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A comprehensive review of impact assessment of indoor thermal environment on work and cognitive performance - combined physiological measurements and machine learning

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Abstract: Ensuring occupants' work or cognitive performance and maintaining thermal comfort are important targets of indoor thermal environment management. Physiological indicators are susceptible to minor differences in air temperature and humidity and play a vital role in thermal environment studies. In recent years, advanced sensing technologies based on physiological measurements and machine learning (ML) approaches have provided a more accurate and effective way to assess the relationship between the indoor thermal environment and the performances of occupants. A review of this emerging field can assist in filling knowledge gaps and provide insights into future research and practice. This review work integrates the results of cognitive tests related to the thermal environment and performance, summarizes the application of existing physiological indicators, and the practice of using sensing technologies and ML technology to assess occupant performance and predict indoor thermal comfort. Cognitive testing results indicate that personal control of temperature and humidity appears to be a key factor in environmental satisfaction. And the introduction of ML technology innovatively integrates various physiological and environmental parameters, with a median prediction accuracy of up to 84%. Among all variables, skin temperature is the most significant physiological variable influencing thermal sensation, air temperature and humidity are the most popular environmental input variables. In summary, these observations support the prospects of novel sensing technologies and thermal comfort prediction model, and indicate the weakness of current works and future directions for improvement.

Keywords: Thermal environment; Cognitive performance; Physiological measurement; Machine learning (ML)；Thermal comfort

Nomenclature and abbreviations

ASHRAE	American Society of Heating Refrigerating and Airconditioning Engineer	SpO_2	Oxygen saturation of blood
		T_a	Air Temperature
AV	Air Velocity	TCV	Thermal Comfort Vote
aPMV	adaptive Predicted Mean Vote	T_g	Globe Temperature
BP	Blood Pressure	TP	Thermal Preference
CLO	Clothing insulation	T_s	Skin Temperature
CO_2	Carbon dioxide	TSV	Thermal Sensation Vote
COPD	Chronic Obstructive Pulmonary Disease	VO2	Oxygen Consumption
ECG	Electrocardiogram	WHO	World Health Organization
EDA	Electrodermal Activity		
EEG	Electroencephalography		
$ETCO_2$	end-tidal CO_2	***Machine Learning and Algorithms***	
ePMV	extended Predicted Mean Vote	ANN	Artificial Neural Network
HR	Heart Rate	CNN	Convolutional Neural Network
HRV	Heart Rate Variability	DT	Decision Tree
IAQ	Indoor Air Quality	DL	Deep Learning
IEQ	Indoor Environment Quality	GBM	Gradient Boosting Machine
IoT	Internet of Thing	KNN	K-Nearest Neighbor
MET	Metabolic rate, met	LR	Logistic Regression
MRT	Mean Radiant Temperature	LSTM	Long short-term memory
MST	Mean Skin Temperature	LDR	Linear Discriminant analysis
PMV	Predicted Mean Vote	ML	Machine Learning
PNS	Parasympathetic Nervous System	NB	Naive Bayes
PR	Pulse Rate	RNN	Recurrent Neural Network
RSP	Respiratory Signals	RF	Random Forest
RH	Relative Humidity	RT	Random Tree
R^2	Correlation coefficients (r) square	SVM	Support Vector Machine
SBS	Sick Building Syndrome		

1. Introduction

Human thermal comfort, cognitive and work performance are closely linked to Indoor Environmental Quality (IEQ). People spend most of their time indoors, and the surrounding built environment influences occupants' welfare, comfort, health, and work performance [1-4]. Previous human-building interaction studies have demonstrated that well-designed environments matter [5, 6]. The IEQ has a more significant impact on work performance than personal factors (psychological state, work attitude) and social environment factors [7]. Maintaining the quality of the indoor environment is undoubtedly one of the crucial contents to ensure work performance.

Since the declaration of the Sick Building Syndrome (SBS) by the World Health Organization (WHO) in 1986, scholars have conducted numerous experimental studies on how various environmental factors affect the physical health of indoor occupants [8-11]. Recent studies have shown significant correlations between the indoor thermal environment and occupants' performance, respiratory diseases, allergies, asthma symptoms, and SBS [9, 12, 13]. The thermal environment was mainly influenced by temperature and humidity. Poor quality of indoor thermal comfort conditions, predisposes to impairments in work and cognitive performance [9, 14-16]. As one of the most critical factors in IEQ, previous assessments of indoor thermal comfort have focused more on thermal feeling feedback surveys (e. g. Thermal Sensation Vote, TSV; Thermal Comfort Vote, TCV) [16]. The Predicted Mean Votes (PMV), adaptive Predicted Mean Votes (aPMV), and extended Predicted Mean Votes (ePMV) have been widely employed for guiding indoor thermal environment design. However, it has been shown that the actual comfort zone often deviates from those obtained through the PMV models, with differences observed based on standardized experimental results [17]. Whether the room is cool or warm has been determined by PMV, the physiological activities of the perceived environment remain poorly understood [18]. In addition, subjective performance can differ depending on gender or age. For instance, females tend to prefer warmer temperatures than males [19-23], and thermal sensation differs between young adults and the elderly [24, 25]. Thus, to accurately address the individual perception of the surrounding environment, it is necessary to further explore the mechanisms behind human environmental perception, to explain the simultaneous occurrence of multiple stimuli belonging to different comfort domains [26] and the human responses to these stimuli, which arise from the individual physiological and psychological reactions [27].

The recent development in physiological measurements highlights the potential for monitoring human perceptual activity. Relevant studies [4, 28, 29] have attempted to uncover further the change in work performance affected by combined indoor environmental factors based on physiological and psychological measurements. In particular, IoT-based advanced sensing technologies provided a more accurate and effective way to assess the relationship between indoor environments and occupants' performance [16, 30, 31]. High-quality data could be captured through flexible and convenient wearable sensors. According to the previous literature, semi-invasive wearable devices without cables have gained increasing popularity[32, 33]. Skin temperature is the most common among the various indicators measured by the sensors [34, 35]. It is direct feedback of the body's thermal stress response and tend to be more objective than questionnaires. Furthermore, since physiological brainwave activity is tightly related to the indoor thermal environment [36], some novel portable devices, such as the EMOTIV [37], innovatively introduced Electroencephalography (EEG) sensing technology to record differences in occupants' neuronal responses caused by environmental changes [38-43] and to classify occupants' real-time thermal comfort status [30]. Besides, several studies [44-46] have found that other physiological indicators (shown in Fig.1) also provide opportunities to explore the relationship between thermal environment and occupants' performance, such as Electrocardiogram (ECG), Electrodermal Activity (EDA), Heart Rate Variability (HRV), blood pressure (BP), end-tidal CO_2 ($ETCO_2$), oxygen saturation of blood (SpO_2), the levels of salivary cortisol and alpha-amylase. These physiological indicators, combined with environmental parameters, are signaled by various sensing techniques to be used as input features in numerous Machine Learning (ML) models for predicting thermal comfort. For instance, personalized thermal comfort, thermal preference, and thermal sensation models [30, 32, 47] have been developed by integrating physiological and environmental parameters in innovative ways, with a median prediction accuracy of up to 84% [48]. In predicting thermal comfort, Random Forest (RF), Support Vector Machines (SVM), Neural Networks (NN), K-Nearest Neighbors (KNN), Gradient Boost Machines (GBM) and Decision Tree (DT) are frequently used ML algorithms [48]. Moreover, individual or group differences in thermal comfort prediction, such as age and gender [49], can be addressed by combining physiological measurements with ML. Thus, real-time ML-based measurements present significant advantages in environmental assessment, overcoming the limitations mentioned above in PMV-based comforts and perceptual biases of the questionnaire-based approaches.

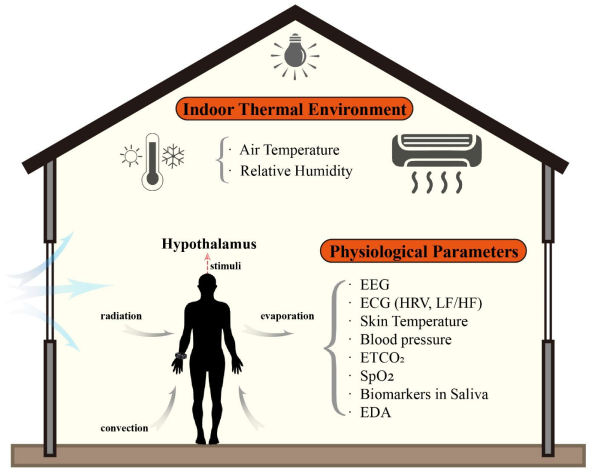

Fig.1 Factors affecting indoor thermal comfort and common physiological parameters.

To summarize the integrated effects of the indoor environment on occupants' performance and thermal comfort, this paper integrates the findings of previous studies on the relationship between indoor thermal environment parameters and performance. Reviews existing physiological indicators applications and the approaches of using sensing technologies and ML approaches to predict occupants' performance and thermal comfort in practice. Moreover, factors affecting the decline in occupants' performance and ways of improvement are discussed. Finally, according to the current research state, the possible directions and applications in the future were proposed. This work will provide references for thermal comfort model assessment approach and better indoor environment design.

2. Review methods

In this work, four main databases (Science Direct, Google Scholar, Web of Science, and China National Knowledge Infrastructure) were consulted to identify relevant studies. We established the following criteria for the inclusion of individual studies through the selection process: Firstly, the study had to report a controlled laboratory/field experiment on the effects of air temperature and/or air relative humidity on occupants' performance. Moreover, include at least one physiological indicator with sufficient quantitative information (e.g. mean, standard deviation, graphs, etc.). Secondly, ML studies must report models of at least one physiological indicator or environmental parameter and provide predicting accuracy. Under these criteria, studies on the effects of ventilation, CO_2, air quality, or any indoor physical properties other than temperature are included if air temperature, relative humidity, and performance indicators were reported.

By the primary retrieval system and the later manual screening, the title keywords of indoor AND “temperature OR heat OR cold” AND “humidity” AND “performance OR efficiency OR productivity’’ AND “work OR cognitive OR learning’’ AND “physiological measurement OR response” AND “machine learning OR data-driven’’ combining with “prediction” were used to do a more comprehensive search of references, while the topic keywords of “thermal environment” AND “thermal comfort” were used to maintain research objectives in the thermal environment. Additionally, 110 published papers on indoor occupants’ work or cognitive performance since 1979 were selected by checking titles, abstracts, and keywords in manual identification.

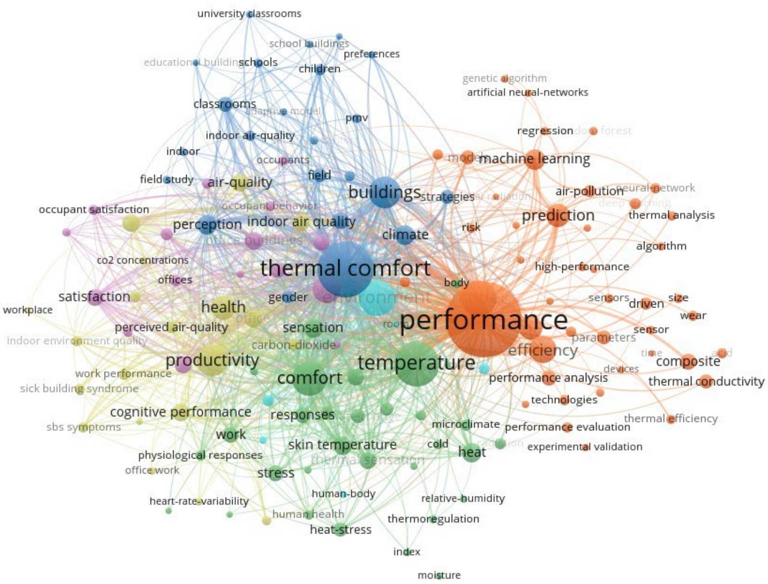

Fig. 2 Keyword co-occurrence analysis of the reviewed papers.

In the retrieved articles, topics and keywords that appeared more than five times were identified and analyzed by VOSviewer [50]. The analysis of related terms and co-occurrence is shown in **错误!**

未找到引用源。错误!未找到引用源。. The size of the nodes represents the frequency of the terms across the literature, while the thickness of the lines reflects the strength of the association between the terms and the color of the same lines shows the closeness of the terms to each other. The terms “thermal comfort’’, “performance’’, “temperature’’, “productivity’’, and “buildings” have the highest occurrences as the search strings.

3. Indoor microclimate parameters

3.1 Temperature

3.1.1 General comments

High and low indoor air temperatures are common risk factors for human performance and health. Concentration is difficult in high temperatures, and manual dexterity is reduced in low temperatures. The brain’s executive functions can be thought of as cognitive flexibility, the management of intervening factors in target-oriented behavior, and the prediction of functional outcomes [51], which may be affected by exposure to temperature and negatively affect the cognitive performance of the individual [2]. Besides, subjective performance can differ depending on gender or age [19-25]. This section summarizes evidence on the effects of air temperature on occupants’ work and cognitive performance, see Table 1 for additional information.

3.1.2 Effects on work and cognitive performance

Temperature can have differing effects (e.g. physiological and cognitive effects) in different environments. Previous work has found that temperature can be regarded as an environmental incentive to exert conscious effort at temperatures out of the comfort zone [22]. Furthermore, the different effects of temperature on task performance mainly depend on the type of task [52]. Ref [53] has discussed the direct impact of indoor thermal environment parameters on different work performances and concluded that decreased IEQ was the primary cause of reduced cognitive performance (such as reading, logical thinking, and arithmetic). In addition, Ref [54] has further elaborated on the mechanisms by which indoor temperature affects the performance of office workers.

An earlier study [55] found that the labor productivity of personnel working in Call Centre decreased by 5~7% when room temperatures exceeded 25℃. Another study [56] reported that work performance decreased by 2% per °C in the temperature range of 25°C to 32°C. Ref [57] reported that self-estimated performance was linearly correlated with thermal satisfaction ($R^2 = 0.94$, $p < 0.001$). Performance of simulated office tasks (multiplication and proofreading) also increased with individual thermal satisfaction ($R^2 = 0.403$ and $R^2 = 0.464$, $p < 0.001$).

As shown in Table 1, many recent studies have suggested that high and low indoor air temperatures affect physiological responses, work and cognitive performance, and learning efficiency.

Motivation for work declines with temperature. Mental alertness begins to decline above 25°C, and concentration cannot be focused or even lost above 30°C [58]. The highest performance on neurobehavioral tests was obtained at 21°C compared to 17°C and 28°C [1, 59]. Cognitive performance decreased significantly at 19°C, 27°C [52, 60], 29°C and 32°C [61] in thermal discomfort temperatures compared to slightly below the neutral temperatures of 22°C, 23°C, and 24°C. Cognitive performance was relatively stable and even slightly promoted at 22°C compared to 24°C [62]. Relative performance exceeded 95% in the temperature range of 22.6°C to 26.0°C [63]. At 28.6°C, the more mental workload was generated to achieve the same performance at 21.7°C (slightly cold) and 25.2°C (neutral) [64]. The optimal performance was from 20°C to 26°C, especially from 22°C to 24°C, which almost corresponded to the optimal thermal satisfaction [65]. Certain comfort and productivity can be improved at 25.8°C compared to 20°C [66]. The highest learning performance was achieved at 22.2°C compared to 17.3°C and 27.1°C [67].

Some studies [2, 68-71] have combined physiological indicators (such as EEG, ECG, HRV, Skin Temperature, MET, and biomarkers in saliva) with cognitive performance and found valid conclusions that cognitive performance can be significantly enhanced in cool environments. Ref [72] proposed a novel method to measure sleepiness by EEG and cognitive performance parameters objectively, allowing insight into the drivers of cognitive performance decline. Ref [68] established a correlational analysis between the concentration index and performance index by EEG signals. The concentration and performance index were found to be lowest at 30°C and highest at 26°C. However, the changes in mean skin temperature of the female group varied more than the male group when experiencing the same temperature step. A study [69] concluded that if cognitive performance is a priority, it is wise to ensure a comfortable cool environment. Cognitive performance decreased by 10% at 26°C and 6% at 28°C compared to 24°C. A similar result was found in another study [70], with an increase in perceived mental workload and a significant decrease in measured performance at a moderately elevated temperature of 27℃ compared to 23℃. By analysis of ECG signals and HRV, Ref [71] monitored a shift of the cardiac autonomic control towards a sympathetic predominance. Short-term memory, verbal ability, and overall cognitive scores were lower at 26.2℃ compared to 22.4℃. Through physiological measurements of ECG and respiratory signals (RSP), Ref [2] found better thermal comfort and the highest accuracy of brain executive function at 22℃ compared to 18℃, 26℃, and 30℃, thus producing a good performance. Ref [73] used HRV and biomarkers in saliva as physiological indicators to evaluate cognitive performance. Conclusions showed the mean percentage of performance accuracy at addition and subtraction was 98.9 ± 0.9 at 26℃ (27.1 ± 0.1 ℃), which decreased to 97.3 ± 1.7 ($P < 0.05$) at 35 ℃ (35.5 ± 0.2 ℃). A study [74] measured three physiological indicators, MST (10 sites), HR, and Oxygen consumption (VO2). While higher levels of brain arousal at 10℃ led to increased task accuracy, it negatively impacted cognitive performance through distraction. An overview [75] of cognitive performance in a thermal environment integrated diverse findings: Under laboratory conditions with fixed clothing values, studies with the weighted mean of 4.34℃, 10.04℃, and 26.68 ℃ increase in the neutral air temperature show about 0.40%, 5.37%, and 7.97% reductions in cognitive performance respectively. Besides, the effects of heat stress appear to depend on the type of cognitive task, the most significant decline in attention-demanding tasks [76].

Ventilation as one of the strategies used to control air temperature and indoor air quality (IAQ) in buildings, may cause harmful diseases in occupants, such as infections, allergies, and SBS, and can reduce work or cognitive performance [77]. In particular, high temperature and CO_2 concentrations can affect the task performance of building occupants [78]. Adding fresh air can improve neurobehavioral task performance in high temperature and low humidity environments. The loss of performance caused by 1~2 ℃ rises could be compensated when fresh air reached 25 l/(s · per) [4, 63]. Several studies [45, 72, 79] have found that CO_2 concentrations above the permissible exposure limit (2500~3000ppm) at 22~24℃ reduced occupants' performance, caused drowsiness and headache symptoms, and decreased executive capacity and cognitive flexibility. The task performance can be improved under 18℃ and at low CO_2 concentrations (1000 ppm) [80]. Personalized ventilation can significantly diminish mental demand and frustration, and boost the ability to work under high temperatures and humidity [81]. A study [12] showed that using personally controlled fans to create air movement in a tropical climate at 26℃ effectively reduced SBS. Thermal comfort and perceived air quality were equal or better at 26 ℃ and 29 ℃ than at 23 ℃ if a personally controlled fan was provided. Another study [82] investigated the effect of personalized ventilation systems delivering 26℃ air to the breathing zone at a background temperature of 20℃. In this condition, thermal comfort was improved. By combining personally controlled air movement devices, the highest cognitive performance was obtained at 26℃ compared to 23℃ and 29℃ [12]. However, the effects of combined temperature and ventilation on performance and physiology are not fully understood due to the neglect of ventilation rates and their measurement details in most studies [83].

Current evidence demonstrated that the optimal performance range was 22~24℃. Brain function and physiological indicators were susceptible to minor differences in air temperature and played a vital role in thermal environment studies. Moreover, gender differences and the combined effects of temperature and ventilation on performance and physiology should also be further explored.

3.1.3 Health effects

Human studies have shown that upper respiratory symptoms significantly correlate with increased indoor temperature [19, 84]. Also, all types of respiratory disease, asthma, and chronic airway obstruction were associated with lower temperature, particularly in younger groups [85]. Cold air inflames the lungs and inhibits circulation, increasing the risk of respiratory diseases, such as asthma attacks or symptoms, and worsening chronic obstructive pulmonary disease (COPD) and infection. Furthermore, the lower temperature was associated with higher blood pressure, recommending the lowest room temperature of no less than 18 ℃ [86].

A human exposure study [13] indicated that the high temperature produced more SBS symptoms and expressed more negative moods. When the subjects felt thermally warm, they thought the perceived air quality was poor. Reducing the inhaled air temperature decreased lip dryness and throat dryness symptoms at 30℃ [46]. Another study [87] reported that when the temperature was above 26℃, thinking difficulty, poor concentration, fatigue, and depression increased with rising temperature. However, it was no more than moderate at the highest temperature (37℃). Conversely, at lower temperatures and humidity, the subjects perceived the air as fresher and more receptive [9]. The frequency of symptoms of fatigue, headache, and difficulty in thinking was also significantly reduced.

3.1.4 Effects of indoor air temperature

- Work and cognitive performance were significantly affected by temperature. High and low indoor air temperatures are common risk factors for human health and performance.
- The optimal work and cognitive performance range from 20 ℃ to 26 ℃, especially 22 ℃ to 24 ℃ in almost accordance with the optimal thermal satisfaction.
- Although higher levels of brain arousal at low temperatures increase task accuracy, it negatively affects cognitive performance through distraction.
- Warmth can reduce an individual's activation state, augment the incidence of SBS, cause distraction, and thus have adverse effects on performance and cognition.
- Cold air increases the risk of respiratory illness, and the minimum temperature should not fall below 18℃.
- The optimal temperature range depends on the specific climate region, and people in different climate regions have various adaptations to temperatures.

Table 1

Key reviews about the impact of indoor air temperature on occupants' performance.

Study	Research focus	Subjects	Exposure	Measurement methods	Main findings
Wu et al. (2020, 2021) [4, 63]	Work performance	18 subjects	20~30 °C, 40~90% RH for 70 min	5 Neurobehavioral tasks in an artificial climate chamber: Perception (Letter search, Stroop, Overlapping), learning and memory (Digital breadth, Meaningless figure recognition, Signal-code test), logical reasoning (Number calculation), expression (Hand-eye coordination test), and executive functional test (Visual reaction).	Work performance was significantly affected by temperature and humidity. When relative performance exceeded 95%, the optimal temperature ranged from 22.6 °C to 26.0 °C and relative humidity from 50% to 68%.
Wang et al. (2019) [64]	Work performance	15 university students	Slightly cool (21.7°C), neutral (25.2 °C), and slightly warm (28.6 °C) with 23% RH for 2 h	4 Cognitive tasks in a research office: Number addition (thinking), forward digit span (working memory), choice reaction (reaction), and visual search (perception). Mental workload using electroencephalography (EEG) signals.	A slightly warm (28.6°C) environment resulted in a relatively higher mental workload than the other two environments to achieve the same performance.
Richardson et al. (2018) [66]	Work performance	25 female office workers	Control of 20.0 °C and warm condition of 25.8 °C for 7 h	Food intake and self-reported productivity in a controlled environment.	Warm conditions acutely influence food intake in young women. Warmer conditions during summer increase comfort and productivity while decreasing caloric intake.
Geng et al. (2017) [65]	Work performance	21 subjects	16~28 °C with a step of 2 °C for 2 h RH = 15~35%	3 Productivity tests in a controlled office: Icon matching*, number summing*, and text memory and typing*.	Optimal productivity ranged from 20~26 °C, especially 22~24 °C in almost accordance with optimal thermal satisfaction.
Vimalanathan and Babu (2014) [1]	Work performance	10 male undergraduate students of the same age group (18 years old)	17 °C, 21 °C, and 28 °C for 40 min	11 Neurobehavioral tasks in a field lab to emulate an office: Letter search, direction, object overlapping, memory span, picture detection, figure-digit, logical sequences, comprehensive reading, numerical addition, logical conclusion, picture match, and reasoning.	The optimum indoor temperature level of 21°C has improved the work performance and health of office workers.
Cui et al. (2013) [61]	Work performance	36 university students	22°C, 24 °C, 26°C, 29°C, 32°C for 150min RH = 30~50% AV = 0.10 m/s	Memory typing task* in an artificial climate chamber.	The optimum temperature range for performance was between 22 °C (slightly cold) and 26 °C (a little higher than neutral). A warm discomfort environment harmed both motivation and performance.

Table 1 (continued)

Study	Research focus	Subjects	Exposure	Measurement methods	Main findings
Li et al. (2022) [16]	Cognitive performance	30 university students	22°C, 26 °C, 30°C for 65 min	4 Cognitive tasks in a climate chamber: Go/No-go test, Stroop tests*, Fast-counting test*, and Working memory test*. EEG signals, including physiological measurement and cognitive performance.	A correlational analysis identified the close relationship between the concentration index and the performance index. The concentration index and performance index were lowest at 30°C and highest at 26°C.
Lan et al. (2021) [69]	Cognitive performance	36 university students	24°C, 26 °C, 28°C for 250 min	7 Neurobehavioral tasks in a low-polluting office: Mental redirection (a spatial orientation test), Grammatical reasoning (a logical reasoning task), Digit span (a traditional test of verbal working memory), Visual earning (a picture memory task measuring spatial working memory), Number calculation (a mental arithmetical test in which the subject has to add and subtract two- digit numbers), Stroop (a test of the attentional focus and flexibility required to overcome perceptual/linguistic interference), and Visual reaction time (a sustained attention task measuring speed and accuracy in response to visual signals). Mental workload by the NASA TLX.	Compared with 24 °C, cognitive performance decreased by 10% at 26 °C and 6% at 28 °C. Where cognitive performance is a priority, it is wise to ensure a comfortably cool environment.
Lan et al. (2020) [70]	Cognitive performance	12 university students	23°C and 27 °C for 275 min	5 Neurobehavioral tasks in a low-polluting office: Mental reorientation (a spatial orientation test), Grammatical reasoning (a logical reasoning task), Digit span memory (a traditional test of verbal working memory), Number calculation (a mental arithmetical test in which the subject has to add and subtract two-digit numbers), and Stroop (a test of the attentional focus and flexibility required to overcome perceptual/linguistic interference). Mental workload by the NASA TLX.	The perceived mental workload increased, and measured work performance decreased significantly at 27°C.
Barbic et al. (2019) [71]	Cognitive performance	20 university students	22.4 °C (Day 1) and 26.2 °C (Day 2) for 2h	3 Cognitive tasks in a classroom: Reasoning, short-term memory, and verbal ability. ECG signals, including heart rate variability (HRV) and cognitive performance.	During 26.2 °C, a shift of the cardiac autonomic control towards a sympathetic predominance was observed compared to 22.4 °C. Short-term memory, verbal ability, and overall cognitive C-score scores were lower at 26.2 °C compared to 22.4 °C.

Table 1 (continued)

Study	Research focus	Subjects	Exposure	Measurement methods	Main findings
Abbasi et al. (2019) [2]	Cognitive performance	35 male students	18°C, 22°C, 26 °C, and 30°C for 50min (each day with a constant temperature)	Cognitive tasks in an air-conditioning chamber: The n-back test was used to evaluate the executive functions in three cognitive levels (low workload (n = 1), medium workload (n = 2), and high workload (n = 3). Physiological measurements by ECG and respiratory signals (RSP).	In moderate air temperature of 22 °C, the participants had better thermal comfort, so they had a good performance (accuracy).
Xiong et al. (2018) [67]	Learning performance	10 university students	17.3 °C, 22.2 °C, and 27.1 °C for 65 min	4 Learning tasks in a university classroom: Perception-oriented task, memory-oriented task, problem-solving-oriented task, and attention-oriented task.	The highest learning performance came at 22 °C with thermos-neutral, and learning efficiency peaked at 22 °C.
Hong et al. (2018) [80]	Cognitive performance	22 building occupants	Three IEQ conditions during an 8-hour working period. CO_2 low (1000 ppm) and high (2400 ppm) T_a = 18°C, 25°C, 28 °C RH = 30 %; AV = 0.1 m/s	6 Cognitive tasks in 5 office rooms: Visual reaction time (VRT), Subitizing, Stroop test, Backward corsi block tapping (BCBT), N-back, Typing task.	The building occupant's task performance can be improved under cold and low CO_2 concentrations.
Liu, Zhong, & Wargocki (2017) [73]	Cognitive performance	12 college-age students	27.1 °C and 35.5 °C for 180min CO_2 concentration = 400~3000 ppm Task time (min)=110 Pre-task time (min)= 10	8 Neurobehavioral tasks in a climate chamber： Mental redirection, grammatical reasoning, digit span memory, visual learning memory, number calculation* (one digit addition & subtraction), one digit multiplication, a Stroop test, and visual reaction time.	The mean percentage of performance accuracy at Addition and Subtract was 98.9 ± 0.9 at 26°C (27.1 ± 0.1 °C), which decreased to 97.3 ± 1.7 ($P < 0.05$) at 35 °C (35.5 ± 0.2 °C). Performance accuracy or speed did not change significantly at other tasks ($P > 0.05$).
Zhang and de (2016) [62]	Cognitive performance	56 university students (2 panels)	22°C and 24 °C for 120 min	4 Cognitive tasks in a climate chamber: Memory (Digit Span task*), concentration (Rotations test*, Feature Match test), reasoning (Odd One Out task, Grammatical Reasoning task), and planning (Spatial Search, Hampshire tree task*).	Cognitive performance was relatively stable or even slightly promoted at 22 °C. Reasoning and planning performance observed a trend of decline at 24 °C. Simpler cognitive tasks are less susceptible to temperature effects than more complex tasks.
Schiavon et al. (2016) [88]	Cognitive performance	56 university students	23 °C, 26 °C, and 29 °C for 90 min (Personally controlled air movement)	4 Cognitive tasks in a classroom: Choice Reaction Time*, Finger Tapping*, Stroop, 2-Back.	• Cognitive tests showed the lowest performance at 23 °C and the highest at 26 °C. • Thermal comfort and perceived air quality were equal or better at 26 °C and 29 °C than at 23 °C if a personally controlled fan was provided. • A higher proportion of people found the thermal environment acceptable at 26 °C (whether with or without the fan) than at 23 °C.

Table 1 (continued)

Study	Research focus	Subjects	Exposure	Measurement methods	Main findings
Melikov et al. (2013) [81]	Work performance	30 students	T_a = 26°C, 28 °C RH = 70% AV < 0.06 m/s Airflow rate from 0 to 18.5 l/s Task time =160min Pre-task time = 75min	Physiological measurements in a climate chamber: Multiplication of randomly generated numbers, randomly generated Sudoku, and Tsai-Partington tests. NASA-TLX test.	• Using personalized ventilation (PV) significantly improved the perceived air quality (PAQ) and thermal sensation and decreased the intensity of Sick Building Syndrome (SBS) symptoms to those prevailing in a comfortable room environment without PV. • At high temperatures and humidity, the personalized flow significantly decreased mental demand and frustration and increased the reported ability to work.
Lan et al. (2011a) [60]	Work performance	12 subjects	22°C and 30 °C for 270 min	7 Neurobehavioral tasks： Redirection, grammatical reasoning, digit span memory, visual learning memory, number calculation (addition*, subtraction, and multiplication), Stroop*, and choice reaction time.	The optimum performance is achieved when people feel slightly cool; thereby, it makes sense to set the PMV limits in workplaces between −0.5 and 0, while thermal discomfort (feeling too warm or too cold) leads to reduced performance.
Lan et al. (2011b) [13]	Work performance	12 university students	22°C and 30 °C for 270 min	7 Neurobehavioral tasks in an office: Mental reorientation (a spatial orientation test), Grammatical Reasoning (a logic reasoning task), Digit Span Memory (a traditional test of verbal working memory and attention), Visual Learning Memory (a picture memory task measuring spatial working memory), Number Calculation (a mental arithmetical test in which the subject has to add, subtract, or multiply numbers), Stroop (a test of attentional vitality and flexibility owing to perceptual/ linguistic interference), and Choice Reaction Time (a sustained attention task measuring response speed and accuracy to visual signals). Mental workload by the NASA TLX.	• The subjects were less willing to exert effort while working, and their performance decreased when they felt warm at 30°C compared with the 22°C condition in which they felt thermally neutral. • The negative effects on health and performance when people feel thermally warm at raised temperatures are caused by physiological mechanisms.
Lan et al. (2010a，2009) [29, 59]	Work performance	21 university students	17°C, 21°C, and 28 °C for 120 min, 3 twice a day RH = 50~80 % AV = 0.10 m/s	13 Neurobehavioral tasks in an ordinary but low-polluting office: Overlapping – Visual choice RT – Event sequence – Conditional reasoning – Memory span – Spatial image – Number calculation – Picture recognition – Creative thinking – Graphic abstracting – Reading comprehension – Hand-eye coordination – Letter search.	Thermal discomfort caused by high or low air temperature negatively influences office workers' performance.

Table 1 (continued)

Study	Research focus	Subjects	Exposure	Measurement methods	Main findings
Mäkinen et al. (2006) [74]	Cognitive performance	10 male subjects	25 °C for 90 min and 10°C for 120 min	6 Cognitive tasks in a climate chamber: Code substitution and code substitution delayed, Logical reasoning, Matching-to-sample, Continuous performance, Simple reaction time, Sternberg Memory Search (Sternberg 6).	Higher levels of brain arousal in the colder state led to increased task accuracy. The hypothermic environment negatively affected cognitive performance by distracting attention.
Review					
Yeganeh et al. (2018) [75]	Work performance	28 reports between 1980 and 2018	Air temperature in a controlled laboratory experiment	Cognitive tasks.	Studies with the weighted mean of 4.34°C, 10.04°C, and 26.68°C increase in the neutral air temperature show about 0.40%, 5.37%, and 7.97% reductions in cognitive performance, respectively. Heat stress causes the most significant decline in the most attention-demanding tasks.

The asterisk (*) indicates that the cognitive task is relevant to the result.

3.2 Humidity

3.2.1 General comments

Despite being a vital microclimate parameter, humidity is often ignored in research [83]. The relative humidity is the relative percentage of water vapor in the room air relative to the total amount of vapor in the same room air at a given temperature [89]. In warm environments, higher humidity could negatively affect subjects' thermal comfort [90], with excess moisture on the skin being a major cause of discomfort [91]. Both physiological and psychological results showed that performance was more affected by relative humidity under high temperature conditions. However, humans generally sense dry or moist air indirectly by the perceived air quality [83] due to the lack of hygroreceptors. No matter the ventilation volume, occupants' perceived air quality is negative when relative humidity exceeds 70% and air temperature is above the comfort zone temperature [92]. For supporting information on work and cognitive performance, see Table 2.

3.2.2 Effects on work and cognitive performance

A review [89] showed that the perceived "dry air" is a widespread and substantial complaint in the work environment, and elevated humidity may have beneficial effects on work performance and IAQ. The optimal relative performance exceeded 95% when the humidity was 50% to 68% and the temperature was 22.6 °C to 26°C [4, 63].

By using neurobehavioral tasks and physiological measurements (body mass, urine osmolality, body temperature) and thirst conditions, Ref [93] found that water loss of body mass (0.72%) showed memory decreases when air humidity is reduced. Thirst decreases memory, while drinking water improves memory and cognitive attention. Ref [94] conducted a field experiment with computerized task-based tests and showed that increasing relative humidity and reducing CO_2 improved short term task performance. Ref [95], by comparison, found that the subjects felt more fatigue at 70% RH, 30 °C than at 30~50% RH. Moreover, the perceived pleasantness of lower humidity was better (more comfortable due to evaporation). A study [96] simulated office work tasks and found that low humidity reduced the performance rate of tasks by 3~7%. More rapid blink rates were observed at 5% than 35%

RH ($P < 0.05$). Similarly, another study [25] found that dry air conditions cause precorneal tear film instability and further trigger a cascade of inflammatory responses. For example, visual disorders such as dry eye are commonly associated with eye fatigue [97].

Ref [9] found that the performance of office work was not significantly affected by temperature and humidity. However, SBS symptoms were alleviated when the subjects worked at low temperature and humidity levels. Prolonged exposure to low temperatures and humidity might improve work performance. By measuring HRV, a study [98] found that workers exposed to 30% to 60% RH were 25% more likely to experience less stress than those exposed to drier conditions most of the time. Additionally, another research [99] indicated that decreasing indoor humidity (70% to 50%) at extremely high temperatures could improve impaired cognitive performance.

3.2.3 Health effects

Dryness of air is an essential and notable risk factor associated with building-related symptoms and is significantly correlated with general symptoms in winter and summer. Moist air was a significant risk factor for general symptoms in summer [100].

Visual illnesses like dry eyes are generally associated with eye fatigue, and office workers feel eye fatigue during typical intensive vision work [25]. Studies [25, 96, 97] have shown that low humidity elevates dry eye symptoms-significantly reducing dry eye symptoms after increasing the humidity [94]. Prolonged exposure to dry air can also lead to airway dryness. Low humidity increases the vulnerability of the nasal cavity and pulmonary regions. Intervention by elevation of the air humidity may be considered a non-pharmaceutical treatment of influenza risk [83]. Although ASHRAE 62.1 and EN 15251 standards recommend some temperature and humidity regulation procedures dealing with health risks [86], neither of these standards presents a clear and consistent strategy on how to design ventilation rates that reference and follow health requirements. Ventilation should be used as a regulating factor, in conjunction with air temperature and humidity, to guide the indoor environment and personnel performance.

3.2.4 Effects of relative humidity

- Prolonged dry indoor air leads to increased water loss, which impairs cognitive and work performance.

- Loss of body mass in low humidity environments leads to memory loss. Thirst reduced memory, and drinking water improved memory and cognitive attention.
- Increasing indoor air humidity reduces complaints about dry air and unfresh air.
- Increased indoor air humidity reduces the risk of dry eye symptoms and fatigue and improves work and cognitive performance.
- Workers' stress levels in indoor humidity of 40~60% were lower than in dry air.
- Ventilation is not a direct but a regulating factor that should be strategically combined with air temperature and humidity for joint control to positively influence indoor occupants' health, cognitive or work performance.

Table 2

Key reviews about the impact of indoor relative humidity on occupants' performance.

Study	Research focus	Subjects	Exposure	Measurement methods	Main findings
Tian (2020) [99]	Cognitive performance	48 healthy subjects	3 exposure conditions: 26℃/70% RH, 39℃/50% RH, and 39℃/70% RH Test time =140 min	Cognitive tasks in a climate chamber: Perception, spatial orientation, concentration, memory, and thinking abilities. Heart rate, core temperature, skin temperature, blood pressure, and body weight.	• At the relative humidity of 70%, increasing indoor temperature from 26℃ to 39℃ caused a significant decrease in the accuracy of these cognitive tests. However, when the relative humidity decreased from 70% to 50% at 39℃, the accuracy of the cognitive tests increased significantly. • Decreasing indoor humidity at extremely high temperatures could improve impaired cognitive performance.
Wu et al. (2020) [4, 63]	Work performance	18 subjects	T_a = 20 ℃, 22 ℃, 25 ℃, 28 ℃, 30 ℃ RH = 40%, 50%, 65%, 80% and 90% Fresh air: 6 l/(s·per), 10 l/(s·per), 15.5 l/(s·per), 21 l/(s·per) and 25 l/(s·per). Test time = 70 min	5 Neurobehavioral tasks in an artificial climate chamber: Perception (Letter search, Stroop, Overlapping), learning and memory (Digital breadth, Meaningless figure recognition, Signal-code test), logical reasoning (Number calculation), expression (Hand-eye coordination test), and executive functional test (Visual reaction).	• Both physiological and psychological results showed that performance was more affected by relative humidity under high temperature conditions, the degree of which was 4~10% greater than that under low temperature conditions. • When relative performance exceeded 95%, the optimal temperature ranged from 22.6 ℃ to 26.0 ℃ and relative humidity from 50% to 68%.
Benton et al. (2016) [93]	Work performance	101 undergraduates	T_a = 30 ℃ RH = 43~62% Test time = 240 min	Neurobehavioral tasks in an artificial climate chamber: Episodic memory: word-list recall, Focused attention: arrow flanker test. Body mass, urine osmolality, body temperature, and thirst.	Body mass loss (0.72%) of water showed memory loss. Thirst reduced memory, and drinking water improved memory and cognitive attention.
Shan et al. (2016) [94]	Work performance	39 healthy university students	RH = 58~74% Test time = 120 min per session, morning, noon, afternoon	Neurobehavioral tasks in two side-by-side tutorial rooms: Short term memory, reaction time, perception, and mental arithmetic.	The exposure to different types of ventilation and draft in a tutorial room with controlled temperature and RH. Elevation of RH from 58% to 74% resulted in significantly fewer dry eye symptoms. The air velocity was considerably higher at the high RH condition; thus, the finding should be considered cautiously. Lowering carbon dioxide and increased RH improved short term work performance, presumably by reducing dry eye symptoms.

Table 2 (continued)

Study	Research focus	Subjects	Exposure	Measurement methods	Main findings
Tsutsumi et al. (2007) [95]	Work performance	12 subjects	70% RH at 30 °C, 15 min; 30, 40, and 50% RH at 25 °C, 180 min	Skin temperature, skin moisture.	• Perceived pleasantness going to lower humidity (more comfortable due to evaporation). • Perceived more tiredness at 70% RH. • No difference in subjectively reported performance at 30~50% RH.
Wyon et al. (2006) [96]	Work performance	30 subjects	T_a = 22 °C RH = 5%, 15%, 25%, 35% Two sessions of 150 min divided by break of 15 min	Simulated office work tasks in a climate chamber.	• Low humidity was found to have reduced three office tasks' performance rate by 3~7%. • A few percent reduced visual data acquisition for specific office tasks was observed concurrently with higher blink frequency at 5% RH compared to 35% RH. Slightly elevated eye symptoms at 5% RH.
Fang et al. (2004) [9]	Work performance	36 university students	20 °C/ 40% RH, 23 °C/ 50% RH, 26 °C/ 60% RH 10 l/s per person 3.5 l/s per person Air velocity = 0.10 m/s	Memory typing task** in an artificial climate chamber.	• Performance of office work was not significantly affected by indoor air temperature and humidity. • SBS symptoms were alleviated when the subjects worked at low air temperature and humidity levels. Long-term exposure to low temperatures and humidity might help improve office work performance. • The optimum temperature range for performance in this study was between 22 °C (slightly cold) and 26 °C (slightly higher than neutral). A warm discomfort environment hurts both motivation and performance.

The asterisk (*) indicates that the cognitive task is relevant to the result.

4. Physiological indicators assessment

For a more in-depth study of the influence of indoor microclimate parameters on occupant thermal comfort and performance, physiological indicators are often used as key input variables in exposure experiments, in conjunction with environmental parameters to predict occupant thermal state (see 错误!未找到引用源。).

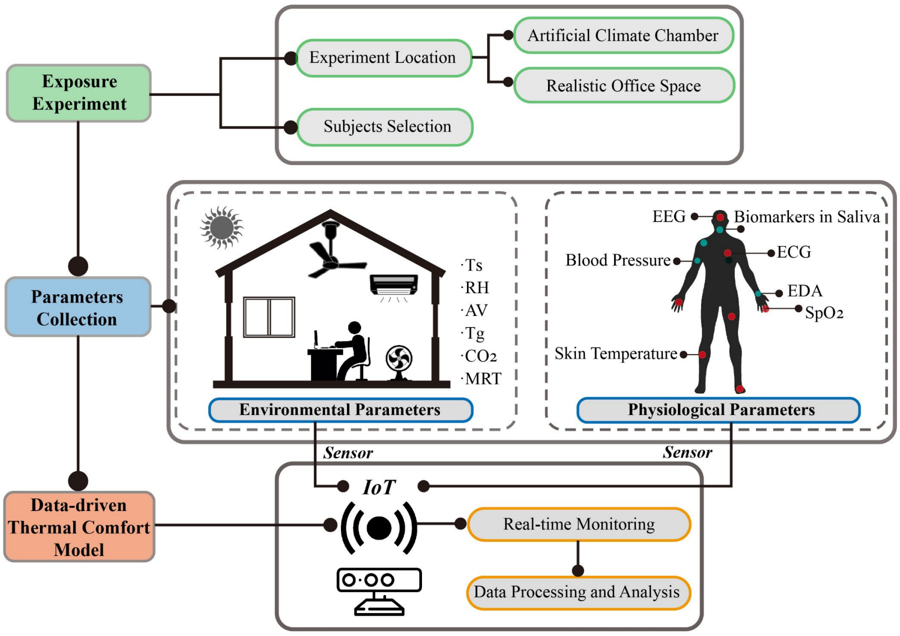

Fig. 3 Approaches used for indoor thermal comfort prediction model development.

Physiological indicator measurement, performance measurement, and subjective questionnaires are the three types of work or cognitive performance measurement [101]. Since the central nervous system shows special sensitivity to environmental disturbances, the neurobehavioral method is neurobiologically justified. Physiological indicators are used because the physiological measurement of activation or arousal is associated with increased activity of the nervous system, which corresponds to increased stress in the occupants. Furthermore, reliance on physiological signals provides a more accurate detection of human thermal sensation [27] and thus can provide potential insight into thermal states. With the available physiological signals, the physiological measurements provide a more accurate and effective way to assess the performance of occupants and IEQ. The performance measurements include neurobehavioral tests and simulated work [102]. The accuracy and response time as two indicators were used to characterize the performance index of occupants while performing tasks [68]. Since subjective evaluation simply indicates an increase in subjective dissatisfaction with environmental conditions, it should not be taken as an indicator of a decline in actual performance [103].

Currently, common physiological indicators include EEG, ECG, Electrodermal activity (EDA), HRV, BP, Skin Temperature, $ETCO_2$, SpO_2, the levels of salivary cortisol and alpha-amylase. Table 3 summarizes the relevant indicators used to determine physiological status at present.

Table 3
Summary of relevant indicators used to determine physiological status.

Approach	Indicator	Location	Analysis software	Ref.
EEG	Arousal, Beta or Alpha band relative power	Global\Prefrontal lobe\Temporal lobe	Powerlab\BrainMap-3D	[105, 111]
	Concentration, [SMR+ Middle Beta]/ Theta	Prefrontal lobe (AF3, AF4)	EEGLAB	[68, 112]
	Mental workload, Beta/ [Theta + Alpha]	Frontal lobe (AF3, AF4, F3, F4, F7, F8, FC5, FC6)	EEGLAB	[28]
	Stress, Theta/ Alpha	Frontal lobe (Theta), Parietal lobe (Alpha)	EEGLAB	[28]
	Fatigue, Beta/ Alpha	Frontal lobe	EEGLAB	[28]
	Activity, Beta Mean – Alpha Mean	F3 (left) – F4 (right)	EEGLAB	[113]
ECG	Stress or Cognitive, HRV (PNN50)	Heart signal	SPSS	[2, 69]
	Thermal comfort, HRV (LF/HF)	Right and left wrist	Powerlab	[59]
Skin Temperature	MST	Forehead\7-site\13-site	SPSS\Python	[32, 68, 114]
EDA	Tonic component (Tonic perc25)	Wrist	EDA toolkit 11	[27]
$ETCO_2$	\	Finger	SPSS	[13]
SpO2	Cognitive	Finger	SPSS	[69, 70]
Biomarkers in saliva	Stress, Alpha-amylase and cortisol	\	SPSS	[13, 69]

Abbreviations: LF, Low-Frequency power; HF, High-Frequency power; SMR, Sensorimotor rhythms

Based on previous works, the specific waves of brain activity can be applied to explain how the surrounding environment influences brain activity and cognition [104]. For instance, the metric [SMR + Middle Beta]/Theta [68] and Beta or Alpha band relative power [105] are often used as assessments of concentration. To achieve better visualization of brain activity on time course, EEGLAB was developed as an EEG analysis tool in the MATLAB environment [106].

Given the high correlation between thermal sensation and skin temperature [107], skin temperature has become a universally popular method. In addition, cardiovascular system measurements are widely used in response to environmental stimuli and workloads [108]. HRV is the change in the time interval between adjacent heartbeats, and pNN50 is a time-domain measure of heart rate variability. A higher pNN50 indicates higher levels of parasympathetic nervous system (PNS) activity [108], and higher PNS activity is a marker of lower stress and increased cognitive performance [109]. The Low-frequency (0.04~0.15Hz) to High-frequency (0.15~0.4Hz), i.e. LF/ HF value, is associated with thermal comfort. It is approximately 1 when subjects feel thermally comfortable [110], and the ratio has also been used to infer the sympathetic nervous system activity [59]. As the skin conductance signal is hypersensitive to physical activity and temperature changes, the EDA phase signal can reflect changes in skin moisture levels in response to stimulus presentation [27].

Peripheral oxygen saturation (SpO_2) indicates the percentage of hemoglobin molecules in arterial blood that are saturated with oxygen. The SpO_2 values of healthy people are usually between 96~99%, and the value should remain above 94%. Higher oxygen saturation is associated with improved cognitive performance [69]. Measuring End-tidal partial CO_2 ($ETCO_2$) can be used to approximate arterial CO_2 non-invasively; an increase in blood CO_2 concentration may induce physiological responses that cause SBS symptoms such as fatigue and headache. The normal values of $ETCO_2$ are 35~45 mmHg [13]. Salivary alpha-amylase is a biomarker for stress-related changes and reflects the activity of the sympathetic nervous system. For healthy adults under no stress, the salivary amylase value thus measured is less than 30 kIU/L; 31~45 kIU/L suggests a low-stress level, 46~60 kIU/L moderate stress, and higher levels indicate severe stress [69, 115].

5. Applications of machine learning in indoor environment assessment

IEQ has long been an important topic for the work and health of the occupants in buildings. Section 3 has highlighted the importance of indoor microclimate parameters. In recent years, new powerful tools, including machine learning methods and data mining techniques, have been proposed to evaluate data innovatively based on large information datasets [116]. Meanwhile, developing various sensing and IoT technologies makes them viable approaches to integrating sensors with modern technologies for environment assessment [117]. For instance, to determine occupants' feelings about IEQ, several studies have used a combination of physiological signal sensing technology and ML prediction to provide and forecast valuable messages. ML models, which consider occupants and building performance, have been increasingly applied in recent research [118].

5.1 Main machine learning approach

Conventional ML approaches include supervised learning and unsupervised learning—different ML algorithms for different types of data sets or problems in the field of environment. Supervised learning models consist of classification and regression. Classification involves Decision Trees (DT) [112], classifiers (e. g. Native Bayes, NB; K-Nearest Neighbor, KNN; and Support Vector Machine, SVM), and Logistic Regression (LR). Unsupervised learning algorithms encompass clustering and various Artificial Neural Networks (ANNs). Clustering can find a structure in a collection of unlabeled data, the most common algorithm for unsupervised learning [119]. Supervised and unsupervised learning models differ in how they are trained and in the training data conditions required. Conventional ML algorithms such as SVM, DT, and ANN have shown better performance with fewer data sample sizes.

Deep learning (DL) is a branch of ML [120]. The popularity of neural network-based algorithms suggests that DL is making significant progress. Deep learning uses graph techniques and neuron transformations to obtain multi-layer learning models and learn data automatically. The most widely used deep learning models are Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) [121]. Other common approaches of ML are shown in Fig. 4 Common approaches of MLFig. 4.

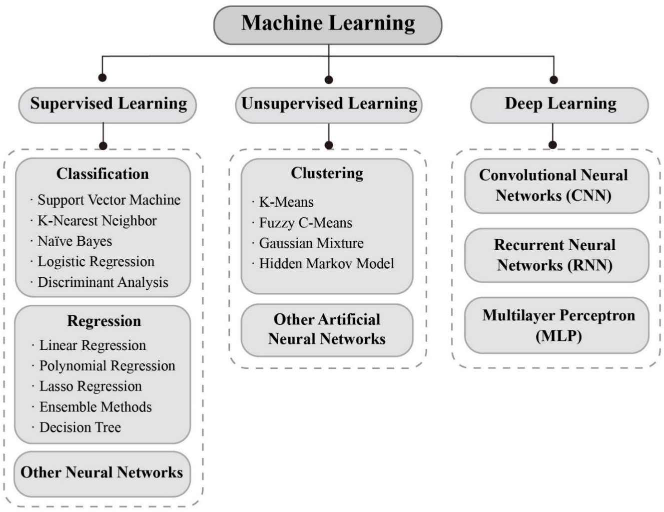

Fig. 4 Common approaches of ML.

5.2 Sensing technology

Following previous literature [122, 123], thermal comfort was generally assessed by PMV models based on massive laboratory experiments. However, in some cases, these models do not provide a good working environment for all occupants. Therefore, most existing literature uses ML to predict thermal comfort or IEQ based on physiological indicators and environmental parameters. Integrating new sensing technologies and data-driven approaches can achieve a better prediction using large amounts of data from physiological, environmental, and other aspects. The data-driven models require a set of input data to train and then test the model. Since anthropometric data (gender, age, height, BMI) remain constant over short periods, thermal comfort models rarely use them as predictor variables. The input data can be personal physiological factors, such as EEG, HRV, and skin temperature; and environmental factors, such as air temperature, relative humidity, and air velocity. Additionally, data from IoT-based sensors have both security and occupant behavior tracking capabilities, bypassing the use of cameras to detect the presence of occupants and thus protecting users' privacy [124]. With powerful machine learning algorithms, wearable sensors are much more efficient in data collection and processing. These data collected by sensors have been used in different statistical classification models, showing the potential for future developments in indoor environmental comfort prediction.

5.2.1 Physiological parameter collecting

The physiological indicators have summarized in section 4. This section explores the physiological factors and other information about occupants for data-driven model development. Thermal comfort prediction is essential for better ambient control, and while it is useful to study environmental factors, a simpler way is to study human physiological parameters directly. The use of a range of sensors (wearable or non-wearable devices) to collect physiological data has become more accessible in recent years, which makes them a promising form of modeling. They can predict occupants' performance or thermal satisfaction based on physiological data, such as monitoring EEG, skin temperature, HRV, metabolic level, blood pressure, and other human physiological parameters [47]. According to the literature reviewed, semi-invasive wearable devices with no cable have gained more popularity, such as EMOTIV [30, 125], Microsoft band 2 [32], Heart Rate Belt, and iButton [33]. Wrist skin temperature measured by wrist bands can develop a personal thermal sensing model [126]. Skin temperature monitoring of different body parts can also be performed using accurate wired thermocouples [127]. Non-contact devices such as FLIR infrared imager can measure skin temperature without attaching remotely [48]. HRV, which response to changes between consecutive heartbeats, can likewise be used to assess thermal comfort using ML [128]. Many studies have revealed a significant relationship between skin temperature and thermal sensation and proposed approaches to predict thermal comfort based on skin temperature. A review showed that skin temperature is the most critical physiological variable influencing thermal sensation in the indoor environment, 70% of the studies reviewed have measured skin temperature, and 39% monitored body core temperature as a physiological parameter [129], which is consistent with the findings of this review. Of the selected studies, only two did not use physiological characteristics. However, most were combined with environmental input, as shown in the Sankey diagram in **错误!未找到引用源。**. The Sankey flow diagram is a specific energy balance chart plotted via an online Visual Paradigm.

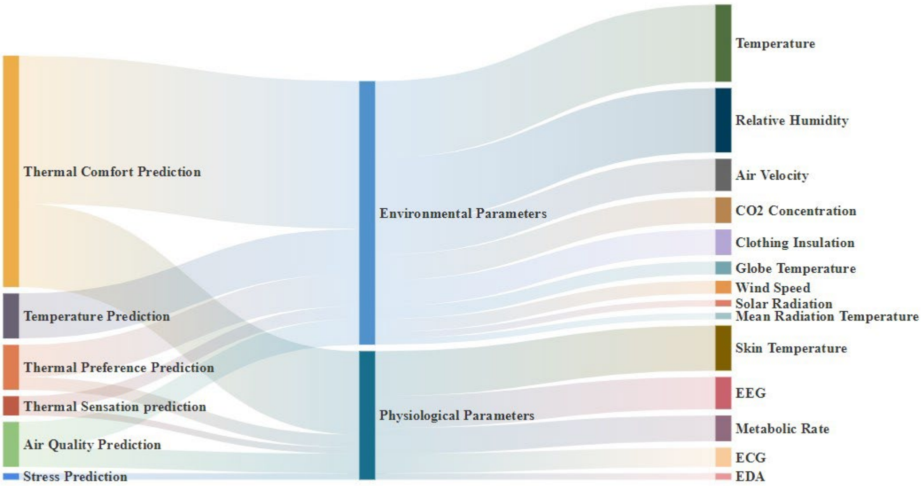

Fig. 5 Sensor parameters collecting and their application.

5.2.2 Environmental parameter collecting

Environmental parameters were also frequently utilized in the data-driven thermal comfort model. Data-driven models only using environmental factors as input showed promising prediction accuracy [130]. A study reported that environmental factors prediction had higher accuracy than physiological data [131]. Likewise, Ref [132] claimed that combining data from environmental and physiological sensors was slightly higher accurate (3~4%) than using only environmental sensors. Similarly, Ref [32] reported that the combination of environmental and physiological parameters (activity level, HR, skin temperature) achieved an accuracy of approximately 80%, with a 24% and 39% increase in classification accuracy compared to using only environmental and only physiological indicators, respectively.

Environmental sensors are typically used to measure ambient conditions, and commonly used data collection parameters are shown in 错误!未找到引用源。. The diagram shows that indoor environmental parameters were used more than outdoor, and temperature and humidity sensors are typically the most used data collection methods. The lesser-used environmental variables were solar radiation and mean radiation temperature (MRT). Environmental sensors (e.g. iBEM, T&D) can be carried by the subjects for flexible measures and accurately assess the impact of the occupant's surroundings. In addition, behavioral factors influenced by the environment, such as clothing insulation and activity levels, have often been considered in personal comfort assessments. Clothing insulation was analyzed as a control variable, and some studies assumed or specified a fixed value [32, 47, 133]. In this review, it is classified as an environmental parameter.

Additionally, although no studies are available to summarize the number of input variables, combining physiological and environmental parameters for predicting occupants' performance does lead to better model performance. Some studies have used only one variable [134], while others have used more than five [47, 135]. It is important to note that while using multiple input parameters can enhance the predictive accuracy of a model, it can lead to higher complexity and computational load when it comes to feature selection and model scalability [136].

5.3 Assessment model

Since the ML model is data-driven, the crucial problem is to determine the correct variables. In general, one or more parameters are used for the prediction model. In order to select the most suitable model, many studies used data mining to discover the driving components. For example, indoor thermal comfort or CO_2 concentration levels can be estimated based on indoor environmental parameters and metabolic level [47, 137]. Similarly, the thermal comfort prediction model can also use indoor environmental parameters and metabolic level. Some reviews have collated a combination of inputs for thermal comfort and IAQ prediction [118, 138]. However, to date, there is no standardized procedure for model development. As presented in **错误!未找到引用源。**, the current assessment models focus on individual thermal comfort prediction, using at least one of these variables as input in the selected studies.

5.3.1 Machine learning algorithm selection

The goal of ML is to make predictions on unknown data. The data is divided into a training dataset for algorithm training and algorithm model creation, and a test dataset for algorithm performance evaluation. Generally, 60~80% of the data is used as the training dataset and the rest as the test dataset [139]. The algorithm selection is often related to the data structure and collection method. However, physiological data and indoor environmental quality are related to many indicators, and it is difficult to recommend a specific algorithm without analyzing the detail of the model. Therefore, testing and comparing different models should be done before choosing the most suitable one [138]. To date, the leading training algorithms used for ML mainly include classification, regression, and clustering. Among these algorithms, the RF, ANN, SVM, KNN, and GBM are frequently used and are often ranked as the best choice due to their excellent performance [114, 140, 141]. Many studies have tested and compared combinations of these algorithms. For example, Ref [33] used 14 commonly used machine learning classification algorithms in four groups: linear methods, non-linear methods, trees and rules, and ensembles of trees. In terms of the four algorithm categories used, the ensembles of trees (e.g. GBM and RF) provided the optimal performance for the personal comfort models developed.

ML algorithms can assist wearable sensors in analyzing data more comprehensively. As sensor data complexity and irregularity, pre-processing of high-dimensional data using dimensionality reduction algorithms are required [139]. These dimensionality reduction algorithms are typically used with traditional ML or DL algorithms for physiological signals, such as EEG classification. EEG classification is to determine a subjects' cognitive state based on some attributes of the EEG data within a short time window. The basis of using time series as features is that activation of different brain areas during task execution generates a specific spatiotemporal pattern of electrical activity across EEG channels. After feature extraction, the next step is to divide the trials into training and test sets, which are used for the learning and evaluation of the classifier, respectively [142]. As an example, EEG-based ML methods can classify the occupants' real-time thermal comfort states. Shan et al. [30] compared the performance of three algorithms (linear discriminant analysis, LDA; Naive Bayes, NB; KNN) and found that all occupants' EEG features can be found by interpolating selected linear continuous EEG features. All algorithms' classification rates were above 90%, while the LDA classifier had the best performance.

According to a study, the regression model is mainly used for long-term forecasting, while ANNs mainly used for short-term forecasting [143]. ANNs with a long-term memory structure are the most commonly used and suitable method for time series prediction [116]. Long short-term memory neural network (LSTM) is a special type of RNN that can learn information to depending on time series. LSTM can process not only single data points but also entire data series or historical states. In addition, some studies indicated that the algorithm with high dimensions control could better predict TSV and

Thermal Preference (TP) [114, 144], such as ANNs, and GBM.

5.3.2 Predicting accuracy

The typical procedure for assessment with sensing and prediction in indoor environments is shown in Fig. 6. According to reviews of predicting using a data-driven model, and most studies produced high-accuracy results. The summary of the popular machine learning algorithms and model accuracy for different applications in the existing literature are shown in

Table 4

Summary of the commonly used machine learning algorithms for different applications.

Study	Application	Environmental sensor	Physiological sensor	Algorithm	Model accuracy
Chai (2020) [47]	Thermal comfort prediction	T_a, T_g, RH, AV, Clo	MET	ANNs, SVM, PMV, aPMV, and ePMV	ANNs model is effective in naturally ventilated residential buildings, with the highest R (0.6984) and R^2 (0.4872) values.
Pigliautile (2020) [135]	Thermal comfort, Air quality prediction	T_a, RH, AV, CO_2	ECG (HRV, LF/HF), EEG, EDA	LDA, KNN, DT, SVM, NB, RF	SVM (84%) and NB (82%) are shown better results for the accuracy of time, frequency, and aggregated indices.
Shan (2020) [30]	Thermal comfort prediction	T_a, RH, AV, CO_2	EEG	LDA, NB, KNN	Performances of different classifiers were satisfactory, with classification rates all above 90%. The LDA classifier had the best performance.
Yuan (2020) [137]	Temperature prediction	T_a, RH, CO_2, T_{out}, outdoor RH, Solar Radiation, Wind speed	\	LSTM, SOM	The SOM-LSTM model shows the best prediction performance, with an accuracy of over 95% for the prediction of indoor temperature and around 90% for the prediction of CO_2.
Alsaleem (2020) [145]	Thermal comfort prediction	T_a, RH	HR, Ts	DT, AdaBoost, GBM, RT, SVM	The SVM model provided a higher accuracy of 87%.
Lee & (2020) [146]	Thermal comfort prediction	T_a, RH[146]	Ts, EDA, HR, MET	KNN, GBM, SVM, RF, LVQ	Predictive models considering metabolic rate yield advanced performance of up to 8.5%.
Liu (2019) [33]	Thermal comfort prediction	T_a, RH, T_{out}, Wind speed, Solar Radiation	HR, T_s at wrist and ankle	14 ML algorithms	The median performance of the best algorithm for each subject is 24%/ 78%/0.79 (Cohen's kappa/accuracy/ AUC).
Du (2018) [147]	Thermal sensation prediction	T_a, RH, AV	T_s at the head, chest, back, arm, hand, thigh, and calf	CT	The results indicated that a classification tree C5.0 model showed a better prediction performance of 83.99%.
Kim (2018) [140]	Thermal preference prediction	T_a, T_g, RH, T_{out}, Clo	\	CT, GPC, GBM, kSVM, RF, regLR, PMV, aPMV	• Personal comfort models produced a median accuracy of 73%, improving the predictions of conventional comfort models (PMV and aPMV). • RF, kSVM, and regLR models produced higher accuracy than the algorithms without them.
Somu (2021) [133]	Thermal comfort prediction	T_a, RH, MRT, AV, Clo	MET	CNN-LSTM	The model proposed provided 60% accuracy predictions.
Chaudhuri (2018) [148]	Thermal comfort prediction	T_a, RH, T_g, AV, Clo	T_s at wrist and fingers	SVM, ELM	The PTS model based on normalized skin features accurately predicted 87% of thermal states.
Chaudhuri (2018) [49]	Thermal comfort prediction	T_a, T_g, RH, AV	T_s, SpO_2, BP, PR, SC	RF	The features identified for males and females could accurately predict 92.86% and 94.29% thermal states, respectively.

Table 5 (continued)

Study	Application	Environmental sensor	Physiological sensor	Algorithm	Model accuracy
Li (2017) [32]	Thermal preference prediction	T_a, RH, CO_2, Clo	T_s, HR, MET	RF, KNN, SVM, LR	RF model can be achieved 80% classification accuracy with a relatively small dataset (approximately 50 samples).
Chaudhuri (2017) [149]	Thermal comfort prediction	T_a, RH, AV, MRT, Clo	MET	SVM, KNN, LR, ANN, LDA, CT	ML method outperformed traditional and modified PMV models. SVM classifier achieved a prediction accuracy of up to 81.2%
Dai (2017) [114]	Thermal demands prediction	T_a, RH, T_{out}, outdoor RH, Clo	T_s	SVM	Using a single skin temperature correctly predicts 80% of thermal demands. Combined skin temperatures from different body segments can improve the model to over 90% accuracy.
Guo (2016) [134]	Stress prediction	\	EEG	SVM	SVM classifier of stress can be recognized with an accuracy of 75%.

Abbreviations: ANNS, Artificial Neural Networks; SVM, Support vector machine; LDA, linear discriminant analysis; KNN, K-Nearest Neighbor; DT, Decision Tree; NB, Naïve Bayes; RF, Random Forest; LSTM, Long Short-Term Memory; SOM, Self-organizing mapping; CT, Classification Tree; GPC, Gaussian Process Classification; GBM, Gradient Boosting Method; kSVM, Kernel Support Vector Machine; regLR, Regularized Logistic Regression; LR, Logistic Regression; CNN-LSTM, Convolutional Neural Networks-Long Short Term Memory neural networks; ELM, Extreme Learning Machine; SC, hand skin conductance; LVQ, learning vector quantization

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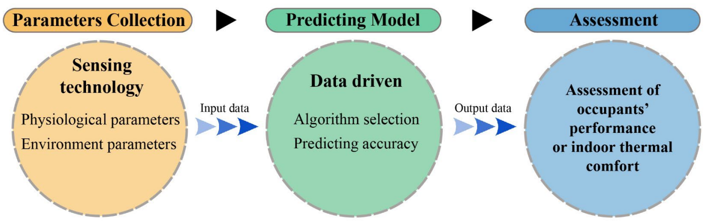

Fig. 6 The assessment procedure in indoor environment studies.

Several recent studies have focused on physiological parameters. For example, Ref [47] used MET to suggest that the ANNs-based thermal comfort model is effective in natural ventilation buildings, which had the highest R^2 (0.4872) values. Performances of different EEG-based ML classifiers were satisfactory, with accuracy all above 90% [30]. Ref [135] demonstrated the tight link between physiological indicators (ECG, EEG, EDA) and thermal comfort, with superior results for both SVM (84%) and NB (82%). Using skin temperatures of the wrist and fingers, Ref [148] proposed a predictive thermal model with an accuracy of 87% in predicting thermal states based on normalized skin characteristics. In a similar study [49], the potential of five physiological responses, including hand skin temperature, hand skin conductance, pulse rate, SpO_2, and BP, to predict thermal status was investigated by using RF. The collective information of the identified features could accurately estimate 92.86% and 94.29% of the thermal states of males and females, respectively. Ref [150] used facial and wrist skin temperature to investigate how heat flux sensing could improve personal thermal comfort inference under transient ambient conditions. It was observed that a median of 97.0% accuracy for RF when using a heat exchange rate and ambient temperature as features. In Ref [114], skin temperature was used as the only input data for the thermal demands model. The result showed that using combined skin temperatures from different body parts could increase the accuracy of the SVM-based model to over 90%. Ref [32] measured physiological parameters, including skin temperature, MET to predict thermal preference. With a relatively small dataset (approximately 50 samples), the RF model can achieve a classification accuracy of 80%. A review showed that skin temperature is the most important physiological variable influencing thermal sensation in the indoor environment, with 70% of the studies measuring skin temperature and 39% monitoring core body temperature as a physiological parameter.

Another study [137] used a self-organizing mapping (SOM) neural network, a non-linear unsupervised clustering algorithm, and combined LSTM to predicting overheating risk. The SOM-LSTM model showed the best prediction performance, with over 95% accuracy in predicting indoor temperature. By comparing conventional comfort models (PMV and aPMV) with the best algorithm for personal comfort models (RF, kSVM, regLR), Ref [140] found that the personal comfort model produced a median accuracy of 0.73, improving on the predictions of traditional comfort models. Similarly, the ML-based thermal comfort model outperformed conventional and aPMV models. SVM classifier achieved a prediction accuracy of up to 81.2% [149]. As seen from reviews, the ML-based thermal comfort model has 5~20% higher accuracy than PMV. A study [48] calculated that the median predicting accuracy was 84%, significantly higher than PMV and other thermal comfort models. The distribution of predicting accuracy reported a standard deviation in the accuracy of approximately 15%. Another study reported that the difference could be due to the input variables, targeted comfort indices, model functions, and other reasons.

Table 4

Summary of the commonly used machine learning algorithms for different applications.

Study	Application	Environmental sensor	Physiological sensor	Algorithm	Model accuracy
Chai (2020) [47]	Thermal comfort prediction	T_a, T_g, RH, AV, Clo	MET	ANNs, SVM, PMV, aPMV, and ePMV	ANNs model is effective in naturally ventilated residential buildings, with the highest R (0.6984) and R^2 (0.4872) values.
Pigliautile (2020) [135]	Thermal comfort, Air quality prediction	T_a, RH, AV, CO_2	ECG (HRV, LF/HF), EEG, EDA	LDA, KNN, DT, SVM, NB, RF	SVM (84%) and NB (82%) are shown better results for the accuracy of time, frequency, and aggregated indices.
Shan (2020) [30]	Thermal comfort prediction	T_a, RH, AV, CO_2	EEG	LDA, NB, KNN	Performances of different classifiers were satisfactory, with classification rates all above 90%. The LDA classifier had the best performance.
Yuan (2020) [137]	Temperature prediction	T_a, RH, CO_2, T_{out}, outdoor RH, Solar Radiation, Wind speed	\	LSTM, SOM	The SOM-LSTM model shows the best prediction performance, with an accuracy of over 95% for the prediction of indoor temperature and around 90% for the prediction of CO_2.
Alsaleem (2020) [145]	Thermal comfort prediction	T_a, RH	HR, Ts	DT, AdaBoost, GBM, RT, SVM	The SVM model provided a higher accuracy of 87%.
Lee & (2020) [146]	Thermal comfort prediction	T_a, RH[146]	Ts, EDA, HR, MET	KNN, GBM, SVM, RF, LVQ	Predictive models considering metabolic rate yield advanced performance of up to 8.5%.
Liu (2019) [33]	Thermal comfort prediction	T_a, RH, T_{out}, Wind speed, Solar Radiation	HR, T_s at wrist and ankle	14 ML algorithms	The median performance of the best algorithm for each subject is 24%/ 78%/0.79 (Cohen's kappa/accuracy/ AUC).
Du (2018) [147]	Thermal sensation prediction	T_a, RH, AV	T_s at the head, chest, back, arm, hand, thigh, and calf	CT	The results indicated that a classification tree C5.0 model showed a better prediction performance of 83.99%.
Kim (2018) [140]	Thermal preference prediction	T_a, T_g, RH, T_{out}, Clo	\	CT, GPC, GBM, kSVM, RF, regLR, PMV, aPMV	• Personal comfort models produced a median accuracy of 73%, improving the predictions of conventional comfort models (PMV and aPMV). • RF, kSVM, and regLR models produced higher accuracy than the algorithms without them.
Somu (2021) [133]	Thermal comfort prediction	T_a, RH, MRT, AV, Clo	MET	CNN-LSTM	The model proposed provided 60% accuracy predictions.
Chaudhuri (2018) [148]	Thermal comfort prediction	T_a, RH, T_g, AV, Clo	T_s at wrist and fingers	SVM, ELM	The PTS model based on normalized skin features accurately predicted 87% of thermal states.
Chaudhuri (2018) [49]	Thermal comfort prediction	T_a, T_g, RH, AV	T_s, SpO_2, BP, PR, SC	RF	The features identified for males and females could accurately predict 92.86% and 94.29% thermal states, respectively.

Table 5 (continued)

Study	Application	Environmental sensor	Physiological sensor	Algorithm	Model accuracy
Li (2017) [32]	Thermal preference prediction	T_a, RH, CO_2, Clo	T_s, HR, MET	RF, KNN, SVM, LR	RF model can be achieved 80% classification accuracy with a relatively small dataset (approximately 50 samples).
Chaudhuri (2017) [149]	Thermal comfort prediction	T_a, RH, AV, MRT, Clo	MET	SVM, KNN, LR, ANN, LDA, CT	ML method outperformed traditional and modified PMV models. SVM classifier achieved a prediction accuracy of up to 81.2%
Dai (2017) [114]	Thermal demands prediction	T_a, RH, T_{out}, outdoor RH, Clo	T_s	SVM	Using a single skin temperature correctly predicts 80% of thermal demands. Combined skin temperatures from different body segments can improve the model to over 90% accuracy.
Guo (2016) [134]	Stress prediction	\	EEG	SVM	SVM classifier of stress can be recognized with an accuracy of 75%.

Abbreviations: ANNS, Artificial Neural Networks; SVM, Support vector machine; LDA, linear discriminant analysis; KNN, K-Nearest Neighbor; DT, Decision Tree; NB, Naïve Bayes; RF, Random Forest; LSTM, Long Short-Term Memory; SOM, Self-organizing mapping; CT, Classification Tree; GPC, Gaussian Process Classification; GBM, Gradient Boosting Method; kSVM, Kernel Support Vector Machine; regLR, Regularized Logistic Regression; LR, Logistic Regression; CNN-LSTM, Convolutional Neural Networks-Long Short Term Memory neural networks; ELM, Extreme Learning Machine; SC, hand skin conductance; LVQ, learning vector quantization

6. Conclusion

This review work discusses the indoor microclimate parameters that affect occupants' work or cognitive performance and introduces how to use the physiological indicators to assess performance, as well as summarizes the variables and accuracy of thermal comfort model predictions based on ML and sensing technologies. Overall, researches in the indoor environment field have focused on occupants' comfort and performance, using different methods of data collection to highlight occupants' discomfort and its relationship to performance. It was observed that studies attempted to predict further the change rules of occupants' performance affected by combined indoor environmental factors using data-driven approaches based on physiological and psychological measurements.

Cognitive test results indicated that high and low indoor air temperatures are common risk factors for human health and performance. Higher levels of brain arousal in a colder state (10℃) improve task accuracy. However, the hypothermic environment may negatively affect cognitive performance by distracting attention. Following previous work, the range for optimal work and cognitive performance was 20 ℃ to 26 ℃, especially 22 ℃ to 24 ℃, which is almost consistent with the optimal thermal satisfaction. Furthermore, it is worth noting that the optimal temperature range depends on the specific climate region, and people in different regions adapt to temperatures differently. However, the integration of current research is still limited.

Prolonged dryness of indoor air may contribute to losing body moisture, which can impair cognitive and work performance. A study has suggested that thirst reduces memory, while drinking water improves memory and cognitive attention, but no individual or gender differences were studied. In addition, considerable studies have agreed that increasing indoor air humidity reduces complaints of dry and unfresh air and diminishes the risk of dry eye symptoms and fatigue, improving occupants' performance. In rooms with 40~60% humidity levels, people experience lower stress levels than in dry air. Hence, personal control of temperature and humidity appears to be the way to achieve a comfortable indoor environment. In summary, elevated humidity may decrease complaint rates and benefit performance compared to very dry air conditions. However, more information is needed to understand how humidity affects performance.

According to reviews, there has been significant growth in the use of ML to predict thermal comfort and occupants' performance, with a median prediction accuracy of up to 84%. Furthermore, with the advent of the IoT and new technologies, data collected by the sensors on environmental and various physiological parameters shows the potential for future developments in indoor environmental comfort prediction. The analysis of several retrospective studies showed that when the models considered both physiological and environmental parameters, the models' predictive performance was relatively higher than those that used only environmental factors or physiological data. In the literature reviewed, the most used variables were skin temperature, indoor air temperature, and relative humidity. Skin temperature, the key physiological variable influencing thermal sensation in the indoor environment, was used at over 70%. It is worth noting that multivariate can lead to higher complexity and computational load regarding feature selection and model scalability. However, few studies have analyzed multiple physiological parameters, let alone joint analyses.

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Previous research has also demonstrated that coordinated control strategies for indoor temperature and humidity are essential to meet the requirements for optimal work or study performance, indoor thermal comfort, and health. However, the combined effects of adding other indoor microclimate parameters (e.g. ventilation conditions) on occupant performance and physiology are not yet fully understood.

7. Implications for Future Research

The various environmental and physiological parameters collected by the sensors show the potential for future developments in indoor environmental comfort prediction. The focus of ML prediction research is shifting to more complex objects, such as occupant cognitive performance and thermal perception, to produce more accurate model predictions and better serve indoor environmental modulation. Further research is proposed in the following segments:

There is still a lack of a more unified and systematic modeling framework for thermal comfort and occupant performance prediction. Different models should be tested and compared when building a statistical model for a dataset before selecting the most appropriate one. Model assessment requires clear comparisons between studies and approaches to make decision-making more straightforward. In addition, while combining physiological and environmental parameters to predict occupant performance will result in better model performance, research should also be conducted to summarize the number of input variables.

Indicators collected through physiological sensing technologies also need to be further investigated. Few studies have analyzed multiple psychological parameters, let alone joint analyses between indicators. Moreover, individual differences in performance and physiology, such as gender and age, should be further explored.

Full-day and real performance should be considered using wearable devices that can be worn for long periods and intervention experiments to validate experimental results. According to the literature review, cognitive performance tests and physiological data are mainly based on experimental laboratory or climate chamber collection. It cannot accurately reflect the full-day performance of the occupants in an actual work or study environment due to the relatively short durations.

As an essential microclimate parameter, humidity is often overlooked in research. Both physiological and psychological results showed that performance and thermal comfort were more affected by relative humidity under high temperature conditions. Thus, further research should be explored the air humidity combined with other environmental parameters. Furthermore, ventilation is not a direct factor but a moderating factor that should be strategically combined with air temperature and humidity for joint control to positively influence indoor occupants' health, cognitive or work performance. Further research is also needed on the differences in occupant performance between different climate zones.

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