Thermal Comfort and Indoor Air Quality in Vehicle Cabins: Assessment, Implications, and Impact on Driving Performance - A Critical Review

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ABSTRACT

Vehicle cabin environments, including thermal conditions and air quality, significantly influence passenger comfort and driver performance. Despite the growing body of research, a systematic review synthesizing the characteristics, assessment methods, comfort improvements, and driving performance impacts of cabin environments are still lacking. This article systematically reviews the literature on cabin environments employing a structured methodology and discusses their impact on driving performance through best-evidence synthesis analysis. Literature was retrieved from Scopus and Web of Science using keyword-based searches, screened through a two-stage PRISMA-guided process, and analyzed to address three key research questions. The review yields the following key findings: 1) The cabin thermal environment is characterized by intense solar heat gain, strong spatial non-uniformity of airflow, and rapid temporal temperature fluctuations, which challenge conventional thermal comfort indicators. 2) While PMV and weighted PMV remain widely used, the UC Berkeley Model better suits the non-uniform and transient cabin environment, though its complexity limits practical application; future research should pursue low-complexity, high-accuracy comfort indicators paired with non-contact sensing. 3) Thermal load moderately correlates with poor driving performance (pooled $r \approx 0.39$), with task completion times increasing 15–21% at higher temperatures, while short low-amplitude cooling reduces drowsiness (pooled $r \approx 0.51$); However, strong cold stress may induce risk-prone control. Evidence for direct CO_2 effects is limited, whereas $PM_{2.5}$ correlates with accident risk at the macro level. Future research should prioritize standardized exposure–outcome reporting, causal identification of thermal–IAQ interactions, dose–response personalization, and real-world validation of humidity and defogging impacts.

KEYWORDS

Vehicle Cabin, Cabin Thermal Environment, Cabin Indoor Air Quality (IAQ), Cabin Thermal Comfort, Driving Performance

1. Introduction

Automobiles represent one of the most vital modes of transportation for residents in modern society[1]. According to American Community Survey 2019[2], individuals spend over 51 minutes of their daily time within vehicles, particularly for urban commutes, where this duration may exceed two hours[3]. This extended occupancy places significant demands on the internal environmental control of the vehicle cabin. An appropriate cabin climate is not only crucial for ensuring occupant comfort[4], [5] but may also substantially impact driver performance[6]. An improper vehicle cabin climate may increase the traffic accidents by influencing drivers' alert and stress[7], [8]. During operation, the vehicle's Heating, Ventilation, and Air Conditioning (HVAC) system provides changes in the cabin internal environment[9]. However, its operation significantly increases vehicle energy consumption and reduces driving range[10]. The air conditioning compressor may increase fuel consumption by approximately 15%[11], with an even more pronounced effect on electric vehicles, potentially consuming over 60%[12] of battery capacity in extremely cold weather. Optimizing the vehicle HVAC system and thermal environment is therefore an essential approach to improve the passenger experience, enhance driving performance and extend vehicle range. Consequently, a thorough analysis of cabin thermal conditions, thermal comfort, and air quality characteristics is necessary. Quantifying the impact of these factors on driving performance can better assist vehicle manufacturers in identifying key areas for cabin environment improvement and inform operational strategies for in-vehicle systems during driving, thereby maximizing comfort and mitigating associated risks.

In buildings, Indoor Environmental Quality (IEQ)[13] encompasses both thermal comfort and Indoor Air Quality (IAQ)[14]. Similarly, for the vehicle cabin environment, the thermal environment is a key factor directly influencing occupant thermal comfort and air quality is also a critical aspect that cannot be overlooked. Compared to buildings, vehicle cabins are more confined and enclosed spaces[15]. Consequently, fluctuations in temperature, humidity, and air quality occur more rapidly and intensely within the cabin. The thermal environment and air quality within the vehicle cabin are influenced by numerous internal and external factors[16], [17]. These include ambient temperature and humidity, solar radiation intensity, the thermodynamic properties of the vehicle body, cabin airtightness, occupant activity, and traffic conditions[18]. In buildings, the impact of solar radiation on indoor thermal dynamics is quantified as solar gains[19], which are jointly influenced by several factors, including the window-to-wall ratio (WWR), window distribution, and more factors[20], [21]. Compared to typical buildings, excluding those enclosed glass curtain walls, a key distinction between vehicle cabins and building envelopes is the significantly larger proportion of window area relative to the total surface area in vehicles. The large front windshield[22], in particular, allows direct solar radiation into the front seating area during summer, causing rapid temperature increases. Direct solar radiation on occupants' skin also elevates localized skin temperatures and induces physiological discomfort[23]. Utilizing external air circulation significantly exposes cabin temperature, humidity, and air quality to the influence of external conditions[24].

Simulation and field experimental methods are widely employed to investigate cabin environments and thermal comfort. Simulation offers a low-cost and rapid approach[25]. Three-dimensional simulation methods, such as Computational Fluid Dynamics (CFD)[26], can accurately predict temperature, air velocity, and the distribution of various airborne substances within the cabin, proving highly valuable for cabin environment studies. Thermal comfort models have also been extensively explored in prior research. Existing models primarily address physiological and psychological aspects of thermal comfort.

Physiological models[27] based on objective parameters can simulate changes in physiological signals (e.g., skin temperature, blood flow rate) under given environmental conditions. Psychological indicators, such as the commonly used Predicted Mean Vote - Predicted Percentage Dissatisfied (PMV-PPD)[28] in building comfort, along with Thermal Sensation Vote (TSV) and Thermal Comfort Vote (TCV), have been adapted for vehicle cabin thermal comfort assessment.

Previous review studies have partially addressed aspects related to thermal comfort, air quality, and driving performance in vehicle cabins. For instance, Chen et al.[29] discussed the non-uniform and transient nature of cabin thermal environments, summarized primary assessment methods and models for cabin thermal comfort, and analyzed their applications and predictive accuracy; however, they lacked a summary of methods for improving passenger thermal comfort and the evaluation of impacts on driver's performance were not discussed sufficiently. Lexén et al.[30] detailed sampling methods for Semi-Volatile Organic Compounds (SVOCs) in cabin environments, concentration levels of several important components, and occupant exposure. Nevertheless, they did not address other significant pollutants within the cabin, such as CO_2 and particulate matter, beyond VOCs. Ni et al.[7] summarized factors influencing Driver Stress (DS), finding that traffic conditions, road conditions, and the driving environment all have significant impacts, with temperature and CO_2 concentration potentially increasing DS levels. But the in-vehicle environment constituted only a minor part of their review and was not thoroughly discussed. Therefore, this paper will comprehensively review the cabin internal environments and their impact on driving performance, encompassing both thermal comfort and air quality, and elucidate the current state of development, challenges, and future research directions in creating optimal climatic conditions within vehicle cabins. The aim of this review is to address the following questions, which are also depicted in Fig. 1,

1. What are the primary characteristics of the cabin interior environment, and which factors contribute to the distinctive nature of the cabin climate.

2. What are the primary methods for assessing thermal comfort within the cabin, what potential impact might thermal comfort have on driver performance, and how can cabin thermal comfort be improved.

3. Which components significantly affect cabin air quality, what is their potential impact on driver performance, and how can the influence of air pollution be mitigated.

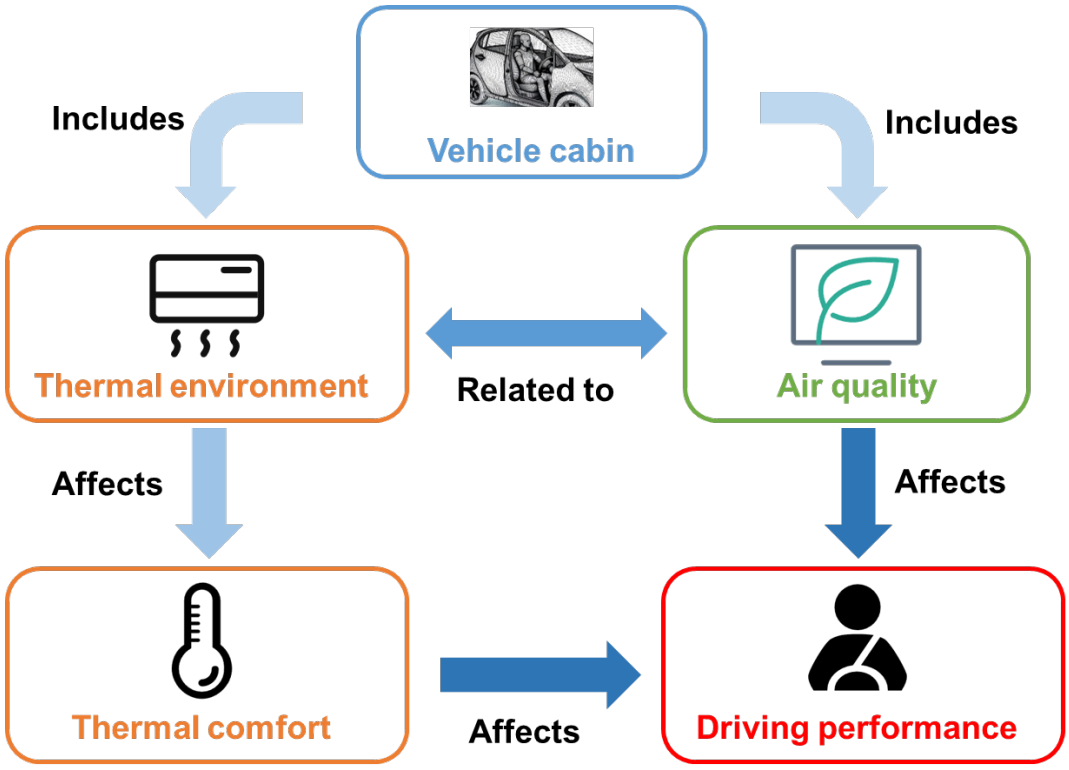


Fig. 1 Research objectives of this review

The subsequent sections of this paper are organized as follows: Section 2 delineates the literature search and screening process, along with a preliminary analysis of the retrieved results. The key questions 1-3 outlined above are addressed in Sections 3 and 4. Section 3 focuses on the characteristics of the thermal environment and aspects related to thermal comfort, while Section 4 examines topics pertaining to in-vehicle air quality. Section 5 synthesizes several significant discussion points. Finally, the conclusion presents a summary of the principal findings derived from this review.

2. Review methodology

2.1. Literature search and screening

Scopus was selected as the primary literature retrieval platform for this review. *Scopus* is one of the world's largest abstract and citation databases, offering extensive coverage, particularly in fields such as engineering, computer science, and life sciences, where it indexes a substantial number of journals. It also demonstrates a strong tendency to cover emerging research areas. Another commonly used database, *Web of Science*, served as a reference for the search, utilizing the same set of search keywords as those input into *Scopus*. The search strategy focused on several core aspects: the thermal environmental characteristics of the cabin, the status of air quality, thermal comfort, and the impact of these factors on driving performance. Preliminary investigation revealed that the key topics could be categorized into two distinct themes: one describing the cabin internal environment and the other concerning driving performance. Consequently, two sets of keywords were established to screen the literature relevant to this review. To ensure comprehensive coverage of studies pertinent to this review, synonyms frequently appearing in the literature were incorporated for each search concept. The first set of keywords comprised the following components: terms representing "vehicle," terms representing "cabin," and terms describing the thermal environment, air quality, and thermal comfort. The second set of keywords added descriptors related to driver performance metrics. The finalized search strings were as follows:

Search 1 = ("vehicle" OR "car" OR "automobile") AND ("passenger compartment" OR "cabin") AND ("thermal comfort" OR "thermal sensation" OR "thermal environment" OR "temperature" OR "humidity" OR "air distribution" OR "air flow" OR "air quality" OR "CO2 concentration" OR "particle concentration" OR "VOC")

Search 2 = ("driver") AND ("attention" OR "cognitive performance" OR "fatigue" OR "drowsiness" OR "distraction" OR "cognitive load" OR "emotion" OR "stress" OR "reaction time" OR "response time" OR "Steering Control" OR "Lane Keeping Ability") AND ("thermal comfort" OR "thermal sensation" OR "thermal environment" OR "temperature" OR "humidity" OR "air distribution" OR "air flow" OR "air quality" OR "CO2 concentration" OR "particle concentration" OR "VOC")

The retrieved records underwent a two-stage screening process. The criteria for the initial screening stage were:

1) Language: Exclude non-English publications; retain only English-language records.

2) Subject Area: Utilize Scopus's subject categorization tools to exclude records from demonstrably irrelevant disciplines.

3) Document Type: Exclude conference papers; retain only full-length journal research articles. Conference papers are typically shorter and may lack sufficient detail regarding models or experimental procedures.

4) Publication Year: Limit results to articles published in 10 recent years to ensure the review incorporates timely findings.

Articles passing the initial screening then underwent a second stage involving standardized information extraction. This involved analyzing titles, keywords, and abstracts to assess high relevance to the review topics. Articles deemed insufficiently relevant or whose primary research objectives did not align closely with the focus of this review were excluded. Articles with unclear research conclusions or poorly described methodologies were also excluded at this stage.

The literature search was conducted in mid-June 2025. Fig. 2 summarizes the search and screening outcomes using a workflow diagram based on the PRISMA methodology[31]. As depicted, the search 1 yielded 2,545 records. Following the first and second screening stages, 570 and 80 articles remained, respectively. Search 2 yielded 3,836 records, with 464 and 23 articles remaining after the first and second screening stages, respectively. Consequently, a total of 103 articles were identified for detailed review in this study.

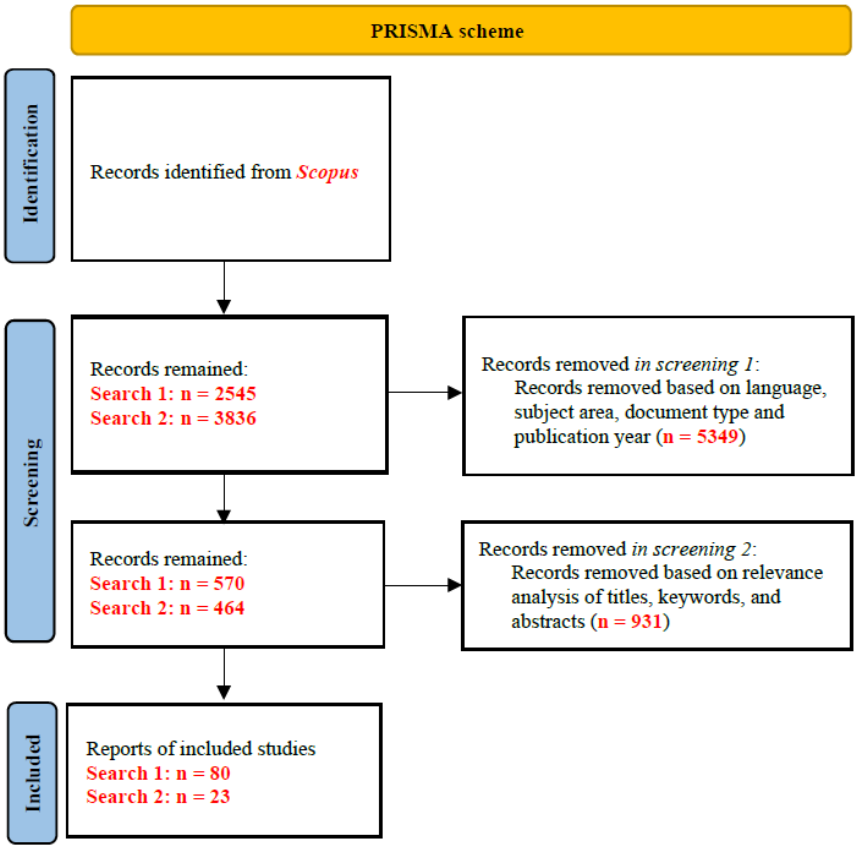


Fig. 2 The PRISMA scheme of literature screening. Search 1: Vehicle cabin thermal environment, air quality and thermal comfort; Search 2: Impacts on driving performance

2.2. General analysis

Given the larger number of articles retrieved for Search 1 (80 articles) and the broader scope of their research content, a preliminary analysis of the general characteristics of these included publications was conducted to guide the subsequent detailed review process. Fig. 3 presents the distribution of publications by year of publication and research theme, also indicating the primary journals (only those publishing at least 3 included articles are listed). As illustrated, research related to cabin internal environments and thermal comfort has exhibited a generally steady upward trend since 2015. Notably, the annual publication count has exceeded 10 articles each year starting in 2022, peaking in 2024. As of mid-2025, six relevant articles have already been published, indicating that this field is attracting increasingly widespread research attention. Regarding thematic distribution, studies focusing on cabin thermal environment characteristics and IAQ have been prominent research focuses from the outset. Research explicitly addressing thermal comfort has shown a marked increase since 2020 and has predominated in 2023 and 2024.

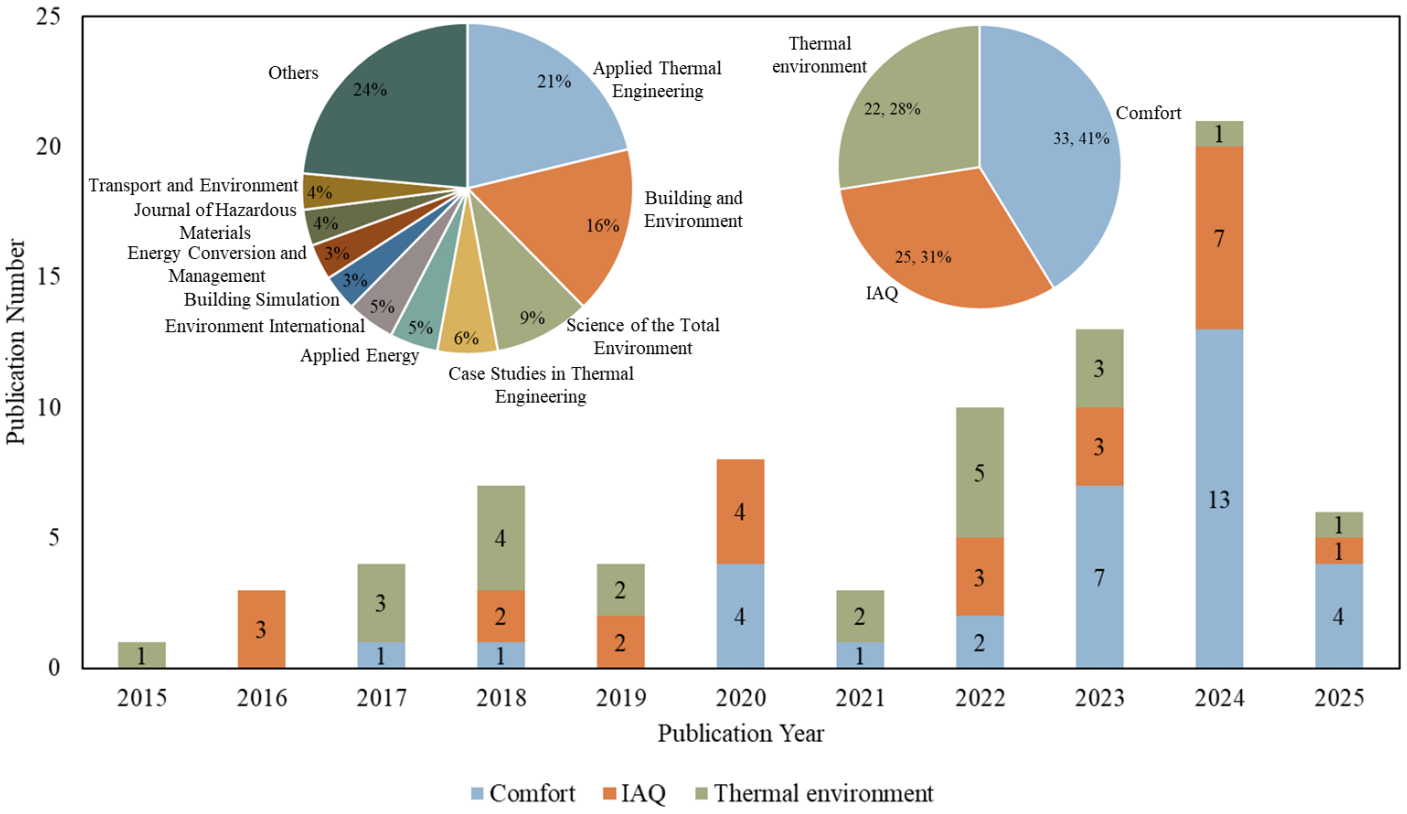


Fig. 3 Publication year, topic and journal of search 1

3. Cabin thermal environment and occupants' thermal comfort

This section aims to answer the first research question by examining numerous internal and external factors that impact the cabin thermal environment. External heat gains or losses can transfer into the cabin through the cabin shell. Fig. 4 illustrates the heat and mass transfer processes occurring between the cabin, the external environment, the internal HVAC system, and the occupants. Solar radiation penetrates the windows directly, heating objects and occupants within the cabin. Ambient temperature affects the cabin air temperature through convection and conduction. Furthermore, the convective heat transfer coefficient at the cabin shell surface changes during vehicle motion, thereby influencing the internal thermal environment[32]. The vehicle's HVAC system serves to regulate the cabin climate within a comfortable and safe range. However, different operational modes of the system exert corresponding effects on the cabin environment. During the exclusive operation of the internal air recirculation mode, CO_2 concentrations can accumulate rapidly within the cabin. Conversely, utilizing the external air intake mode may introduce outdoor pollutants, particularly in traffic-congested areas or when surrounded by significant vehicle exhaust emissions. Additionally, uncontrolled air leakage due to poor cabin sealing can significantly alter the internal climate.

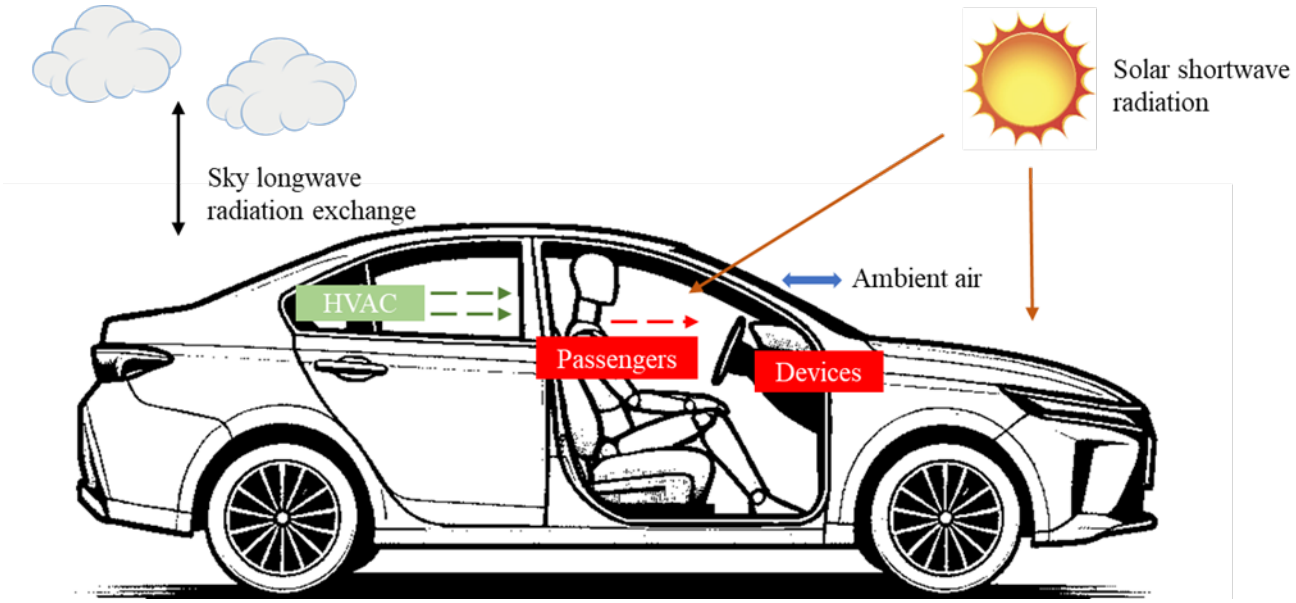


Fig. 4 Cabin heat transfer with environment and internal objects

3.1 Characteristics of cabin thermal environment

3.1.1 Intense solar radiation

Research investigating the thermal environment within vehicle cabins frequently highlights the challenge of intense solar radiation. 17 studies explicitly address this issue; their key information is summarized in Table 1. Among these, 10 studies employed experimental testing to obtain data, while the remaining 7 utilized simulation methods to investigate the cabin thermal environment. These studies, using either soak tests or simulations, examined the maximum temperatures attainable within vehicles exposed to strong summer solar radiation. Notably, Srusti et al.[33] recorded a peak air temperature of approximately 85°C at the dashboard location. Ravindra et al.[34], investigating temperature records in differently colored vehicles after solar exposure in tropical regions, found that black vehicles reached an average cabin temperature of 64.9°C. The majority of other studies also recorded maximum average cabin temperatures exceeding 50°C. Regarding solar irradiance values, in tropical and subtropical regions during summer afternoons under clear skies, total solar irradiance typically exceeds 900 W/m². Lahimer et al.[35] documented the highest recorded value of 1241 W/m². According to Chen et al.[36], the difference of parked orientation will result in different distribution in the cabin, with the highest average air temperature of 60°C when the car is heading east. Consequently, these studies reveal that the extreme heat generated by intense solar radiation can cause significant thermal discomfort for cabin occupants. Several also emphasize the potential life-threatening risks posed by such extreme temperatures to passengers or pets left inside vehicles. Setiyo et al.[37] employed the Heat Index (HI) as a metric for assessing temperature-related safety hazards within the cabin.

Table 1. Brief of research related to intense solar radiation

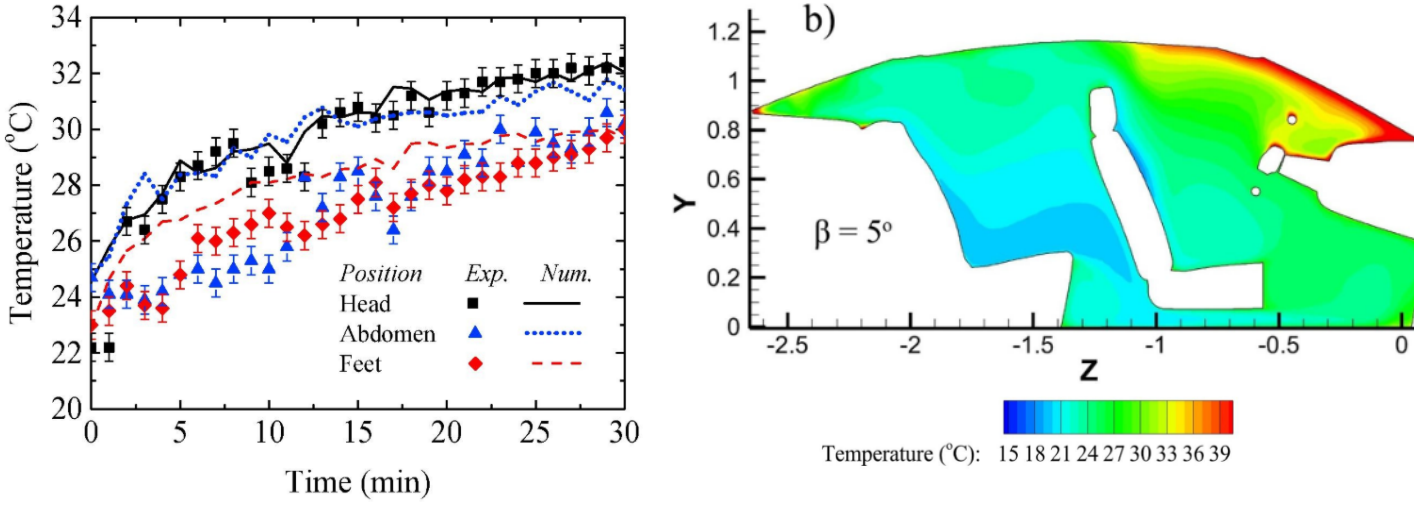
Author	Year	Methodology	Max solar radiation (W/m²)	Max cabin temperature (℃)	Solution	Effects on cabin temperature
Wang[38]	2025	Experiment	/	60	Car cover + PCM	< 22.5℃
Çelik[39]	2024	Experiment	800	/	Solar assisted water tank	3℃→15℃
Ahmed[40]	2023	Simulation	900	68.5	PV + Thermo-electric cooling	47.5℃→24℃

Suhaimi[23]	2023	Simulation	900	/	/	/
Aceros[41]	2023	Simulation	900	Over 50	/	/
Chen[36]	2022	Simulation	/	66	/	/
Srusti[33]	2022	Simulation	/	85 (at panel)	PCM	10.4℃ reduction
Srivastava[42]	2022	Simulation	900	/	Solar assisted cooling/heating	17℃ reduction in summer 15℃ increase in winter
Setiyo[37]	2021	Experiment	/	55	Solar assisted cooling	9.8℃ reduction
Lv[43]	2021	Experiment	977	65.6	High reflective car cover	31.1℃ reduction (19.6 ℃ better than traditional cover)
Afzal[44]	2020	Experiment	/	49.7	PCM	13℃ reduction
Ravindra[34]	2020	Experiment	Over 1000	64.9 (black car)	/	/
Lahimer[35]	2019	Experiment	1241	51.6	Solar chimney	12.4℃ reduction
Kolhe[45]	2018	Experiment	/	57	PV	37.6℃ to 28.26℃
Soulios[46]	2018	Simulation	/	/	Spectrally selective glazing (with solar reflective opaque surface)	12.5℃ reduction (23.8℃ reduction together)
Lahimer[47]	2018	Experiment	550	/	Solar reflective cover	17.7℃ reduction
Qi[48]	2017	Experiment	/	55~60	Solar assisted PCM	< 32℃

3.1.2 Non uniform environment

The confined space of the vehicle cabin, coupled with the distribution of air vents that varies significantly depending on vehicle model and manufacturer design, results in a highly non-uniform thermal environment. Alterations to the air supply strategy, such as adjusting the supply air velocity or opening/closing vents at different locations, can further exacerbate the non-uniformity in temperature and airflow distribution. In [49], the compartmentalized simulation of a vehicle cabin, found a maximum average temperature difference of 1.5 K between the driver and passenger zones; this result was also shown to vary with changes in orientation and glazing properties. Experimental and simulation results from [50] demonstrated that during summer cooling conditions, the temperatures of windows, seats, and occupant surfaces were significantly higher than the supply air temperature at the vents. Conversely, during winter heating, a pronounced vertical temperature gradient was observed, with head-level temperatures substantially exceeding those at foot level by up to 6°C. [51] and [52] respectively analyzed the uneven airflow distribution arising from vent locations and air supply strategies. [51] reported that due to the presence of the windshield, airflow velocity reached 1.5 m/s in only 40% of the cabin area. [52] found velocities reaching 3 m/s in the front jet region, while speeds in the floor zone remained below 0.5 m/s. CFD simulation results by Bandi et al. indicated a maximum temperature difference of 22°C between the front and rear cabin compartments when the deflector angle was ⩽15 degrees; under conditions where the windshield temperature reached 40°C, the rear cabin temperature ranged between 18°C and 24°C.

To address the issue of temperature non-uniformity within the cabin, the most effective approaches involve increasing vent size, adjusting vent positions, or modifying the jet velocity and direction. Pan et al.[53] utilized a solar-assisted fan system to improve temperature distribution uniformity. Tan et al.[51] significantly reduced stagnant zones (areas with near-zero velocity) within the cabin by optimizing the structure and length of the air ducts.



a) b)

Fig. 5 Temperature distribution in vehicle cabin: a)temperature variation of front passenger in [50], b) temperature distribution in [54]

3.1.3 Transient environment

Another prominent characteristic of the thermal environment within vehicle cabins is its transient nature. This arises from several factors. Firstly, the cabin's confined volume[55], combined with materials and wall thickness differing significantly from those in buildings[56], [57], results in a thermal mass substantially lower than typical building materials. Within the cabin itself, the primary source of thermal mass is the occupants' seats[58]. A second factor is the relative velocity between the moving vehicle and the surrounding air during driving. This significantly increases the convective heat transfer coefficient at the vehicle body surface compared to stationary conditions. Furthermore, the frequent entry and exit of passengers causes instantaneous fluctuations in the cabin thermal environment. Previous studies indicate that in urban traffic scenarios, 85% of single trips cover distances of less than 18 km and 15~30 minutes[59]. The research [32] demonstrated that the cabin thermal load undergoes significant variations driven by dynamic changes in vehicle speed and solar altitude angle. The peak total thermal load occurred at 13:15, preceding the peak ambient temperature at 14:47. In [60], the author observed that during summer, the cabin temperature rose dramatically from 25°C to 50°C within 50 minutes of vehicle parking. In contrast, [61] found that activating the air conditioning system reduced the cabin temperature from 55°C to 25°C within just 40 minutes.

3.1.4 Humidity

Water vapor present in the cabin air constitutes another significant element of the in-vehicle environment[62]. When cabin humidity is high and the temperature near the windows falls below the dew point temperature, water vapor condenses and adheres to the window surfaces. While this phenomenon typically does not cause negative consequences in buildings, it can severely impair driver visibility and compromise driving safety within vehicles[63]. Consequently, the defogging performance of automotive air conditioning systems is often a critical evaluation factor. [64] investigated humidity levels in passenger vehicle cabins during summer operation in temperate climates with the air conditioning activated. With five occupants (driver and passengers), the relative humidity (RH) stabilized at approximately 30% during air conditioning operation. Upon deactivating the air supply, the cabin RH rapidly increased to about 50% within 15 minutes, while the absolute humidity rose from 6 g/m³ to 23 g/m³. This demonstrates that controlling relative humidity is crucial for automotive

HVAC systems, particularly within the confined space of a fully occupied cabin. Liu et al.[65] developed a cabin temperature and humidity model to study windshield fogging characteristics. They proposed limiting cabin humidity by controlling the return air ratio, finding that the maximum allowable return air ratio increased with rising ambient temperature and decreasing ambient humidity, but decreased with increasing vehicle speed. In general, there are relatively few studies on cabin humidity, and within research focused on cabin humidity and defogging, most investigators prioritize the fogging phenomenon itself. However, the impact of humidity on the thermal comfort of drivers and passengers is rarely mentioned or explored in depth.

3.2 Thermal comfort in vehicle cabin

The key characteristics of the 33 studies pertaining to thermal comfort in vehicle cabins are summarized in Table 2. This table details the authors, publication year, thermal comfort metrics employed, research methodology (simulation or field experiment), and a brief description of the research focus for each included study. These studies can be broadly categorized into two main areas: (1) investigations into thermal comfort metrics and predictive methodologies for vehicle cabins, and (2) research focused on strategies for enhancing cabin thermal comfort. Regarding enhancement strategies, some studies propose optimizations during the vehicle design phase. Examples include utilizing non-conventional heating or cooling devices, adjusting the parameters of interior trim materials, or modifying air supply designs. Other studies focus on operational phase optimizations. These involve proposing novel operational strategies based on experimental findings and expert knowledge or designing control algorithms that can regulate the vehicle's HVAC system in real-time based on cabin conditions to improve occupant thermal comfort. The subsequent subsections will provide an in-depth discussion and analysis of these research themes.

Table 2. Brief of research on cabin thermal comfort

Author	Year	Thermal comfort indicators	Methodology	Research objective keywords
Zhang[66]	2025	Temperature	Simulation (Lumped parameter)	HVAC control algorithm
Liu[67]	2025	Equivalent temperature, thermal sensation deviation	Simulation (CFD)	New thermal comfort and energy efficiency indicator
Gopi[68]	2025	Physiological signals	Real car (climate chamber)	Thermal comfort prediction based on physiological signals in transient environment
Gopi[69]	2025	Berkeley model	Real car (climate chamber)	Berkeley model evaluation
Paredes[70]	2024	Berkeley model	Real car (climate chamber)	Local heating elements
Gopi[71]	2024	Mean skin temperature	Real car (climate chamber)	Local heating elements
Wu[72]	2024	PMV, SET, Operation temperature	Real car (outdoor)	Personal comfort system
Zhang[73]	2024	PMV	Simulation (Lumped parameter)	HVAC control algorithm
Duan[60]	2024	SET	Simulation (CFD)	Thermal comfort improvement with new windows
Hou[61]	2024	TSV	Real car (outdoor)	HVAC control algorithm
Lyu[74]	2024	TSV	Real car (outdoor)	Thermal sensation assessment model
Zhou[75]	2024	TSV	Real car (outdoor)	Thermal comfort prediction model
Zhang[76]	2024	TSV	Real car (outdoor)	Thermal comfort prediction model
Liang[77]	2024	Temperature	Simulation (Lumped parameter)	HVAC control algorithm
Yang[78]	2024	Temperature	Simulation (Lumped parameter)	HVAC control algorithm
Guo[79]	2024	Temperature	Simulation (Lumped parameter)	HVAC control algorithm

Ma[80]	2024	Temperature	Simulation (Lumped parameter)	HVAC control algorithm
Ham[81]	2023	PMV-PPD	Lab field test	Thermal comfort improvement with different seats
Wang[82]	2023	PMV	Simulation (Lumped parameter)	HVAC control algorithm
Suhaimi[23]	2023	MRT	Real car (outdoor)	Thermal comfort evaluation under solar radiation
Lan[58]	2023	PMV-PPD	Simulation (Lumped parameter)	Thermal comfort evaluation with different heating strategy
Zong[83]	2023	Weighted-PMV	Simulation (CFD)	HVAC control algorithm
Deng[84]	2023	Temperature	Simulation (Lumped parameter)	HVAC control algorithm
He[85]	2023	Weighted-PMV	Real car (outdoor)	Thermal comfort prediction model
Xie[86]	2022	PMV	Simulation (Lumped parameter)	HVAC control algorithm
Metzmacher[87]	2022	Berkeley model	Lab field test	Personal comfort system
Xie[88]	2021	PMV	Simulation (Lumped parameter)	HVAC control algorithm
Afzal[44]	2020	Temperature and humidity	Real car (outdoor)	Thermal comfort improvement with PCM
Abou Jaoude[89]	2020	Berkeley model	Lab field test	Berkeley model evaluation
Ravindra[34]	2020	PMV-PPD	Real car (outdoor)	Thermal comfort evaluation under solar radiation in different cars
Xie[90]	2020	PMV	Simulation (Lumped parameter)	HVAC control algorithm
Dehne[91]	2018	ET	Lab field test	Thermal comfort evaluation with different vertical ventilation strategy
Hatoum[92]	2017	Berkeley model	Lab field test	Thermal comfort improvement with seats cooling system

3.2.1 Thermal comfort indicators

The thermal comfort evaluation metrics employed in the studies summarized in Table 2 can be categorized into the main groups illustrated in Fig. 6.

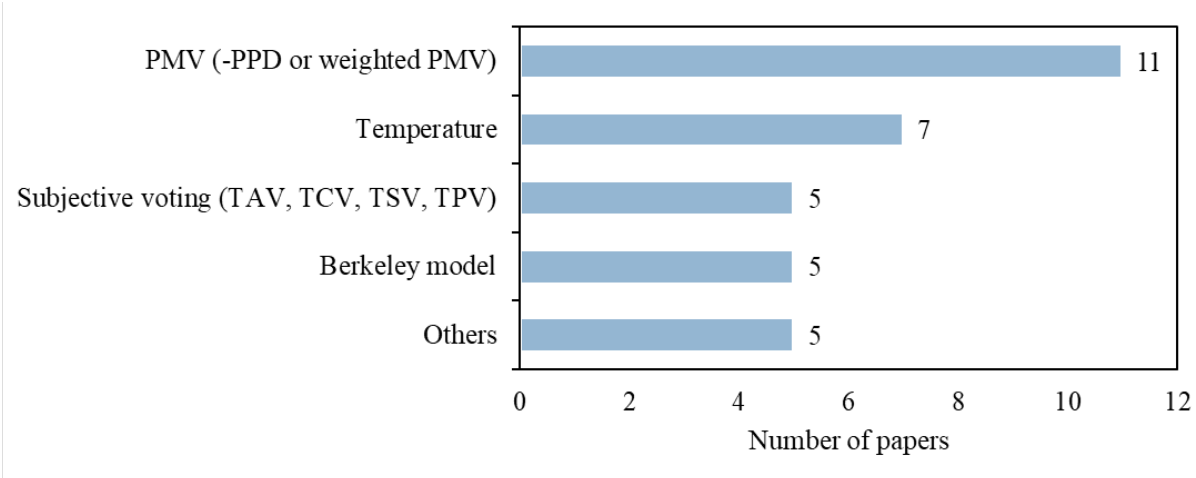


Fig. 6 Thermal comfort indicators in the surveyed articles

PMV (-PPD or weighted PMV)

The most frequently encountered metric is the PMV and its variants. PMV is a well-established psychological model of

thermal comfort, first proposed by Professor Fanger in 1970[28]. It is often used in conjunction with the Predicted Percentage Dissatisfied (PPD) to describe the level of thermal comfort and dissatisfaction. The model integrates multiple factors, including human metabolic rate, clothing insulation, and environmental parameters such as air temperature, humidity, air velocity, and mean radiant temperature. PPD is derived from the PMV calculation and aims to predict the percentage of people likely to feel thermally uncomfortable in a non-uniform environment. The calculation formulas for PMV and PPD are described as Equation (1) and (2),

$$PMV = (0.303e^{-0.036M} + 0.028) \times TL \quad (1)$$

$$PPD = 100 - 95\exp\left[-(0.03353PMV^4 + 0.2179PMV^2)\right] \quad (2)$$

Where M is the human metabolic rate, and TL is the heat accumulation within the human body, which can be calculated as Equation (3) to (8):

$$TL = (M - W) - Q_{conv} - Q_{rad} - Q_{skin} - Q_{sweat} - Q_{breathe} \quad (3)$$

$$Q_{conv} = f_{cl}h_c(t_{cl} - t_a) \quad (4)$$

$$Q_{rad} = 3.96 \times 10^{-8} f_{cl}[(t_{cl} + 273)^4 - (\overline{t_r} + 273)^4] \quad (5)$$

$$Q_{skin} = 3.05[5.733 - 0.007(M - W) - P_a] \quad (6)$$

$$Q_{sweat} = 0.42(M - W - 58.2) \quad (7)$$

$$Q_{res} = 1.73 \times 10^{-2} M(5.867 - P_a) + 0.0014M(34 - t_a) \quad (8)$$

Where $(M - W)$ is the metabolic heat after reduction of mechanical work to the environment, and Q_{conv}, Q_{rad}, Q_{skin}, Q_{sweat}, Q_{res} represent the heat transfer through the convection, radiation, skin evaporation, sweat evaporation and respiratory, respectively. t_a is the air temperature, and P_a is the water vapor partial pressure. t_{cl} is the clothes temperature and f_{cl} represents the body area covered by the clothes.

Some researchers have applied PMV to control automotive HVAC systems. Xie et al.[90] learned passengers' historical temperature setpoints to predict their preferred PMV value, which was then used as the target for the HVAC control strategy, maintaining the cabin PMV around 0.5 (based on the learned preference). Lan et al.[58], based on PMV-PPD, proposed that different ventilation temperatures should be adopted for urban open roads, tree-lined avenues, and underground parking garages to maintain occupant thermal comfort.

However, PMV assumes occupants are in a thermally uniform and steady-state environment, leading some scholars to question its applicability to the highly non-uniform and transient conditions typical of vehicle cabins. Consequently, several studies employed modified weighted PMV approaches to evaluate occupant comfort in such environments. Recognizing the non-uniform skin temperature distribution, these approaches divide the human body into major segments and assign corresponding weights. [93] segmented the body into Forehead, Chest, Hand, Thigh, and Lower leg, deriving weights of

0.21, 0.30, 0.18, 0.20, and 0.10, respectively. The overall PMV is then calculated as a weighted average of the PMV values for these segments. This process enhances PMV's predictive performance for thermal comfort in non-uniform environments. He et al.[85] divided the cabin into distinct thermal zones, predicted thermal environment parameters non-invasively for each zone, and used these to calculate weighted PMV for assessing passenger comfort across all locations. Zong et al.[83] utilized the calculated weighted PMV as a control signal for the HVAC system, enabling interaction between a one-dimensional thermal management system model and a three-dimensional cabin thermal comfort model, arguing that a lumped parameter model better reflects cabin thermal environment characteristics.

Cabin air temperature

A second common approach is to use cabin air temperature directly as a proxy for occupant thermal comfort. The primary advantage of this metric is its simplicity, making it suitable for real-time control without significantly increasing computational complexity. The analysis of the studies in Table 2 reveals that this direct use of cabin air temperature is the most frequent method in research proposing HVAC control algorithms aimed at improving thermal comfort while reducing energy consumption of the vehicle thermal management system. However, this simple indicator cannot perfectly predict occupant thermal comfort and is considered a simplified substitute.

Subjective voting

Several studies employed the ASHRAE 7-point TSV[61], [74], [75], [76], ranging from -3 (Cold) to +3 (Hot), to represent passengers' thermal sensation. Strictly speaking, thermal sensation and thermal comfort are not equivalent. In transient conditions, occupants can simultaneously feel warm yet comfortable, or neutral yet uncomfortable. For example, a passenger entering a vehicle from a hot outdoor environment (e.g., 35°C) might perceive a cooler sensation as more comfortable. [68] utilized occupants' average heart rate and heart rate variability to predict TSV, TCV, Thermal Acceptability Vote (TAV) and Thermal Preference Vote (TPV), enabling the estimation of thermal sensation without requiring direct occupant voting.

Berkeley thermal comfort model

The Berkeley Model, proposed by Professor Zhang[94], [95], [96], has been applied to vehicle cabin occupant comfort assessment in recent years. Its calculation involves examining local sensations and local comfort levels for each body segment to study physiological responses, making it conceptually well-suited to the non-uniform and transient nature of cabin thermal environments. The calculation formulas for the local thermal sensation and local thermal comfort in Berkeley Model are as follows,

$$S_{local}^{(i)} = 4\left(\frac{2}{1+\exp\left\{-C_1^{(i)}\left(T_{skin}^{(i)}-T_{skin,set}^{(i)}\right)-K_1^{(i)}\left[\left(T_{skin}^{(i)}-\bar{T}\right)-\left(T_{skin,set}^{(i)}-\bar{T}\right)\right]\right\}}-1\right)+C_2^{(i)}\frac{dT_{skin}^{(i)}}{dt}+C_3^{(i)}\frac{dT_{core}}{dt} \tag{9}$$

$$C_{local}^{(i)} = \left\{\frac{\frac{-4-\left(C_6^{(i)}+C_{71}^{(i)}|S_o^-|+C_{72}^{(i)}|S_o^+|\right)}{\left|-4+C_{31}^{(i)}|S_o^-|+C_{32}^{(i)}|S_o^+|+C_8^{(i)}\right|^{n^{(i)}}}-\frac{-4-\left(C_6^{(i)}+C_{71}^{(i)}|S_o^-|+C_{72}^{(i)}|S_o^+|\right)}{\left|4+C_{31}^{(i)}|S_o^-|+C_{32}^{(i)}|S_o^+|+C_8^{(i)}\right|^{n^{(i)}}}}{\exp\left[15\left(S_{local}^{(i)}+C_{31}^{(i)}|S_o^-|+C_{32}^{(i)}|S_o^+|+C_8^{(i)}\right)\right]+1}+\frac{-4-\left(C_6^{(i)}+C_{71}^{(i)}|S_o^-|+C_{72}^{(i)}|S_o^+|\right)}{\left|4+C_{31}^{(i)}|S_o^-|+C_{32}^{(i)}|S_o^+|+C_8^{(i)}\right|^{n^{(i)}}}\right\}\left|S_{local}^{(i)}+C_{31}^{(i)}|S_o^-|+C_{32}^{(i)}|S_o^+|+\right.$$

$$C_8^{(i)}\Big|^{n^{(i)}} + C_6^{(i)} + C_{71}^{(i)}|S_o^-| + C_{72}^{(i)}|S_o^+| \quad (10)$$

Where S_o represents the overall thermal sensation, S_o^- means $S_o < 0$ and S_o^+ is the opposite, $S_{local}^{(i)}$ and $C_{local}^{(i)}$ are the local thermal sensation and comfort respectively, and $C_6^{(i)}$, $C_8^{(i)}$, $C_{31}^{(i)}$, $C_{32}^{(i)}$, $C_{71}^{(i)}$, $C_{72}^{(i)}$ and $n^{(i)}$ are regression coefficients based on different part of the human body, which derives from the experiments. Then, the overall thermal comfort is determined by statistically aggregating local thermal comfort results. The primary aggregation principles are as follows[97]:

1) In transient thermal environments or scenarios where subjects have control over the thermal conditions, the overall thermal comfort is calculated as the average of the two lowest and the single highest local thermal comfort values.

2) Under other conditions, overall thermal comfort is the average of the two lowest local thermal comfort values.

3) However, if both hands or both feet simultaneously represent the most uncomfortable body segments, the second-lowest local discomfort value is disregarded, and the third-lowest local thermal comfort value is used instead.

[89] investigated the Berkeley model's applicability in transient, quasi-uniform automotive environments. Based on human subject votes, they demonstrated that the model predictions aligned well with the votes, particularly for local thermal comfort, though overall thermal sensation prediction required some correction. [69] also evaluated this model's applicability in a cold outdoor transient cabin scenario, confirming its satisfactory performance in predicting overall sensation and comfort (maximum RMSE = 0.15), but noted poorer performance for the local comfort model (maximum RMSE = 1.96). These differing conclusions under varying conditions highlight the need for further evaluation and potential calibration of the model's applicability across diverse environmental contexts. Metzmacher et al.[87] utilized Berkeley Model to assess the performance of a developed personalized air conditioning system, and [70] conducted similar experiments using this model.

Others

Other thermal comfort indicators include various calculated environmental parameters, such as Equivalent Temperature (ET), Operative Temperature (Top), Mean Radiant Temperature (MRT), Standard Effective Temperature (SET*), and physiological indicators. The advantage of using environmental parameters or their derivatives lies in their non-invasive nature, eliminating the need for sensors on occupants or subjective voting. Conversely, physiological indicators can effectively capture the occupant's genuine response to the environment, providing insights potentially unmatched by environmental measurements or voting.

Summary

Current research indicates that simpler thermal comfort metrics find wider application in controlling the cabin thermal environment. In contrast, more complex metrics, which account for the cabin's non-uniform and transient thermal characteristics, remain largely confined to the laboratory stage. These sophisticated metrics lack effective integration with the optimization of HVAC system control during actual vehicle operation. Furthermore, the implementation of most

complex metrics necessitates either multi-point measurements or relies on invasive experimental procedures. The requirement for intricate data acquisition poses potential challenges for real-world driving tests. Unlike PMV, which assumes spatial uniformity and steady state, the Berkeley Model resolves local sensations and local comfort by body segment and includes transient responses to skin and core temperature change rates. These features mirror cabin realities such as solar asymmetry, cold jets, and rapid transitions during start, stop, and ingress or egress. In-vehicle studies report good agreement with human votes for local comfort and overall sensation in transient scenarios, with calibration improving accuracy under cold, rapidly changing conditions[69], [89]. The model has also distinguished the benefits of localized interventions such as heated seats, heated steering wheels, and directed airflow, supporting personalized comfort systems where PMV provides limited guidance[70], [87]. At the same time, its computation and data demands remain high for embedded, real-time optimization and control. This gap motivates a low-complexity yet high-accuracy comfort indicator that can serve as a real-time reference for cabin climate optimization.

3.2.2 Investigation methods

The research methodologies employed in the studies listed in Table 2 are categorized statistically in Fig. 7. Simulation (Fig. 8) and field test (Fig. 9) represent the two most prevalent approaches for investigating thermal comfort in vehicle cabins. Simulation offers significant advantages in terms of time and resource efficiency. It enables rapid assessment of cabin environmental characteristics and occupant thermal comfort responses. Furthermore, by adjusting model and environmental parameters, it facilitates the analysis of various operating condition combinations, making it a highly efficient method. Field test typically yields more accurate thermal comfort analysis for particular scenarios, especially under the non-uniform and transient conditions characteristic of vehicle cabins. Within field experimental studies, a subset of researchers conducted thermal comfort measurements directly in actual vehicles. These vehicles were either parked within climatic chambers simulating outdoor environmental conditions or subjected to outdoor road tests to obtain more realistic results. Another subset of studies simulated the cabin environment within laboratory settings.

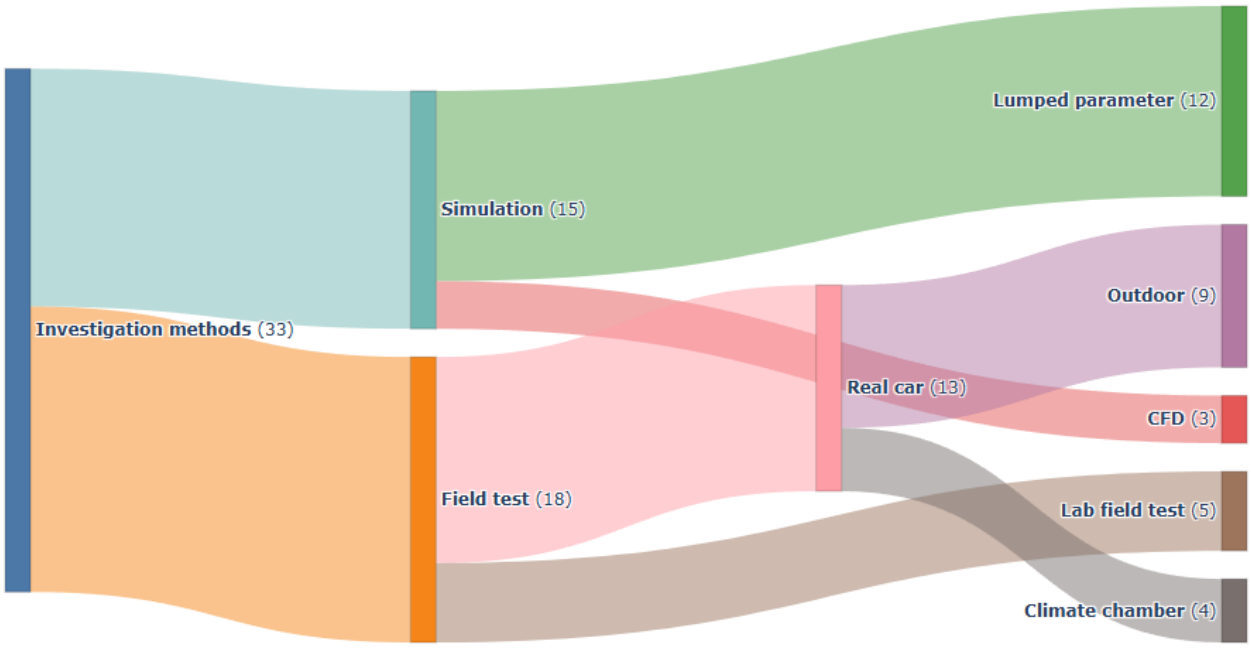
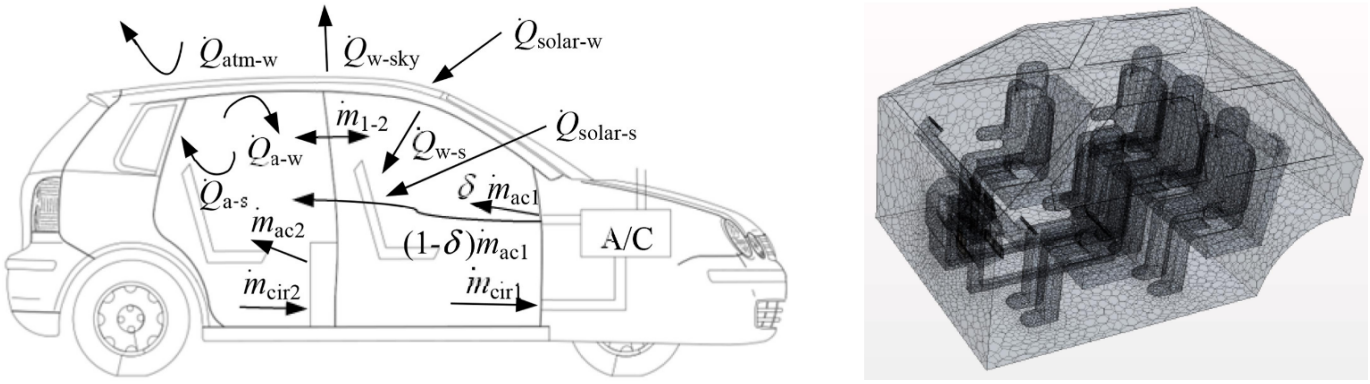


Fig. 7 Investigation methods in the surveyed articles

Literature employing simulation methods primarily focused on developing control algorithms for HVAC systems to enhance cabin thermal comfort while reducing overall system energy consumption, thereby extending vehicle driving range. Most of these studies utilized lumped parameter methods to simulate the cabin thermal environment. Thermal comfort values for occupants are calculated based on the resulting environmental parameters and subsequently used as control targets for the algorithms. The lumped parameter method[98] is computationally inexpensive and efficient, treating the cabin as one or more nodes with uniform temperature distribution within each node. This enables rapid calculation of cabin temperature, aligning well with control-oriented requirements. However, its limitations are also evident: it sacrifices most details of the cabin thermal environment, such as temperature and airflow distribution patterns, failing to capture its inherent non-uniformity and transient nature. Partitioning the cabin into distinct thermal zones can partially address this issue by enabling temperature calculations for different regions, as implemented in [58]. CFD methods, involving the construction and numerical solution of three-dimensional flow field models, represent a high-fidelity approach. CFD excels at accurately capturing cabin thermal environmental characteristics. Furthermore, incorporating manikins on seats within the 3D model allows simultaneous computation of heat and mass transfer between the human body and the environment, as adopted by [67], [83].



a) b)

Fig. 8 Models for simulation-based research: a) zonal lumped parameter model[58], b) CFD model with occupants inside[83]

Lab field tests typically involve positioning human subjects or manikin models on seats identical to those found in vehicles. The thermal environment is replicated by controlling radiation and air supply parameters within the laboratory. This approach effectively minimizes experimental costs by eliminating the need for full-vehicle testing. [70], [87], [92] use manikin models for investigation, which is a valuable strategy, as it circumvents ethical concerns associated with human subject testing and can also be utilized in outdoor vehicle parking experiments. Parking a vehicle within a climatic chamber provides highly stable and controllable external environmental conditions, as parameters like radiation intensity, temperature, and humidity of the simulated "outdoor environment" can be precisely adjusted to the researchers' specifications. However, this method incurs the highest costs, requiring both a complete vehicle and a sufficiently large climatic chamber to simulate the external environment. Full-vehicle outdoor testing represents the most frequently employed experimental method. It offers the highest fidelity in reflecting real-world external vehicle environmental characteristics. Experiments can be conducted across different seasons and times of day (day/night), with environmental parameters recorded via sensors installed on the vehicle body. Since parameters such as solar radiation angle and convective heat transfer coefficient at the vehicle shell change during driving, experiments in [76] are conducted while the vehicle is in motion.



Fig. 9 Field test for cabin thermal comfort: a) Lab field test[92], b) Real car in climate chamber[68], c) Real car outdoor test[34]

3.2.3 Thermal comfort improvements

Optimal design

These encompass modifications to vehicle design elements that influence occupant thermal comfort, including adjustments to the HVAC system design, altering materials in specific body sections, and incorporating seats with personalized cooling or heating functions. These optimizations typically address perceived design shortcomings or integrate novel thermal comfort regulation devices, guided by the latest thermal comfort theories, into the vehicle's thermal management system design.

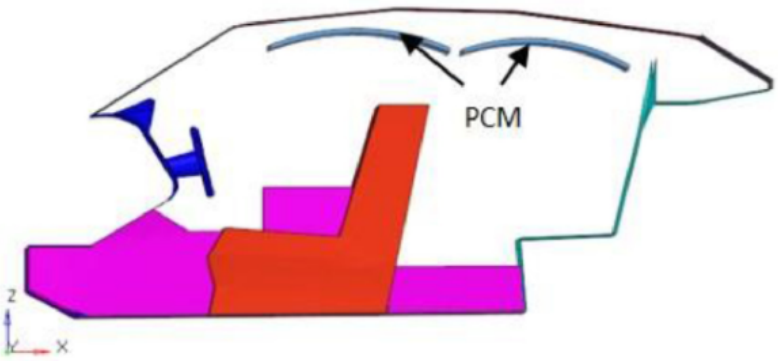
To mitigate the influences of the intense solar radiation, most researchers proposed effective mitigation strategies. The simplest and most effective approach is the direct physical insulation of parked vehicles using car covers as shown in Fig. 10**Error! Reference source not found.** a). Lv et al.[43] demonstrated that a novel high-reflectivity car cover reduced cabin temperature by 31.1°C compared to an uncovered vehicle, and by 19.6°C compared to a traditional commercial car cover. The primary advantage of this solution is that it requires virtually no structural modifications to the vehicle and incurs no operational costs beyond the initial investment. The use of Phase Change Materials (PCM) represents another effective method for significantly moderating cabin temperatures, as shown in Fig. 10 b). When the melting point of the PCM lies between the daily maximum and minimum cabin temperatures, it can effectively mitigate temperature fluctuations. Srusti

et al.[33] and Afzal et al.[44] achieved average cabin temperature reductions of 10.4°C and 13.0°C, respectively, using PCM. Wang et al.[38] combined a car cover with PCM, maintaining the cabin temperature below 22.5°C when the ambient bare vehicle temperature exceeded 60°C. Other researchers utilized photovoltaic (PV) panels to harvest solar energy, converting it into electricity to power auxiliary cooling devices, as shown in Fig. 10 c). These devices can directly provide cooling or heating to the cabin or be integrated with PCM for thermal energy storage. Furthermore, PV panels continue generating electricity while driving, reducing the energy consumption of the primary HVAC system. Ahmed et al.[40] employed a system combining PV with thermoelectric cooling, reducing the cabin temperature from 47.5°C to 34°C and decreasing daily battery energy consumption in an electric vehicle by approximately 19%. Lahimer et al.[35] utilized a solar chimney, lowering the average cabin temperature by 12.4°C, reducing compressor power consumption by 85%, and increasing the urban driving cycle range by 26.25 km. Duan et al.[60] proposed a thermal management strategy combining electrochromic glazing and radiative cooling technology. Compared to standard windows, the coupled window reduced passenger SET* by approximately 7°C, significantly enhancing comfort.

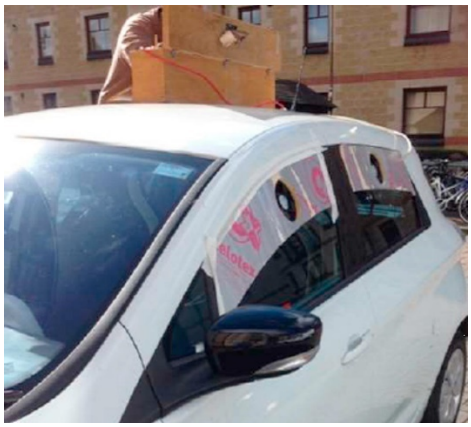
Conversely, during winter, solar radiation can be harnessed to pre-heat the cabin. This strategy elevates the interior temperature before occupants enter the vehicle, enhancing thermal comfort and reducing HVAC energy consumption. Çelik et al.[39] utilized solar panels to heat water in a radiator, storing solar thermal energy for pre-heating the cabin before winter trips. Experimental data indicated that, with ambient temperatures between 0°C and 5°C, activating the radiator raised the cabin temperature from 3°C to 15°C within minutes. Srivastava et al.[42] similarly tested the performance of a solar-assisted electric heating system in winter, demonstrating an increase in cabin temperature from 4°C to 19°C.



a)



b)



c)

Fig. 10 Solutions to mitigate heat soak: a) Car cover[43], b) PCM[33] c) Solar assisted device[45]

To address the issue of temperature non-uniformity within the cabin, the most effective approaches involve increasing vent

size, adjusting vent positions, or modifying the jet velocity and direction. Pan et al.[53] utilized a solar-assisted fan system to improve temperature distribution uniformity. Tan et al.[51] significantly reduced stagnant zones (areas with near-zero velocity) within the cabin by optimizing the structure and length of the air ducts. Dehne et al.[91] compared three vertical ventilation systems to a conventional dashboard-mixing ventilation system. Results demonstrated that vertical ventilation significantly improved temperature uniformity and heating efficiency. Furthermore, the average air velocity for vertical ventilation remained below 0.14 m/s, effectively mitigating draft sensation (>0.31 m/s) associated with traditional ventilation.

Other Personalized Comfort System (PCS) and Local Comfort System (LCS) are also popular for enhancing vehicle occupant thermal comfort. Metzmacher et al.[87] validated the performance of a combining infrared heaters and fans, simulating energy savings of up to 60%. Wu et al.[72] utilized an electrically heated vest and insoles as a PCS for winter conditions. Under identical ambient conditions, this system lowered the neutral SET* and T_{op} by 2.7°C and 1.6°C, respectively, demonstrating potential for reducing system temperature setpoints and HVAC energy consumption. Paredes et al.[70] employed heated seats and a heated steering wheel to lower the winter HVAC temperature setpoint by 2°C, resulting in a significant total energy reduction of approximately 17% without altering the passengers' overall thermal perception. Gopi et al.[71] used a lower-body localized radiant warming device to reduce the HVAC setpoint from 25°C to 18°C, achieving a 45.3% reduction in energy consumption. Seats have proved to be suitable auxiliary cooling or heating devices. Hatoum et al.[92] developed a cooling system based on embedded heat pipes, leveraging the temperature difference between the passenger's back and cabin air for passive heat dissipation. With 17 heat pipes, the passenger back reached thermal neutrality, improving overall thermal comfort by 30%. Ham et al.[81] investigated the effectiveness of ventilated seats and water-cooled seats for enhancing passenger thermal comfort in summer conditions. The water-cooled seat reduced the passenger's back temperature to 25.6°C, 6.4°C and 8.7°C lower than the ventilated seat and baseline seat, respectively, achieving maximum thermal comfort and increasing system Coefficient of Performance (COP) by approximately 19%.

Design-stage thermal comfort optimizations are demonstrably effective for improving occupant comfort and are well-suited to the highly non-uniform and transient nature of cabin thermal environments. However, this approach comes at a higher cost, requiring greater initial investment.

Optimal operation

These focus on improving thermal comfort without altering the vehicle's physical design by adjusting HVAC operating modes or air supply parameters. The most common strategy involves developing more efficient HVAC control algorithms to reduce system energy consumption[61], [66], [73], [77], [78], [79], [80], [82], [83], [84], [86], [88], [90]. These algorithms typically achieve more precise setpoint tracking than conventional on-off or PID control, shorten the time to reach the setpoint, and enhance energy efficiency. Incorporating thermal comfort metrics as control objectives and adjusting their weighting allows for simultaneous improvements in both comfort and energy efficiency.

Operational optimizations also include formulating expert knowledge-based HVAC adjustment strategies for different environmental conditions. Lan et al.[58] demonstrated that at an outdoor temperature of 34.1°C, supply air temperatures of 10.5°C, 15.8°C, and 20.5°C should be used for open roads, tree-lined avenues, and underground parking garages,

respectively. The underlying logic is that different solar radiation intensities necessitate distinct HVAC strategies. Liu et al.[67] calculated optimal airflow parameters for an outdoor temperature of 42°C and solar radiation of 1000 W/m²: a supply air temperature of 14.45°C, air velocity of 5 m/s, and front/rear air supply angles of 29.75° and 36.69°, respectively. This strategy achieved system energy savings of 20.2%.

Operational phase optimizations offer a pathway to improved thermal comfort and reduced energy consumption with relatively lower investment costs. However, their effectiveness is generally more limited compared to design-phase solutions. Furthermore, for most control algorithm research, the use of overly simplified models often fails to adequately account for non-uniform and transient thermal comfort conditions.

3.3 Impacts on driving performance

3.3.1 Metrics

Operational tasks

Multiple experiments have demonstrated that elevated cabin temperatures adversely affect fundamental vehicle control and operational performance. Exposure within the 20–30 °C range showed a correlation between increasing temperatures and longer reaction times, higher error rates in cognitive tests, and decreased reactivity[99]. Simulated night driving studies further revealed that a cabin temperature of 28°C significantly worsened driving variability metrics, including increased speed fluctuations, pitch/yaw rates, and altered throttle usage, compared to cooler conditions of 18°C and 23°C[100]. The stability of vehicle control can also be compromised by inappropriate thermal interventions. For instance, strong localized cooling of the torso was found to induce risk-prone operational behavior, manifesting as shorter following distances and delayed braking initiation[101]. Conversely, positive effects have been observed with optimized thermal management; brief cold stimuli were shown to improve lane keeping performance[102], [103], and the use of seat heaters alone during winter driving led to higher driver concentration levels compared to full HVAC use[104].

Tactical tasks

The execution of tactical driving tasks, which involve complex interaction and decision-making, is also sensitive to the thermal environment. Research investigating visual interaction efficiency under different temperature and interface layouts (22–32 °C) found performance to be highly non-linear. Optimal task completion efficiency and gaze performance were consistently observed in the 22–24 °C range, while significant deterioration occurred at 28–30 °C[105]. This suggests that maintaining a thermally neutral cabin is crucial for tasks requiring higher cognitive engagement. Furthermore, macro-level evidence from city-scale analyses indicates a significant positive correlation between thermal indices (PET, air temperature, MRT, vapor pressure) and rates of accidents/traffic violations[106]. This implies that increased thermal load elevates risk exposure at a tactical decision-making level, potentially contributing to unsafe maneuvers and traffic infractions.

Driver state

The driver's physiological and psychological state serves as a critical pathway through which the thermal environment

influences driving performance. Studies employing integrated thermal comfort indices have established a clear link between thermal load and drowsiness. PMV-based research during real highway driving revealed an inverted U-shaped relationship, with the peak increase in drowsiness occurring near a "slightly warm" PMV of +0.2[107]. Objective physiological markers corroborate these findings; brief cold stimuli significantly reduced subjective drowsiness (KSS) and were accompanied by pupil dilation, increased skin conductance, and reduced eye closure[102], [103]. Temperature cycling protocols (e.g., 26↔23 °C) have proven effective in maintaining alertness and comfort over extended 90-minute periods[108].

The vulnerability of mood and job-specific performance under thermal stress is particularly notable for professional drivers. Bus drivers exhibited deterioration in mood states (POMS) and reaction capabilities under heat exposure, with fatigue escalating over consecutive working hours and the 55–60 age group being most affected[18]. Taxi drivers showed significant declines in performance metrics (speed, precision, attention) during summer night shifts, which coincided with less comfortable WBGT, PPD, and PMV conditions[109]. Even when thermal comfort is reported, as with over 90% of subjects at 22–23 °C in winter, overall cognitive performance can remain suboptimal and decline with age[110].

Personalized climate control strategies show promise in positively modulating driver state. Vest-based water cooling in summer demonstrated more stable advantages in improving EEG/HRV indices and restoring subjective thermal comfort compared to other localized cooling methods[111]. Optimal HVAC settings, such as "cabin 27.5 °C / supply air 11 °C" for cooling and "cabin 22.5 °C / supply air 40 °C" for heating, have been identified to effectively reduce physiological stress (LF/HF ratio) and optimize comfort and stability[112]. Collectively, the evidence indicates that rising thermal load coincides with increased drowsiness and negatively impacts emotional state, subsequently compromising driving behavior and safety outcomes.

3.3.2 Best-evidence synthesis analysis

Significant heterogeneity exists across the studies included in this review concerning cabin environmental factors (constant temperature, dynamic cold/heat stimuli, integrated thermal comfort indices, air quality, olfactory channels), driving performance metrics (task time/accuracy, drowsiness, HRV/EEG, vehicle control, safety incidents), and statistical outcomes (mean/SD, t/F/Z, correlation r). The limited number of studies within comparable "environmental factor - driving performance" suitable for direct combination into a unified effect size precludes reliable estimation of heterogeneity and publication bias using traditional random-effects meta-analysis[113]. Without sacrificing interpretability, this section adopts a best-evidence quantitative synthesis strategy[114]: for each comparable relationship, the standardized effect size and interval from individual studies are reported, with small-scale pooling using fixed-effects models presented solely for sensitivity purposes. This approach preserves effect size information while avoiding overinterpretation under conditions of sparse data.

A) Correlation of temperature or PMV with poor performance

Two studies directly reported statistical correlations between thermal metrics and driving performance measures. Under controlled temperatures (20/23/26/30 °C), temperature showed a positive correlation with composite cognitive test time (r

= 0.371, N = 10[99]), indicating slower task completion under warmer conditions. However, the 95% confidence interval was wide (r 95% CI ≈ -0.34 to 0.81) due to the small sample size. During real highway driving, PMV also correlated positively with drowsiness change after 15 minutes (r = 0.394, N = 234 time windows[107]), with a narrower confidence interval (r 95% CI ≈ 0.28–0.50). Both pieces of evidence are highly consistent in direction and magnitude, suggesting a moderate-strength linear association between increased thermal load and poor driving performance (prolonged test time/increased drowsiness). For sensitivity analysis, fixed-effect pooling using Fisher's z transformation yielded a pooled correlation r ≈ 0.39 (95% CI 0.28–0.50).

B) Impact of high temperature on task performance

Comparing "high temperature (28–30 °C) vs. comfortable temperature (approx. 22–24 °C)", two independent studies reported significantly increased task completion times. [99] observed an approximately 14.5% increase in total cognitive test time at 30 °C compared to 20 °C (742.1 ± 108.6 s vs. 647.9 ± 62.8 s, N=10), with a conservatively estimated Hedges' g ≈ 1.02 (95% CI ≈ 0.08–1.95). [105] reported an approximately 21.4% increase in interface operation completion time at 28 °C compared to 22 °C (19.522 ± 1.938 s vs. 16.083 ± 3.548 s), with a standardized effect size g ≈ 1.13 (precise interval estimation was hindered by differences in tasks and experimental designs between the studies). Both results demonstrate "large effect size" magnitude increases in time consumption across different task types, indicating robust adverse effects of elevated temperature on driving performance efficiency across tasks. Formal meta-analysis was not conducted due to one study being a small-sample repeated-measures design and the other a multi-condition crossover design, alongside unaccounted within-subject correlations. Nevertheless, the consistency in effect size magnitude and percentage increase (approx. 15–21%) holds substantial meaning.

C) Immediate effect of cooling intervention on subjective drowsiness

Two independent trials testing short-term cold stimuli (15–17 °C) against thermoneutral conditions both observed significant reductions in subjective drowsiness (KSS). The effect size from the 6-minute cooling versus control condition in [102] corresponded to r ≈ 0.624 (95% CI ≈ 0.36–0.80, N=34). [103] found an effect size of r ≈ 0.362 (95% CI ≈ 0.02–0.63, N=34) for 4-minute cooling. The direction of effect was perfectly consistent, with medium-to-large effect magnitudes, confirming the reliable immediate alerting effect of "moderate-intensity and duration cold stimuli." Sensitivity fixed-effect pooling yielded r ≈ 0.51 (95% CI 0.30–0.67). It is crucial to emphasize that the dose-response relationship for cold stimuli is not monotonic: [101] observed shorter following distances and later braking initiation under stronger cold load (localized torso cooling + seat cooling + air blast) (t-values ≈ 2.1–2.2, corresponding to r ≈ 0.31–0.32), suggesting that excessive cold load may induce risk-prone behavior. This finding does not contradict the conclusion that "mild, short-term cooling reduces drowsiness" but rather, together, they define an "effective and safe" cooling window.

4. Air quality in vehicle cabin

4.1 Air quality indicators

Among the surveyed literature, 25 studies specifically addressed IAQ within vehicle cabins. The research focus and the specific IAQ indicators examined varied considerably across these studies. Fig. 11 illustrates the IAQ metrics reported in these articles. It is important to note that because some studies investigated multiple indicators, the counts presented in the figure involve duplicate entries. As depicted in Fig. 11, VOCs are the most frequently studied metric, examined in 12 studies. Carbon dioxide (CO_2) and particulate matter (encompassing PM_1, $PM_{2.5}$, PM_{10}, etc.) are the next most common, each mentioned in 9 studies. Other indicators investigated include ultrafine particles (UFPs), carbon monoxide (CO), nitrogen dioxide (NO_2), and aerosols. The research content and findings related to these specific IAQ metrics will be detailed in the subsequent subsections.

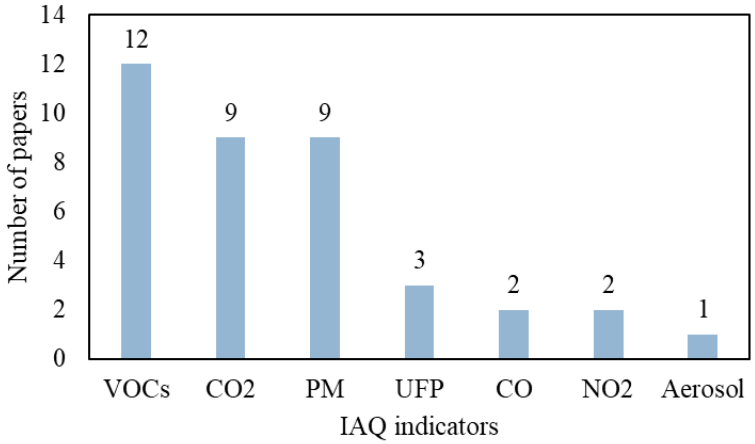


Fig. 11 Indicators of cabin IAQ

3.2.1 VOCs

VOCs represent a broad category of organic chemicals, some of which may pose health risks to humans[115]. VOC concentrations also serve as an indicator of perceived air freshness within the vehicle cabin[116]. [117] detected over 200 distinct VOCs across 86 vehicles, identifying 52 as "commonly occurring." These comprised 37 aliphatic, carbonyl, and aromatic compounds, with 13 identified as potentially posing risks to human health.

While VOCs in buildings typically originate from emissions of various construction and finishing materials, within vehicle cabins, significant sources include materials such as seats, carpets, interior trims, and door panels. Identifying the contribution of common cabin materials to VOC contamination aids manufacturers in implementing source control strategies. [118] investigated the dynamic emission characteristics of VOCs from four key cabin interior materials: seat leather coating (LCS), dashboard (DB), pillar interior (PI), and ceiling (CE). Their study revealed significant differences in VOC contributions from different materials at varying temperatures. VOC emission intensity increased non-linearly with rising temperature, exhibiting a 3- to 36-fold increase for various components when temperature rose from 25°C to 60°C. At 25°C, LCS primarily released carbonyl compounds and aromatic hydrocarbons, whereas at 60°C, DB and PI contributed over 80% of aliphatic compounds. Wang et al.[119], [120] employed the C-history method to determine key emission parameters—initial emittable concentration (C_0), diffusion coefficient (D_m), and partition coefficient (K)—for six major

VOCs emitted from roof trim, carpet, and seats. Acetaldehyde was identified as the primary cabin pollutant, exceeding Chinese national standard limits by 2.5–7 times at room temperature and by 15–40 times at 65°C. Seats were determined to be the largest pollution source, contributing over 50% of total acetaldehyde emissions. In subsequent work, the same team[121] reported C_0, D_m, and K values for formaldehyde emissions from carpet, door panels, sealing strips, and two types of adhesives using the same methodology. Similar testing of VOC emissions from cabin interior materials was conducted by [122], who investigated the cause of increased VOC emissions from surface-coated thermoplastic polyester elastomer (TPEE). After applying solvent-based primer and clearcoat paints, total VOC (TVOC) levels increased by 12.1-fold, rising from 2,066 μg m^{-3} to 24,983 μg m^{-3}.

[123] reported on the influence of temperature and vehicle age on emissions of different VOCs. TVOC emission rates in summer were 32 times higher than in winter. Furthermore, TVOC emission rates decreased with increasing vehicle age, with the peak in the second summer being 23% lower than in the first summer. Aromatic hydrocarbons decayed significantly over time, while alkene/alkane emissions decayed more slowly. Emission rates of ketones, aldehydes, esters, and alcohol showed no consistent negative correlation with vehicle age. Yesildagli et al.[124] found that winter heater operation immediately increased concentrations of some VOCs by 54.62%. However, preventing direct sunlight on the windows reduced VOC emissions under heater operation by 65.42%. [125] also noted that the average gas-phase levels of semi-volatile organic compounds (SVOCs) at 80°C were 18 to 16,000 times higher than those at 25°C.

While spraying air fresheners may reduce cabin particulate matter concentrations, it concurrently increases TVOC levels[126]. Introducing fresh air is recognized as the most effective method for removing VOCs from the cabin. In the absence of external VOC sources, both window ventilation and mechanical ventilation can reduce cabin concentration[127], achieving removal efficiencies ranging from 40% to 62.83%[121], [124], [125], [126]. Notably, the required ventilation time increases with rising cabin temperature.

3.2.2 CO_2 and Particulate matters

The primary source of carbon dioxide (CO_2) within the vehicle cabin is the metabolic activity of occupants. Both the rate of increase and the final stabilized level of cabin CO_2 concentration rise significantly with an increasing number of passengers. [128] observed that with three occupants and the HVAC system operating in internal air recirculation mode, the cabin CO_2 concentration reached 5000 ppm within 39 minutes during real-world driving tests. Furthermore, traffic congestion contributes to higher CO_2 concentrations compared to normal driving conditions, with levels significantly elevated during low-speed driving (average 15 mph) versus high-speed highway driving (60 mph)[129]. Introducing fresh air (external air intake) effectively reduces cabin CO_2 levels, as demonstrated by studies from [128], [130], [129], [131], and [132]. CFD simulations under typical conditions with five occupants indicated that supplying fresh air at rates of 2.5, 4.0, and 9.2 L/s per person resulted in cabin CO_2 concentrations of approximately 2850 ppm, 1810 ppm, and 1000 ppm, respectively[130].

However, introducing fresh air raises concerns regarding cabin PM levels. Ambient PM concentration is a major determinant of in-cabin PM concentration[133]; thus, increased fresh air intake can elevate occupant PM exposure. Cabin PM levels are

significantly correlated with the type and PM emission level of the preceding vehicle. Following a diesel-powered vehicle result in 83% higher PM exposure compared to following a gasoline-powered vehicle[134]. Concentration levels and the In-cabin/Out-cabin (I/O) ratio are widely used metrics for assessing PM exposure. [128], [135] experimentally demonstrated that activating internal air recirculation removed 71% of PM_{10}, 51% of $PM_{2.5}$, and 44% of PM_1 within the cabin. [131] showed an I/O ratio of 60% during external air intake mode, compared to 25% during internal recirculation mode.

Nevertheless, as previously discussed, internal recirculation significantly increases cabin CO_2 levels. To balance CO_2 and PM concentrations, utilizing activated carbon filters[136] or other filtration devices[137] within the vehicle's HVAC system while operating in external air intake mode enables concurrent control of both pollutants. However, PM filtration efficiency degrades over the filter's service life. Activated carbon filters used for 6-15 months resulted in an increase in cabin $PM_{2.5}$ concentration from 2.5 $\mu g/m^3$ (observed with a new filter) to 4.7 $\mu g/m^3$[136].

3.2.3 Others

UFPs: Defined as particulate matter with a diameter less than 0.1μm, UFPs are a key indicator of traffic-related pollution[138], alongside PM, and pose threats to human health. Mitigation strategies for UFPs are similar to those for PM. Activating the HVAC system in internal air recirculation mode and utilizing filtration devices are effective countermeasures. [139] reported an average In-cabin/Out-cabin (I/O) ratio of 0.2 for UFPs across 92 vehicles operating in recirculation mode, compared to 1.1 in external air intake mode. [137] reached similar conclusions in their research.

CO: While CO represents a serious health hazard, its concentrations within vehicle cabins are typically low. [140] reported levels ranging from 5.7 to 10.2 ppm. As this pollutant cannot be removed by standard filters, vehicle owners are advised to prioritize vehicle maintenance, avoid vehicles with significant exhaust leaks, and select optimized routes. Driving on highways, compared to commercial roads, can reduce in-cabin CO levels by 10%.

NO_2: Exposure to NO_2 significantly increases the risk of reduced lung function and cancer[141]. This gas originates primarily from fuel combustion and emissions from vehicle interior materials[142]. [136], [143] demonstrated that closing windows while in internal recirculation mode reduced NO_2 concentrations by a factor of 1.6 compared to driving with windows open. Employing activated carbon filters enhanced this reduction by a factor of 14.3, whereas standard pollen filters yielded minimal effects.

Aerosols: During pandemic periods, the airborne transmission of respiratory droplets attracted significant research attention due to their role as a major pathway for viral spread. Optimizing ventilation[52] strategies offers an effective approach. Directing airflow towards the front seats creates localized recirculation zones that can almost completely block the transmission of droplets from front-row to rear-row occupants. Simulation results indicated that this method could ensure zero inhalation exposure for rear-seat passengers within 15 minutes.

4.2 Impacts on driving performance

4.2.1 Metrics

Operational Tasks

Evidence regarding the direct impact of specific air pollutants on fundamental vehicle control metrics remains limited and inconclusive. Simulated driving experiments investigating CO_2 and body odor have shown that under conditions of short-duration driving and cognitive tasks, elevating CO_2 levels from approximately 800 ppm to around 3500 ppm did not produce consistent, significant main effects on core operational driving performance metrics[144], [145]. The influence of body odor on task performance was also relatively small in magnitude and inconsistent in direction[144], [145]. A postulated pathway for air quality impact on vehicle operation involves particulate matter (PM) exposure. Respiratory and ocular irritation from PM is theorized to lead to attentional distraction, consequently reducing operational stability, an effect that may be more pronounced when combined with thermal load[146]. However, most current studies focus on exposure characterization and lack direct, simultaneous causal measurements of operational driving behavior under pollutant exposure.

Tactical Tasks

Macro-level evidence provides the strongest indication of air quality's impact on safety outcomes related to tactical decision-making. Analyses at city or regional scales have shown a more direct safety implication: a 1 $\mu g/m^3$ increase in urban $PM_{2.5}$ was associated with an approximately 4% increase in same-day traffic accident rates[147]. This offers compelling external evidence that pollution load adversely affects collective safety outcomes, which inherently involve tactical judgments on the road. The type of preceding vehicle also presents a tactically relevant exposure scenario; following diesel vehicles significantly increases in-cabin fine particle exposure compared to following gasoline vehicles[134], suggesting a modifiable external risk factor during driving.

Driver State

The primary pathway for in-cabin air quality to influence driving performance appears to be through the modulation of the driver's physiological and cognitive state. While short-term, direct behavioral effects of CO_2 are unstable, its impact is more likely to manifest indirectly through increased drowsiness and discomfort in prolonged, low-ventilation scenarios, although current causal evidence for this remains insufficient[145]. Volatile Organic Compounds (VOCs) and Semi-VOCs primarily influence perceived comfort and health risk thresholds in the short term, potentially contributing to distraction or discomfort. Conversely, research on olfactory interventions and state recognition supports their potential to positively influence driver state. Composite fragrances have been shown to shorten reaction times in cognitive tasks and are accompanied by improvements in EEG features, suggesting enhanced cognitive readiness[144]. Furthermore, monitoring techniques such as distraction and vigilance recognition—combining perinasal perspiration indices and thermal imaging—achieved high accuracy in controlled scenarios[148], [149]. These findings support application pathways centered on state monitoring, offering the potential for closed-loop triggering of IAQ strategies (e.g., activating ventilation or filtration upon detecting drowsiness or distraction). Ventilation and filtration strategies themselves are highly effective in managing the state-relevant

exposure; using external air intake significantly raises in-cabin PM and UFP levels compared to internal recirculation, while high-efficiency/activated carbon composite filters can markedly reduce the I/O ratio, albeit with diminishing efficiency due to filter aging[134].

4.2.2 Best-evidence synthesis analysis

Quantitative and qualitative integration was performed for comparable relationships between localized in-cabin exposures and driving performance metrics, aiming to preserve the readability of effect directions and magnitudes. Regarding CO_2 and body odor, simulated driving and cognitive task studies across a CO_2 concentration range of 800–3500 ppm observed no stable main effects. The effect sizes of body odor on accuracy and reaction time in tasks like N-back were relatively small and directionally inconsistent[144], [145]. Consequently, current research does not robustly support the conclusion that short-term, moderate increases in CO_2 significantly degrade core driving performance. A more plausible hypothesis is that CO_2 exerts influence indirectly through physiological drowsiness factors under prolonged, low ventilation driving conditions, but this requires validation through stronger causal study designs[145].

For particulate matter and UFP, the macro-level association, an approximate 4% increase in accident rate per 1 $\mu g/m^3$ $PM_{2.5}$ aligns in direction with in-cabin exposure evidence, constituting strong justification for the engineering necessity of exposure control[147]. Exposure variability linked to preceding vehicle type (e.g., significantly higher fine particle exposure when following diesel vehicles[134]) also suggests actionable risk scenario management, providing contextual basis for following distance strategies and external air intake activation.

Concerning VOCs, although the findings now are not yet strongly coupled with driving performance, within multi-objective control frameworks balancing comfort, energy consumption, and safety, VOCs and odors contribute secondary risks through discomfort and distraction. It is recommended to integrate VOC monitoring and control strategies alongside CO_2 and PM[127].

Finally, regarding evidence from olfaction, thermal imaging, and state recognition, composite fragrances were associated with medium-to-large statistical effect sizes for improved reaction times in Oddball/Go-NoGo/Stroop tasks (behavior tasks)[144]. The fusion of thermal imaging and physiological signals achieved high accuracy in distraction/fatigue recognition[148], [149]. While these results do not represent direct negative effects of IAQ factors, they provide practical means for state-centric closed-loop management. For instance, upon detecting increased drowsiness or distraction, the system could trigger external air intake and high-efficiency filtration to reduce in-cabin CO_2/PM levels, or employ short-duration, low-intensity environmental micro-stimuli to enhance alertness, while monitoring impacts on energy consumption and comfort. This forms a practical IAQ-State-Control chain.

5. Discussion

5.1. Key characteristics of the cabin interior environment and contributing factors

Research has clearly identified the main features that define the vehicle cabin environment: intense solar radiation leading

to rapid heat soak, strong spatial variations in temperature and airflow, and fast-changing conditions due to vehicle operation and occupant movement. These factors, combined with the challenge of balancing CO_2 buildup against particulate matter (PM) intrusion when managing ventilation, create a unique and complex environmental system. To address these issues, various solutions have been proposed, including advanced materials like phase change materials (PCM) and electrochromic glazing, solar-powered devices, and optimized seats. Operational strategies like zoned air supply and occupant-centric control are also effective. However, moving forward, several gaps need attention. Measurements of environmental exposure and their reported effects are currently inconsistent across studies. There is a need for a standardized set of measurements and reporting practices. Furthermore, while humidity and defogging are recognized as critical for safety, their direct impact on driver visibility and performance requires more detailed, causal investigation. The interaction between thermal conditions and air pollutants like VOCs and PM also needs clearer identification through controlled experiments. Finally, the long-term effectiveness and real-world energy benefits of many proposed design solutions need more validation.

5.2. Methods for assessing and improving cabin thermal comfort and its impact on driving performance

The assessment of thermal comfort in cabins relies on metrics like PMV/PPD and the more complex Berkeley Model, supported by both simulation and experimental methods. However, the non-uniform and transient nature of the cabin environment limits the direct applicability of traditional metrics like PMV. The Berkeley Model, which considers local body sensations and transient effects, is a better fit conceptually and has shown promise in evaluating localized comfort systems. Its complexity, however, makes it difficult to use for real-time control. A promising future direction is the development of hybrid approaches that combine simpler physical models (like zoned lumped parameter models) with data-driven corrections from non-contact sensors. This could lead to a practical, low-complexity comfort indicator accurate enough for real-time optimization. Control strategies themselves should evolve to multi-objective optimization that simultaneously considers comfort, indoor air quality (IAQ), energy use, and safety constraints. Regarding impacts on driving, the evidence consistently shows that higher thermal loads impair cognitive function and vehicle control. Warmer temperatures increase task completion times and drowsiness, while brief, mild cooling can counteract drowsiness. However, strong cooling can sometimes lead to riskier driving behavior, indicating that the intensity of thermal interventions must be carefully calibrated.

5.3. Components affecting cabin air quality, their impact on driver performance, and mitigation strategies

Key cabin air quality concerns include VOCs emitted from interior materials, CO_2 from occupant respiration, and PM from the ambient environment. Mitigation primarily involves source control (e.g., selecting low-emission materials), ventilation strategies, and filtration. The choice between recirculation (which reduces PM but allows CO_2 to build up) and fresh air intake (which dilutes CO_2 but may bring in PM) represents a fundamental trade-off, which can be managed using filters, though their efficiency decreases with age. The direct impact of these pollutants on driving performance is less straightforward than that of temperature. While short-term, moderate increases in CO_2 show inconsistent effects on driving tasks in experiments, $PM_{2.5}$ exposure shows a clear correlation with increased accident rates at a population level. This suggests that IAQ effects may be more subtle or long-term or may interact with other factors like fatigue. VOCs primarily affect perceived air quality and comfort, which could indirectly influence driver distraction. Future research should focus on establishing clearer causal links between specific pollutants, driver state (e.g., drowsiness, cognitive load), and safety-

critical performance metrics.

6. Conclusion

Based on systematic retrieval and screening, this comprehensive review critically examined the vehicle cabin interior environment (thermal environment and IAQ), cabin thermal comfort (metrics and improvement strategies), and the impacts of the cabin environment on driving performance/safety. This review sets out to clarify what most characterizes the cabin environment, how thermal comfort can be assessed and improved under those constraints, and how these conditions bear on driving performance and safety. The principal conclusions are as follows:

1) The vehicle cabin environment is distinguished from building interiors by intense solar radiation, significant spatial non-uniformity in temperature and airflow, and rapid transients. These factors, combined with the inherent ventilation trade-off between cabin CO_2 accumulation and external particulate matter (PM) intrusion, define the core challenges. Effective mitigation involves both design-stage solutions—such as high-reflectivity covers, phase change materials (PCM), and advanced glazing—and operational strategies like zoned air supply and coordinated filtration, which can substantially improve thermal conditions and energy efficiency.

2) Assessing and improving thermal comfort requires metrics that account for non-uniform and transient exposure. While PMV and its variants are pragmatically used in control systems, their underlying assumptions limit accuracy. The Berkeley Model offers a better physiological match, but its computational complexity hinders embedded application, pointing to the need for a low-complexity, high-accuracy indicator derived from hybrid modeling and non-contact sensing. The thermal environment directly impacts driving performance; elevated temperatures impair cognitive efficiency and vehicle control, increasing task time and drowsiness, whereas short, mild cooling can counter drowsiness. However, strong cold stress can induce risk-prone behavior, highlighting the need for calibrated interventions.

3) Cabin air quality is primarily influenced by volatile organic compounds (VOCs) from interior materials, CO_2 from occupants, and PM from the ambient environment. Mitigation relies on source control, ventilation strategy, and filtration. The impact of these pollutants on driving performance varies, evidence for direct behavioral effects of CO_2 is limited in controlled settings, whereas $PM_{2.5}$ exposure shows a clear positive correlation with accident rates at the macro level. This underscores the safety imperative of effective cabin air filtration and the need to bridge micro-level mechanisms with macroscopic safety outcomes.

7. Declaration of interests

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.

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9. Appendix

Table A1: Brief of research on driving performance

Author	Year	Cabin environment metrics	Driving performance indicators
Wang[100]	2025	Temperature, ambient lighting color	Speed and its SD, pitch/roll rate, throttle usage, 2-back accuracy/RT, subjective sleepiness/satisfaction, NASA-TLX, SAM
Shin[111]	2025	Temperature	EEG CI and DFI, HRV (SI/SDNN)
Zhang[150]	2024	Wet bulb globe temperature	Accuracy in multiple cognitive tasks, NASA-TLX, ECG (RRI/RMSSD/LF–HF), fNIRS (ALFF/functional connectivity)
Li[144]	2024	Odor	Oddball/go–nogo/Stroop RT and accuracy; EEG z-scores (alpha/beta/theta/delta), TAB index
Wang[145]	2024	CO_2 concentration, odor	Speed/acceleration/lateral control; N-back accuracy/RT; NASA-TLX, SSS, SAM
Vosugh[148]	2023	Perinasal perspiration index	Distraction detection/recognition ACC, AUC, F1
Zhou[149]	2023	Facial thermal image	Binary classification accuracy for alertness vs fatigue (deep network)
Metin[106]	2023	Ambient temperature, humidity, wind velocity, weather	RTA (monthly road traffic accidents), RTRV (violation rate)
Sunagawa[107]	2023	PMV, temperature/humidity, heat index	Drowsiness level, drowsiness at +15 min, change in drowsiness (drowsiness delta)
Kim[104]	2023	Temperature, RH, supply-air velocity, solar radiation	HRV (LF/HF, RMSSD, stress index), EEG (CI/Valence/Arousal)
Dabaghi[109]	2023	Wet bulb globe temperature, PMV/PPD	Speed/precision/attention/errors, concentration, short-term memory, mental fatigue
Wang[99]	2023	Temperature	Three cognitive task times/errors, reaction time; EEG (AL, FEA, waveform entropy); NASA-TLX
Alkaabi[146]	2022	Temperature inside and outside, RH. CO_2, vehicle body temperature	Subjective discomfort—body fatigue, eye fatigue, body heat, skin dryness
Yang[105]	2022	Temperature	Eye movements (FD/FT), task completion time (CT)/total completion time (TCT); ELM/BPNN prediction; entropy weighting
Gwak[108]	2022	Temperature	Drowsiness level (0–4)
Dabaghi[110]	2022	Temperature, RH, PMV/PPD	Speed/precision/attention/errors, short-term memory, mental fatigue, concentration (active/passive)
Ahmadi[147]	2021	PM2.5/PM10/NO2/CO	Daily accident counts (panel 2SLS)
Schmidt[103]	2019	Temperature	KSS, ADACL, HR, pupil diameter, subjective fatigue; effect duration
Xianglong[18]	2018	Temperature	POMS (six dimensions); speed estimation/choice reaction/action judgment
Schmidt[102]	2017	Temperature	KSS, SCL, HR, pupil diameter, eye-closure AU43; lane keeping, steering abruptness
Shin[112]	2017	Temperature	PPG (stress index/LF–HF/SDNN/RMSSD), EEG (relative β/α)
Morris[101]	2016	Temperature	Following distance, brake onset timing and maximum braking force, PVT/MMDT
Goto[151]	2016	Temperature	Facial-expression drowsiness level, HRF, EEG α/β

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