The Influence of Cabin Environment on Takeover Performance in Conditional Automated Driving

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Abstract:

Environmental factors such as temperature and carbon dioxide concentration have been widely studied for their effects on cognitive and physical performance. However, their impact on takeover performance in the context of driving automation remains underexplored. This study investigated how temperature and carbon dioxide concentration influence drivers' takeover performance in conditional automated driving. Using a driving simulator, the experimental setup simulated modern vehicle cabin conditions, with three levels of temperatures (i.e., slightly cool, neutral and slightly warm) and two realistic carbon dioxide concentrations (i.e., high level, corresponding to recirculation ventilation and low level, corresponding to outside air ventilation). In total, 60 gender-balanced drivers participated in the study and a between-subjects experiment design (temperature and carbon dioxide concentration) was adopted. Each participant experienced three types of typical takeover scenarios, as initiated by visual and auditory takeover requests in a vehicle with conditional driving automation. The results showed that a slightly cool temperature and high carbon dioxide concentration negatively affected longitudinal speed control, while a slightly warm temperature resulted in quicker takeover actions and more stable lateral control. The analyses of gaze-related metrics suggested that elevated carbon dioxide concentrations may increase fatigue, while slightly cool temperatures appeared to reduce fatigue, leading to faster on-road attention. Finally, high carbon dioxide can counteract the favorable effects of temperature at the cognitive level. This study provides insights into the design of cabin environment control to improve driving safety in the context of driving automation.

Keywords: Cabin Environment; Takeover Performance; Conditional Driving Automation; HVAC Systems; Electric Vehicles

1 INTRODUCTION

The conditional driving automation, also known as the SAE (American Society of Automotive Engineers) Level 3 automation, can manage the complete dynamic driving task (DDT) in the operational design domain (ODD). However, human drivers must remain responsible for system failures (SAE, 2021), making takeover performance crucial for driving safety in the context of automated driving. Thus, numerous studies have been conducted to explore the influential factors of takeover performance, which can be classified into three main categories from the perspective of human-machine cooperation, i.e., human-related factors or individual characteristics such as age, gender, personality traits, driving style (Chen et al., 2024; Gasne et al., 2022; Chao Huang et al., 2024; Lin et al., 2020; Wu et al., 2020; Y. Zhang et al., 2024), non-driving-related tasks (NDRT) engagement before a takeover request (TOR) (Guo et al., 2023; Hu et al., 2024; Shi & Bengler, 2022; Zhang et al., 2023), drivers' states (Hergeth et al., 2017; Jin et al., 2021; Sahaï et al., 2021), as well as their prior knowledge of autonomous vehicles (AVs) (Du, Zhou, et al., 2020; Jin et al., 2021); vehicle-related factors such as the human-machine interface (HMI) (Huang & Pitts, 2022; W.-C. Huang et al., 2024; Ko et al., 2022; Lee et al., 2023; Pakdamanian et al., 2022; Talukder et al., 2024; Xing et al., 2021); and environmental factors such as road, lighting, and weather conditions, as well as the criticality and density of surrounding traffic (Dogan et al., 2019; Gold et al., 2016; Heo et al., 2022; Roche et al., 2022; Roche et al., 2020).

However, despite the cabin environment, such as temperature (Ormuž & Muftić, 2004), vibration (Azizan et al., 2017; Ormuž & Muftić, 2004; N. Zhang et al., 2024), noise (Ormuž &

Muftić, 2004), and odor (Sjörs Dahlman et al., 2024) has been shown to affect drivers' alertness and comfort in the context of manual driving, to the best of our knowledge, little attention has been paid to the effects of cabin environment factors in the context of driving automation, especially on takeover performance. The only one we could identify was by Tang et al. (2021), who found that the peppermint odor can improve drivers' takeover quality when they engaged in NDRT.

At the same time, the cabin environment has become increasingly important with the popularity of electric vehicles (EVs). In general, temperature and carbon dioxide concentration are primarily regulated by the heating, ventilation, and air conditioning (HVAC) system of vehicles, which consumes a lot of energy. Unlike traditional internal combustion engine vehicles, EVs lack the inherent heat generation associated with engine operation (Wang et al., 2016; Zhao et al., 2024). For example, a simulation shows that thermal comfort achieved through cabin cooling can decrease the range of EVs by as much as 26%, and a field study demonstrated that HVAC systems contribute to a 5.4% increase in battery consumption in summer and a 12.0% increase in winter (Kambly & Bradley, 2015; Lee et al., 2024). In addition, the HVAC system typically operates in either recirculation (RC) or outside air (OA) modes (Zhao et al., 2024). While RC mode enhances thermal efficiency, it also restricts fresh air exchange, leading to carbon dioxide buildup from occupants' exhaled breath. Studies have reported that carbon dioxide levels in vehicles with multiple occupants can reach approximately 2500 parts per million (ppm) within minutes (Angelova et al., 2019; Hudda & Fruin, 2018). Under worst-case conditions—such as prolonged idling with limited air exchange—carbon dioxide concentrations may rise from 1601 ppm (one occupant) to 6587 ppm (four occupants)

(Mathur, 2020), and may exceed 2000 ppm within 10 minutes (Zhao et al., 2022). Given that in other disciplines, both temperature and carbon dioxide have been found to affect cognitive and task performance (Lan et al., 2022; Liu et al., 2017; Snow et al., 2019; Xia et al., 2020; Xie et al., 2024; Yeganeh et al., 2018), which may then affect takeover performance (Du, Kim, et al., 2020; Liu et al., 2024; Zeeb et al., 2016), it is necessary to understand the relationship between cabin environment factors and drivers' takeover performance in the context of driving automation.

Thus, in this study, through a driving simulator study, we investigated how cabin temperature and carbon dioxide can affect drivers' takeover performance in vehicles with SAE Level 3 automation. To simulate real-world driving scenarios, being different from previous research that used relatively short experimental durations (e.g., 10 minutes to 1 hour) (Chowdhury, 2015; Daanen et al., 2003; Mackie & O'Hanlon, 1977; Morris & Pilcher, 2016; Schmidt & Bullinger, 2019; Schmidt et al., 2017; Sunagawa et al., 2023) and extreme temperatures (e.g., low temperature between 5-20°C and high temperatures between 30-40°C) （Chowdhury, 2015； Daanen et al., 2003； He et al., 2024； Sun & Dong, 2022； Wu et al., 2023）, we focused on more realistic temperature and carbon dioxide ranges in a relatively long driving period in highway scenarios, where most SAE Level 3 is designed for and drivers are more likely to expose to high-density carbon dioxide environment due to closed windows and recirculation mode of HVAC (Zhao et al., 2022). Drivers' visual behaviors and takeover performance are compared across different conditions, aiming to provide insights into cabin designs that can balance driving safety and energy efficiency.

2 LITERATURE REVIEW

2.1 Influence of Temperature on Driving Behavior

Both too-low and too-high ambient temperatures can impair drivers' cognitive states and manual driving performance. For example, the extreme temperatures can lead to slower reaction times (Sun & Dong, 2022 [Treatment: 28-32 °C, 32-36 °C, 37-41 °C; 90 min each]; Wu et al., 2023 [5–10 °C, 20–25 °C, 30–35 °C; unknown duration]; Wyon et al., 1996 [21 °C, 27 °C; 60 min each]), poorer dynamic speed adjustment (Chowdhury, 2015 [10.56-15.56 °C, 16.11-21.11°C, 21.67-26.67 °C; 15 min each]; He et al., 2024 [14–18 °C, 24–28 °C, 34–38 °C; 15 min each]), shorter time headway (He et al., 2024; Morris & Pilcher, 2016 [21 °C ambient temperature with/without a 0 °C cooling vest; 13 min each]), increased lateral position deviation (Daanen et al., 2003 [5 °C, 20 °C, 35 °C; 14 min each]), and more frequent large steering corrections (Mackie & O'Hanlon, 1977 [18.89-20 °C, 32.22 °C; 600 km (more than 7 hours) each]). In field studies, Mackie & O'Hanlon (1977) and Sun & Dong (2022) found that long exposures to high temperatures are associated with fatigue, slower reaction times, and deteriorated driving performance during extended highway driving.

Besides, the effect of the cabin temperature on driving behavior can be moderated by the traffic conditions. For example, in low-risk traffic scenarios, drivers tend to drive faster under extreme temperatures compared to those under moderate temperatures. In contrast, in medium- and high-risk scenarios, extreme temperatures can impair dynamic speed adjustments, increasing the risk of crashes (He et al., 2024). Furthermore, at medium or high speeds, the Urelation between ambient temperature and cognitive effort becomes more pronounced, and both low and high temperatures demand greater cognitive effort from drivers (Wu et al., 2023).

Additionally, in addition to stable ambient temperature, dynamic temperature has also been found to affect drivers' states. For example, cold stimuli have been shown to reduce fatigue and enhance driving safety. Several studies indicate that short-term cooling, such as facial cooling during monotonous driving, lowers subjective sleepiness ratings, improves lane-keeping and steering control, and boosts physiological markers of alertness (Landstrom, 2006; Schmidt & Bullinger, 2019; Schmidt et al., 2017). These findings suggest that active, dynamic climate control strategies may help sustain driver alertness, especially on long journeys in stable cabin environments.

Despite growing interest in the impact of ambient temperature on driver performance, several research gaps remain. First, most studies examining temperature have been conducted over relatively short durations—typically between 10 minutes and 1 hour—limiting their validity and applicability to prolonged real-world driving conditions. Second, existing studies on temperature have predominantly focused on extreme conditions, such as low temperatures between 5–20 °C or high temperatures between 30–40 °C. However, modern vehicle cabins are generally maintained within a moderate thermal range, which remains underexplored. Third, none of the previous research has considered the context of driving automation. Given that driving automation can lead to increased fatigue (Matthews et al., 2019; McKerral et al., 2023) and that task performance (e.g. reaction time, attention/perceptual, mathematical processing, reasoning, learning, and memory) was found sensitive to task type, duration, and environmental conditions in built environment (Pilcher et al., 2002), it is necessary to investigate how ambient temperature affects takeover performance in conditionally automated driving scenarios.

2.2 Influence of Carbon Dioxide on Driving Behavior

Prior research in built environments has demonstrated that elevated carbon dioxide levels can impair cognitive performance, with noticeable declines observed at concentrations exceeding approximately 2000 ppm (Satish et al., 2012; Snow et al., 2019; Zhang et al., 2017). In the driving domain, the effects of carbon dioxide on driving safety have been under-investigated. While some studies have investigated how HVAC control strategies and driving conditions can affect the accumulation of carbon dioxide in vehicle cabins, few studies have specifically explored its effects on driving safety. Some research suggests that carbon dioxide concentrations do not significantly influence driving performance in terms of speed or lateral control in manual driving vehicles (C. Wang et al., 2024). However, other studies indicate that higher carbon dioxide concentrations can lead to more frequent braking, increased traffic violations, and higher accident rates in manual driving vehicles (Magaña et al., 2020). Studies have also linked carbon dioxide levels to heightened mental workload (Chen et al., 2020; Magaña et al., 2020; Mathur, 2016; Solis Marcos & Hummelgård, 2022), eye fatigue (Alkaabi & Raza, 2022), and mental fatigue (Mathur, 2016) in manual driving vehicles. Given that carbon dioxide concentrations in vehicles can rapidly rise to 2500 ppm within minutes (Angelova et al., 2019; Hudda & Fruin, 2018), and automated driving has shifted the role of drivers from an operator to a supervisor. It is more urgent to examine how carbon dioxide accumulation affects driving performance, particularly in safety-critical takeover scenarios, which are both cognitively and physically demanding and thus can be potentially influenced by carbon dioxide concentration.

2.3 Research Gaps and Current Study

In summary, existing research has mostly focused on the influence of extreme cabin temperature in manual driving conditions, especially with relatively short exposure. Even fewer studies have focused on the influence of carbon dioxide on drivers' performance, and all were in vehicles without driving automation. Given that long-term driving with automation may further exaggerate the negative impact of the sub-optimal environmental factors in the cabin, our study aims to answer the following three research questions related to the relationships between cabin environment and driving performance in SAE Level 3 vehicles. RQ1: Can a slight shift within the thermally comfortable temperature range influence takeover performance? RQ2: Does an increase in carbon dioxide concentration—resulting from the use of RC mode—affect takeover performance? RQ3: Can the temperature and carbon dioxide concentration jointly affect takeover performance?

3 METHODS

3.1 Participants

Participants were required to have held a valid C1/C2 driver's license in China for at least three years and had an accumulated mileage of at least 5000 km in the past year (Chunxi Huang et al., 2024; Weng et al., 2024) to reduce variability due to inexperience, which has been shown to affect takeover performance (Chen et al., 2021). On the day of the experiment, they were instructed to avoid alcohol and caffeine consumption and to ensure a normal sleep the night before. Recruitment was carried out through advertisements placed on the university campus and in the surrounding downtown areas. A total of 71 participants were initially recruited. Based on self-reported screening data, 11 participants were excluded due to noncompliance with pre-experiment requirements—specifically, recent caffeine intake, insufficient sleep, or excessive fatigue from overwork—resulting in a final sample of 60 valid participants, which is enough to detect a moderate effect size (f = 0.38) with our experiment design, with a power of 0.8 at 0.05 significance level according to the G*Power software. Table 3 presents participants' demographic information across different groups. As desired, no significant difference was found in the mean ages of drivers across the different conditions.

The experiment lasted approximately two hours, and participants were compensated at a rate of 80 RMB/h. An additional monetary incentive of 20 RMB/h was offered to encourage engagement in an NDRT while maintaining alertness for TOR. The study was approved by the Ethics Compliance Committee at **[Placeholder for double-blinded review]**.

3.2 Cabin Environments

3.2.1 Cabin Temperature

The three temperature conditions in this study were determined using the Predicted Mean Vote (PMV) model, one of the most widely used standardized thermal comfort models in both building and vehicle research (Huo et al., 2023; Zhao et al., 2021). The PMV model predicts thermal comfort on a scale ranging from -3 to +3, where "-3" represents "Cold," "-2" is "Cool," "-1" is "Slightly cool," "0" is "Neutral," "+1" is "Slightly warm," "+2" is "Warm," and "+3" is

"Hot." It evaluates thermal comfort by combining environmental variables (air temperature, radiant temperature, relative humidity, air velocity) and personal variables (metabolic rate, clothing insulation) based on the assumption of human heat balance under steady-state conditions (Fanger, 1970). For this experiment, participants were required to wear trousers and a short-sleeve shirt, providing a clothing insulation value of 0.57 clo. The metabolic rate was estimated at 1 met, matching the seated activities during takeover tasks. The indoor air velocity was 0 m/s, and relative humidity (RH) was around 60% with its variation considered negligible (Tartarini et al., 2020). Using these fixed parameters, three temperature conditions (22.5 ℃, 25.0 ℃, 27.5 ℃) corresponding to different thermal comfort levels (Slightly Cool, Neutral, Slightly Warm) were calculated based on the PMV model.

3.2.2 Carbon Dioxide Concentration

This study designed two carbon dioxide levels to simulate common HVAC ventilation modes: high level, corresponding to RC mode, and low level, corresponding to OA mode. Following previous studies, the low carbon dioxide concentration was designed to be maintained at 1200 ppm, and the high concentration at 4200 ppm (Angelova et al., 2019; Hudda & Fruin, 2018; Mathur, 2020; Zhao et al., 2022). The measured environmental conditions in the experiment are shown in Table 3.

3.3 Driving Scenarios and Takeover Tasks

The experiment was conducted on a simulated highway with a speed limit of 120 km/h, mimicking realistic high-speed driving conditions. Highway scenarios were selected because current SAE Level 3 automation is primarily designed for highways, where traffic conditions are more controlled and interactions with other road users are limited (Hawkins, 2023; Reuters, 2023). Additionally, highway driving typically involves a prolonged cruising stage with windows closed and HVAC in recirculation mode, leading to more stable in-cabin conditions and greater carbon dioxide accumulation compared to urban scenarios (Zhao et al., 2022). Participants were instructed to engage the driving automation whenever possible and only take control of the vehicle when required. The SAE Level 3 automated driving system (ADS) could be activated or deactivated by using the virtual buttons on the interactive screen, positioned next to the steering wheel. Participants could also deactivate the ADS by either pressing the brake or turning the steering wheel.

As shown in Table 2, following previous studies, three typical takeover scenarios were designed, varying in urgency, environmental complexity, and demands on different driver capabilities, which can be affected differently by environmental factors, as has been observed in the built environment. For instance, exposure to cold or hot temperatures can increase reaction time and impair performance in reasoning tasks, learning tasks, memory tasks, attention or perception tasks, and mathematical processing tasks (Pilcher et al., 2002).

- Foggy road scenario, in which participants encountered a sudden onset of fog, reducing visibility ahead, requiring drivers to assess road conditions and prepare for potential hazards hidden by low visibility (Heo et al., 2022; Li et al., 2018).
- Lane change scenario, in which a construction zone appears on a highway, requiring drivers to take over the control of the vehicle. In this scenario, the participant was required to change lanes twice to avoid obstacles (Roche et al., 2022; Shi et al., 2024).

- Braking scenario, in which a vehicle ahead of the ego-vehicle performed an emergency braking and lane change maneuver. Participants were expected to take over control and apply the brakes promptly to avoid a collision. This scenario was designed to evaluate the drivers' reaction times and braking performance under sudden, high-risk situations (Roche et al., 2020; Wu et al., 2022).

In the foggy road scenario and lane change scenario, we set the TOR lead time to 7 s, which is widely suggested (Wu et al., 2022) for safe consideration and corresponds to a distance of 200 m at 100km/h. While in the braking scenario, the TOR was initiated when the lane change started. In this study, the TOR was with both visual and auditory modalities, as the multimodal TOR was found to be more effective compared to single-modality TOR (Huang & Pitts, 2022; Yoon et al., 2019). Specifically, when a TOR was issued, a warning icon appeared on the interactive screen, accompanied by a voice prompt stating, "Foggy area ahead, please take over the vehicle", "construction road ahead, please take over the vehicle", or "The vehicle in front brakes sharply; please take over the vehicle", depending on the types of scenarios they encountered.

Table 2 Description of the takeover scenarios

Scenario Sketch	Driver's View of the Scenarios and Descriptions
	 Scenario 1: Foggy Road Scenario The ego-vehicle (in yellow) followed a leading vehicle (in white) at a speed of 100 km/h, 100 meters ahead, in the right lane of a two-lane highway. The highway had moderate oncoming and incoming traffic, traveling at 100 km/h as well. The ADS detected a dense fog area 200 meters in advance and issued a TOR to the driver. Simultaneously, the leading vehicle began decelerating to 72 km/h at a deceleration of 3 m/s^2. The fog road was 500 m long and consisted of two 200 m long (600 m radius of curvature) curves and a 100 m straight section.

Scenario 2: Lane Change Scenario

The ego-vehicle followed a leading vehicle at a speed of 100 km/h, 100 meters ahead, in the right lane of a two-lane straight highway. The first construction sign was in the right lane and the second construction sign was in the left lane. The longitudinal distance between the two construction signs was 100 m. The ADS detected construction signs 200 m in advance and issued a TOR to the driver. Simultaneously, the leading vehicle began decelerating to 72 km/h at a deceleration of 3 m/s^2 and performed lane change twice to avoid obstacles.

Scenario 3: Braking Scenario

The ego-vehicle was in the right lane of a two-lane highway at a speed of 100 km/h. The first vehicle was in the left lane, also traveling at 100 km/h,

	and was 30 m ahead of the ego-vehicle. As the first vehicle in the left lane quickly approached the second vehicle in the same lane traveling at 80 km/h, it began to decelerate and initiate a lane change into the right lane. Simultaneously, the ADS detected the situation and issued a TOR to the driver.

At the same time, serving as the NDRT, an iPad mini 5 tablet was mounted to the right of the interactive screen and played the same video documentary (i.e., animal world content) for all participants. Participants were required to focus on the video documentary and to answer questions related to the documentary content at the end of the experiment, thus ensuring their engagement.

3.4 Experiment Design

A 2×3 between-subject design was adopted with carbon dioxide concentration (High Concentration, Low Concentration) and temperature (Slightly Cool, Neutral, Slightly Warm) as the between-subject factors (Table 3). The different combinations of temperature and carbon dioxide concentration led to 6 distinct groups, with 10 gender-balanced participants (i.e., 5 females and 5 males) randomly assigned to each group.

Table 3 Experiment conditions and participant age

Group	Carbon Dioxide Condition (Mean, Min-Max, Standard Deviation [SD], [ppm])	Temperature Condition (Mean, Min-Max, SD, [°C])	Age (Mean, Min-Max, Standard Deviation [SD])
HC	High Concentration (4342.43, 3908.26-4708.19, 251.03)	Slightly Cool (22.64, 22.22-22.90, 0.17)	26.4, 23-35, 4.1
HN	High Concentration (4247.76, 3873.36-4676.63, 262.59)	Neutral (24.87, 24.45-25.83, 0.49)	26.9, 23-33, 3.5
HW	High Concentration (4341.83, 3855.59-4987.52, 350.56)	Slightly Warm (27.63, 27.24-27.88, 0.22)	28.0, 22-35, 5.2
LS	Low Concentration (1155.11, 1069.71-1354.38, 91.33)	Slightly Cool (22.55, 21.91-23.37, 0.51)	28.0, 22-38, 4.9
LN	Low Concentration (1021.04, 823.73-1314.33, 146.20)	Neutral (25.02, 24.51-26.12, 0.45)	27.0, 23-35, 4.5
LW	Low Concentration (1203.86, 1047.86-1307.98, 93.98)	Slightly Warm (27.76, 26.91-28.46, 0.51)	26.9, 22-44, 6.5

3.5 Apparatus

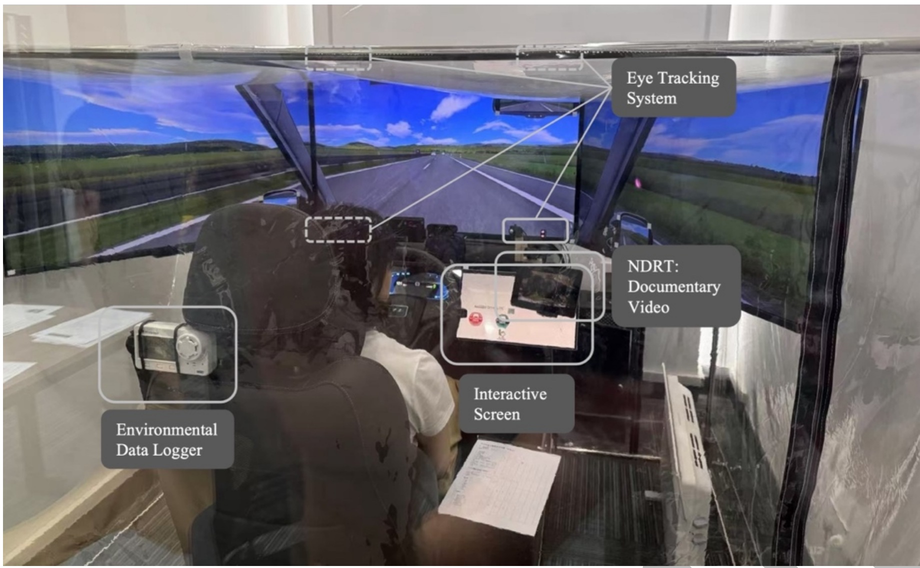


Figure 1 Driving Simulator and Cabin Environment

As illustrated in Figure 1, the scenarios were created in a fixed-base driving simulator, with the hardware provided by Info Tech and the software by SILAB 7.1 software (WIVW GmbH, Germany). Three 43-inch screens (each with a resolution of 1920 x 1080) positioned about 1 m from the participants' eyes provided a 150° and 47° horizontal and vertical field of view. Driving data was recorded at 60 Hz via the simulation software, while eye-tracking data was captured at the same frequency (60 Hz) using a remote 4-camera tracking system (Smart Eye Pro) with Smart Eye Pro 10.2. The experimental devices were synchronized via the network time protocol (NTP) before experiments.

The simulated cabin was constructed by enclosing the driving simulator with transparent plastic film, as shown in Figure 1. Temperature and carbon dioxide concentration were monitored near the driver's head using a Bluetooth-enabled environmental data logger (HOBO MX data logger MX1102A). The temperature measurement accuracy was ±0.21°C, and carbon dioxide concentration measurement accuracy was 50 ppm ±5% of the reading, at 25°C, with a relative humidity of less than 90% (non-condensing) and atmospheric pressure of 1,013 mbar.

High carbon dioxide concentration was achieved by injecting carbon dioxide from a gas cylinder, while the low concentration condition was primarily maintained through the participant's exhalation, combined with adjustments to the opening and closing of the plastic film enclosure. The temperature was independently regulated using a combination of ice packs and heater, allowing thermal control without introducing ventilation that could alter carbon dioxide concentration. Specifically, for the slightly cool condition, hundreds of ice packs were evenly distributed throughout the cabin interior to ensure uniform cooling. For higher temperature conditions, a heater was used to raise the temperature.

To control the environmental variables, we first pre-set the cabin environment before participants entered the room. Then, we fine-tuned the environments in the first 5-10 minutes of a trial based on the real-time data from an environment sensor, including adjusting the setup of the air conditioner (using a panel outside of the cabin), manual adjustment of a plastic film closure behind the participant, and adjusting the carbon dioxide injection, delivered through a 2-meter-long tube positioned at the side of the simulated cabin. All these maneuvers were quiet and outside of drivers' eyesight. Thus, they would not attract drivers' attention.

3.6 Procedures

Upon arrival, participants were provided with an overview of the tasks they would perform. They reviewed and signed a consent form, confirming their understanding of the requirements of the study and their agreement to participate. Prior to the start of the formal experiment, a five-minute training session was provided on the driving simulator. This session familiarized them with the controls of the driving simulator, including how to initiate and disengage automation and respond to TOR.

Then, the formal experiment began, which was a 90-minute drive with the assistance of ADS on a highway (Figure 2). Participants experienced five takeover scenarios spaced at predefined intervals. The first four scenarios were introduced at 15-minute intervals, while the final scenario involving emergency braking occurred 30 minutes after the fourth task. After each TOR, participants manually drove the vehicle for approximately 500 meters before receiving a voice command to turn on the ADS and resume NDRT (watching the documentary). The braking scenario was intentionally put near the end of the drive to generate an extended period without events, followed by an urgent event, simulating real-world driving scenarios with relatively reliable ADS. It should be noted that the order of the five scenarios was fixed, as we were not interested in the effect of the scenarios.

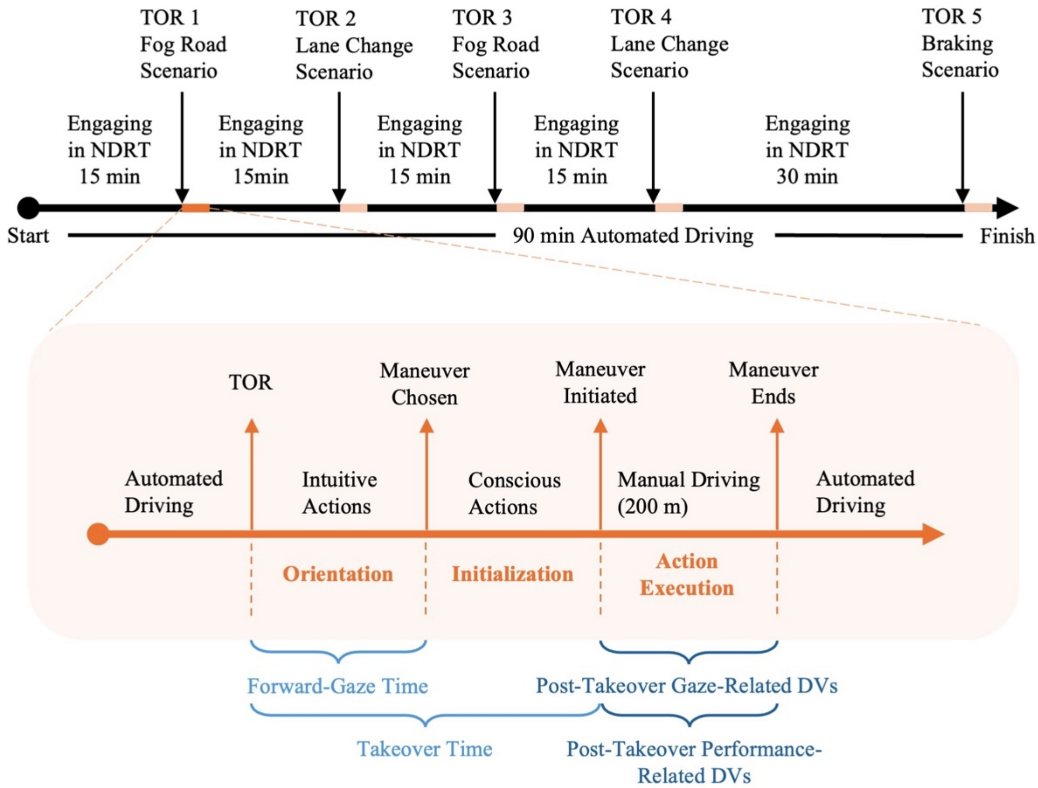


Figure 2 Experimental Procedure and the Extraction of Dependent Variables

3.7 Data Analysis

Takeover performance was evaluated using time-related and quality-related metrics in three stages—orientation, initialization, and action execution (Cao et al., 2021), as illustrated in Figure 2 and the metrics in each stage are listed in Table 3 and Table 4.

- The orientation stage is from the TOR to the drivers' first gaze on the road, during which drivers collect information regarding the environment and intuitively react to the TOR by shifting attention from the NDRT to the driving situation. In this stage, we focused on forward-gaze time, which reflects the length of the orientation stage.

- The initialization stage is from the first gaze on the road to the vehicle being taken over, during which the drivers select and conduct actions. In this stage, we cared about takeover time, which refers to the time between the issuance of a TOR and the driver's initiation of a conscious maneuver.
- The action execution stage is from the vehicle being taken to 200 meters after the takeover. During this, we evaluated the post-takeover performance based on the quality of manual driving. We also incorporated visual behavior metrics to examine how environmental conditions affected drivers' attention allocation strategies and states (Bafna & Hansen, 2021; A. Wang et al., 2024; Zhang et al., 2020) at this stage. The visual behavior metrics (gaze, fixation, and blink) were based on the ISO 15007:2020 Standard and previous research. Among them, the saccade filter length (ms), the saccade threshold (deg/s), the fixation threshold (deg/s), and the dilation filter length (ms) in Smart Eye Pro 10.2 were set to 200, 35, 15, and 300, respectively. We only considered the middle screen of the driving simulator as the area of interest (AOI) for gaze-related metrics, as more than 98% of fixations were on the middle screen after participants took over the vehicle.

Table 4 Takeover performance metrics

Metrics	Description
Forward-Gaze Time	The time elapsed from the onset of a TOR to the driver's first gaze towards the screens or the dashboard (Abe et al., 2019; Cao et al., 2021).
Takeover Time	The time elapsed from the onset of a TOR to the driver's first control maneuver, defined as a 2° steering wheel angle change or 10% brake pedal actuation (Gold et al., 2013).
Time to Collision (TTC)	The time remaining before a potential collision with a reference obstacle ahead (Vogel, 2003).
Longitudinal Control Metrics	The SD of longitudinal speed and acceleration (Cao et al., 2021).
Latitudinal Control Metrics	Offset from Lane Center: the mean, max and SD of the deviation from the lane center of the ego-vehicle (Cao et al., 2021). Time to Lane Crossing (TLC): the time remaining before crossing the lane boundary, given the current speed and direction of the ego-vehicle (Zeeb et al., 2015).

Table 5 Gaze-related metrics

Metrics	Description
Pupil Size	The mean pupil size (Bafna & Hansen, 2021; Charles & Nixon, 2019; Marquart et al., 2015).
Saccade Metrics	The saccade peak velocity, and the saccade frequency (Di Stasi et al., 2012; Schleicher et al., 2008; Yang et al., 2024).
Fixation Metrics	The mean fixation duration (Bafna & Hansen, 2021; Charles & Nixon, 2019; Zhang et al., 2020), the SD of fixation locations vertically and horizontally (Kummetha et al., 2020), and the average nearest neighbor index (ANNI) calculated from fixation locations — representing the ratio of the mean minimum distance from the observation points to the expected mean distance under a random distribution and serving as an indicator of spatial dispersion (Chunxi Huang et al., 2024; Pillai et al., 2022).
Blink Metrics	The mean blink duration, and the blink frequency (Benedetto et al., 2011; A. Wang et al., 2024).

The mixed linear model was used to analyze the effects of cabin temperature, carbon dioxide concentration, and their two-way interactions on drivers' visual behavior and takeover performance metrics. All models were constructed using Proc Mixed in "*SAS OnDemand for Academics*," with the repeated measures (participants) being accounted for. As different takeover tasks vary in urgency, environmental complexity, and road geometric properties, the post-takeover behaviors may also differ in different types of scenarios. Consequently, takeover task type (a categorical variable) was omitted and was treated as random effects in statistical models.

To account for the between-subject design and individual differences, variables from each participant's first takeover event were included in the model as a covariate. Accordingly, only the subsequent four takeover events were used as dependent observations in the analyses. It should be noted that participants had already been exposed to their assigned environmental conditions for approximately 15 minutes before the first takeover event; thus, individual differences at this stage may have been partially confounded with early environmental effects. Post-hoc contrasts were performed for all significant effects ($p < .05$) or marginally significant effects (p < .10) using Tukey's test. Cohen's d effect sizes were computed for all post-hoc pairwise comparisons to quantify the magnitude of group differences (Borenstein et al., 2021).

Each participant experienced five takeover scenarios. However, one participant from groups LC and LN mistakenly accidentally touched the steering wheel during the NDRT, causing a rollover and a loss of data for the braking scenario. Consequently, a total of 298 takeovers (60 participants * 5 scenarios with two losses) events were available for analysis. In addition, it should be noted that as we are interested in drivers' responses to TOR, we intentionally excluded the cases with reactions before the TOR. Specifically, given that the saccadic reaction time (the time between the onset of a visual stimulus and the initiation of a saccadic eye movement) is longer than 100 ms even with auditory stimuli (Colonius & Diederich, 2004; Noorani & Carpenter, 2016; Steenken et al., 2008; Yamagishi & Furukawa, 2020). After data screening, 226 valid forward-gaze samples and 296 takeover time samples were retained for analysis. Due to missing first-event data in some participants, the number of valid observations used in the final mixed-effects models varied slightly across metrics, yielding 160 samples for the forward-gaze time model, 236 for the takeover time model, and 238 for post-takeover driving performance and gaze-related measures.

4 RESULTS

4.1 Takeover Performance

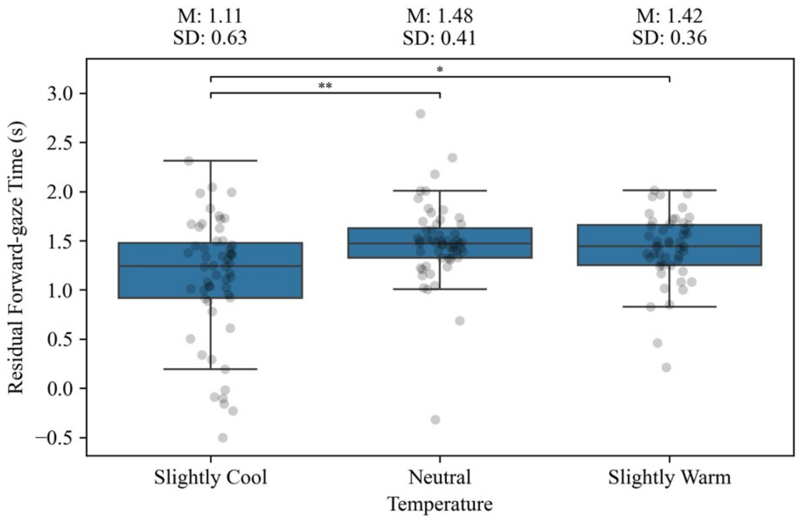
4.1.1 Reaction Times

As shown in Table 6 and Figure 3, we observed the *Temperature* effect on the *Forward-Gaze Time* and *Takeover Time.* Specifically, a slightly cool temperature resulted in faster forward-gaze times compared with neutral temperatures (difference [Δ] of -0.26, 95% confidence interval [CI] of [-0.51, -0.02], $t(153) = -2.60$, $p = .03$, Cohen's d [d] of 0.56) and slightly warm temperatures (Δ = -0.22, 95% CI [-0.46, -0.02], $t(153) = -2.17$, $p = .08$, d = 0.46). At the same time, compared with neutral temperatures, a slightly warm temperature led to faster takeover times (Δ = -0.35, 95% CI: [-0.56, -0.13], $t(229) = 3.85$, $p = .0004$, d = 0.62).

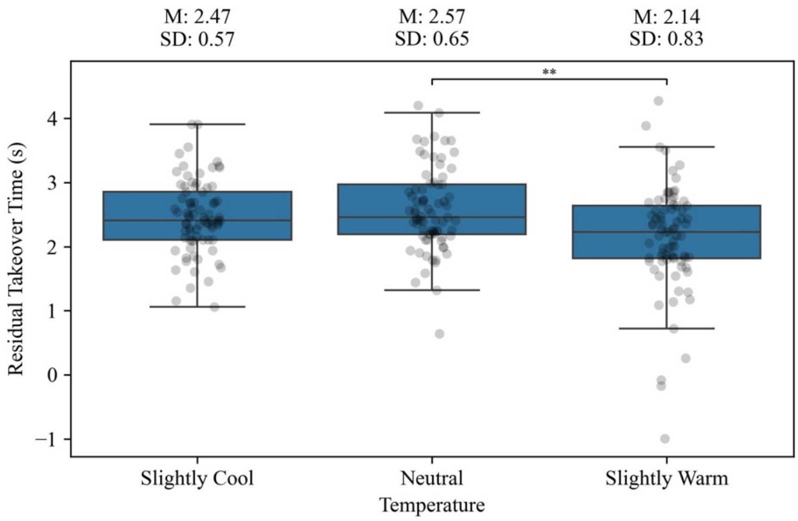
Table 6 Model results for reaction times

Dependent Variables (Model)	Independent Variables	F-value	*p*-value
Forward-Gaze Time	Temperature Condition	$F(2, 153) = 3.71$	.03**
	Carbon Dioxide Condition	$F(1, 153) = 1.97$	.2
	Temperature Condition × Carbon Dioxide Condition	$F(2, 153) = 0.92$	.4
	First Forward-Gaze Time	$F(1, 153) = 169.60$	< .0001**
Takeover Time	Temperature Condition	$F(2, 229) = 7.44$	.0007**
	Carbon Dioxide Condition	$F(1, 229) = 0.29$	.6
	Temperature Condition × Carbon Dioxide Condition	$F(2, 229) = 0.95$	.4
	First Takeover Time	$F(1, 229) = 142.74$	< .0001**

Note: In this table and the subsequent ones, the asterisk ** indicates significant results ($p < .05$) and * indicates marginally significant results ($.05 < p < .1$).



(a) *Forward-Gaze Time*



(b) *Takeover Time*

Figure 3 The effect of *Temperature* Conditions on (a) *Forward-Gaze Time* and (b) *Takeover Time*. In this plot and the subsequent ones, ** indicates significant ($p < .05$) and * indicates marginally significant ($.05 < p < .1$) post-hoc comparisons, respectively; the grey dots indicate residuals of participants' performance in the latter four takeover events relative to their performance in the first takeover event, which control for baseline differences but may not fully reflect model-adjusted estimates; the box represents the interquartile range (IQR) and the median, while the whiskers indicate 1.5 times IQR from the first and third quartiles. M stands for mean, and SD stands for standard deviation.

4.1.2 Post-Takeover Performance

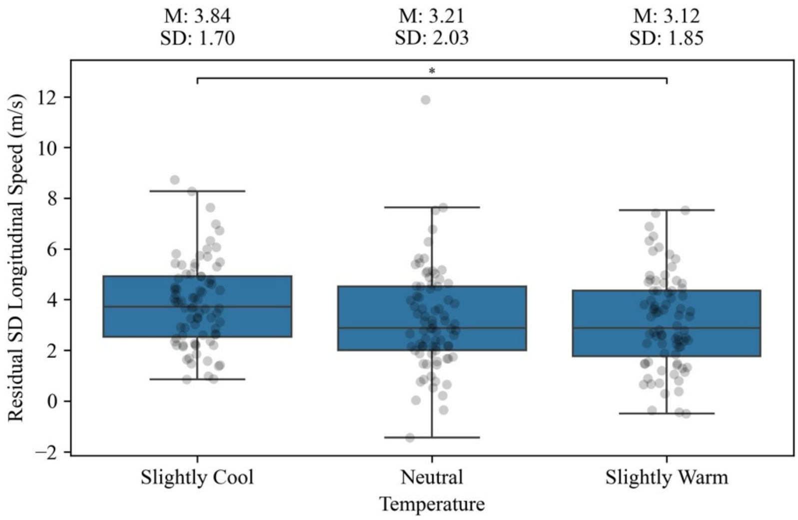
Longitudinal Control Metrics. Table 7 shows the model results for post-takeover performance. Temperature conditions were associated with longitudinal control metrics. Compared to neutral conditions, cool temperatures led to a higher SD of longitudinal acceleration (Figure 4b, Δ = 0.28, 95% CI [−0.037, 0.60], t(229) = 2.09, p = .095, d = 0.33). Similarly, compared to warm conditions, cool temperatures resulted in a higher SD of longitudinal speed (Figure 4a, Δ = 0.53, 95% CI [−0.056, 1.11], t(229) = 2.13, p = .09, d = 0.34).

When comparing carbon dioxide levels, higher carbon dioxide concentrations led to increased variability in driving performance, as reflected by higher SD of longitudinal speed (Figure 5a, Δ = 0.49, 95% CI [0.092, 0.89], t(229) = 2.43, p = .02, d = 0.31) and higher SD of longitudinal acceleration (Figure 5b, Δ = 0.30, 95% CI [0.084, 0.52], t(229) = 2.74, p = .006, d = 0.35).

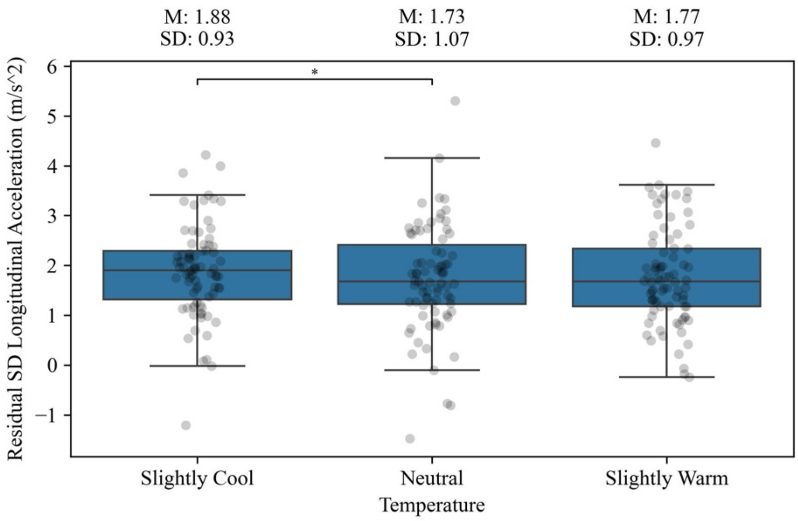
Latitudinal Control Metrics. We also observed the temperature effect on the mean offset from lane center (Figure 4c). The mean offset from lane center was lower with slightly warm temperature, as compared to neutral temperature (Δ = -0.069, 95% CI: [-0.13. 0.0062], t(229) = -2.59, p = .03, d = 0.39).

Table 7 Model results for post-takeover performance

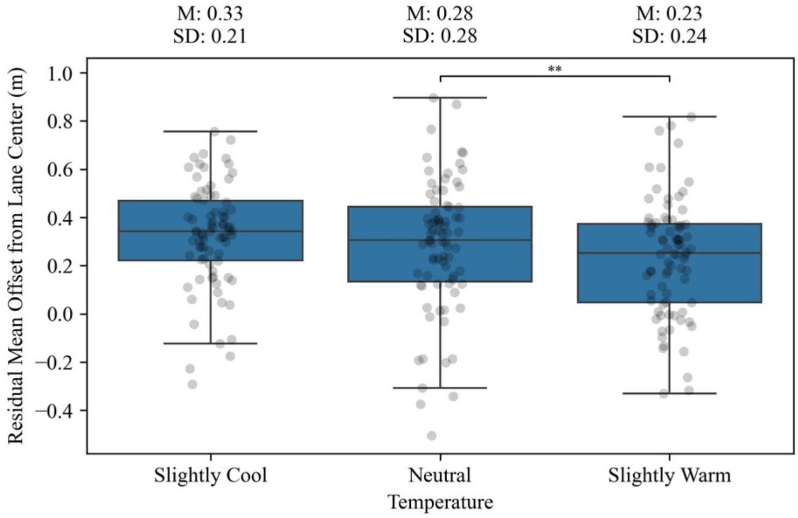
Dependent Variables (Model)	Independent Variables	F-value	*p*-value
SD Longitudinal Speed	Temperature Condition	$F(2, 229) = 2.75$	.07*
	Carbon Dioxide Condition	$F(2, 229) = 5.88$	.02**
	Temperature Condition × Carbon Dioxide Condition	$F(2, 229) = 1.42$	.2
	First SD Longitudinal Speed	$F(2, 229) = 28.75$	$< .0001$**
SD Longitudinal Acceleration	Temperature Condition	$F(2, 229) = 2.38$	.09*
	Carbon Dioxide Condition	$F(2, 229) = 7.51$	.007**
	Temperature Condition × Carbon Dioxide Condition	$F(2, 229) = 0.37$	.7
	First SD Longitudinal Acceleration	$F(2, 229) = 35.43$	$< .0001$**
Mean Offset from Lane Center	Temperature Condition	$F(2, 229) = 3.46$	.03**
	Carbon Dioxide Condition	$F(2, 229) = 0.14$	.7
	Temperature Condition × Carbon Dioxide Condition	$F(2, 229) = 2.25$	.1
	First Mean Offset from Lane Center	$F(2, 229) = 30.60$	$< .0001$**



(a) *SD Longitudinal Speed*

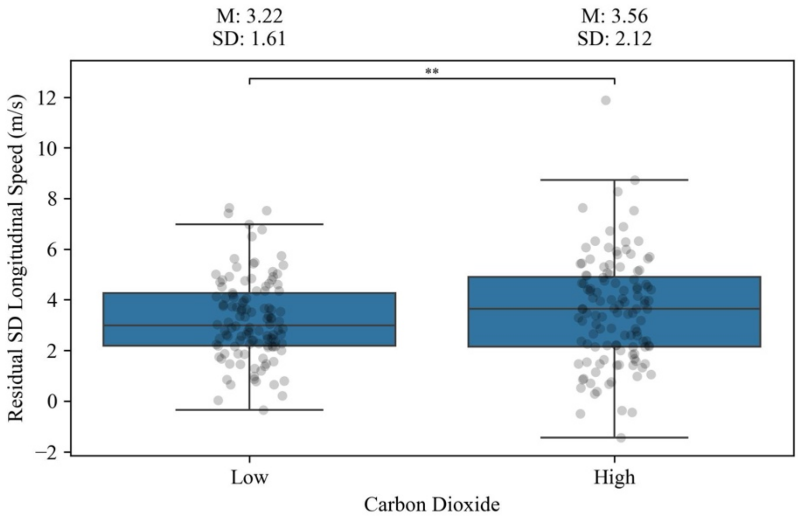


(b) *SD Longitudinal Acceleration*

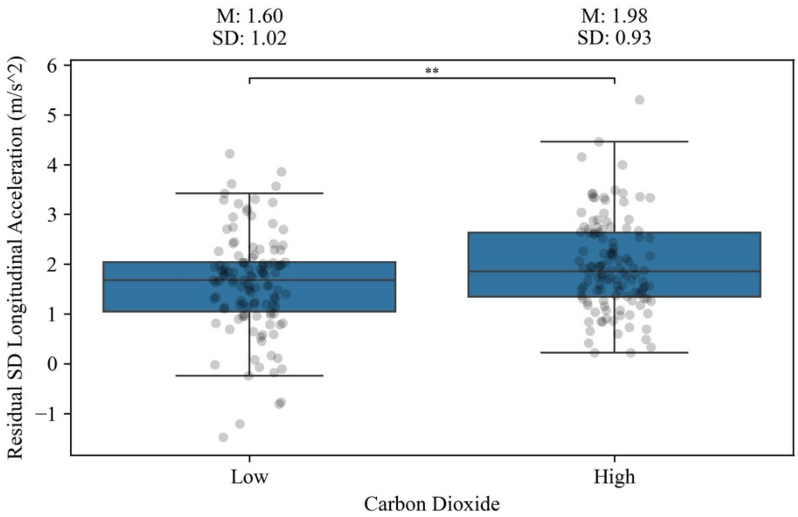


(c) *Mean Offset from Lane Center*

Figure 4 The effect of *Temperature* Conditions on post-takeover performance.



(a) *SD Longitudinal Speed*



(b) *SD Longitudinal Acceleration*

Figure 5 The effect of *Carbon Dioxide* Conditions on post-takeover performance.

4.2 Gaze-Related Metrics

Effect of Temperature. Table 8 shows the model results for post-takeover gaze-related metrics. The slightly cool temperature led to a higher saccade frequency compared to neutral temperatures (Figure 7a, Δ = 0.30, 95% CI: [0.0078, 0.59], t(230) = 2.42, *p* = .04, d = 0.39) and slightly warm temperatures (Figure 7a, Δ = 0.29, 95% CI: [-0.0087, 0.58], t(230) = 2.29, *p* = .06, d = 0.37). At the same time, the slightly cool temperature was associated with shorter mean fixation duration (Figure 7b, Δ = -0.46, 95% CI: [-0.82, -0.095], t(229) = -2.97, *p* = .009, d = 0.47) compared to neutral temperatures. In addition, with low carbon dioxide concentrations, deviation to the neutral temperature decreased blink frequency (Figure 9, Slightly Cool vs. Neutral, Δ = -0.13, 95% CI: [-0.28, 0.0078], t(229) = -2.72, *p* = .08, d = 0.57; Slightly Warm vs. Neutral, Δ = -0.17, 95% CI: [-0.31, -0.023], t(229) = -3.35, *p* = .01, d = 0.70).

Meanwhile, the temperature is also associated with the range of visual attention. Specifically, slightly cool temperature resulted in larger SD of fixation positions in horizontally (Figure 7c, Slightly Cool vs. Neutral, Δ = 0.014, 95% CI: [0.0025, 0.026], t(229) = 2.85, *p* = .01, d = 0.45; Slightly Cool vs. Slightly Warm, Δ = 0.011, 95% CI: [-0.00030, 0.023], t(229) = 2.30, *p* = .06, d = 0.35) and vertically (Figure 7d, Slightly Cool vs. Neutral, Δ = 0.0049, 95% CI: [-0.00054, 0.010], t(230) = 2.12, *p* = .09, d = 0.34). This is in line with the larger ANNI values under slightly cool temperature (Figure 7e, Δ = 0.017, 95% CI: [-0.0015, 0.035], t(229) = 2.16, *p* = .08, d = 0.34), as compared to neutral temperature.

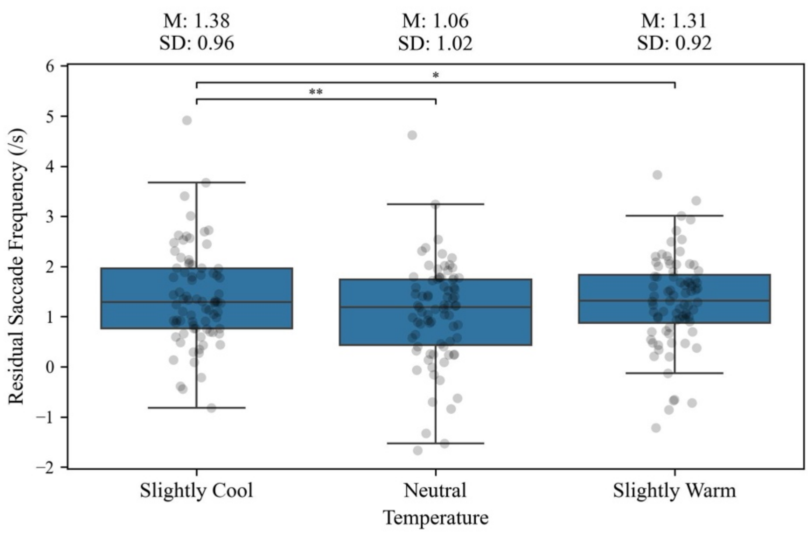
Effect of Carbon Dioxide: As shown in Figure 8, high carbon dioxide concentrations was associated with longer mean fixation duration (Δ = 0.25, 95% CI: [0.0021, 0.50], t(229) = 1.99, *p* = .048, d = 0.26) and longer mean blink duration (Δ = 0.028, 95% CI: [0.001, 0.057], t(229) = 1.90, *p* = .058, d = 0.25), compared to that with low carbon dioxide concentrations.

Table 8 Model results for post-takeover gaze-related metrics

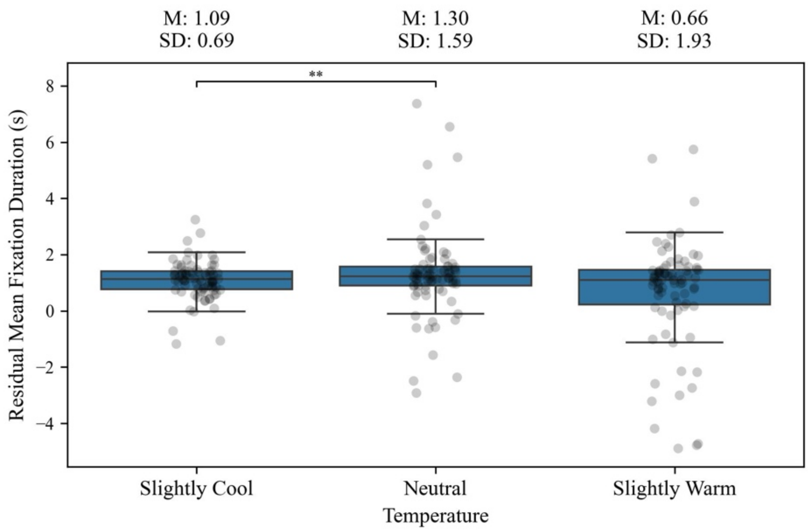
Dependent Variables (Model)	Independent Variables	F-value	*p*-value
Saccade Frequency	Temperature Condition	F(2, 230) = 3.73	.03**
	Carbon Dioxide Condition	F(2, 230) = 1.05	.3
	Temperature Condition × Carbon Dioxide Condition	F(2, 230) = 0.41	.7

	First Saccade Frequency	F(2, 230) = 28.45	< .0001**
Mean Fixation Duration	Temperature Condition	F(2, 229) = 4.50	.01**
	Carbon Dioxide Condition	F(2, 229) = 3.95	.048**
	Temperature Condition × Carbon Dioxide Condition	F(2, 229) = 1.32	.3
	First Mean Fixation Duration	F(2, 229) = 4.61	.03**
Mean Blink Duration	Temperature Condition	F(2, 229) = 0.34	.7
	Carbon Dioxide Condition	F(2, 229) = 3.62	.06*
	Temperature Condition × Carbon Dioxide Condition	F(2, 229) = 1.11	.3
	First Mean Blink Duration	F(2, 229) = 22.72	< .0001**
Blink Frequency	Temperature Condition	F(2, 229) = 2.04	.1
	Carbon Dioxide Condition	F(2, 229) = 3.37	.07*
	Temperature Condition × Carbon Dioxide Condition	F(2, 229) = 4.75	.01**
	First Blink Frequency	F(2, 229) = 112.24	< .0001**
SD Horizontal Fixation Positions	Temperature Condition	F(2, 229) = 4.46	.01**
	Carbon Dioxide Condition	F(2, 229) = 0.48	.5
	Temperature Condition × Carbon Dioxide Condition	F(2, 229) = 0.28	.8

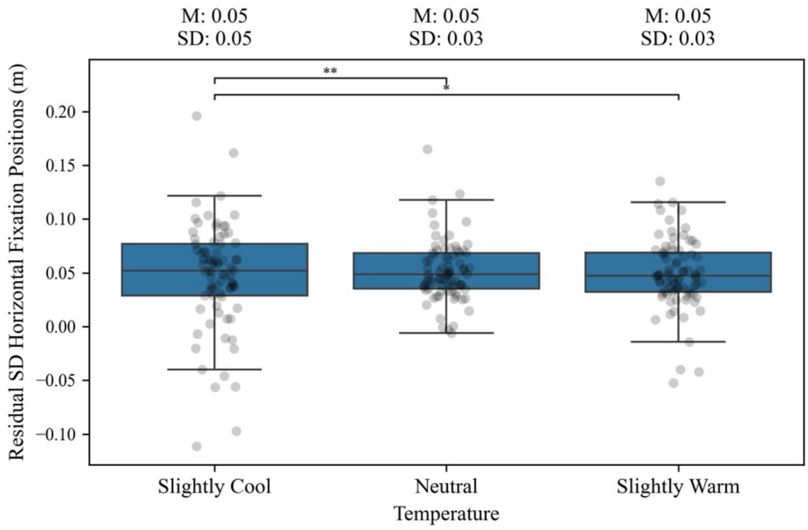
	First SD Horizontal Fixation Positions	F(2, 229) = 9.52	.002**
SD Vertical Fixation Positions	Temperature Condition	F(2, 230) = 2.53	.08*
	Carbon Dioxide Condition	F(2, 230) = 0.46	.5
	Temperature Condition × Carbon Dioxide Condition	F(2, 230) = 0.43	.7
	First SD Vertical Fixation Positions	F(2, 230) = 17.81	< .0001**
ANNI	Temperature Condition	F(2, 229) = 2.59	.08*
	Carbon Dioxide Condition	F(2, 229) = 0.79	.4
	Temperature Condition × Carbon Dioxide Condition	F(2, 229) = 0.75	.5
	First ANNI	F(2, 229) = 35.80	< .0001**



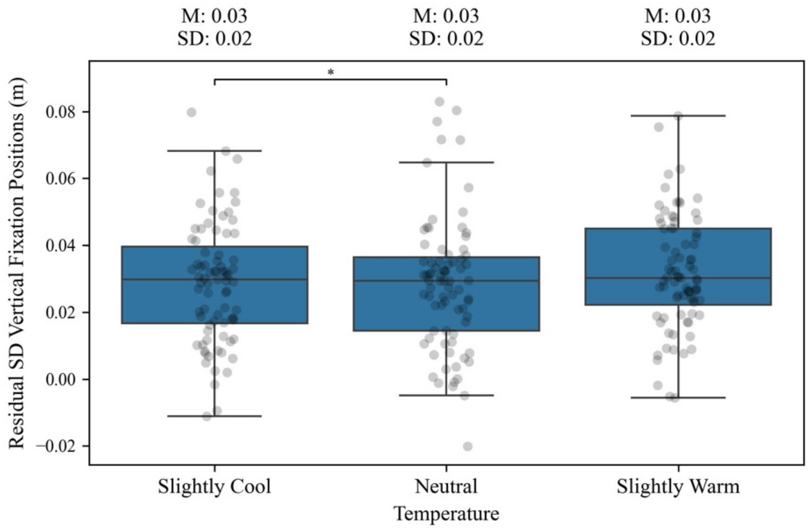
(a) *Saccade Frequency*



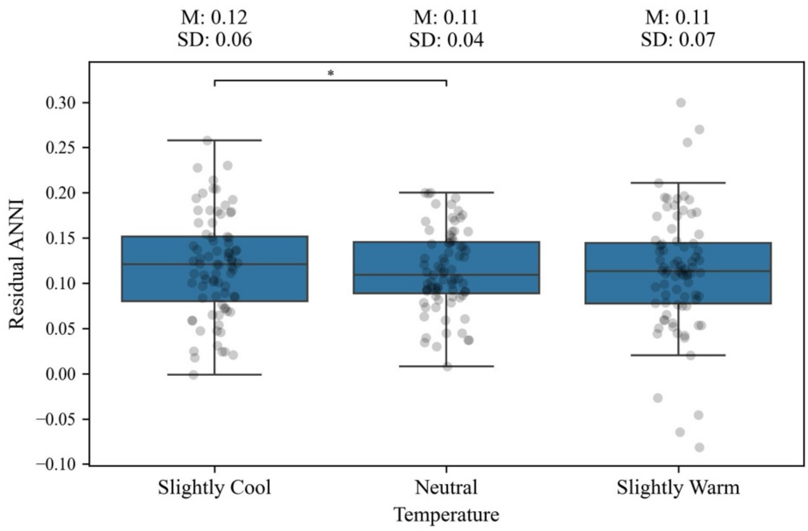
(b) *Mean Fixation Duration*



(c) *SD Horizontal Fixation Positions*

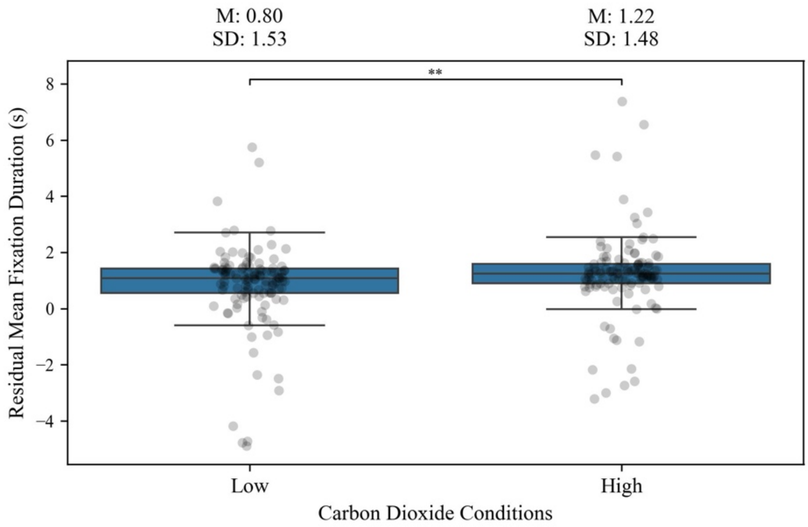


(d) *SD Vertical Fixation Positions*

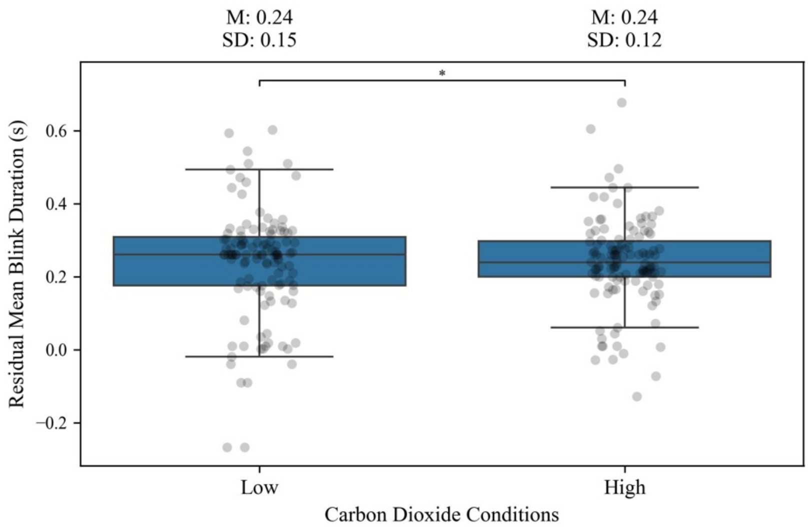


(e) *ANNI*

Figure 7 The effect of *Temperature* Conditions on gaze-related metrics.



(a) *Mean Fixation Duration*



(a) *Mean Blink Duration*

Figure 8 The effect of *Carbon Dioxide* Conditions on gaze-related metrics.

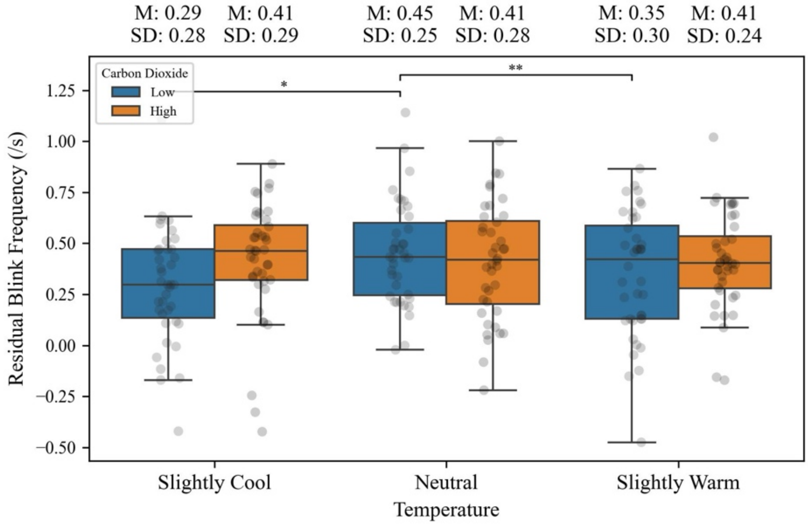


Figure 9 The interaction effect of *Temperature* Conditions and *Carbon Dioxide* Conditions on *Blink Frequency*.

5 DISCUSSIONS

Through a driving simulator study, we investigated the influence of cabin environment (specifically, temperature and carbon dioxide concentrations) on drivers' takeover performance in vehicles with SAE L3 automation. The results indicate that the HVAC setups can affect takeover speed, takeover quality, and drivers' visual behaviors in takeover events.

5.1 The Influence of Cabin Temperature

Slightly Cool Temperatures. In general, a slightly cool temperature could benefit drivers cognitively. Specifically, we found that compared to neutral or slightly warm temperature conditions, a slightly cool temperature resulted in higher saccade frequency, lower blink frequency, and more dispersed fixation positions. These are metrics that suggest reduced driver fatigue (Bafna & Hansen, 2021; Di Stasi et al., 2012; Schleicher et al., 2008), lower perceived workload (Benedetto et al., 2011; Charles & Nixon, 2019; Kummetha et al., 2020; Marquart et al., 2015; A. Wang et al., 2024) and enhanced situation awareness (Yang et al., 2024; Zhang et al., 2020). This is in line with previous research that exposure to moderate cool temperatures can enhance cognitive states, promoting higher alertness (through increased parasympathetic nervous system activity) and reducing mental load (Lan et al., 2022; Nelson et al., 2007; Tham & Willem, 2010; Wang et al., 2019). This cognitive facilitation effect of cooler environments was further supported by the shorter forward-gaze time observed under this condition.

However, this improvement in cognitive capabilities did not benefit takeover performance. In contrast, the slightly cool temperature resulted in higher SD of longitudinal acceleration as compared to neutral temperature, and higher SD of longitudinal speed as compared to warm temperature. These differences suggest that participants had less stable speed control with lower temperature. This may be explained as worse physical performance under low temperature, as has been suggested in previous studies in non-driving domain (Enander, 1987; Mäkinen et al., 2006; Pilcher et al., 2002; Provins & Clarke, 1960; Rammsayer et al., 1995).

Slightly Warm Temperatures. In contrast, slightly warm conditions resulted in quicker reactions and more stable lateral control simultaneously, as evidenced by faster takeover responses and smaller mean lane deviations compared to neutral temperatures. Such benefits differ from previous findings, which often reported performance impairments in high temperature environments. Two factors may account for this discrepancy. First, the warmer condition in this study remained within a moderate range, unlike the extreme heat exposures in prior research.

Second, a moderate increase in warmth may have elevated drivers' physiological arousal (Luo et al., 2023), thereby improving sensorimotor readiness (Racinais et al., 2017).

Thus, it seems that the temperature affected different driving-related capabilities differently. Given that conducting takeover tasks and post-takeover (manual control) tasks involve multiple resources, including sensory, physical (motor), and cognitive processes (Anstey et al., 2012; McDonald et al., 2019; Naujoks et al., 2018) and the takeover and manual driving performance can be moderated by the availability of these resources (Anstey et al., 2012; Anstey et al., 2005; He & Donmez, 2020; Marmeleira et al., 2012), we may need to consider the trade-off between different capabilities when identifying the "ideal" environmental temperature for the driving tasks in future works.

5.2 The Influence of Carbon Dioxide and Its Interaction with Temperature

The cabin carbon dioxide concentration can be affected by the HVAC setup. In this study, two realistic carbon dioxide concentration levels due to HVAC mode (i.e., recirculation ventilation and outside air ventilation) were investigated. In general, we found that high carbon dioxide concentration negatively impacted post-takeover performance, as indicated by increased variability in speed control (i.e., higher SD of longitudinal speed and acceleration). At the same time, elevated carbon dioxide concentration was associated with a longer mean fixation duration and longer mean blink duration, which can be considered as an indicator of increased fatigue (Bafna & Hansen, 2021; Di Stasi et al., 2012; Feldhütter et al., 2017).

Furthermore, carbon dioxide concentration appeared to moderate the influence of temperature. The beneficial effects of temperature on alertness were offset under high carbon dioxide exposure. Specifically, under low carbon dioxide levels, deviation from the neutral temperature (toward cooler or warmer conditions) was associated with reduced blink frequency (which can be associated with increased alertness (Bafna & Hansen, 2021; Di Stasi et al., 2012; Feldhütter et al., 2017)); whereas this effect was absent under high carbon dioxide levels.

5.3 Limitations and Future Work

Though noticeable effects of temperature and carbon dioxide levels were observed in our study, several limitations should be noted.

- Although this study included a relatively large sample and controlled key demographic variables (e.g., age, gender, sleep status) for the sake of a between-subjects experiment design, individual differences in susceptibility to environmental stressors can hardly be controlled. Prior research suggests that emotional states (Wang & Liu, 2020), medical conditions (Downs et al., 2005), and lifestyle habits (e.g., smoking, alcohol consumption) (Terborg et al., 2002; Yoda et al., 2008) can influence individual responses to environmental stressors. Future work should therefore consider adopting within-subject designs or incorporating more diverse and heterogeneous samples to characterize how individual susceptibility moderates the relationship between environmental conditions and takeover performance. Such insights would support the development of personalized, adaptive in-cabin climate control strategies in autonomous vehicles.
- The effects of environmental conditions are not uniform across different driver capabilities (sensory, physical, and cognitive). Moreover, takeover scenarios with

varying levels of urgency and complexity place different demands on these capabilities. Hence, future studies could investigate how specific cabin environmental factors affect driver performance across different types of takeover scenarios, enabling a more nuanced understanding of these interactions.

- Future research should extend these findings to dynamically changing environmental exposures. For example, in urban driving contexts, drivers may frequently open and close windows, resulting in fluctuating carbon dioxide concentrations. Similarly, changes in solar radiation and window status can lead to dynamic variations in cabin temperature. Such transient environmental changes may interact differently with driver physiology and behavior compared to steady-state exposures, and thus merit dedicated investigation.
- This study was conducted in a driving simulator. Though it can allow better control of experimental factors, it may not fully replicate realistic driving risk (e.g., collision risk), and the frequency of TORs one may typically encounter in a drive. Further, real-world in-cabin environments are inherently more dynamic compared to those in a driving simulator. The environmental factors (e.g., humidity, solar radiation, noise and vibrations) may jointly influence driver state and behavior and may vary gradually. Thus, future studies should be conducted in naturalistic settings or climate-controlled real vehicles, where such complexities can be better captured and modeled.
- The relatively long driving duration in the experiment, though, has replicated the real-world long-distance driving with driving automation, may have introduced a fatigue effect and influenced the results. Future research may adopt a more targeted experiment

design to isolate the fatigue effect and the cabin environment effects (e.g., by dividing the experiment into shorter sections and allowing rests between takeover events).

- Finally, it should be noted that to control for the potential individual differences, we included the metrics from the first takeover event as the covariate in all models. Although using metrics from a real takeover event instead of simple in-lab tasks would improve the validity of the baseline data, the baseline metrics were extracted after approximately 15 minutes of driving. Thus, the baseline data may have already been affected by the environmental factors (as the environmental factors were pre-set to avoid the influence of the transient environment). Future research is needed to better isolate the individual effect.

6 CONCLUSIONS

For the first time, we explored the effects of cabin environment (cabin temperatures and carbon dioxide concentration levels) on drivers' takeover performance in conditional automated driving. We found that:

- A slightly cool temperature can impair post-takeover performance, while the slightly warm temperature tested in our experiment did not. Future HVAC control strategies should take this into consideration, for example, by moderately raising the cabin temperature during summer or providing localized heating to hands and feet in winter, to ensure timely and effective driver performance while optimizing energy efficiency.

- The impact of environmental factors on different capabilities (i.e., sensory, physical, and cognitive) is not uniform. Specifically, slight cool temperature, though impaired post-takeover performance, seemed to have improved drivers' cognitive capabilities and reaction time. Thus, future HVAC may need to consider the contribution of different capabilities on driving performance when designing adaptive cabin environment control strategies.
- The high carbon dioxide concentration, simulating the recirculation ventilation, can deteriorate takeover performance and drivers' cognitive states. Future HVAC design should take carbon dioxide into consideration. More research is needed to identify the critical carbon dioxide level threshold in the cabin to ensure driving safety.

6.1 Practical Applications

The influence of environmental factors on human performance has been extensively studied in built environments, with standards such as the ASHRAE (American Society of Heating, Refrigerating and Air-Conditioning Engineers) Standard 62.1 specifying carbon dioxide as a metric for acceptable indoor air quality (not exceeding 700 ppm above atmospheric levels, i.e., an absolute value of no more than about 1200 ppm) (ASHRAE, 2016), along with the increasing adoption of smart energy management systems in homes (Kim et al., 2021). However, the automotive industry still lacks regulations and standards for cabin environments. This gap is critical, given the complexity of driving tasks and the strong association between cabin environment and driver performance we have identified. The diversity of the "ideal" environment of different driver states also introduces challenges for controlling the cabin environment to balance different capabilities. Future vehicle HVAC systems should integrate the information from environmental sensors, expert knowledge, and occupant states to balance energy efficiency, driving safety, and occupant well-being. The findings of this study provide a valuable reference for policymakers and manufacturers in developing relevant regulations and standards, thereby supporting the advancement of safer and more sustainable intelligent vehicles.

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[Placeholder for double-blinded review]

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

[Placeholder for double-blinded review]

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