experiment where the indoor conditions could be controlled precisely. PMV model provides a mathematical model for predicting the thermal sensation of a large group of subjects in terms of four environmental factors and two personal factors as mentioned above. It is the default thermal comfort model adopted for building design and operation nowadays.

The PMV index is applied by ASHRAE for predicting the mean response of a large group of people on a 7-points thermal scale from cold (-3) to hot ($+3$) [39] which is termed as "ASHRAE scale". Zero represents thermal neutrality which is an ideal value. A user would state a value close to 0 for the PMV in an environment that he/she deems comfortable. Typically, the recommended thermal comfort range is between -0.5 and $+0.5$ [37].

2) PREDICTED PERCENTAGE DISSATISFIED (PPD)

The Predicted Percentage Dissatisfied (PPD) is an indicator that is used to predict the percentage of people who are dissatisfied with a certain thermal condition, for feeling either too warm or too cold as suggested from their PMV values above and below zero (thermally neutral) [40]. Thus, PPD index is closely related to PMV and this dependency is demonstrated in the equation developed by Fanger [38].

Both PMV and PPD indices can be applied to estimate the human thermal perception in indoor environments with mechanical cooling system for the space [15].

3) ADAPTIVE MODEL

The adaptive comfort model [41], [42] was developed based on the data collected from field studies that allowed building occupants' interaction with their environment by controlling clothing, windows or fans etc [41]. In the model, the comfort indoor temperature was expressed as a function of outdoor effective temperature while taking into consideration that the occupants may change the physical factors and adjust their clothing, activity level or expectation accordingly so as to adapt to the environment [43]. It provides an alternative thermal comfort model for naturally-conditioned space.

The thermal adaptions of human in indoor environment are commonly classified into three types: physiological, psychological and behavioral [35]. The in-depth review and discussion on the contributions dealing with adaptive model methods are presented in [44], [45].

4) EXTENDED PREDICTED MEAN VOTE (EPMV)

The Extended Predicted Mean Vote (ePMV) was proposed in [46]. While the PMV model can be applicable for the buildings equipped with air-conditioning system, ePMV is only suitable for buildings without air-conditioning or ventilation systems, in warm and humid climates of regions where the indoor air temperature increases remarkably [34].

5) EMPIRICAL PMV MODELS (EPPMV)

The original PMV model is not practically useful for either real-time control systems or for design purposes due to the complex nature of the model and unavailability of certain input parameters [47], [48].

These constraints have been calling for the development of new empirical models which express the PMV based on variables that can be measured easily from an indoor environment. For instance, Kansas State University developed an empirical equation which expressed the PMV index as a function related to temperature and partial vapor pressure only and it had been adopted by ASHRAE [33], [49].

B. DATA COLLECTION METHODS FOR THERMAL COMFORT STUDY

To study human thermal comfort in indoor environment, a few research teams prefer questionnaires to existing comfort models such as PMV and PPD as they believe that comfort is a subjective matter [50], [51]. Nevertheless, most of the research groups choose to apply either the conventional comfort models (covered in section II-A) or their own model derived from training machine learning algorithms to predict thermal comfort.

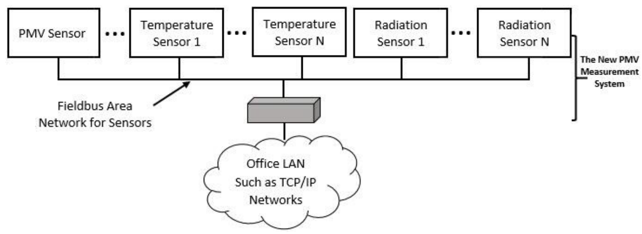

FIGURE 3. The network configuration of the real-time PMV measurement [55].

When applying the existing comfort models, some research studies leverage on publicly available datasets to perform analysis [52]–[54], while other groups collect the data by employing wearable or non-wearable sensors. Their data collection methods are briefly described as follows:

The study presented in [33] adopted an empirical PMV model from the ASHRAE Handbook which expressed the PMV index as a function of air temperature and partial vapor pressure only. In order to include control variables and architectural parameters as predictors, a two-stage regression representation of the ASHRAE empirical PMV model was proposed. The environmental data was collected from a building that was equipped with a sensor network and HVAC control system. Vast amount of current and past data measured from the HVAC system was supplied to validate the proposed regression model.

It was reported in [55] that a distributed sensor network was used in an office environment to perform real-time measurement of PMV. Real-time computation of PMV values has long been considered challenging due to the complex nature of PMV index. To achieve thermal comfort-driven control of the air conditioning system, it is necessary to develop a practical measurement system that is capable of providing real-time PMV values in office environments. The real-time measurement system proposed in [55] consists of three types of sensors which were radiation sensors, air temperature sensors and PMV sensors. These intelligent sensors were distributed across various locations in the office and linked to network shown in Fig. 3. The measured data was transferred via network and gathered in the PMV sensor to process and integrate the data. Subsequently, PMV values were derived by using a table lookup method. The solution provided a more efficient way to obtain real-time PMV values by reducing the computational load associated with solving the PMV equations. Laboratory experiments and a case study were conducted to examine the feasibility and economic benefit of the proposed novel PMV measurement system. The study results revealed that by integrating the new PMV measurement system with the air-conditioning control in an office, it helped to achieve better occupants' thermal comfort and energy saving of 5.8% as well under typical operating condition [55].

A new measurement system was developed which integrated multiple sensors on Arduino platform for collecting data related to thermal, acoustic, visual and respiratory comfort [10]. Sensor combos named "Comfort Box" was employed to measure the following parameters: temperature, humidity, wind speed, illuminance, sound level, CO_2 level, presence of the user. The sensing system was designed based on the index of Predicted Mean Vote (PMV) to compute the thermal comfort.

Acknowledging the challenges present in the measurement of parameters for PMV comfort model that requires bulky and expensive equipment, some researchers [32] explored the feasibility of adopting wearable devices to measure and monitor human thermal comfort in indoor environment. To derive the thermal comfort model, their work attempted to collect environmental data and human physiological data by integrating a mobile application with the sensors in mobile phones and wearable devices. The captured parameters included air temperature, location, relative humidity, perspiration rate, heart rate and skin temperature. The experimental results suggested variation in the accuracy of the existing sensors in wearable devices.

Another application example of wearable devices was demonstrated in [56] where such devices were employed to measure personal sensory data. A mobile application was developed to serve as the central hub for gathering human heart rate data and environmental data [56]. The human subjects' heart rate was collected from both a smartwatch and a compatible chest strap which were connected to a mobile app via Bluetooth Low Energy (BLE). The temperature and humidity values were measured from the sensors worn by the human subjects. In the study, heart rate was chosen as the proxy for the metabolic rate in view of the research findings reporting the close correlation between heart rate and metabolic rate [41]. The metabolic rate of the human occupant was one of the required inputs for PMV model which was closely related to thermal comfort [57]. However, it was relatively difficult to measure. Thus, they selected heart rate as a surrogate to facilitate autosensing. Other than gathering raw sensor data, the mobile app was also meant for capturing the occupants' thermal comfort perception data by allowing the user to vote on the 7-point ASHRAE scale. That data was used as "ground truth" data for training the comfort model.

Apart from PMV comfort model, a new method called Predicted Thermal State (PTS) model was introduced to evaluate human thermal comfort in indoor environment [58]. That model was used to predict the subject's thermal state based on the peripheral skin temperature and the corresponding gradient features extracted from a single body location. Experiments were conducted on human subjects by measuring each subject's skin temperature using a sensor device while simultaneously recording the indoor and outdoor environmental parameters. Indoor air temperature, air velocity and relative humidity were measured with an air velocity meter, while outdoor air temperature and relative humidity were obtained from the weather station nearby through Weather@SG service. The experimental results suggested the great potential of that method for evaluating building occupants' thermal state. Another work presented in [59] aimed to provide a more straightforward method for thermal state prediction. In that study, the thermal state (Discomfort/Comfort) of human subjects was evaluated according to the input features of personal physiological parameters. The features included skin conductance, skin temperature, oxygen saturation, pulse rate, and blood pressure which were extracted using wearable sensors. To evaluate the prediction performance, new prediction models were compared with the existing models using the available validation dataset.

The classical PMV comfort index is a statistical prediction measure that is applicable for a large group of people, though the actual thermal perception of an individual occupant could vary significantly from the predicted value derived from this model. In view of the constraints mentioned above, considerable research effort has been put in developing personalized comfort models. Such personalized models would be useful for developing personalized conditioning systems which aim to fulfil the individual comfort needs and meanwhile to achieve energy consumption on demand. The review contribution from [60] discussed how various personalized conditioning systems affected human thermal comfort and the performance of building energy. The following part of this section lists a few example studies in developing personalized comfort models.

The work reported in [3] attempted to make use of individual occupant's heating and cooling behaviour as a new way of feedback to develop personal comfort models. A personal comfort system (PCS) was designed to pick up the individual heating and cooling behaviour. In that way, each individual subject was taken as the stand-alone unit of analysis instead of a large group of people. The collected field data included environmental conditions, PCS control behaviour and mechanical system settings. Particularly, air temperature, relative humidity, heating/cooling intensity (in a scale from 0 to 100%), heating/cooling location (seat, back) and chair occupancy were recorded by each PCS chair. Six machine learning algorithms were explored on processing the data to develop the personal thermal comfort model.

A neural network-based method was presented in [61] to establish predictive models for its application in controlling personalized heating systems. The study carried out in [24] introduced a human-building interaction framework to incorporate occupants into the control loop of HVAC. Room temperature data was collected via a sensor network and occupants' comfort perception data (in terms of comfort votes) was collected via participatory sensing. Those data were used to learn the personalized comfort preferences which served as the basis to control the HVAC system. In terms of similar data acquisition methods, some research groups [53], [62] also reported using various sensors to pick up environmental data and human subject data (parameters related to clothing, metabolic rate) while concurrently collecting participants' thermal sensation votes to predict individual thermal comfort.

Following adaptive model approach, a study reported in [63] explored the reliability of adopting an IoT platform integrated with machine learning algorithm for assessing and improving personal thermal comfort of building occupants. In that study, the researchers employed a nearable device built from low-cost sensors (placed nearby an occupant) to monitor indoor environmental parameters such as air temperature, relative humidity while using a wearable device (wristband) for measuring the physiological data from the occupants. The wristband was a wearable medical device equipped with several sensors including a photoplethysmography (PPG) sensor for heart rate detection. Six parameters were considered in the model, namely operative temperature, relative humidity, skin surface temperature, heart rate, electrodermal activity and user. A web-based survey was designed for collection of occupants' thermal sensation vote.

The review work presented in [25] highlighted the possibility of transforming normal buildings into smart buildings by deploying sensors and Internet of Things (IoT). Working with machine learning and big data analytics, such buildings would provide a lot of automated services to create a comfortable indoor environment for the occupants. Their work summarized various types of sensors that could be employed in smart buildings.

C. DATA ANALYSIS METHODS FOR THERMAL COMFORT STUDY

There are significant research achievements on exploring applying machine learning algorithms to establish human thermal comfort model for the indoor environment. Most of them adopt supervised machine learning algorithms which are generally grouped into two major methods, namely Regression and Classification. Regression refers to the process of estimating the relationship between a dependent variable and one or more independent variables. It is usually used to make predictions of continuous outcomes [64]. Classification refers to the process of training an algorithm to recognize and categorize certain types of objects based on past sample data [65]. The most commonly used supervised algorithms include Linear Regression, Logistic Regression, Neural Networks, Support Vector Machines (SVM), Gradient Boosting Trees, Random Forest, Decision Trees, Nearest Neighbor and Naive Bayes [64], [65].

The following content of this part summarizes the algorithms employed in studying thermal comfort. They are mainly divided into three categories: Regression, Classification and Other Algorithms.

1) REGRESSION ALGORITHM

Following the regression method reported in [66], a two-stage regression representation of the empirical PMV model (epPMV) was proposed which included architectural parameters and control variables [33]. The epPMV regression model was developed in two stages and it was evaluated with the data in the validation set. Their research findings suggested the capability of the proposed two-stage regression

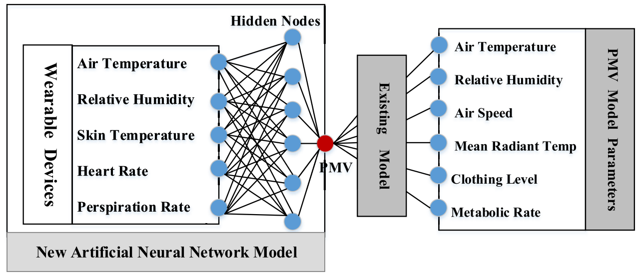

FIGURE 4. Framework of artificial neural networks [32].

models in terms of predicting the PMV in short term or long term with good accuracy. The author highlighted the adaptive feature of the model that allowed it to be updated when there was any change in HVAC control strategy or operation profiles. A machine learning approach was proposed in [56] to analyse the combined dataset of human heart rate and environmental data (room temperature, humidity data) so as to automatically derive human thermal comfort from the raw sensor data. To find the relation between the thermal comfort and measured data, the researchers used two regression methods: linear regression (outputs values on continuous scale) and logistic regression (outputs values on discrete ASHRAE scale). The analysis results showed it was possible to achieve high accuracy of prediction when the regression model was trained using individual thermal sensation data. A conclusion drawn from the study was that thermal perception reflected a personal experience which should not be generalized for other people.

The study presented in [32] built an Artificial Neural Network (ANN) to analyse the correlation between the estimated PMV index and the input parameters measured from wearable devices which include human physiological data and indoor environmental parameters. Fig. 4 showed the framework of the ANN that was composed of three layers: input layer, hidden layer and output layer. The indoor environmental parameters and human physiological parameters served as the input variables, while the predicted PMV was the output variable of the ANN. The authors had identified the input parameters of the best model which were air temperature, skin temperature, heart rate, square root of the summation of perspiration and air temperature, summation of perspiration and relative humidity. Experimental result suggested the potential of building new models to predict the PMV index by employing the data collected from wearable devices. Nevertheless, variation in the accuracy of the existing sensors in cell phone and wearable devices informed the need for increasing the accuracy and reliability of such sensors. Another application example of ANN was reported in [61] where dynamic recurrent nonlinear autoregressive neural network with exogenous inputs (NARX) was used to develop thermal comfort models for controlling the heating settings automatically. Through online testing of the models, it revealed that the human participants expressed their satisfaction with the heating settings automatically controlled by the prediction model.

In consideration of individual differences in thermal perception and its dynamic nature, a novel method was introduced in [62] for online modeling of the personalized and dynamic human thermal comfort. Their work followed the general framework proposed in [38] that related human comfort perception to environmental factors and applied Recursive Least Square Estimation with forgetting factor method to learn the personal thermal comfort profile. Validation and comparison results supported the conclusion that the model accurately depicted the individual differences and dynamics present in thermal comfort. A personalized thermal comfort model proposed in [52] was developed with a kernel based method which was termed as Robust Locally Weighted Regression with Adaptive Bandwidth (LRAB). The model was trained with the historical data to learn individual occupant's thermal comfort profile. Publicly available data was used to validate the prediction performance of the new model. As compared with PMV and other standard kernel method (Nadaraya-Watson method), the analysis results proved that the proposed model provided a significantly more accurate prediction on individual comfort sensation. It demonstrated the valuable potential of that model to be incorporated into a smart control system in an office environment which could adjust the room temperature based on the comfort needs of individual occupants.

Development of thermal comfort prediction model involves data collection of human thermal perception votes. However, collected thermal perception data usually contains considerate artefact and noise. To solve this problem, the study presented in [67] explored using Gaussian Process (GP) Regression to extract human subjects' thermal preferences from the collected data contaminated with measurement noise. Their analysis showed that the GP method effectively rejected outliers/deadband and achieved accurate prediction of human subjects' thermal preference. It was also demonstrated that the GP estimates could be used to determine when was the best time to poll the subjects for their thermal perception so that the expected response would maximize the information about their thermal comfort profile. Such active learning strategy helped to minimize interaction with the human subjects which would lead to reduced noise present in the collected thermal perception data.

2) CLASSIFICATION ALGORITHM

An IoT solution was adopted [63] to measure the environmental and human subjects' physiological parameters. The collected dataset was split into two groups with 80% of the data used for model-training and 20% used for validation. To identify which algorithms would best fit the dataset, their work compared the prediction performance of six different machine learning algorithms that were grouped into linear methods (Linear Discriminant Analysis, Logistic Regression) and nonlinear methods (Classification and Regression Trees, Support Vector Machines, K-Nearest Neighbors and Gaussian Naive Bayes). It was observed that the Classification and the Regression Trees (CART) algorithm outperformed the rest algorithms in terms of the accuracy in predicting thermal comfort perception under given environmental condition. CART [68] was one of the non-parametric supervised learning methods which were ideal when one had lots of data but without prior knowledge about it [69].

To develop a personal thermal comfort model, the study presented in [3] explored using six machine learning algorithms to process the collected data. The collected data went through a 4-step preparation procedure: data cleansing, feature creation, data merging and pre-processing. Considering the high dimensional nature and small size of the collected dataset, six machine learning algorithms were chosen which did not rely on strong assumptions on the dataset, namely Random Forest (RF), Gradient Boosting Method (GBM), Kernel Support Vector Machine (kSVM), Regularized Logistic Regression (regLR), Gaussian Process Classification (GPC), Classification Tree (CTree). An exhaustive grid search approach was used to determine the best performing parameter settings for each machine learning algorithm. The performance comparison of the six learning algorithms showed that the algorithms that achieved higher accuracy were those having the ability to control high dimensions and noise presented in the data such as kSVM, RF and regLR. However, such algorithms were computationally more costly. Therefore, the authors argued that the choice of learning algorithm depended on the needs of the specific application. The overall analysis results also revealed that the personal comfort models developed in the study demonstrated significantly improved predictive accuracy as compared with the conventional PMV or adaptive comfort models.

It was reported in [70] using an adaptive stochastic modeling approach to build personalized thermal comfort model. In the study, a probability distribution was fit to the dataset of each comfortable condition (uncomfortably cool, comfortable, and uncomfortably warm), then the overall comfort of an individual was determined by combining the distributions in a Bayesian network. A binary Bayesian optimal classifier was trained through online learning to identify the comfortable environmental conditions. A sliding window-based algorithm was used for the purpose of detecting comfort variations over time. The performance of the model was evaluated by comparing it with other standard classification methods that were applied on the collected human thermal comfort data. The work presented in [53] also reported using machine learning based approach to derive the individual thermal comfort model with the aim to predict individual's thermal sensation of three types which were "uncomfortably cold (-1)", "neutral (0)" and "uncomfortably warm (1)". First, a feature vector was formed by extracting the best set of features from the raw data collected with sensors. Subsequently, the feature vector and the ground-truth thermal sensation votes were fed into a classifier to train the model. By utilizing a publicly available dataset, the prediction performance of the following machine learning classifiers was evaluated: Support Vector Machine, Random Forest and Adaboost algorithm. Their validation results revealed that using SVM classifiers achieved much higher accuracy than using the traditional Fanger's model.

When developing the new PTS (Predicted Thermal State) model proposed in [58], Support Vector Machine (SVM) and Extreme Learning Machine (ELM) classifiers were applied to analyse the collected data (refer to section II-B for the details of data collection). The trained PTS model (derived from normalized skin parameters) demonstrated the ability to predict the Discomfort/Comfort thermal state with high accuracy based on the input skin temperature and its gradient features. In another study reported in [59], the researchers experimented using two new novel methods to predict the Discomfort/Comfort thermal state (TS). The first method called CNN-(Tsk)TP employed deep convolutional neural network (CNN) to determine TS based on the 2D sensor data of skin temperature temporal profile (TP) that had been transferred into the image domain. Such idea was inspired by the fact that CNN had been widely used in the field of image classification. The second classifier called SVMphy employed a Support Vector Machine (SVM) model that used six independent physiological parameters as input. The performance of four types of the kernel (linear, polynomial, sigmoid and radial) was evaluated. The validation results suggested both of their proposed methods achieved highly satisfactory prediction accuracy.

3) OTHER ALGORITHMS

Besides the machine learning algorithms mentioned above, there were other algorithms applied for human comfort study. For instance, the traditional PMV model [38] focusing on specific factors were used for evaluating thermal comfort. Some extended models [39]–[44], [46], [47] based on the conventional PMV model could deal with other different scenarios.

A fuzzy rule-based algorithm was proposed in [24] to develop a predictive model for occupants' thermal comfort. The performance of the proposed algorithm was assessed by using both the comfort perception data collected from human subjects and the synthesized data. Their work also introduced a building management system (BMS) controller to activate the HVAC system that adjusted the room temperatures according to the occupants' thermal comfort needs. The testing results showed that the proposed framework was able to detect correctly the nonlinear underlying pattern present in the human thermal comfort sensation scale.

III. VISUAL COMFORT

A. CRITERIA FOR VISUAL COMFORT AND VISUAL COMFORT INDICATORS

Visual comfort has great impact on the wellbeing and productivity of building occupants [71], [72]. Appropriate lighting condition and illumination are important building requirements in workplaces as they directly affect occupants' visual comfort. Research findings have shown that office occupants have a preference to work near the window or in the place with natural lighting. Artificial lighting is necessary where the access to natural lighting is limited [73].

The review work presented in [74] summarized the state-of-the-art literature covering the close relationship between visual comfort and the health and wellbeing of the building occupants, followed by discussing the implementation of green practices in building design e.g. excessive use of artificial lighting should be avoided while still maintain certain level of balance [75].

In terms of studying visual comfort, evaluation has been carried out to investigate the relationship between the light environment and human needs. More than 30 indices for assessing visual comfort were covered in the review study [76]. Generally, these indices could be categorized into four groups [15]: 1) Amount of light on a surface (level of illumination), 2) Glare, 3) Colour rendering and 4) Daylight availability. For each group, a comprehensive list of visual comfort indices extracted from literatures was provided in [15].

B. DATA COLLECTION AND ANALYSIS METHODS FOR VISUAL COMFORT STUDY

Visual comfort is commonly assessed based on the level of illumination and extent of glare. For predicting human visual comfort, various daylight and glare metrics have been developed for several years which are classified into two categories: static and dynamic metrics.

For example, a study was conducted [77] on the visual parameters measured in a daylit office to determine the visual comfort thresholds of the office occupants. Photography was employed to capture the luminance distribution, and sensors were used to measure horizontal and vertical illuminance. The work described in [78] reported results from the obtained physical data and the surveys. In that study, daylight illuminance was measured with photometric sensor. The total horizontal illuminance was measured with a set of sensors on tripods arranged in a row placed at work-plane level. HDR Images were captured with a digital camera for glare evaluation. These images were then processed adopting an algorithm to compute the daylight glare probability (DGP). The sensing system introduced in [10] was designed based on the level of illumination to define the visual comfort. The sensor used for data collection in their study was described in Section II-B.

An integrated adaptive system proposed in [79] was composed of individual movable modules with the aim to improve occupants' visual comfort in indoor environment. The proposed system was evaluated based on the improvement of lighting levels and reduction of glare issue.

Due to the high-cost and time-consuming process involved in collecting the field daylight data, some researchers chose to use simulation methods to analyse daylight availability and glare [80]. The study reported in [80] evaluated visual comfort and daylight performance through a subjective survey and simulation based metrics in classrooms. Dynamic and static daylight and glare metrics were compared in terms of their ability to represent the perception of human subjective reactions in classrooms. The experimental results suggested a strong correlation between dynamic daylight metrics and students' perceptions.

To address the needs for achieving both personalized visual comfort and energy efficiency in open-plan office environment, the research work presented in [29] proposed a novel intelligent algorithm termed as ReViCEE to provide recommendations for optimum control of building lighting system. In the study, the researchers relied on distributed wireless sensor actuator network (WSAN) to collect the data. Each integrated WSAN sensor node hosted illumination sensor to measure room luminance, and infrared array sensor to detect the presence of the human subject in their respective location. In that way, the individual preferences for visual comfort were collected and stored as historical data which were used to train ReViCEE, the Recommender-system based algorithm. Such algorithm was designed to learn the individual preferences for visual comfort as well as the similarities between the preferences of different occupants by making use of the existing recommender-system tools [81]–[83]. The trained system was enabled to give recommendations for intelligent lighting controls in the building.

IV. ACOUSTIC COMFORT

A. CRITERIA FOR ACOUSTIC COMFORT AND ACOUSTIC COMFORT INDICATORS

Acoustic comfort can be achieved by either removing the source of noise or isolating the room from the source in some situations, however this may not always be practical. In such a situation, the acoustic comfort level needs to be assessed using noise indices. A comprehensive review [15] provided a variety of noise indices used for evaluating acoustic comfort in indoor environment. These indices were used to assess noise in specific aspects including sound pressure levels, sound reverberation and acoustic quality of the room [15].

A widely used noise index, the A-weighted equivalent continuous sound pressure level LeqA was also covered in work [15]. Such parameter provided an overall assessment of noise which was designed to represent "the duration and the variation of sound pressure level of a noise and the sensitivity of the ear at different frequencies" [15], [84].

B. DATA COLLECTION AND ANALYSIS METHODS FOR ACOUSTIC COMFORT STUDY

For example, an acoustic comfort evaluation was conducted for a conference room [85]. The researchers measured the inside and outside ambient noise, the reverberation time and interior sound insulation following international standards. With regard to equipment, they employed a commercial acoustic system to take the measurements. The measurement system encompassed a complete set of diagnostic aspects of sound characteristics. To evaluate the acoustic comfort level of the conference room, they compared the measurement results with the guidelines and reference values recommended by international or certain national standards. The comparison results suggested poor acoustic quality of the room due to the high level of ambient noise and insufficient sound insulation etc. In another study [86], to choose the optimal acoustic design for a classroom in a school, the research team followed the measurement and assessment methods present in ISO. They measured the key acoustic indicators (Index of Clarity of the Word, Speech Transmission Index and Reverberation Time) with an Integrated Impulse Response method and set up the parameters accordingly for the simulated classroom model. Verification was performed to assess the acoustic performances of the classroom after the realization of the intervention for the acoustic design.

As mentioned in Section II-B, the work covered in [10] introduced the designed sensor combos named "Comfort Box" integrated with multiple sensors including a sound level sensor. It was believed that less distraction by outside noise would improve the productivity of the building occupants. To provide an acceptable acoustic comfortable environment, it was suggested that a maximal noise level (in terms of decibel) should be defined first, moreover it should also take into the account the fact that the sensitivity of human hearing varies according to sound frequencies. Hence, the study proposed using the Noise Rating curves as an established method to determine the comfortable acoustic environment in a building.

V. RESPIRATORY COMFORT

A. CRITERIA FOR RESPIRATORY COMFORT AND RESPIRATORY COMFORT INDICATORS

Many studies have established the link between indoor air quality (IAQ) and respiratory health of the building occupants [19], [87]. As specified in ASHRAE standard [88], the indoor air quality is considered acceptable when "there are no known contaminants at harmful concentrations, as determined by the competent authority and for which a substantial majority of exposed persons (at least 80%) does not express dissatisfaction" [88]. Hence, it is proposed in the review work [15] that the indoor air quality should be assessed by referring to the international level or national level standards or guidelines that have specified the exposure limit values for a variety of air pollutants.

Among the commonly studied indoor air quality parameters, CO_2 (Carbon Dioxide) is one of the main indicators for IAQ. Due to the reason that CO_2 is the waste product of human metabolism, the concentration of CO_2 will change with the presence of occupants in a room [89]. For that reason, CO_2 sensor can be used for occupancy detection. According to the well-established ANSI/ASHRAE standards [90], the air is considered stale with CO_2 level of 1500 ppm. A level below 1000 ppm is recommended by the ASHRAE's standards.

B. DATA COLLECTION AND ANALYSIS METHODS FOR RESPIRATORY COMFORT STUDY

The following studies demonstrate the application of carbon dioxide sensors. For example, the sensing system proposed in [10] was designed based on the CO_2 level to determine occupants' respiratory comfort. CO_2 sensors were also used for estimating the number of occupants which served as an input to a model based controller for the ventilation system to improve IAQ according to demand [91]. Similarly, another study [92] also applied CO_2 sensor to detect the level of occupancy so that the ventilation air delivery could be adjusted to a rate proportional to it. Incorporating CO_2 sensor for ventilation controller brings dual benefits to both respiratory comfort and energy efficiency.

The review study presented in [93] talked about deploying sensor networks in smart homes for the purpose of creating comfortable living conditions for the occupants. The study provided an evaluation of the modern sensor technologies that enabled real-time measurement of the concentration of indoor air pollutants such as Total Volatile Organic Compounds (TVOCs), carbon dioxide (CO_2) and particles. The measured data could be stored in Home Energy Management Systems (HEMS) which was the basis for smart homes.

In terms of data analysis, although there are studies reported applying machine learning approaches for air quality prediction [94]–[97], we could hardly find literature that uses data analytics methods to model indoor respiratory comfort. This could be due to the reason that currently IAQ is simply evaluated by benchmarking the measured parameters against the acceptable range defined in the well-established standards.

VI. VALIDATION METHODS FOR MACHINE LEARNING BASED COMFORT MODELS

For machine learning model, we usually divide the dataset into training data and testing data according to the specified proportion. When we obtain a trained model based on a training dataset, we need to make sure that the model has strong robustness for the accuracy of the prediction. Generally, we utilize a testing dataset to validate the effectiveness of the model. Validation provides a statistical estimation of the difference between the predicted results and the actual data in the dataset. The validation process makes sure that the established model well fits the existing dataset. After the model has been built, it may be applied in different scenarios. Evaluation of the effectiveness of the model for various scenarios should be carried out to decide whether the model is underfitting, overfitting or well generalized according to the performance of the trained model applied on the unseen data. The unseen data could be either those unused data from the existing dataset or the new data obtained from designed experiments. Some popular and effective validation methods are K-Fold Cross Validation [98], Holdout method [98] and Repeated random sub-sampling validation [98].

VII. DISCUSSION

From the previous studies, there is no common good indicator which can represent thermal comfort or human comfort. We have known that PMV [38] is a classical index for evaluating thermal comfort. However, the PMV model only focuses on the specific parameters. It cannot scale well to other environmental factors or human factors. Although some extended models [39]–[44], [46], [47] based on the conventional PMV model can deal with different scenarios, the key approach has low prediction accuracy about 41.68-65.5% as pointed out in [54]. Thus, it is far from good (the best accuracy is 100%).

A few of research groups use questionnaires to get human comfort information and take them into consideration when developing the comfort models. However, even under the same condition, different human subjects may have different responses. The questionnaire results vary among people with different ages, genders, countries, incomes and so on. In addition, human comfort is a relatively subjective matter [50], [51] and conducting questionnaires involves high-cost and time-consuming process of data collection. We also cannot make sure the results are correct since they depend on individual participants' responses. These situations make it difficult to come up with a common reliable indicator.

Different research groups choose specific indicators to represent thermal comfort in their own way. However, they do not provide convincing justifications for their choice or explain whether it is the best indicator. The reason behind this could be lack of a standardized good indicator to reflect the human comfort. As a result, there is hardly any well-received commercial product to monitor the real state of human comfort. Human comfort is a relatively subjective matter [50], [51] which is affected by many environmental, psychological and physiological factors. Furthermore, the occupants' perception about comfort may be influenced by numerous external conditions instantly. Thus, it is difficult to propose a specific indicator to represent or reflect human comfort. To build a robust model with high accuracy, we need to consider more factors related to human comfort and develop a good indicator to characterize it. It will bring positive impacts on human wellbeing. Furthermore, the corresponding commercial solutions will have a promising market.

VIII. CONCLUSION AND FUTURE WORK

In the contemporary era, people spend about 90% of their time on indoors. For this reason, it becomes one of the major goals of smart buildings to offer a comfortable living or working environment for the occupants besides achieving energy efficiency. Improvement of human comfort in office buildings not only promotes health and wellbeing of individual employees, but also brings significant financial benefits to employers by reducing the operating cost of business.

Human comfort in indoor environment is commonly evaluated from four aspects: thermal comfort, visual comfort, acoustic comfort and respiratory comfort. In order to improve them, we need to understand the criteria for assessing different types of comfort and the environmental factors that have direct impact on them. Subsequently, data needs to be collected from the environment and human subjects in order to identify the relationship between environmental factors and human comfort.

In this literature review, we surveyed the area of human comfort studies conducted for various aspects of comfort with a special focus on the assessment criteria, data collection methods and data analysis methods employed by different research groups. Among the four aspects of comfort, thermal comfort is the area that presents most of the research contributions as it was considered of greater importance compared with other types of comfort. With the advance of the Internet of Things (IoT) solutions and sensor technology, it is possible to collect the environmental data using distributed sensor networks. Machine learning algorithms have been applied to extract the useful information from the large amount of data collected via the sensors. Specifically, in the context of human comfort analysis, the collected data is used to train a thermal comfort model that can predict human comfort perception based on the new environmental data input into the model. Such comfort model is expected to be integrated into the HVAC control system of a smart building to empower it to automatically adjust the temperature, ventilation rate etc. according to the comfort needs of the occupants.

With regard to other aspects of indoor comfort (visual, acoustic and respiratory comfort), although sensor technology has been widely used in the data collection, there were few literatures that reported applying data analytics approach to build the comfort model. We assume that one of the reasons could be that the relevant comfort indices are relatively straightforward. To determine whether the environmental condition is within the acceptable range, usually the measured parameters are directly compared with the values recommended in the international or national guidelines.

In addition, we propose the following future research areas in relation to indoor human comfort studies:

(1) Currently the thermal comfort model is trained based on the comfort perception votes collected from the user survey. Due to the subjective nature of such survey, the established model may not accurately reflect the users' thermal preference. Therefore, we suggest exploring using certain human physiological parameters to replace the survey method. Such parameters can be measured with wearable sensor or wearable device and they will be used as objective indices to indicate the comfort level.

(2) Human comfort perception is a complex matter which depends on both environmental factors and the personal characteristics of the individual occupant. Most of the current thermal comfort models only consider the influence of environmental factors. Future study may consider incorporating relevant personal factors such as gender, age etc into the model.

(3) Visual comfort is similar to thermal comfort in the sense that it is subject to an individual occupant's personal preference. In order to accommodate to each individual occupant's needs for visual comfort, it is necessary to develop the personalized visual comfort models that can serve as the basis for building lighting controls. Hence, more research work is expected to be conducted in this area by applying machine learning algorithms to learn the visual preferences of individual occupants.

(4) Previous studies have placed more emphasis on thermal comfort. To address other IEQ aspects, composite comfort indices could be designed by incorporating additional environmental factors related to visual, acoustic and respiratory comfort. Furthermore, machine learning algorithms capable of building scalable comfort models could be an option for considering other three comfort aspects. Improved indices of human comfort and more accurate prediction outcome will ensure reliable control over building HVAC systems in order to provide a more comfortable and responsive indoor environment. It may also contribute to a smart building with improved energy efficiency.

In summary, this paper has presented a review of the state-of-the-art research in human comfort studies. It would provide some insights for future researchers who are looking for information about assessment criterion, data collection and data analytics methods for studying occupants' comfort in indoor environment.

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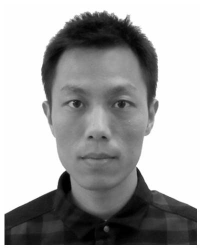

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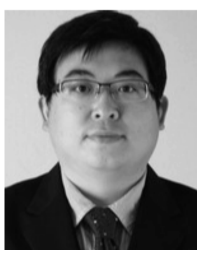

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