Energy & Buildings 226 (2020) 110392

Contents lists available at ScienceDirect

Energy & Buildings

journal homepage: www.elsevier.com/locate/enb

Review on occupant-centric thermal comfort sensing, predicting, and controlling

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ARTICLE INFO

Article history:
Received 4 April 2020
Revised 19 July 2020
Accepted 7 August 2020
Available online 13 August 2020

Keywords:
Personal comfort model
Data-driven
Internet of Thing (IoT)
Building control

ABSTRACT

Ensuring occupants' thermal comfort and work performance is one of the primary objectives for building environment conditioning systems. In recent years, there emerged many occupant-orientated technologies aiming to optimize thermal comfort while saving energy. These attempts offered opportunities to move the indoor thermal environment control from the one-fits-all approach toward a new paradigm with occupant-centric merits. A timely review of this emerging field would help to fill the knowledge gap and provide new insights for future research and practice. This study performed a literature review to summarize recent occupant-centric thermal comfort practices following a framework with three themes: sensing, predicting, and controlling. The results show that occupant-centric thermal comfort control has become a hot research topic in recent years. A wide range of variables and data-collecting sensors were utilized to support the concept. Among all the potential variables, occupants' comfort feedback, skin temperature, and air temperature are the top three popular input features for thermal comfort prediction. Using different machine learning algorithms, data-driven thermal comfort models were reported to have a median predicting accuracy of 84% and some of them can predict thermal comfort at a personal level. Cases implementing occupant-centric thermal comfort control strategy were reported to save air-conditioning energy by 22% and improve thermal comfort by 29.1%. These observations from the literature support the prospects of the new thermal comfort paradigm. Additionally, the challenges and opportunities in this emerging field were discussed.

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https://doi.org/10.1016/j.enbuild.2020.110392
0378-7788/

Nomenclature

Algorithms abbreviations

ANN	Artificial Neural Network
AB	Adaboost
BT	Boosted tree
BN	Bayesian Networks
CART	Classification And Regression Trees
CFD	Compute Fluid Dynamics
CT	Classification Tree
DT	Decision Tree
ENN	Edited Nearest Neighbours
ELM	Extreme Learning Machine
GBM	Gradient Boosting Machine
GNB	Gaussian Naïve Bayes
GPR	Gaussian Process Regression
GPC	Gaussian Process Classification
KNC	K-Neighbour Classifier
KNN	K Nearest Neighbours
LDR	Linear discriminant analysis
LR	Linear Regression
LoR	Logistic Regression
ML	Machine Learning
MLP	Multi-Layer Perception
NB	Naive Bayesian
NN	Neural Networks
RF	Random Forest
ROS	Random Over Sampling
RBC	Rule-Based Classifier
SVM	Supportive Vector Machine
SMO	Synthetic Minority Oversampling technique edited nearest neighbours
TR	Tree regression

Thermal comfort related abbreviations

CLO	Clothing insulation, Clo
CO_2.	Carbon dioxygen concentration, ppm
EHT	Equivalent homogeneous temperature, °C
HR	Heart rate, n/min
MET	Metabolic rate, met
PMV	Predicted Mean Vote
PPD	Percentage of Predicted Dissatisfaction
RH	Relative humidity, %
TCV	Thermal Comfort Vote
TP	Thermal Preference
TSV	Thermal Sensation Vote
T_{air}	Air temperature, °C
T_r	Radiant temperature, °C
T_g	Globe temperature, °C
T_{clo}	Clothing surface temperature, °C
T_{out}	Outdoor air temperature, °C
T_{skin}	Skin temperature, °C
Vel	Air speed, m/s

Other abbreviations

AC	Air-Conditioned buildings
HVAC	Heating, Ventilation, and Air-Conditioning
IoT	Internet of Thing
MSE	Mean Square Error
NV	Naturally Ventilated buildings
OOC	Occupant-Centric Control
PCS	Personal Comfort System
R^2	Correlation coefficients (r) square

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1. Introduction

The indoor environment affects occupants' health [1], productivity [2–4], and well-being [5,6]. Among different indoor environment factors, thermal comfort ranked as the top important aspect [7,8]. Ensuring thermal comfort and work performance is one of the primary objectives for building environment conditioning systems such as the centralized heating, ventilation, and air conditioning (HVAC) and the decentralized personal comfort systems (PCS). To maximize comfort while saving environment conditioning energy, it is important to know more nuanced aspects of occupants' thermal comfort, especially individual demand. To this end, occupant-centric thermal comfort predicting models [9] and interfering solutions [10–12] have been proposed as important supplements to the conventional one-fit-all control strategy [13,14]. A timely review of the advances in this emerging field can help guide its future applications in building design, operation, and research activities.

1.1. Thermal comfort in buildings

Building occupants' thermal comfort is determined by environmental factors, including air temperature (T_{air}), radiant temperature (T_r) [15], airspeed (Vel) [16,17], relative humidity (RH), and so forth; and personal factors such as metabolic rate (MET) [18], clothing insulation (CLO) [19], and possible age [20], gender, adaptation aspects [21,22]. Many models have been developed to estimate how these factors would affect occupants' thermal comfort from a group averaged perspective [23]. The predicted mean vote (PMV) model [24] and the adaptive comfort model [25,26] are two classic examples that have been widely accepted by building environment evaluation standards [27,28]. Other models can be found in relevant reviews [29,30]. However, when applying these models in real practice, the following issues may occur.

First, the prediction of these models is the average comfort for a group of people, not personal thermal comfort because of the nature of the aggregate modeling method [31]. Using group-averaged prediction to guide building environment control may not satisfy the individual's thermal comfort requirement because there exist significant individual differences among occupants [21,23]. Especially for groups with varying thermal neutralities and comfort preferences, even the most optimized group neutrality may leave a substantial proportion of the group (~20%) either too warm or too cold [32]. ***Second***, regression models usually lack self-learning and self-correction capabilities. Once the empirical coefficients were determined, they can only apply to a certain context [33]. Zhou et al. [33] explained the self-learning and self-correction capabilities as follows. 1) A model has self-learning capability if it can find the relationships between occupants' thermal comfort and the affecting factors by itself without inputting the explicit knowledge of each factor's physical effects. 2) A model has self-correction capability if it can correct or adjust the 'thermal comfort-affecting factor' relationship in 1) by itself when applying to different contexts. According to these two criteria, the adaptive comfort model [25] has self-learning capability to some extent but limited self-correction ability. This may explain why efforts are needed to develop independent adaptive comfort models in different countries and climate zones [25,26,34]. The PMV model has neither self-learning nor self-correction capability, which makes its performance a contested topic [35]. When applying these models to new contexts, such as a new climate condition or a new building operation mode [36,37], their accuracy can be rarely satisfied. Many efforts have been made to allow modifying these models based on occupants' feedback and field measurement [38–41] but their complexity requires the audience to have cutting-edge knowledge on thermal comfort. ***Third***, the input parameters needed for human body heat balance calculations are difficult or cost expensive to be obtained during the building design and even the operation phase [31]. Taking the PMV for example, its inputs of the T_r and Vel need professional instruments, which are often not within the scope of building environment monitoring. Meanwhile, the two personal factors of CLO and MET are often assumed or simply estimated with considerable errors because lacking sensors to measure them in real-time [18], thus greatly reducing the accuracy and reliability of human body heat status calculation [42].

1.2. The emerging of occupant-centric thermal comfort

To overcome the issues of conventional thermal comfort approach, alternative comfort predicting and interfering solutions are being produced with the application of emerging technologies such as the Internet of Things (IoT) [43,45], and data-driven method. The advances in sensing technology [46,47], machine learning (ML) predicting [48], and comfort-driven controlling offered great opportunity to bridge thermal comfort needs and energy-saving purposes. Integrating new sensing technology and data-driven method can achieve better thermal comfort perdition using a variety of measured data from environmental [33], physiological [49], behavioral [9], and other aspects [50]. Applying data-driven thermal comfort models to control indoor thermal environment conditioning systems such as the HVAC and PCS can move toward a new thermal comfort paradigm [51]. As an outcome of these emerging technologies, the occupant-centric thermal comfort approach has been emerging.

In the past several years, the popularity of this new paradigm can be seen from the exponential growth of academic publications. To give a glimpse of this field, Table 1 summarizes 9 selected publications in 2019 from perspectives of thermal comfort data collecting, predicting, and controlling. The following observations are noteworthy. ***First***, the sensing technologies (the 'sensors' column in Table 1) and targeted parameters (the 'environmental factors' and 'human factors' columns in Table 1) for data collection varied among studies. Cosma [55] selected the non-invasive sensor for convenience; Liu [54] chose wearable sensors with higher accuracy; Lu [56] took advantage of the publicly available thermal comfort database. Some studies [53–59] targeted both environmental and personal factors; some [55,59] only measured one type of factor; while others explored new parameters such as skin heat flux [58] and human body posture [57]. The indices of thermal comfort feedback also varied significantly. Some studies used thermal sensation vote (TSV) [53,56]; some used thermal comfort vote (TCV) [55]; some used thermal preference (TP) [54,58,59]; while others used their combinations [57]. The scale units of these indices also varied from 3-point to 7-point unit scales. ***Second***, a wide range of ML algorithms was applied to predict thermal comfort. Algorithms such as Random Forest (RF), Neural Networks (NN), Support Vector Machine (SVM), K Nearest Neighbors (KNN), Gradient Boost Machine (GBM), and Decision Tree (DT) are frequently used (see the 'Algorithms' column in Table 1). Compared to conventional thermal comfort models, the performance of ML-based data-driven comfort models is overwhelming (see the 'Performance' column in Table 1). Moreover, the data-driven approach can establish either personal [53–55] or group [56,61] comfort models, depending on the input data. ***Third***, the comfort-driven environmental control has been reported to have the potential of saving HVAC energy while maximizing occupants' thermal comfort. But how to achieve collective thermal comfort for populations with different thermal demands [60], especially when there exist conflicting preferences, still needs investigation. While most of the current evidences supporting the comfort-driven environmental control were from simulation or estimation [60,61], more quantitative results from field measurements are needed to be produced [59].

1.3. The necessity of a literature review

When looking at the 'Performance' of comfort predicting and the 'Results' of environmental controlling in Table 1, it's easy to notice that the data-driven comfort model and comfort-driven environmental control are promising but the means of data collection, model development, and control strategy varied remarkably. This leads to questions such as why the research method and outcome varied so significant? Are there standardized procedures and preferred solutions to support the occupant-centric thermal comfort? Answers to these questions can help to guide future research and practical activities.

To better understand the cutting edge in the field, a timely systematic review of relevant technologies and practices would be of great value. This paper gives a review of occupant-centric thermal comfort technologies from sensing, predicting, and controlling perspectives. The summary and outlook from existing literature could be useful for more advanced environment conditioning strategies in building design, operation, and control.

Table 1
Selected publications about data-driven thermal comfort model and comfort-driven control (note, only 9 papers publications in 2019 were selected as examples).

Ref.	Data collecting						Comfort predicting				Controlling	
	Data source	Sample size	Thermal comfort index	Environmental factors	Human factors	Sensors	Input features	Method (Algorithms)	Model type	Performance	Method	Results
[52]	6-day test in an office	2 subjects	7-point TSV	T_{clo}, T_{air}, RH, Clo	T_{skin} at cheek and HR	• Infrared camera (FLIR B840) for T_{skin} • T_{air} and RH sensor (DHT22)	• A: T_{air}, RH, Tskin at cheek, T_{clo} • B: T_{skin} difference)	• RF • SVM	Personal model	Linear kernel SVM has 100% precision and recall for female subjects, 97.5% and 96.1% for male subjects	–	–
[53]	Field study in daily life	14 subjects	3-point TP	T_{air} around subject, T_{out}, humidity, wind speed, solar radiation	T_{skin} at wrist and ankle, HR, and wrist accelerator	• iButton (DS1923) for T_{skin} • Polar H7 • strap for HR • Small cell-phone for accelerator	T_{skin} at wrist and ankle, T_{air} around subject, HR, wrist accelerator, T_{out}, humidity, wind speed, and solar radiation	14 MLalgorithms	Personal model	The median performance of the best algorithm for each subject is 24%/78%/0.79 (Cohen's kappa/accuracy/AUC)	–	–
[54]	Chamber tests	24 subjects	Wrapped 3-point TCV	–	T_{skin} and T_{clo} at different body parts (arm, torso, head)	RGB-DT camera	• A: mean T_{skin} athead, elbow, and hand.• B: mean T_{skin} at where skin is visible and mean T_{clo}.• C: B plus temperature variance within face.• D: B plus temperature difference.• E: B plus temperature gradient;• F: all features	• SVM • GPC • KNC • RF	Personal model	>80% accuracy for personal comfort prediction and > 85% accuracy in predicting mean time to warmdiscomfort	–	–
[55]	Subset of ASHRAE RP884	5576 samples	7-point TSV	T_{air}, RH, T_{out}	Met, Clo	–	T_r, T_{air}, RH, and Clo	• KNN • RF • SVM	Group average	Compared with PMV, the recall of three algorithms increased 6.3%, 5.4%, and 5.4%	–	–
[56]	Field study	369 subjects	• 7-point TCV • 3-point TP	–	–	Normal camera	Pose category	Classification	–	86.4% average accuracy	–	–
[57]	Field study	18 subjects	3-point TP	T_{air}	T_{skin} and heat flux at cheek and wrist	• FluxTeq for heat flux • DHT22 for T_{air} and RH	T_{air}, T_{skin} and heat flux at cheek and wrist	• RF • SVM • LoR	Personal model	Adding heat flux improves model performance by 3.8%	–	–
[58]	Field study	7 subjects	3-point TP	Time, T_{air}, T_{out}, CO_2, Occupancy status	T_{air} setpoint changes	• HMI for T_{air} setpoint • Motion sensor • Energy meter • T_{air}, RH, and CO_2 sensors	T_{air}, T_{out}, RH, and CO_2	• GNB • DT • SVC • ANN	Temperature preference	Over 90% accuracy	Rule-based control in real buildings	4–25% energy saving

Table 1 (*continued*)

Ref.	Data collecting						Comfort predicting				Controlling	
	Data source	Sample size	Thermal comfort index	Environmental factors	Human factors	Sensors	Input features	Method (Algorithms)	Model type	Performance	Method	Results
[59]	6 actual comfort profiles and 15 synthesized profiles from actual data		3-point TP	T_{air}	–	–	T_{air}	Bayesian network method	Overall comfort profile	–	Agent-based modeling	Achieve collective comfort better
[60]	Training data was from chamber test bed, testing data was from real building measurements.		7-point PMV	T_{air}, Vel, RH, T_g	–	HD32.3 instrument by Della OHM for Tair, Vel, RH and T_g	T_{air}, Vel, RH	• GPR	Group average	The predicted and actual values are almost equal	Simulation and deep Q-learning	Minimize energy consumption while satisfying thermal comfort

2. Methods

There are many literature databases and search engines when preparing this article. The Scopus was chosen because it claims to be the largest abstract and citation database of peer-reviewed literature. Given the convenience and easy accessibility for literature researching, Google Scholar was used as an alternative search engine to look for extra publications. The citation-tracking capability of Scopus and Google Scholar was used to rank the publications with high impact within the field. Given most of the publications are recent research activities, the impact of individual study and its original contribution to the field were considered when organizing the content. Studies with high citations and new solutions were introduced in the text, otherwise, they were listed in tables or references.

When searching the literature, keywords of 'thermal comfort', 'thermal sensation', 'thermal preference', and 'personal thermal comfort' combining with 'personalized', 'data-driven', 'machine learning', 'occupant-centric control', 'personal environmental control', and 'Internet of Thing' were used to obtain the first-stage literature list. For building environmental control studies, only thermal comfort-related studies were included to narrow down the scope of the review. Irrelevant publications were screened after reading their abstracts and in-depth searching was performed among references of the first-stage publications.

Through the above processes, 105 peer-reviewed publications including 87 journal articles and 18 conference manuscripts were selected for further reviewing. Fig. 1 shows the regional distribution and increasing trend of these publications. Two interesting observations are noteworthy. First, the number of publications in this field grew exponentially during the past 3–5 years, indicating the popularity of this research topic. Second, the research activities in this field happened mostly in the USA, China, South Korea, Singapore, and European countries.

Fig. 2 shows the occurrence of different keywords in the collected publications. The top keywords such as 'thermal comfort', 'machine learning', 'Internet of Thing', 'skin temperature', and 'HVAC control' are consistent with words used for literature searching. To render tractable, the publications were classified into three themes as shown in Fig. 3. The ***'Sensing'*** theme includes different data categories and their collecting methods, which is the groundwork for the development of data-driven thermal comfort models. The ***'Predicting'*** section emphasizes model developing methods such as ML algorithms, targeted thermal comfort indices, model performance (predicting accuracy), and features of the model. The ***'Controlling'*** part involves methods of interfering occupants' thermal comfort after knowing their demands. These three themes form the basic structure of this review and will be further divided into sub-topics to provide new insights into the field. The sub-topics were identified based on the common interests in the publications. To make a more objective standing point and clearer structure, Section 3 introduces the general observations in the three themes. Then, the knowledge gap and future research directions are discussed in Section 4.

3. General observation

3.1. Thermal comfort sensing technology

The data-driven thermal comfort models require a set of input data to train and test the model. The input data can be environmental factors, such as T_{air}, T_r, RH, and Vel; personal factors from physiological or behavioral aspects; and subjective feedbacks, such as TSV, TCV, and TP. Fig. 4 groups these factors into six categories.

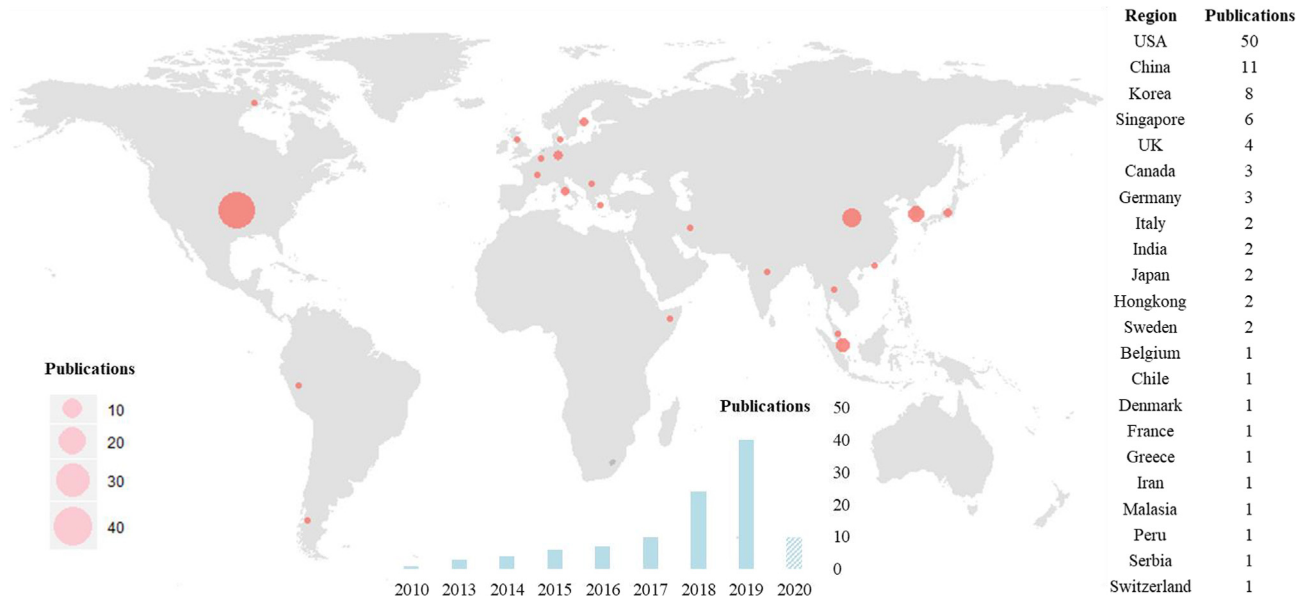

Fig. 1. Regional distribution and increasing trend of the publications. (Note, the nationality of the publications was based on the first author's first institute. The background map was the Patterson world map without Antarctica. The publication database was formed by Feb. 25th, 2020, and expanded by Jul. 17th, 2020).

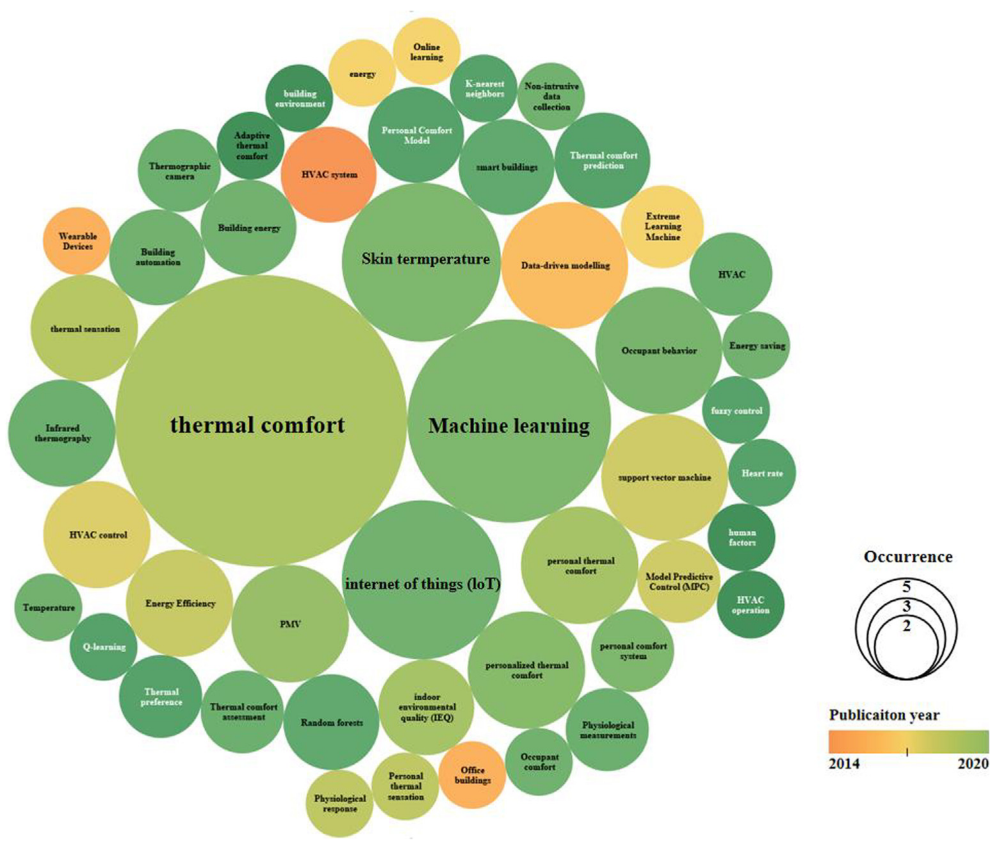

Fig. 2. Keywords analysis of the collected publications.

These categories together with a recent review from Kim et al. [31], which presents a framework for personal comfort model development, were utilized to organize the literature and formed the basic structure of Table 2 (see the first two columns of Table 2). Then, data types and data collecting methods in each publication were summarized in the right-side columns of Table 2 so that to provide a glimpse of this topic.

3.1.1. Subjective feedback collecting

In thermal comfort studies, questions like TSV, TCV, and TP are used to collect subjective evaluation on building thermal conditions [27,75]. As shown in Fig. 5, TSV, usually with a 7-point scale [27], is the most prominent question to describe what extent the occupant feels cold or hot. The TCV is used to record whether a specific thermal condition can be considered comfortable or not.

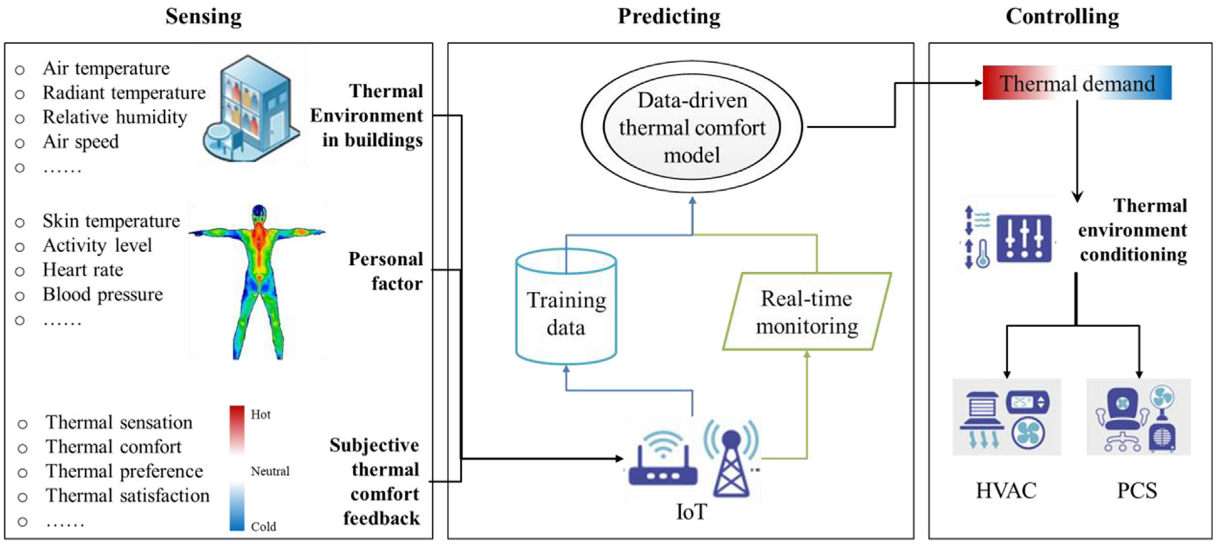

Fig. 3. The framework of the review.

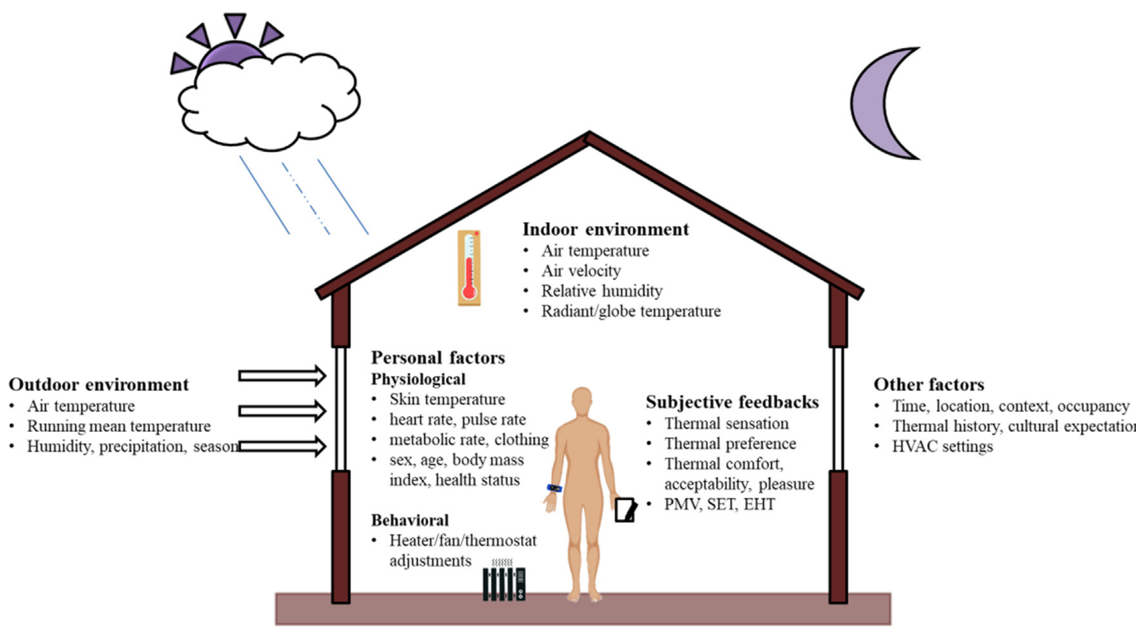

Fig. 4. Factors affecting building occupants' thermal comfort.

Meanwhile, the TP with 'Cooler', 'No change', and 'Warmer' choices is the most relevant and straightforward vote specifying which action an HVAC system should take [31]. The relationships among these thermal perception scales have been under investigation in recent research of 'the scales project' leading by Schweiker [76,77].

As shown in Fig. 5b, the TSV and TP are the most frequently used votes, followed by the TCV. Most studies simply chose one of these votes to represent occupants' thermal perception without distinguishing the difference between 'thermal sensation' and 'thermal comfort'. A widely applied assumption is that the middle three anchors of TSV, i.e. 'slightly cool', 'neutral', and 'slightly warm', represent thermally 'comfortable' or 'no change' preference. But this classic assumption may not hold in certain cases [64], especially in non-uniform and transient thermal conditions with local heating/cooling or temperature changes [78]. In such cases, the 'comfort' perception is related to the combination of core temperature, the initial thermal status of the human body, and the adding of local heating/cooling stimulus [79,80]. To this end, data-driven comfort studies involving non-uniform and transient conditions should think about which question can represent occupants' thermal comfort and thermal sensation. The study from [81] investigated the difference between TSV and TCV and proposed a new label called 'Combined Thermal Sensation and Comfort'. But the reliability of this method needs to be validated in more circumstances.

As shown in Fig. 5c, there are two common ways to collect subjective thermal comfort feedbacks in existing studies. More than half of them used dedicated smartphone apps or web tools to collect responses from the occupants [62,82]. The study from Laftchiev et al. [83] even applied speech recognition to enhance the convenience of data collection for occupants' input. The advances in IoT reduced the difficulty of collecting occupants' responses by a large margin, making it promising to use these feedbacks into the environmental control loop. Some studies [84,85] leveraged

Table 2
Data types and collection methods for data-driven thermal comfort model development.

Category	Data types	Ref. of sensing studies	Ref. of sensing and predicting studies																													
			[47]	[61]	[62]	[63]	[64]	[89]	[9]	[33]	[46]	[49]	[50]	[54]	[58]	[65]	[66]	[67]	[68]	[69]	[70]	[71]	[72]	[73]	[74]	[82]	[83]	[86]	[91]	[95]	[97]	[99]
Subjective feedbacks	sensation	9-point																								**						
		7-point								*		*					**			*	*						**	**				**
		5-point																					*	**							**	
		3-point									**	*	*									*								*		
	preference	**	**			**			**				**				**											**				
	comfort, acceptability, satisfaction, pleasure															**									**	**					**	
	PMV, SET, EHT																							*								
Personal factors xxx	Physiological	Skin temperature	xxx					xxx			xxx		x	xx			xxx		xxx	x		x	x			xx	xx	xx	xx	x	xxx	xx
		Heart rate, pulse rate												xx								x				xx	xx	xx	xx	x		
		Metabolic rate, clothing insulation			xxx	xxx									x										x		xx		xx			
		Sex, age, body mass index, health status							y			y								y	y					y	y					
	Behavioral	Heater/fan/thermostat adjustments							xx																							
Environmental factors	Indoor	Air temperature							y	y		y		y				y		y	y		y	y	y	y		y	y			y
		Air velocity								y		y								y	y		y	y	y	y		y				
		Relative humidity							y	y		y		y				y		y	y		y	y	y	y		y	y			
		Radiant/globe temperature							y	y														y	y	y						
	Outdoor	Air/running-mean temperature							y	y		y									y											
		Humidity, precipitation, season																														
Others	time, location, context, occupancy thermal history, cultural expectation										y																					

'*' means collecting subjective feedbacks through paper questionnaires, '**' means using website tools or smartphone applications to collect subjective feedback.
'xxx' means using non-invasive sensors, 'xx' means using semi-invasive sensors, and 'x' means using invasive sensors.
'y' means the data was collected.

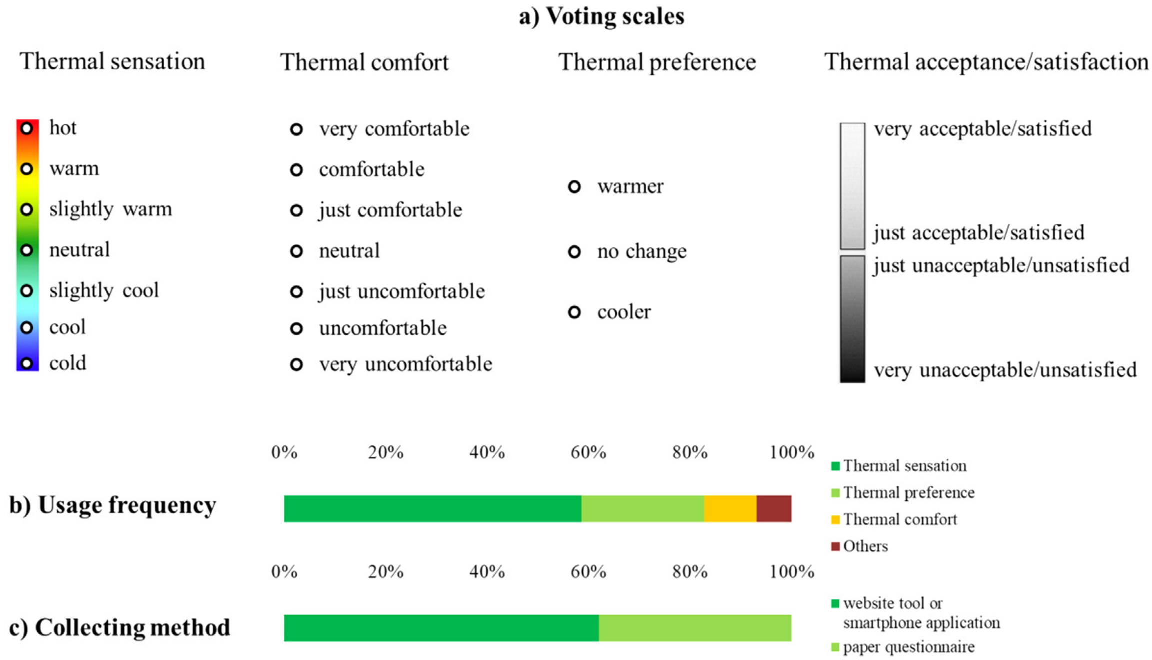

Fig. 5. Voting scale, occurrence, and collecting method of thermal comfort questionnaire.

this concept as ‘Human-in-The-Loop’, which will be discussed in the ‘controlling’ theme.

3.1.2. Personal factor collecting

Different from conventional heat transfer calculation models, the unprecedented data-collection abilities and the data-driven approach allow us to use a new set of precise input variables for thermal comfort predicting so that to avoid imprecise variables such as clothing insulation and metabolic rate [86,87]. All the personal factors shown in Fig. 4 are potential substitutes for clothing insulation and metabolic rate so that it is valuable to explore the performance of different personal factors.

As shown in Fig. 6a, a wide range of personal factors including skin temperature, heart rate/pulse rate, and other occupant information were explored for data-driven comfort model development. Given the high correlation between thermal sensation and the skin temperature [88], using skin temperature and its derivatives has been the most popular practice [46,67]. The heart rate and pulse rate were the second popular personal factors because of their excellence in reflecting metabolic rate changes when occupants change activity levels [53]. Current commercialized wearable devices such as the Fitbit [89,90] make it possible to collect real-time heart rate/pulse and activity data inexpensively and accurately. The easy connections between these data recorders and smartphone/website applications make it possible to embody biometrics into a data-driven thermal comfort model conveniently. Besides biometrics, the study from Kim et al. [9] successfully predicted personal thermal preference via occupant’s interaction with background air conditioning system and local heating/cooling chair. Shetty et al. [91] also achieved 95% thermal preference predicting accuracy utilizing desk fan usage behavior. These two studies showed that occupants’ behavioral interactions with building components, such as HVAC and PCS, can be used to predict thermal comfort at a personal level, offering an alternative possibility for data-driven thermal comfort model development.

Given its encouraging performance in thermal comfort predicting, many skin temperature sensing technologies are being explored. Based on the intrusiveness of the sensor, they can be classified into three categories: invasive, semi-invasive, and non-invasive [47,92]. Fig. 6b shows the three sensor categories for personal factors collecting and Fig. 7 shows typical examples for each skin temperature sensor type.

Invasive sensors typically are thermocouples and thermistors with connecting cables, which were widely used in early thermal comfort studies [93]. This type of sensor usually has advantages of high accuracy and high reliability, but the cables and wires indeed hindered their convenience of the application by a significant margin. Until now, invasive sensors with high accuracy are still widely used in thermal comfort research [93,94]. ***Semi-invasive sensors*** with no cables occurred a little bit later but soon

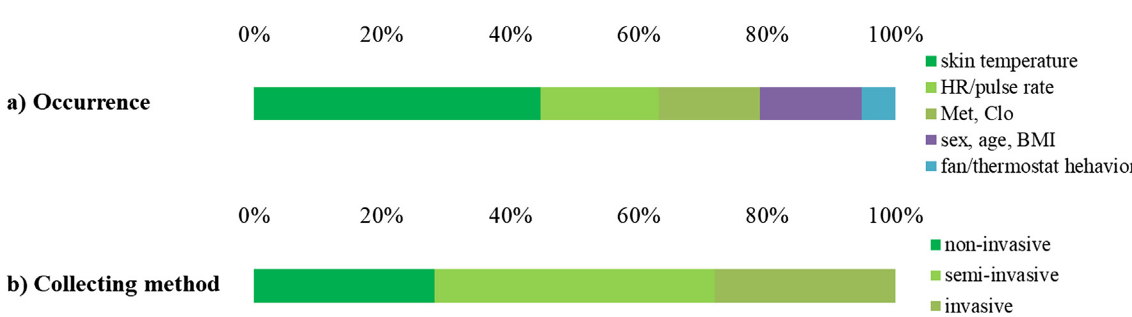

Fig. 6. Occurrence and collecting method for personal factors.

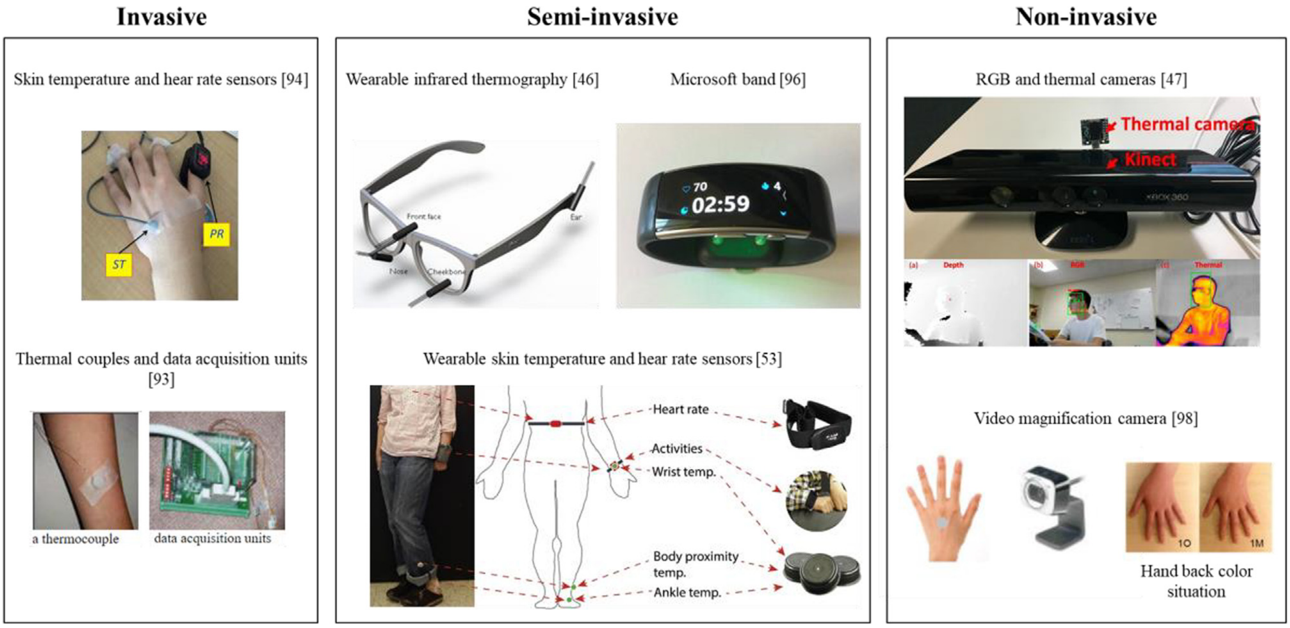

Fig. 7. Typical skin temperature sensors.

gained popularity [9,53]. As shown in Fig. 7, the ibutton [53,95] and wearable wristbands [96] are two representatives of this type of sensor. Besides that, new semi-invasive sensors are being proposed. Ghahramani et al. [46] developed glasses with an infrared sensor to measure the facial skin temperature. The wearable semi-invasive sensors largely reduced the restriction of cables and wires, but not every occupant is willing to wear the device. The attendance rate is potentially a limitation for this sensor type. Researchers also turned to ***non-contact and non-invasive sensors*** such as infrared cameras [68] and RGB cameras [92,97,98]. These new sensors can measure the occupant's skin temperature over a distance without attaching on the human body, making it possible to predict thermal comfort with no invasiveness to the occupant. However, it is worthy to note that the current accuracy of non-invasive sensors is not yet promising, and they can only detect skin temperature from body parts that are exposed to the ambient environment, such as the facial area [66,97] and hand back [92]. Although these two body parts are important for thermal sensation prediction in steady-state thermal conditions, there is no solid evidence showing that they can achieve sound prediction in transient and non-uniform conditions.

In addition to developing new sensing technologies, studies comparing the performance different skin temperature sensors are also valuable. Two such examples are a study from Aryal and Becerik-Gerber [99] that compared the accuracy of wrist-worn and thermal camera and a study from Kobiela et al. [82] that compared the smartwatch and professional invasive instruments. Both suggested that cost-effective skin temperature sensors with high accuracy should have higher priority for thermal comfort prediction.

3.1.3. Environmental factor collecting

In addition to personal factors, environmental factors were also frequently utilized in the data-driven comfort model (see the 'environmental factors' category in Table 2). Fig. 8 shows the occurrence of different environmental variables, among which the air temperature, air velocity, and relative humidity are the top three frequently used parameters. Cheung and Schiavon [35] found that using single air temperature can predict thermal sensation with 35% accuracy, which is comparable to that of PMV with six input parameters. Luo et al. [49] found that the model accuracy slightly decreased from 66.2% with 12 input parameters to 60.2% with only the air temperature. Another comparative study [100] showed that using environmental data along to predict thermal comfort can produce higher accuracy than only using physiological data (either from a wearable sensor or thermal camera). Combining environmental factors and physiological factors lead to only 3%–4% higher accuracy than using environmental factors along. Other data-driven models [68,74] only using environmental factors as input also showed promising predicting accuracy. These results indicate that physiological parameters are not necessarily the only choice to produce high-performance data-driven thermal comfort models; environmental factors such as air temperature and air velocity can also contribute to the model performance.

Additionally, too many input variables may cause higher costs in sensor installation and data management, it is common to compromise the number of input variables to be cost-efficient when developing data-driven thermal comfort models. As shown the Table 2, some studies [58,100] used only one or two input variables while others utilized more than six [75,82]. Normally, more input variables can achieve better model performance but that means

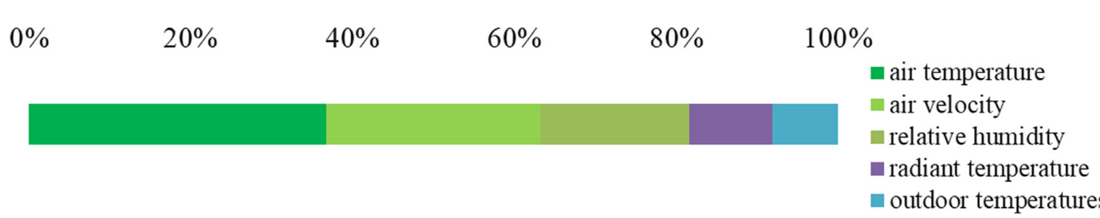

Fig. 8. Occurrence of different environmental factors.

more extra sensors are needed. It would be helpful if future studies can investigate how many input variables would be enough for high-performance model development.

3.2. Thermal comfort predicting

As shown in Fig. 3, the data-driven thermal comfort model bridges the data collected from sensing nodes and the actions of environmental controlling systems. Unlike the conventional heat balance model that requires fixed input variables, the data-driven thermal comfort model has larger flexibility in input variables and learning algorithms. Section 3.1 summarized the input variables. This section focuses on model development and performance.

There are many choices when developing data-driven thermal comfort models. For example, which algorithm should be applied? Is the model a personal model or group-average model? To date, there is no standardized procedure for model development. The study from Luo et al. [49] investigated how different algorithms, sampling methods, cross-validation, training proportion, precoding, and hyperparameter tuning would affect the model performance. Following the framework in [49], this review further summarized algorithms adopted in recent literature and their model function and performance. These sub-topics formed the basic structure of Table 3.

3.2.1. Algorithm selection

Data-driven methods directly mine thermal comfort principles from the data. As shown in Fig. 9, a wide range of algorithms, from linear regression (LR) to the hidden Markov model (HMM), were utilized for thermal comfort prediction. Among the algorithms, the random forest [20], artificial neural networks, support vector machine [105], K Nearest Neighbors, and Gradient Boosting Machine are frequently used and often ranked as the top choices with outstanding performance [9,49,54]. It is believed that algorithms with capabilities to control high dimensions (such as the RF, ANN, GBM, etc.) can achieve better TSV and TP prediction than other algorithms without them [31,49], but no mathematical explanation on this has been reported. As there is no solid conclusion on algorithm selection, the popular strategy in current studies is using multiple algorithms in one task to minimize the prediction biases, preventing over- or under-prediction caused by one specific algorithm. A systematic comparison between the frequently used algorithms and identifying each algorithm's application scope using common thermal comfort data would be of great value for future studies.

3.2.2. Model function

Predicting building occupants' thermal comfort is a complex task. The model performance may vary depending on different contexts. For example, individual thermal comfort may be different from the group average [23]; thermal comfort in the non-uniform and transient conditions is different from that in uniform steady-state conditions [80,81]; thermal comfort in extremely cold or hot conditions could be different from those near thermal neutralities [106]. To this end, when developing data-driven comfort models, the application scope of a specific model, especially the model functions, should be noteworthy. Fig. 10 summarizes the occurrence of three model functions.

Personal or group thermal comfort model? Given the commonly existing large individual difference in building occupants' thermal comfort [21,23], an advantage of the data-driven model is the capability of predicting at both the personal level and group-average level. The feature of the data-driven model relies on the training data: if the training data is from an individual subject, the trained model should have the ability to predict that subject's thermal comfort; if the training data is from a group of people, the trained model can predict that group of population. As shown in Fig. 10a, the personal comfort model has gained its popularity with the emergence of data-driven methods.

Steady-state or transient thermal comfort model? Fig. 10b shows that more than 60% of the data-driven models were trained using steady-state data and some of them are from extreme conditions [107] that rarely happen for the normal indoor environment. It is more challenging but also more valuable to predict occupants' subtle thermal comfort perceptions near thermal neutral conditions than the cold/hot sensations in extreme conditions because occupants normally spend most of their time in conditions near thermal neutralities. There are also applauding examples in the literature. For instance, Liu [54] and Li [91] trained their comfort models using data collected in real daily life. Jung [58], Cosma [55], Choi [73], and Aryal [99] trained their models in gradually changing temperatures. Youssef et al. [83] trained their model in step-changing conditions. Guenther et al. [108] collected data with elevated air movement.

Whole-body or local thermal comfort model? Another noteworthy issue is whether the model predicts whole-body or local thermal comfort. As shown in Fig. 11c, over 90% of the current models focused on whole-body thermal sensation or overall thermal preference. Only a few studies [9,73] applied local heating and cooling within body segments during their data collection and even less study [73] trained their model to predict local thermal comfort.

3.2.3. Predicting accuracy

When evaluating the performance of data-driven models, the predicting accuracy is an important aspect. An encouraging observation from the literature is that most of the studies reported promising results when using data-driven approach. Fig. 11 shows the predicting accuracy distribution reported in the literature. The accuracy varied in a wide range with a standard deviation of around 15%. This variance may be caused by multiple reasons such as the targeted comfort indices, the input variables, the model functions, and so forth [49]. But the median predicting accuracy, which is 84%, is promising, significantly higher than previous thermal comfort models such as the PMV [35]. These observations suggest the prospect of predicting building occupants' thermal comfort status using ML algorithms. In addition to pursuing predicting accuracy, other metrics such as recall (positive) [56], specificity (negative), a trade-off between precision and recall, confusion matrix, ROC and AUC curve [54] are also under investigation.

3.3. Thermal comfort controlling

The broader definition of occupant-centric building control (known as OOC) refers to control systems utilizing data from occupants, indoor environment, and outdoor climate to regulate indoor environments (including illuminance, temperature, humidity, CO2, noise) via components like the thermostat, light switch, window, blind, fans, sound masking system [85,109,110]. Ultimately, these attempts can improve both occupant comfort and energy efficiency. More information in this field can be found in recent reviews [85,110–112]. This review adopts the concept of OCC but emphasizes more on thermal comfort practices to narrow down the scope of the reviewing. Many OCC studies focused on the implementation of the control [113–115] but did not involve the concept of occupant-centric thermal comfort so that they were not included in this review.

Occupant-centric thermal comfort control refers to systems utilizing occupants' feedback or responses (see Section 3.1) and data-driven thermal comfort models (see Section 3.2) to regulate indoor thermal environments at the local scale, personal scale, or whole-

Table 3
Algorithms and features of existing data-driven thermal comfort models. (Note, the model predicting accuracies are not listed in this table because each study may have multiple predicting accuracies. They will be presented in Fig. 11.)

Category and Ref.		[9]	[20]	[33]	[46]	[49]	[50]	[55]	[54]	[56]	[58]	[66]	[68]	[70]	[73]	[82]	[83]	[92]	[93]	[96]	[100]	[100]	[101]	[102]	[103]	[104]
Algorithms	Linear regression (LR)											x										x				
	Tree regression (TR)																					x		x		
	Classification tree (CT)	x							x					x										x		
	Linear discriminant analysis (LDA)								x					x							x					
	Logistic regression (LoR)	x				x			x		x			x									x			
	Decision tree (DT)					x			x						x				x							
	Boosted trees (BT)																		x							
	Bayesian network (BN)													x												
	Bayesian modeling																									x
	Naive Bayes (NB)					x			x				x													
	Artificial neural networks (ANN)					x			x			x	x	x											x	
	K nearest neighbors (KNN)					x		x	x	x								x			x	x	x			
	Adaboost (AB)					x																				
	Gradient boosting machine (GBM)	x				x			x														x			
	Support vector machine (SVM)	x		x		x	x	x	x	x	x			x			x	x		x	x	x	x		x	
	Random forests (RF)	x	x			x		x	x	x	x	x						x	x	x	x		x			
	Gaussian process classifier (GPC)	x						x																		
	Rule-based classifier (RBC)								x																	
	Fuzzy logic												x			x										
	Extra tree															x										
	Hidden Markov model (HMM)				x																					
Function	Personal model or group model	p	p	g	p	g	p&g	p	p	g	p	p	p	p	p	p	p	p	p	p	p	p	p	p	g	p
	Steady-state or transient condition	s	s	s	t	s	s	t	t	s	t	s	s	s	t	s	t	t	s	s	t	t	s	s	s	s
	Local or whole-body comfort	w	w	w	w	w	w	w	w	w	w	w	w	w	l	w	w	w	w	w	w	w	w	w	w	w

'x' means the algorithm was applied.
'p' means the model was the personal model; 'g' means group model.
's' means the model was trained using data from the steady-state condition; 't' means the model was trained using data from the transient condition.
'l' means the model can predict local thermal comfort; 'w' means the model predicts whole-body thermal comfort.

Fig. 9. Occurrence of different learning algorithms.

Fig. 10. Model functions.

building scale (see Fig. 12). These systems have garnered increasing attention because of the potential benefits of improving thermal comfort satisfaction while reducing energy consumption [116–118]. Studies have been conducted using simulation [119,61] or field measurements [59,74,120,121] to estimate its thermal comfort and energy benefits. However, implementing this new strategy in real buildings is challenging. Only a small body of such cases has been implemented in real buildings. Table 4 gives a summary of these studies from the following dimensions: 1) What building type was investigated? 2) The research method was simulation or field implementation? 3) What systems were utilized to implement the control? 4) To which level the control was? 5) How much comfort and energy benefits were achieved?

3.3.1. Systems and their levels of control

There are many heating and cooling systems or devices that can fulfill the occupant-centric thermal comfort controlling purpose (see Fig. 12). A centralized HVAC system at the building level or zone level affects all occupants in the entire building or a thermal zone simultaneously. Decentralized HVAC at a group or personal level influence a smaller portion of occupants. PCS [11,12] controls the micro-environment around an occupant or even a local body part. Among these three levels, the HVAC at room level and zone level are the most frequently used systems to implement occupant-centric thermal comfort control (see the 'Control level' column in Table 4). Given its scale and system size, HVAC systems usually have multiple occupants sharing a terminal unit or a

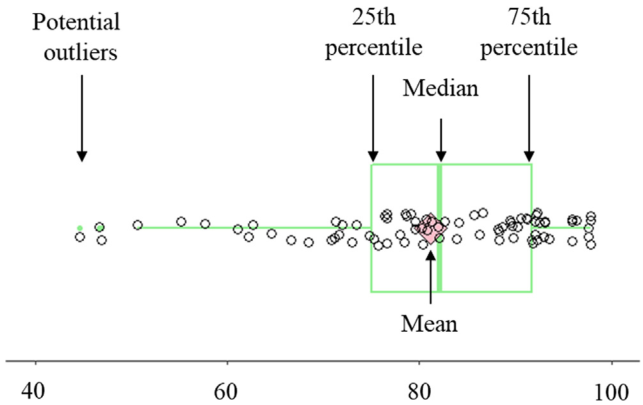

Fig. 11. Predicting accuracies of data-driven thermal comfort models.

thermostat, it is challenging to balance different thermal comfort demands from the personal level [116,117]. Consequently, their control levels were mainly at the room or zone level. PCS devices have advantages of providing personal or localized levels of thermal comfort control with large flexibility. The studies from Kim [134] and Aryal [134] are such examples showing the promise of the local heating and cooling devices. More potential systems offering the personal level of thermal control can be found in a recent review [135].

3.3.2. Comfort and energy benefits

The goal of occupant-centric thermal comfort control is to improve thermal comfort while saving energy. Fig. 13 shows the energy-saving and comfort improvement from existing occupant-centric thermal comfort control studies. The median energy saving and comfort improving is 22% and 29.1%, respectively.

The energy-saving of this concept can be attributed to multiple reasons, among which expanding the temperature setting point [136,137] is a common practice. For examples, using the consensus temperature based on each individual's request has the potential of saving 20% heating and cooling energy [138]; adjusting temperature based on occupants' cold/hot complaints can achieve 24% saving [131]; re-setting the temperature based on occupants' thermal expectation can save 39% [139]. However, Fig. 13a also shows large energy-saving variance among different studies. Some cases [140] even reported higher energy consumption for occupant-centric thermal comfort control because the subjects preferred narrower temperature range than the default setting. To this end, factors such as individual thermal preferences, number of occupants, building types, climate, and environmental control systems should be considered when estimating the energy saving of this new strategy [142].

Regarding the thermal comfort improvement shown in Fig. 13b, the positive effects of occupant-centric control seem to be more consistent. Because the concept of this new strategy is to customize the thermal environment around occupants and meet their demands. But, how to ensure collective thermal comfort in shared space is still challenging when tuning a centralized HVAC system according to individual request [141]. Although personal comfort models helped to learn thermal comfort demands at the personal level, it is still not easy to aggregate multiple comfort profiles into an action command for the HVAC system that in line with most of the thermal preferences while minimizing energy consumption [125]. The common use of thermal zones (several rooms conditioned by one HVAC unit simultaneously) in current commercial buildings makes it even harder to address this conflicting issue. In the literature, especially those from Jazizadeh and Jung [117,118], several strategies can help to solve this issue. The first one is using the group-averaged thermal comfort model like PMV without considering individual thermal comfort demands [126,127,142]. The second one is to adjust the HVAC setpoint based on most of the votes [139]. For example, accumulating each preference as an aggregated preference profile. The Third way is to minimize the gap between the desired temperatures and the set-point [143] or to optimize the setpoint with consideration of each user's thermal sensitivity [118].

4. Summary and discussion

4.1. Challenges of occupant centric thermal comfort solutions

Based on the above observations, the following challenges were identified which are potential research directions or issues worth attention.

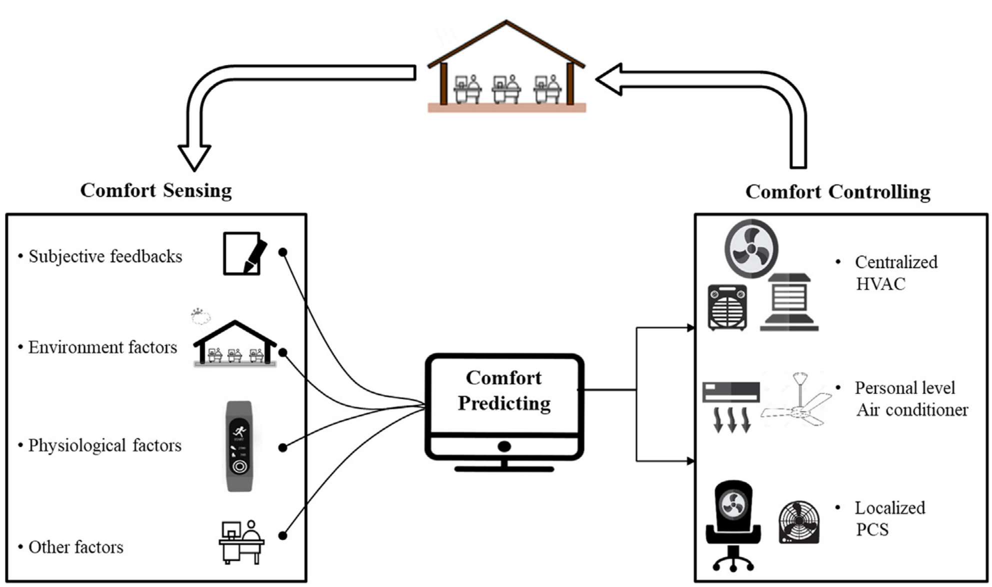

Fig. 12. Occupant-centric thermal comfort control.

Table 4
Occupant-centric thermal comfort control.

Ref.	Building type	Research method	System type	Control level	Energy-saving (%)	Comfort improving (%)
[59]	Office	Field measurement	Room HVAC	Room level	4–25	–
[61]	Office	Simulation	Room HVAC	Room level	12.4–32.3	–
[73]	Residential & office	Field measurement	Room HVAC	Personal level	–	53.7
[74]	Office	Field measurement	Zone HVAC	Zone level	26–39	~30
[84]	Laboratory	Field measurement	–	Personal level	24–45	44.3
[120]	Laboratory	Simulation	Centralized HVAC	Building level	>50	~20
[122]	Office	Field measurement	Zone HVAC	Zone level	–	–
[122]	Office	Simulation	Room HVAC	Room level	36.5	19.8–21.2
[123]	Laboratory	Field measurement	Room HVAC	Room level	6–21	31–72
[124]	Office	Simulation	Zone HVAC	Zone level	23	–
[125]	Office	Field measurement	Room HVAC and PCS	Room level	–	–
[126]	Residential	Simulation	Room HVAC	Room level	–	–
[127]	Office	Field measurement	Room HVAC	Room level	1–6	–
[128]	Residential & laboratory	Field measurement	Centralized HVAC	Building/zone level	23.6	–
[129]	Office	Simulation	Centralized HVAC	Building/zone level	0–6.5	25–40
[130]	Laboratory	Field measurement	Room HVAC	Room level	11.8	9
[131]	Office	Field measurement	Room HVAC	Room level	13	28.2
[132]	Office & laboratory	Field measurement	Room HVAC	Room level	18.9–37	59.4
[133]	Office	Field measurement	HVAC/PCS	Personal level	–	16

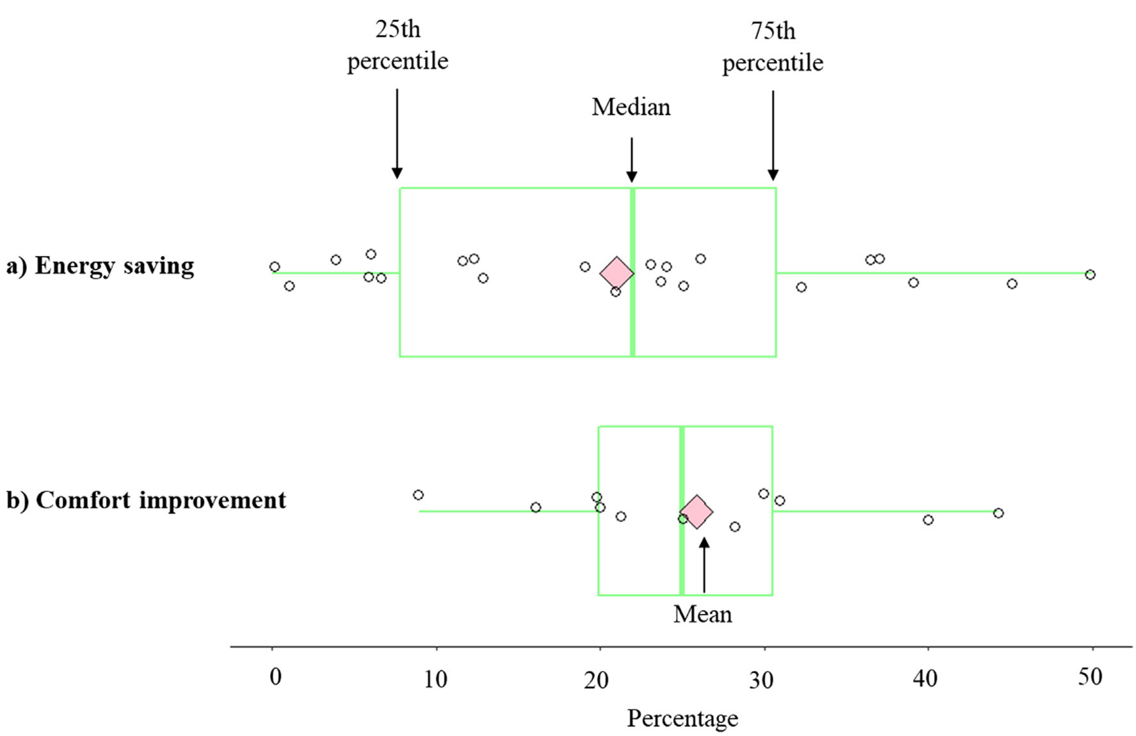

Fig. 13. Energy saving and comfort improvement potential of occupant-centric thermal comfort control.

4.1.1. Sensing technology

As seen in Section 3.1, a wide range of data-collecting methods has been utilized in this field. Sensors with different functions (e.g. standing along or network connected, invasive or non-invasive) were applied. With the advances in IoT and sensing technologies, it is worth exploring new data collecting methods with the pursuit of higher accuracy and convenience. Two such examples are the speech recognition for subjective feedback collecting [84] and contactless skin temperature measuring [99].

There also have some issues in the literature. *The first one* is about the voting scale when collecting subjective thermal comfort feedbacks. Taking the thermal sensation as an example, its voting scale varied from 3 points to as many as 9 points, and often the standard ASHRAE 7-point scale was wrapped into a 3-point scale for the data-driven comfort model development. The less-unit scale is relatively easier to be classified but also sacrifices nuanced information which is useful to distinguish the degrees of occupants' cold/hot sensation [49]. When choosing the voting scale, one should decide whether the purpose is to pursue higher predicting accuracy or capture more detailed information on occupants' thermal perception. *The second issue* is using data from the simulation without real measurement. For example, some studies use simulated results from the CFD [66] and the human body thermoregulation model to avoid difficulties in data collection. When doing this, one should note that learning from these streamlined results may lead to errors in real applications.

4.1.2. Predicting model

The performance of data-driven comfort models shown in Fig. 11 is encouraging. The machine learning technologies offered an alternative approach for thermal comfort prediction. In the future, the following directions worth further attention. *The first one* is moving toward personal comfort models. Shifting from the group model to a personal model can help the practice of occupant-centric strategies [144,145]. But as this is a new branch in the thermal comfort field, many issues need further exploration [31]. *The second one* is balancing model accuracy and input features. Given the cost of sensing, computing, and data management, it is common to compromise the number of input variables to be cost-efficient. Some pilot studies have tried to answer this question [35,49,50] but further investigation is needed to be produced to provide more solid answers. *The third one* is public accessibility. Like previous thermal comfort databases [146,147,148] and the online comfort tool http://comfort.cbe.berkeley.edu/, publicly available resources can boost the collaborations among researchers and leverage the benefit to the industry. To date, only a few data-driven comfort studies have made their code [49,73], data [9,54,100], model [33], web tool [33] or product publicly available. Efforts should be made to make the data-driven comfort models publicly available so that to avoid unnecessary repetitive work for future successors.

4.1.3. Controlling strategy

The energy-saving and comfort improvement shown in Fig. 13 are encouraging, but we also see large variances in energy-saving and challenges in field implementations of the occupant-centric thermal comfort control strategy. There are several topics needed to be further investigated. *The first one* is the reasons causing the energy-saving variance. It would be valuable if the effects of different factors such as occupants' thermal preferences, number of occupants, building types, climate, and air conditioning systems can be quantified [82]. *The second one* is to implement this new strategy in real buildings, especially those with energy usage and thermal comfort monitoring [59]. The current field implementation cases are still limited. *The third one* is to try new systems that can offer more flexibility in occupant control. Among the potential systems, PCS devices with the personal level of control are worth exploring [135]. *Last but not least,* it would be helpful to integrate the occupant-centric thermal comfort control with the broader view of OCC systems [109,112].

4.2. Limitations of this review

Some limitations of this review should be mentioned. The first one is that the literature searching maybe not thorough enough to collect all relevant publications. Especially for recent studies published as conference proceedings or degree thesis; they may be not included in the Scopus database. The second limitation is that the controlling part only includes publications emphasizing thermal comfort. For those who want to know a broader view of occupant-centric control and more detailed technics for the control implementation, please refer to other reviews such as [109,112].

5. Conclusion

This paper presents a review of occupant-centric thermal comfort studies from perspectives of sensing, predicting, and controlling technologies. The following observations are noteworthy.

1) Occupant-centric thermal comfort has become a hot research topic. The number of publications in this field increased exponentially in recent years. But there lack of standardized guidelines for data collection, model development, and field implementation.
2) A wide range of variables (e.g. subjective feedbacks, occupants' factors, indoor and outdoor parameters) and data-collecting sensors (including invasive and non-invasive, standing along, and network-connected) have been utilized in this field. Among all the variables, occupants' comfort feedback, skin temperature, and air temperature are the top three popular input features for the data-driven comfort model.
3) With a median predicting accuracy of 84%, the data-driven thermal comfort model shows its advantages in model performance and flexibility of input features. The gradual popularity of the personal comfort model can help the practice of occupant-centric thermal comfort control.
4) The 22% energy saving and 29.1% comfort improvement observed from the literature proved that occupant-centric thermal comfort control has great potential to maximize building occupants' thermal comfort while saving energy. More efforts especially filed implementations are needed to promote this new thermal comfort paradigm.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This study was funded by the National Natural Science Foundation of China (51908414), and China Postdoctoral Science Foundation (2019M651584 and 2017M620442).

Author contribution clarification

Luo, Zhang, and Xie conceived the study; Li C., Li H., and Xie did the literature searching, analyzing, preliminary reviewing, and drafted the manuscript; Li H. and Xie drafted some of the tables; Li C drafted some of the charts; Zhang supervised the study, confirmed the reviewing, and revised the manuscript; Luo revised the manuscript, finalized the reviewing, and approved the final manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enbuild.2020.110392.

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