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Leveraging peripheral interactions to improve drivers' situation awareness and NDRT efficiency

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Abstract: L3 automated driving has introduced a trend of drivers engaging in non-driving-related tasks (NDRTs), but it also poses safety challenges for reconstructing drivers' situation awareness (SA). Two consecutive empirical studies in a driving simulator were conducted to investigate the effect of two peripheral interactions (airflow conveying the intended behaviors of vehicles and surround sound conveying the information of road users) on drivers' SA performance, NDRT efficiency, workload, and user experience. The first study (n=21) explored the differential effects of airflow, surround sound, and their integration. The second study (n=30) investigated how the integrated interaction performed across different NDRT difficulties. Results demonstrated that airflow and surround sound could significantly improve drivers' SA when used individually, each having distinct advantages. The integration of these two interactions yielded the best results. Notably, the integrated interaction showed greater effectiveness in improving SA during hard NDRT compared to the easy one. Furthermore, drivers reported reduced subjective workloads and enhanced user experience when leveraging these peripheral interaction methods. Our work offers insights for designing in-vehicle interaction systems that not only reconstruct drivers' SA but also support NDRT participation, ensuring safety and productivity.

Key words: Automated driving; Situation awareness; Non-driving-related tasks; Peripheral interaction; Surround sound; Airflow

1 Introduction

Automated driving technology is transforming the driving experience. SAE (2021) classified automated driving into six levels (L0–L5), among which each level has special requirements on drivers' situation awareness (SA). L2 automated driving systems maintain drivers' SA and support their monitoring of driving, thus keeping drivers vigilant and ready to intervene when necessary (National Transportation Safety Board, 2018; DeGuzman and Donmez, 2024). L3 automated driving has introduced a new trend in which drivers engage in non-driving-related tasks (NDRTs), offering a productive use of travel time (Wörle and Metz, 2020; SAE, 2021). However, it also introduces new challenges between safety and drivers' productivity. This shift to NDRT engagement in L3 systems results in a decrease in SA and an increased workload of drivers (Zangi et al., 2022). Drivers need to disengage from NDRT and "reconstruct" SA to take control when facing situations that exceed the automated vehicle's operational design domain (Clark et al., 2017; Chen et al., 2024). This is risky and diminishes the NDRT efficiency. Therefore, how to support drivers in reconstructing SA while maintaining NDRT efficiency in L3 automated driving systems has become a critical issue.

1.1 Information required to reconstruct situation awareness

SA is a significant safety factor for performing complex tasks, such as aircraft control and driving (Endsley, 1995, 2001). Endsley's model structured SA into three hierarchical levels: (1) Level 1—perception of the elements in the environment; (2) Level 2—comprehension of the current situation; (3) Level 3—projection of future status in the dynamic environment. In each level of SA for automated driving, two types of elements are considered: road users (e.g., other vehicles, pedestrians, and cyclists) and the state of the automated vehicle (e.g., operational modes and intended behaviors such as

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lane changing and braking) (Endsley, 2020).

Road users are characterized by their direction and relative speed (Xing et al., 2017; Li et al., 2019; Löcken et al., 2020), which supports the perception level of SA. A higher SA level requires dynamic information, such as the trajectory and changing distance, which is absent from most studies. Researchers have begun to address this gap by using signals such as red arrows to indicate the forward trajectories of nearby vehicles and pedestrians (Naujoks and Neukum, 2014; Yang Z et al., 2019), and to communicate the information of blind-spot road users (Xing et al., 2017).

Supplementing the information on the vehicle's intended behavior enriches situational information and may improve drivers' SA. However, recent research that exhibits behaviors such as braking, steering, and turning overlooks their continuous and dynamic nature by using a fixed form, such as a 0.5 Hz pulse light emitting diode (LED) for turning (Yang YC et al., 2018). Automated vehicles move and continuously influence the distance, relative speed, and potential risks associated with nearby road users, calling for a dynamic presentation of vehicle behaviors.

In summary, foundational SA theory underscores the importance of integrating two key informational elements: the status of external road users and the vehicle's intended behaviors. Existing studies have begun to explore the presentation of each element individually. However, the effective co-presentation of these two information streams, particularly their dynamic relationship over time, has been overlooked. Therefore, investigating how to communicate this interplay effectively is a crucial step to support driver SA reconstruction.

1.2 Interaction methods that convey situational information

While visual methods are effective in conveying road user and vehicle information (Stapel et al., 2019; Colley et al., 2021a; Detjen et al., 2021), their high demand on drivers' attention and visual workload creates a conflict (Wandtner et al., 2018; Chai et al., 2024). This is particularly problematic in L3 driving, where NDRT participation is expected and permitted, and visual-demand NDRT is the most popular activity (Pfleging et al., 2016). This necessitates an exploration of less obtrusive interaction methods. The automated driving systems should balance drivers' SA with minimal disruption to their NDRT, which might be achieved through unobtrusive interaction methods that minimize competition for sensory and cognitive resources.

Peripheral interaction offers a promising approach for resolving this conflict, which aims to make interaction systems accessible in the periphery of attention (Bakker, 2013; Bakker et al., 2015). It is important to clarify that this concept refers to the periphery of a user's attention, rather than their physiological peripheral vision. Peripheral interaction allows users to remain focused on their NDRTs while receiving and processing information from the automated system through low-load cues in the periphery of their attention. This design enables them to easily shift their focus back to the driving task when required.

Spatial auditory interaction is a prime candidate for implementing peripheral interaction and can be intuitively interpreted by humans without requiring high-level cognitive processing, making it well-suited as a medium for peripheral interaction. It provides directionality and positional awareness by blending the surrounding physical world into auditory content and augmenting users' real acoustic environments (Zhao et al., 2018; Yang J et al., 2022). For example, Schoop et al. (2018) warned cyclists of a blind spot when there are approaching vehicles by sonifying road objects in real-time 360 degrees to augment the users' field of view. This system mapped the direction of dangerous objects to sound direction and proximity to rhythm and pitch. Wang MJ et al. (2017) provided advisory information through the surround sound inside the vehicle, including directions of other road users and risk levels.

The display method is an important factor in peripheral auditory interaction. The two studies above presented types of road objects by earcons, which might lead to confusion when multiple road users are present in the nearby area and often result in comprehension difficulties (Beattie et al., 2015; Wang MJ et al., 2017). In contrast, auditory icons impose a low cognitive load as they leverage humans' inherent ability to recognize natural sounds, making information processing more intuitive and efficient. They could communicate situational information effectively by matching different types of road users to distinct sound effects, making it easier for users to isolate and identify different sounds (Hermann et al., 2011; Schoop et al., 2018). Some research also indicated that the compressed auditory icons prompted driving performance over other auditory displays (Song et al., 2022; Chai et al., 2024). Given these findings, using auditory icons to display spatial auditory interactions merits further exploration for enhancing drivers' comprehension of traffic situations.

Beyond the auditory channel, airflow offers another promising method to convey the behavioral information in a minimally disruptive manner. Previous research delivered directional cues in the cockpit by reproducing senses of touch through force feedback and vibration (Kern et al., 2009; Borojeni et al., 2017; Cohen-Lazry et al., 2019; Meinhardt et al., 2024). Alternatively, research in other fields has investigated air-based feedback to recreate the feeling of movement in a relatively calm environment. For instance, Rietzler et al. (2017) and Tseng et al. (2022) modulated bursts of compressed air to the face and provided directional cues to improve the experience of virtual teleportation. Their findings revealed that carefully calibrated airflow duration and speed significantly improved users' motion perception. While airflow has been proven effective in delivering motion information, its application in in-vehicle interaction remains nascent. Recently, preliminary research has also begun to explore the use of airflow in in-car virtual reality (VR) environments to enhance passengers' motion perception and immersion (Yeo et al., 2025), but this application is still focused on creating an overall atmosphere rather than conveying more detailed dynamic information, such as the vehicle's behavioral risks. Considering the natural association between airflow and motion, airflow may be particularly suitable for the enclosed cockpit environment, where the absence of natural air resistance makes the perception of airflow more pronounced.

Airflow's suitability is particularly evident when compared to traditional haptic feedback, such as vibration. The vehicle's natural operation generates constant vibrations from the engine and road surface, which can interfere with and mask deliberately generated vibrotactile signals, reducing their effectiveness for in-vehicle interaction. Airflow, in contrast, utilizes a distinct and less occupied sensory channel, avoiding this issue of sensory masking. By leveraging the natural association between air movement and physical motion, airflow may provide drivers with unambiguous cues about the vehicle's intended behaviors in a way that is robust against the inherent sensory noise of the driving environment.

1.3 Interaction timing and duration that convey situational information

Determining the appropriate timing and duration of initiating interactions with drivers constitutes a fundamental challenge since drivers require time to reconstruct SA when resuming control from NDRT participation. Samuel et al. (2016) found that drivers needed a lead time of at least 8 s to detect a latent pedestrian hazard, while Lu et al. (2017) discovered that drivers required at least 20 s to assess relative speeds. However, the interval between the automated system's request and the takeover is relatively short in some critical scenarios. Such limited duration impedes drivers' comprehensive awareness of the traffic situation and potentially leads to high cognitive load (Du et al., 2020; Xu CL et al., 2022). Consequently, the short duration of information presentation typically limits it to describing only instantaneous states (e.g., pedestrians' location and moving direction), with little presentation of continuous and dynamic motions (e.g., the trend of relative speed and fluctuating distance). Most of the interaction methods described above only initiate interaction when takeover is required, which restricts drivers from understanding and predicting traffic conditions.

The two-stage transition procedure, which separates the process into monitoring and takeover, would be an effective approach for addressing the temporal challenge (Epple et al., 2018; Ma et al., 2021; Xu LL et al., 2022). Hasegawa et al. (2024) demonstrated that two-stage methods could promote drivers' proactive gaze behavior and enhance the construction of SA. However, they also claimed that such an approach is likely to increase driver pressure, tension, and workload. Moreover, Nahin Ch et al. (2024) found that when drivers were allowed a longer takeover time (30 s versus 10 s), they were more likely to interleave between NDRT and driving rather than immediately stopping the NDRT and switching directly to driving. Extended takeover time budgets were associated with increased driver engagement in NDRTs, indicating that temporal constraints substantially influence how drivers allocate their attentional resources during transitions. These findings emphasize the importance of providing adequate preparation time for drivers to manage both their NDRT completion and the resumption of driving responsibilities. This insight informs the design of more effective driver–vehicle interaction systems.

1.4 Aim of our work

Investigating interaction methods for information delivery to enhance drivers' SA in L3 automated driving is an engaging research topic. Our work further explores how to improve drivers' performance in NDRT while simultaneously reconstructing their SA and maintaining driving safety. Peripheral interactions offer a promising solution to balance SA performance and NDRT efficiency. Specifically, leveraging peripheral interactions involving surround sound and airflow to convey dynamic situational information in vehicles has great potential to support our goal. Besides, few studies have explored the effects of these two interactions on SA performance or their effectiveness under different levels of NDRT difficulty. Filling in these gaps can offer valuable insights into optimizing interactive system design in L3 automated driving, thereby improving driver experience. Thus, we coded the attributes of road users by surround sound and the intended behaviors of the automated vehicle by airflow. Two consecutive empirical studies were conducted to verify the effects of the interaction methods. The first one compared the impacts of only airflow, only surround sound, and the integrated interaction on drivers' SA performance and NDRT efficiency. The second one further explored the effect of integrated interaction across NDRTs of different difficulties. Our work was guided by the following research questions:

RQ1: How do surround sound and airflow affect drivers' SA performance and NDRT efficiency?

RQ2: How does the integrated interaction of surround sound and airflow affect drivers' SA performance under NDRTs of different difficulties?

RQ3: How do the surround sound and airflow affect drivers' workload and user experience?

2 Methods

2.1 Participants

In Study 1, we recruited 21 participants (male=10, female=11) through a posting on campus. They had an average age of 23.10 (SD=3.15) and an average driving experience of 2.86 years (SD=1.77). In Study 2, a total of 30 participants (male=16, female=14) with an average age of 23.57 years (SD=2.62) were invited, and their average driving experience was 4.06 years (SD=1.99). Participants were free from any musculoskeletal, neurological, cardiac, or vascular disorders and were not taking medications that could impair driving performance. No one reported visual or auditory impairments. All of them signed a consent form, which included safety instructions and the use of collected data. After the study, participants received 60 RMB (roughly 8 USD) as compensation.

A power analysis was conducted using G*Power (Version 3.1) to determine the sufficient sample size. We aimed to detect a medium-to-large effect size (f=0.30), as we were interested in identifying interaction methods with a substantial impact on driver performance on SA. Based on parameters for a repeated measure analysis of variance (ANOVA) (power=0.80, significant level α=0.05, four measurements), the analysis indicated a required minimum sample size of 17 participants. Our recruited sample sizes for Study 1 (n=21) and Study 2 (n=30) both exceeded this requirement, ensuring adequate statistical power for our analyses.

2.2 Experimental variables

Studies 1 and 2 both utilized a within-subject 2×2 design. Study 1 investigated how airflow and surround sound affected drivers' SA performance, NDRT efficiency, workload, and user experience. The independent variables were airflow presence (with/without) and surround sound presence (with/without). This allowed a comparison between the surround sound and airflow and investigated their interaction effect. Study 2 tested whether the integrated interaction of surround sound and airflow performed well under NDRT of different difficulties. The independent variables were the interaction method (baseline/integrated interaction) and NDRT task difficulty (easy/hard). The dependent variables included SA, NDRT efficiency, workload, and user experience.

2.3 Coding of surround sound and airflow

The surround sound encodes three key attributes of road users: category, relative distance, and spatial direction to the automated vehicle. Airflow informs drivers of the vehicle's intended behaviors, including longitudinal (braking) and lateral (steering and lane-changing) behavior modes. The rationale for selecting airflow is its connection to motion perception. Humans naturally associate the sensation of airflow with dynamic movement, a perceptual cue that is lost within the relatively enclosed environment of a vehicle cockpit. By artificially generating directional airflow, our method aims to restore this sensory feedback, creating a simulated sense of motion that is directly and intuitively linked to the vehicle's own behaviors. Specifically, airflow focuses on braking because it is closely linked to safety concerns that might even escalate the accident potential, while acceleration generally does not directly result in a collision. In addition, both interaction methods convey risk levels determined jointly by road users and vehicle behaviors.

2.3.1 Road user information conveyed by surround sound

Presenting the category of road users by sound effects. We use sound effects to represent the road user category, which is shown in Table 1. They are collected from real-world traffic to help drivers quickly link auditory information to road users.

Presenting the direction and distance of road users by sound angle and volume. This intuitively conveys the relative direction and distance of road users. Specifically, the sound angle matches the angular position of the road user relative to the vehicle, with the sound volume increasing linearly as the distance decreases. When the automated vehicle is in immediate proximity to other road users, the volume at the driver's location is around 60 decibels (Lerner et al., 2015; Šabić et al., 2021).

Low-risk road users are presented with a baseline rhythm (60 beats per minute, each lasting 600 ms), while the medium and high risks accelerate to 120 beats per minute, each lasting 300 ms, and 240 beats per minute, each lasting 150 ms, respectively. Note that the rhythm for road users changes with their risk levels.

Presenting information from multiple road users. To reduce the confusing cacophony, we reduce the number of icons by merging similar road users. Similar road users include: (1) belonging to the same category; (2) moving in the same direction.

When integrating similar road users, the risk level is determined by the highest road user, while auditory icons persist from the initial appearance of the earliest road user until the final disappearance of the latest road user. Road users who do not meet the criteria are presented as individual auditory icons.

2.3.2 Vehicle behaviors conveyed by airflow

Presenting the behavior modes by airflow direction. Lateral behaviors are presented by airflow from the corresponding side. During high-speed movement (such as cycling), people naturally experience forward airflow when moving straight forward and a shift of airflow toward the turning side when changing direction. Our method amplifies this directional change by controlling side airflow, enhancing the perception of natural variation in relative airflow direction that occurs during lateral movements.

Braking is encoded by forward airflow, which appears counterintuitive given the reduced frontal airflow experienced during deceleration. However, we discover that people are less sensitive to rear airflow than forward airflow. Furthermore,

Table 1 Mapping between driving information and encoded auditory and airflow cues

Driving information	Attribute	Value	Cue type	Cue value
Road user information	Category	Pedestrian Bicycle Vehicle	Sound effect	Footsteps Ringing bells Motor roar
	Direction	–	Sound angle	–
	Distance	–	Sound volume	–
	Risk level	Low Medium High	Sound rhythm (duration/interval)	60 beats/min (600/400 ms) 120 beats/min (300/200 ms) 240 beats/min (150/100 ms)
Intended behaviors	Behavior	Braking Left movement Right movement	Airflow direction	Front Rear left Rear right
	Risk level	Low Medium High	Airflow frequency (duration/interval)	60 times/min (800/200 ms) 120 times/min (400/100 ms) 240 times/min (200/50 ms)

participants experiencing a brief training period could reliably recognize this interaction, making forward airflow an effective signal for braking.

2.3.3 Risk level classification and presentation

The risk level serves as a unifying variable that dynamically modulates both the surround sound and airflow interactions. It is determined by time to collision (TTC) (Wang MJ et al., 2016), which assesses the safety of road users by calculating the time remaining before a collision if two road users continue on the same route at the same speed (Vogel, 2003). TTC further classifies risks into three levels (low, medium, and high) based on prior studies (Vogel, 2003; Wang MJ et al., 2017), as shown in Table 2. Note that the risk level arising from the relationship between road users and vehicle behaviors influences each other and continuously evolves over time. The surround sound and airflow interact with drivers when the road users and intended behaviors reach the threshold of low risk and end when TTC>10 s. During this process, risk levels may gradually shift from low to high, and this dynamic change will subsequently influence the coding of follow-up information.

Table 2 Risk levels and their corresponding time to collision (TTC)

Risk level	No risk	Low	Medium	High
TTC (s)	>10	6–10	3–6	2–3

Presenting the risk level of road users by sound rhythm. The rhythm of sound (the times that auditory icons are repeated in one second) is utilized to express the risk level. Studies have shown that the rhythm of sound could express urgency (McNeer et al., 2007). Compared to the tradition of using pitches for attention (Edworthy et al., 1991), rhythm does not distort auditory icons. Besides, it does not result in chaos when multiple road users exist. Aligning with human perception, we establish a baseline rhythm of 60 beats per minute, corresponding to a standard quarter-note rhythm.

Presenting the risk level of behaviors by airflow frequency. The specifics are shown in Table 1. For low-risk behaviors, intermittent airflow is emitted from the corresponding side at 60 bursts per minute, with each burst lasting 800 ms followed by a 200 ms interval. This frequency aligns with common sound rhythms, reducing drivers' learning effort and cognitive load by leveraging their inherent familiarity with rhythmic patterns.

2.3.4 Implementation and apparatus

Surround sound was delivered through a 5.1-channel surround sound system (EDIFIER R501BT). Four speakers were placed separately in the left front, right front, rear left, and rear right of the driver (Fig. 1). To enhance the sense of reality, the surround sound also reproduced realistic ambient sounds (including engine sounds and wind noise) at around 40 decibels. We utilized Adobe Audition to create the 5.1-channel audio clips for the experimental scenarios. These clips were integrated into the Unity simulation and triggered when corresponding road users occurred.

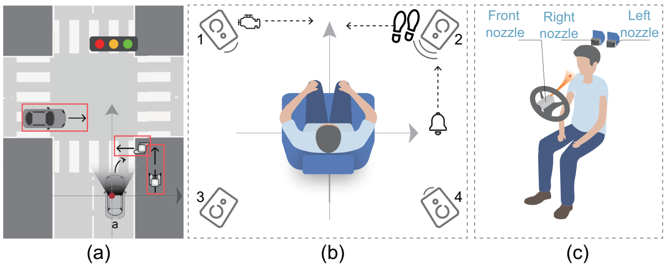

Fig. 1 Conceptual illustration of the proposed multimodal coding for conveying road user information and intended vehicle behaviors through surround sound and airflow cues. (a) A scenario. (b) According to (a), drivers hear the sound of a footstep from speaker 2, a motor roar from speaker 1, and a ringing bell mainly from speaker 2. The sound will move along the dotted line in the speakers. (c) When drivers hear the footstep sound from the right front, they will feel the airflow from the front nozzle, which indicates braking

The device consisted of three main components: a 24-liter air tank for storing compressed air, an electro-pneumatic pressure regulator (SMC-ITV2050) for adjusting airflow pressure, and three solenoid valves (DELIXI-2V025-08). These valves were connected to three corresponding cylindrical nozzles (2 mm inner diameter), which were positioned behind the steering wheel and at either side of the driver's seat (Fig. 2). The airflow device generated a concentrated and coherent airstream, which was approximately 4 m/s (Gentle Breeze level, Beaufort scale). The selection criterion for the airflow velocity was to balance clear perceptibility with driver comfort, determined through pilot testing. The electro-pneumatic regulator (5–900 kPa) was governed by a 0–10 V signal from a PWM-voltage converter connected to Arduino Uno (255 PWM steps). Unity software communicated road user attributes to Arduino through the serial port, which controlled solenoid valves to generate frequency-specific airflow. To ensure the consistency and stability of airflow velocity, the output from each nozzle was calibrated to the selected velocity at the position of the driver's head using a digital anemometer (UT363BT).

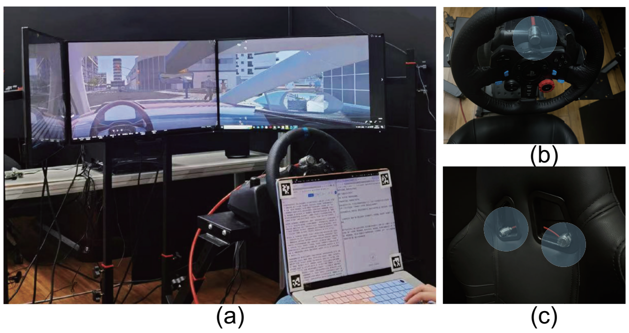

Fig. 2 Physical implementation of the proposed airflow system in the driving simulator: (a) the driving simulator is presented on three 27-inch displays; (b) the front nozzle is behind the steering wheel; (c) the rear nozzles are mounted to the seat

2.4 Experimental settings

2.4.1 Driving simulator

The driving simulator consisted of three 27-inch monitors to display the first-person view from the car's windshield, side windows, and rearview mirrors (Fig. 2). A Logitech G29 Racing Wheel was installed in front of the participants, overlaying the steering wheel presented on the screen within their field of view. The urban traffic environment and all the scenarios were constructed using Unity 3D.

2.4.2 Non-driving-related task

In our studies, typing was selected as the productive NDRT. This task was chosen for two primary reasons: (1) realism and productivity—it represents a highly realistic and productive activity, simulating common in-vehicle behaviors in which drivers are likely to engage, such as handling work emails, sending messages, and creating content; (2) high attentional demand—typing is an activity with high visual and cognitive demands, which creates a direct competition for the attentional resources required to maintain SA. By occupying the driver's visual resources, this task provides a rigorous test case to evaluate the effectiveness of our non-visual interaction methods. Its common adoption as a benchmark in previous research further validates the rationale for this choice (Zeeb et al., 2015; Shi E and Bengler, 2022; Zhang N et al., 2023; Nahin Ch et al., 2024). Participants performed this task on a 16-inch MacBook Pro. To ensure a standardized posture and interaction context across all participants, they were instructed to place the laptop on their laps for the duration of the task. In Study 1, participants typed passages from the vernacular Chinese version of *Dream of Red Mansions*, which is easy to understand and helps maintain focus on the task, allowing us to assess the impact of two interaction methods on drivers' SA performance. In Study 2, we introduced passages from both the vernacular and classical Chinese versions of *Dream of Red Mansions*. Vernacular Chinese aligns with current language habits, while classical Chinese is more obscure and challenging to type. By using passages from a single source, we ensured that the primary variable affecting NDRT difficulty was the language style, providing a controlled comparison.

2.4.3 Simulated traffic scenarios

Referring to previous work (Wang MJ et al., 2017; Park et al., 2022), we present three common types of road users and five categories of their behaviors (Table 3). These user–behavior pairs may occur simultaneously within one traffic scenario.

We defined 14 scenarios in total (Table 4). The number of road users within each scenario varied from one to three. For example, Scenario 7 features two pedestrians crossing the road at medium risk, a car approaching from behind at medium risk, and a bicycle navigating a high-risk path by making a left turn ahead.

2.5 Measurements

1. Situation awareness

We adopted a query technique called the situation awareness global assessment technique (SAGAT) to measure drivers' SA performance (Endsley, 1988). SAGAT employs a freeze-probe technique, where the simulation is paused immediately after a traffic scenario, requiring participants to answer memory-based questions. Research has proved that the freeze will not influence the performance of participants' SA or workload (Durso et al., 2006; Loft et al., 2015; Endsley, 2021). However, SAGAT may interfere with the NDRT participation, a limitation confirmed in our pilot study, where participants reported the requirement of additional time to reorient and locate their previous typing position following each freeze. To

Table 3 An overview of road users and their behaviors

Road user type	Oncoming	Approaching from behind	Decelerating in front	Cutting in	Crossing/Jaywalking
Vehicle	+	+	+	+	+
Bicycle	–	+	+	+	+
Pedestrian	–	–	–	–	+

"+" means we defined the road user behavior in our studies and "–" means we did not

Table 4 Fourteen scenarios used in the studies

Scenario	Road user behavior	Scenario	Road user behavior
1	Oncoming vehicle* Rear vehicle approaching***	8	Oncoming vehicle* Pedestrian crossing**
2	Front vehicle decelerating* Pedestrian crossing***	9	Rear vehicle approaching** Bicycle crossing***
3	Oncoming vehicle** Pedestrian jaywalking***	10	Front vehicle decelerating* Pedestrian crossing**
4	Bicycle crossing* Vehicle crossing***	11	Front vehicle decelerating** Bicycle jaywalking***
5	Oncoming vehicle* Front bicycle decelerating**	12	Front vehicle decelerating* Pedestrian jaywalking***
6	Oncoming vehicle* Bicycle crossing**	13	Rear vehicle approaching* Vehicle cutting in***
7	Pedestrian crossing** Rear vehicle approaching** Bicycle jaywalking***	14	Rear vehicle approaching* Vehicle cutting in** Pedestrian crossing***

*, **, and *** refer to risk levels of low, medium, and high, respectively

mitigate this impact, the formal procedure required participants to identify their prior typing position before resuming.

The design of our SAGAT questions was guided by the goal of creating a comprehensive measure of a driver's overall SA. Rather than analyzing performance on each of Endsley's SA levels separately, our criterion was to ensure that the question set provided full coverage across all three levels of SA. To this end, questions were formulated to probe the perception of basic elements (e.g., road user categories), the comprehension of their meaning (e.g., the reason for a vehicle's action), and the projection of their status (i.e., risk assessment). The detailed SAGAT standardized questions are listed in Table 5.

Our SAGAT measurement was composed of three parts: road user information, vehicle behaviors, and risk assessment. For Questions 1, 5, 7, and 8, participants must provide the correct answer accurately. For Question 6, participants were required to identify the specific road user who directly caused the vehicle's behavior. Questions 2, 3, and 4 allowed for a margin of perceptual errors. For example, the right answer to "what is the moving direction of the pedestrian" might be "from 1 o'clock position to 10 o'clock position." Due to the vehicle's movement and perception errors, we gave a +/− 1 o'clock error margin. Thus, a response like "I think the pedestrian began crossing the road at my 2:00 position and finished crossing at my 9:30 position" would be considered correct.

Two researchers assessed the participants' responses based on correct answers. The SAGAT score for a single scenario was the ratio of the number of correct answers to the total number of questions, and the average score of four scenarios was taken as the SAGAT score for the trial.

2. NDRT efficiency

We calculated the number of correct characters per minute (CPM) to quantify participants' NDRT efficiency. This metric reflects the participants' typing speed and their typing accuracy.

3. Workload

We treated "typing in the automated L3 vehicle and reconstructing SA" as a unified task and measured the associated workload using the raw NASA-TLX questionnaire (Hart and Staveland, 1988). NASA-TLX is one of the most commonly used subjective rating techniques for detecting workload. Participants were asked to rate each sub-scale from one (strongly disagree) to seven (strongly agree).

4. User experience

The user experience questionnaire (UEQ) with questions about trust and sense of control was selected. Each sub-scale rates from one (e.g., very unattractive) to seven (e.g., very attractive) (Laugwitz et al., 2008), which is commonly used to measure drivers' UX with the automated driving systems (Löcken et al., 2020). In addition, we measured participants' trust and sense of control as supplements and carried out semi-structured post-interviews after they finished driving.

2.6 Procedure

The procedure is shown in Fig. 3. It includes three parts: familiarization, driving with a typing task, and an after-driving survey.

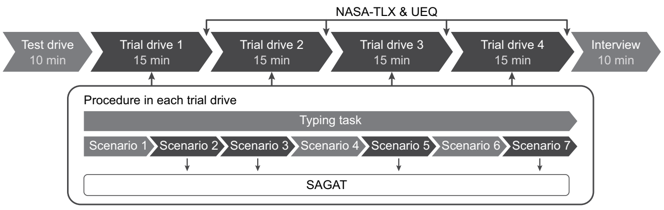

Fig. 3 Overview of the procedure. Participants completed four driving trials. Each trial contained seven scenarios, among which four were randomly selected for SAGAT questionnaires. After each drive, participants filled out the NASA-TLX and UEQ questionnaires

1. Familiarization. The empirical study began with an overview and a demographic questionnaire. Participants were informed that they would be in a vehicle equipped with an L3 automated driving system. The instructions explained that the system would manage the primary dynamic driving tasks, including steering, acceleration, and braking, in most situations, allowing them to focus on the typing task. However, they were explicitly told that the system cannot handle every possible traffic event and that maintaining awareness of the driving environment was necessary. Next, participants were introduced to the encoding rules for auditory and airflow feedback, followed by sample clips to facilitate learning. To ensure that participants understood the information coding, a recognition test was conducted, requiring an accuracy rate of over 90% as a prerequisite for proceeding. Then, participants would take a 10-minute drive to become familiar with automated driving and the interactions. After the test drive, participants were required to answer SAGAT questions using the clock-face method several times to ensure that they were fully familiar with the SAGAT approach.

Table 5 SAGAT questions in two studies

Category	SAGAT question	Answer
Road user information	1. What are the categories of road users in the scenario?	Pedestrian/bicycle/vehicle
	2. What is the relative position of the road user when it appears?	Twelve directions on the clock
	3. What is the relative position of the road user when it is closest to your vehicle?	Twelve directions on the clock
	4. What is the moving direction of the road user?	E.g., from 2 to 5 o'clock
Vehicle behaviors	5. How does the vehicle intend to behave in response to the scenario?	Braking/left (right) movement
	6. What is the reason for taking these actions?	E.g., "brake to avoid pedestrians"
Risk assessment	7. What is the risk level of the road user?	High/medium/low
	8. What is the risk level of the behavior in the scenario?	High/medium/low

2. Driving with a typing task and the SAGAT test. Each participant was required to complete four trials. During each trial, participants started typing as soon as the automated driving began. They were presented with a random text from the Chinese *Dream of Red Mansions* on the left side of a laptop and asked to type the material on the right side (the laptop was carried by the driver on their legs). Each trial contained seven traffic scenarios. For the four randomly selected scenarios designated for SAGAT assessment, the simulation paused immediately after the scenario, and the screen turned black. Participants were asked to temporarily stop typing and verbally answer the SAGAT questions. Their responses were audio-recorded by the researchers for subsequent analysis. Upon completing their responses, participants identified the point where they had last stopped typing before resuming the task. Each trial drive lasted about 15 min (SAGAT not included).

3. After-driving survey. After each trial, participants submitted the typed text, and the researchers provided a new text passage on the MacBook for the subsequent trial. In addition, participants filled out the NASA-TLX and UEQ questionnaires to measure their user experience. When they had completed four trials, researchers conducted a semi-structured interview to collect their opinions on each interaction method.

Both studies employed a within-subject design, with conditions balanced using a Latin Square design to ensure equal distribution. Each condition consisted of seven traffic scenarios selected from the predefined scenario pool (Table 5) using a balanced sampling approach. Specifically, scenarios were chosen to ensure a total of 14 road users across all trials, with a balanced distribution of low, medium, and high risks. Four scenarios were randomly chosen for SAGAT assessment, while the remaining three served to minimize learning effects (Endsley, 1988). The order of scenarios was also randomized. To control for potential confounding variables, we disabled typing assistance features (associative and auto-correction) to prevent participants from gaining unintended advantages in speed and accuracy.

3 Results

Before the statistical analysis, a review of the data collected for both Study 1 and Study 2 confirmed that there were no missing data points across all participants and conditions, and revealed no outliers by using a criterion of ±3 standard deviations from the mean for each condition. Consequently, all subsequent statistical analyses were conducted on the original data.

3.1 Study 1: effect of surround sound, airflow, and integrated interaction

A Shapiro–Wilk test indicated that the distribution of dependent variables did not deviate from normality across all conditions (p>0.05). Then, we used a 2×2 (airflow presence and surround sound presence) repeated measures ANOVA design with Greenhouse–Geisser correction and Bonferroni-corrected post hoc tests to explore the main effect and interaction effect between airflow and surround sound. Furthermore, we implemented a 1×4 (interaction method as the independent variable) ANOVA (sphericity checked with Mauchly's test, p>0.05) to compare differences between any two conditions.

3.1.1 SA performance

Since the surround sound and airflow conveyed different information, the analysis of SA performance had three parts: SA-U (SA of road user information, Questions 1–4 in Table 5), SA-B (SA of vehicle behaviors, Questions 5–6), and SA-O (overall correctness of SAGAT, Questions 1–8).

1. SA for road users

The 2×2 ANOVA analysis yielded significant main effects for airflow presence and surround sound presence (Table 6). In addition, a significant interaction effect was found between these two factors ($F(1, 20)$=9.74, p=0.005, η^2=0.33).

Table 6 Main effects of airflow presence and surround sound presence on SA performance

SA performance	Airflow presence			Surround sound presence		
	$F(1, 20)$	p	η^2	$F(1, 20)$	p	η^2
SA-U	12.03	0.002	0.38	65.17	<0.001	0.77
SA-B	138.09	<0.001	0.87	6.61	0.018	0.25
SA-O	73.78	<0.001	0.79	50.75	<0.001	0.72

The results of 1×4 ANOVA revealed a significant effect of the interaction method on SA-U (Table 7). When only surround sound was presented, drivers achieved a high perception accuracy of 90.87% (SD=6.46%) for road user information, which is close to 92.57% (SD=7.88%) under the condition of integrated interaction (p=0.27) and significantly higher than that in the case of only presenting airflow ($p < 0.001$). Surprisingly, airflow also significantly raised drivers' SA-U from 60.57% (SD=17.77%) of baseline to 75.9% (SD=11.91%) (p=0.002).

2. SA for vehicle behaviors

Analyzing the 2×2 ANOVA data, we discovered that airflow presence and surround sound presence each had significant main effects on SA-B, as detailed in Table 6. However, the interaction effect was not significant ($F(1, 20)$=3.75, p=0.067).

The main effect of the interaction method on SA-B was significant (Table 7). Drivers could only notice 51.27% (SD=20.15%) of the vehicle behaviors in the baseline. Airflow performed better than surround sound in improving the rate of SA-B. Under the condition of only airflow, drivers' recognition accuracy of vehicle behaviors reached 94.05% (SD=8.80%), significantly higher than 61.90% (SD=16.79%) in the case of only surround sound (p<0.001).

3. Overall SA for road users, vehicle behaviors, and risk level assessment

The findings from the 2×2 ANOVA indicated significant main effects for both airflow presence and surround sound presence (Table 6), along with a notable interaction effect between them ($F(1, 20)$=8.67, p=0.008, η^2=0.30).

The interaction method significantly affected SA-O (Table 7). Drivers had the highest SA-O under the integrated interaction (M=91.49%, SD=6.36%, $p < 0.001$). We were surprised to find that the condition of only airflow raised SA-O to 82.20% (SD=6.63%), which resulted in a significant

Table 7 Overview of 1×4 comparison results in terms of SA performance, NDRT efficiency, workload, user experience, and other factors

Measurement	Subscale	Comparison result	Statistical result
SA	SA-O	B<S<A<AS	$F(1.90, 38.00)=51.12$, $p<0.001$, $\eta^2=0.72$
	SA-U	B<A<[S, AS]	$F(2.03, 40.64)=34.83$, $p<0.001$, $\eta^2=0.64$
	SA-B	B<S<[A, AS]	$F(2.27, 45.48)=68.43$, $p<0.001$, $\eta^2=0.77$
NDRT	Typing speed	B<[A, S, AS]	$F(2.39, 47.76)=32.73$, $p<0.001$, $\eta^2=0.62$
Workload	Mental demand	[AS, S]<A<B	$F(1.87, 37.38)=53.88$, $p<0.001$, $\eta^2=0.73$
	Physical demand	[AS, A, S]<B	$F(3, 60)=34.59$, $p<0.001$, $\eta^2=0.63$
	Temporal demand	AS<[A, S]<B	$F(2.16, 43.28)=32.36$, $p<0.001$, $\eta^2=0.62$
	Performance	[AS, A, S]<B	$F(3, 60)=24.65$, $p<0.001$, $\eta^2=0.55$
	Effort	AS<[A, S]<B	$F(3, 60)=26.30$, $p<0.001$, $\eta^2=0.57$
	Frustration	[AS, A, S]<B	$F(3, 60)=21.97$, $p<0.001$, $\eta^2=0.52$
UX	Attractiveness	B<[A, S, AS]	$F(3, 60)=32.14$, $p<0.001$, $\eta^2=0.62$
	Dependability	B<[A, S]<AS	$F(3, 60)=56.77$, $p<0.001$, $\eta^2=0.74$
	Perspicuity	B<[A, S]<AS	$F(1.75, 35.02)=36.40$, $p<0.001$, $\eta^2=0.65$
	Efficiency	B<[A, S]<AS	$F(2.05, 40.96)=35.49$, $p<0.001$, $\eta^2=0.64$
	Stimulation	B<[A, S, AS]	$F(1.74, 34.85)=27.43$, $p<0.001$, $\eta^2=0.58$
	Novelty	B<[A, S, AS]	$F(1.94, 38.82)=28.31$, $p<0.001$, $\eta^2=0.59$
Trust	Trust	B<[A, S]<AS	$F(1.86, 36.71)=58.95$, $p<0.001$, $\eta^2=0.75$
	Sense of control	B<S<A<AS	$F(3, 60)=41.47$, $p<0.001$, $\eta^2=0.86$

B: baseline; A: only airflow; S: only surround sound; AS: integrated interaction including airflow and surround sound

improvement compared to 75.44% (SD=9.31%) in the case of only surround sound (p=0.027). The results suggested that only airflow was more effective than only surround sound in enhancing SA-O. The average scores are shown in Fig. 4.

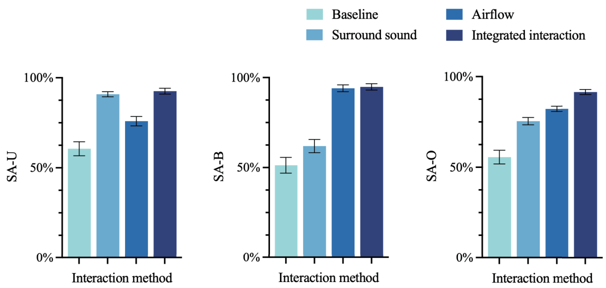

Fig. 4 Average scores of SA-U (score of road user information), SA-B (score of vehicle behaviors), and SA-O (overall SA). Error bars indicate the standard errors of the means

3.1.2 NDRT efficiency

The results of 2×2 ANOVA indicated that the main effects of airflow presence and surround sound presence were both significant (Table 8). In addition, a significant interaction effect was found between these two factors ($F(1, 20)=10.72$, $p=0.004$, $\eta^2=0.34$).

Table 8 Main effects of airflow presence and surround sound presence on NDRT efficiency

Condition	$F(1, 20)$	p	η^2
Airflow presence	50.98	<0.001	0.71
Surround sound presence	49.03	<0.001	0.70

The 1×4 ANOVA showed that the main effect of the interaction method on NDRT efficiency was significant (Table 7). In the baseline condition, participants only typed 26.87 CPM (SD=9.34). Under the condition of integrated interaction, drivers could type at 39.29 CPM (SD=12.06), which was significantly improved compared to typing at 35.50 CPM (SD=10.56) with only surround sound presented (p=0.008). The condition of only airflow (M=36.77 CPM, SD=12.35) had no significant difference from those of only surround sound (p=0.16) and integrated interaction (p=0.083). The results shown in Fig. 5 indicated that the condition of only surround sound or only airflow could enhance performance on typing tasks, and that the effect was better when presented simultaneously.

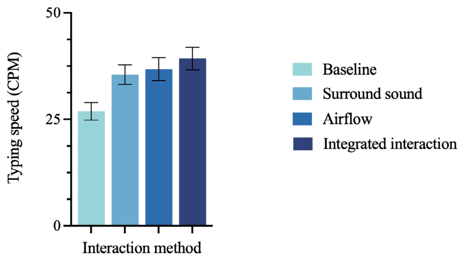

Fig. 5 Average typing speed under four conditions of the interaction method. Error bars indicate the standard errors of the means

3.1.3 Workload

The 2×2 ANOVA revealed significant main effects of both airflow presence and surround sound presence on all six subscales of the NASA-TLX questionnaire (Table 9). Effect sizes (η^2) ranged from 0.49 to 0.77 for airflow presence and from 0.56 to 0.75 for surround sound presence, indicating large effects for both variables. The interaction effects were significant only on mental demand ($F(1, 20)=28.69$, $p<0.001$, $\eta^2=0.59$), physical demand ($F(1, 20)=16.00$, $p=0.001$, $\eta^2=0.44$), performance ($F(1, 20)=7.85$, $p=0.011$, $\eta^2=0.28$), and frustration ($F(1, 20)=13.16$, $p=0.002$, $\eta^2=0.40$).

Table 9 Main effects of airflow presence and surround sound presence on NASA-TLX subscales

NASA-TLX subscale	Airflow presence			Surround sound presence		
	$F(1, 20)$	p	η^2	$F(1, 20)$	p	η^2
Mental demand	67.07	<0.001	0.77	58.38	<0.001	0.75
Physical demand	40.54	<0.001	0.67	38.71	<0.001	0.66
Temporal demand	36.66	<0.001	0.65	55.18	<0.001	0.73
Performance	18.95	<0.001	0.49	50.41	<0.001	0.72
Effort	28.86	<0.001	0.59	49.23	<0.001	0.71
Frustration	24.32	<0.001	0.55	25.07	<0.001	0.56

The 1×4 ANOVA showed that the interaction method had a significant main effect on all factors of the NASA-TLX questionnaire (Table 7). The integrated interaction brought the least workload in every factor (Fig. 6). In terms of physical demand, performance, and frustration, there was no significant difference between single and integrated interaction. The comparison between two single interactions showed that the condition of only airflow (M=3.62, SD=0.80) resulted in higher mental demand than that of only surround sound (M=3.05, SD=0.92) (p=0.025).

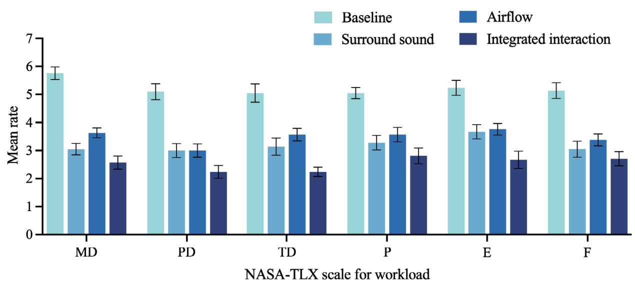

Fig. 6 NASA-TLX results in different conditions. MD: mental demand; PD: physical demand; TD: temporal demand; P: performance; E: effort; F: frustration. Error bars indicate the standard errors of the means

3.1.4 User experience

The 2×2 ANOVA demonstrated that both airflow presence and surround sound presence significantly influenced all factors of user experience (Table 10). The interaction effects were all significant (attractiveness: $F(1, 20)$=16.90, p=0.001, η^2=0.46; dependability: $F(1, 20)$=18.06, $p<0.001$, η^2=0.48; perspicuity: $F(1, 20)$=15.00, p=0.001, η^2=0.43; efficiency: $F(1, 20)$=9.05, p=0.007, η^2=0.31; novelty: $F(1, 20)$=28.31, p=0.002, η^2=0.40; stimulation: $F(1, 20)$=11.14, p=0.003, η^2=0.39; trust: $F(1, 20)$=29.34, $p<0.001$, η^2=0.60; sense of control: $F(1, 20)$=47.80, $p<0.001$, η^2=0.71).

Table 10 Main effects of airflow presence and surround sound presence on user experience factors

UEQ subscale	Airflow presence			Surround sound presence		
	$F(1, 20)$	p	η^2	$F(1, 20)$	p	η^2
Attractiveness	40.35	<0.001	0.67	31.97	<0.001	0.62
Dependability	87.41	<0.001	0.81	61.33	<0.001	0.75
Perspicuity	48.43	<0.001	0.71	35.59	<0.001	0.64
Efficiency	54.98	<0.001	0.73	35.16	<0.001	0.64
Novelty	26.74	<0.001	0.57	43.47	<0.001	0.69
Stimulation	19.91	<0.001	0.50	70.95	<0.001	0.78
Trust	76.18	<0.001	0.79	58.79	<0.001	0.75
Sense of control	251.58	<0.001	0.93	88.90	<0.001	0.82

The main effect of the interaction method on UX and trust was significant from 1×4 ANOVA (Table 7). The average scores are shown in Fig. 7. Drivers who drove without any interaction had the worst experience, with scores of all the UX factors under 3.5 out of 7, and were significantly lower than those in the three other conditions ($p<0.001$). On the contrary, the condition of integrated interaction had the highest score among all UX factors (over 5.3 out of 7, $p<0.001$), but the performance of single interactions varied. Regarding perspicuity and stimulation, only surround sound scored higher than only airflow, while for attractiveness, dependability, efficiency, novelty, and trust, only airflow had higher scores. However, the differences between conditions of only airflow and only surround sound were not significant. The results indicated that drivers felt more in control of automated driving when experiencing only airflow, which scored 5.0 (SD=0.49), compared to 4.6 (SD=0.94) in the case of only surround sound (p=0.037).

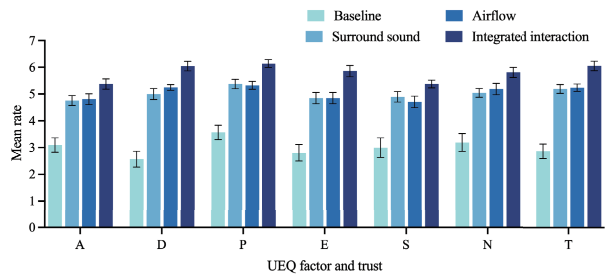

Fig. 7 Mean values for UEQ factors and trust (p<0.05) in different conditions. A: attractiveness; D: dependability; P: perspicuity; E: efficiency; S: stimulation; N: novelty; T: trust. Error bars indicate the standard errors of the means

3.1.5 After-driving survey

Our after-driving surveys showed that 15 of 21 participants mentioned that they tended to focus more on "what my vehicle will do" rather than "what is happening in the surrounding environment." Therefore, when behavior-related information was communicated to them, they paid greater attention to this driving scenario. Participants (11 of 21) also claimed that they could infer partial road user information based on the vehicle's intended behaviors. For example, when the vehicle warned of a risky turn, they would speculate whether a road user was approaching from behind. Besides, 19 of 21 participants stated that when there were interactions, they could engage more deeply in typing tasks. Although they were aware that L3 automated driving could handle most traffic situations, they still hesitated to fully rely on the automated driving system. It was the interaction method that made them comfortably perform NDRT.

3.2 Study 2: effect of task difficulty and the interaction method

To evaluate the main and interaction effects of the interaction method (IM, baseline/integrated interaction) and task difficulty (TD, easy/hard) that influenced drivers' SA performance, we performed a 2×2 repeated-measure ANOVA. The normality assumption was verified by the Shapiro–Wilk test, which indicated that the data did not violate the normality assumption across all conditions (p>0.05). Bonferroni-adjusted post-hoc tests were conducted to detect differences between the conditions per scale, controlling the family-wise error rate at a 5% significance level. Additionally, to quantify the magnitude of the interaction effect, we calculated Cohen's d for the comparison between the integrated interaction method and the baseline across easy and hard tasks.

3.2.1 SA performance

The results showed that the main effect of IM (F(1, 29)=121.05, $p<0.001$, η^2=0.81), TD (F(1, 29)=16.17, $p<0.001$, η^2=0.36), and their interaction effect (F(1, 29)=4.69, p=0.039, η^2=0.14) were all significant. The results are shown in Fig. 8. The integrated interaction raised SA-O from 52.27 % (SD=15.81%) to 83.50% (SD=8.78%) under hard TD (Cohen's d=1.53) and from 64.96% (SD=19.31%) to 87.89% (SD=8.84%) under easy TD (Cohen's d=2.44). The results indicated that the integrated interaction of airflow and surround sound showed greater potential in raising drivers' SA when performing hard tasks than easy ones.

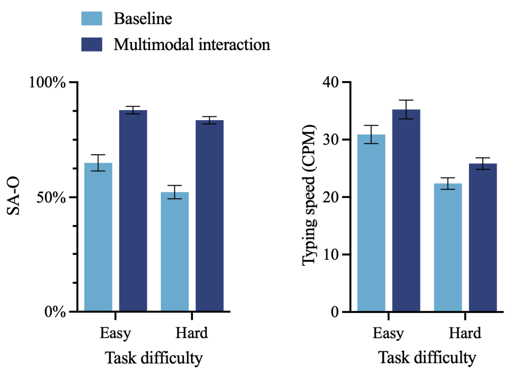

Fig. 8 Average performance of SA-O and typing speed. Error bars indicate the standard errors of the means

3.2.2 NDRT efficiency

IM (F(1, 29)=9.03, p=0.05, η^2=0.24) and TD (F(1, 29)=92.56, $p<0.001$, η^2=0.76) had significant main effects on NDRT efficiency. Their interaction effect was not significant (F(1, 29)=0.20, p=0.66). The integrated interaction (M=35.25 CPM, SD=8.96) led to a higher typing speed than the baseline (M=30.88 CPM, SD=8.69) under easy TD (Cohen's d=0.50). Under hard TD, the integrated interaction had a typing speed of 25.83 CPM (SD=5.49), which was higher than the speed of 22.36 CPM (SD=5.54) of the baseline (Cohen's d=0.63). The results are shown in Fig. 8.

3.2.3 Workload

IM had significant main effects on all six subscales (mental demand: F(1, 29)=29.90, $p<0.001$, η^2=0.51; physical demand: F(1, 29)= 13.47, p=0.001, η^2=0.32; temporal demand: F(1, 29)=21.48, $p<0.001$, η^2=0.43; performance: F(1, 29)=4.73, p=0.038, η^2=0.14; effort: F(1, 29)=18.62, $p<0.001$, η^2=0.39; frustration: F(1, 29)=13.38, p=0.001, η^2=0.32). The mean rates are shown in Fig. 9. TD only significantly influenced temporal demand (F(1, 29) =9.62, p=0.004, η^2=0.25). No significant interaction effects were found between IM and TD for any of the workload subscales.

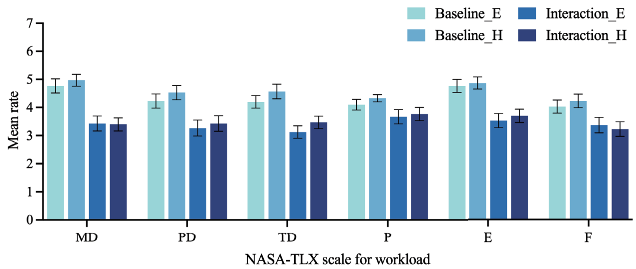

Fig. 9 NASA-TLX results in different conditions. E means easy task while H means hard task. MD: mental demand; PD: physical demand; TD: temporal demand; P: performance; E: effort; F: frustration. Error bars indicate the standard errors of the means

3.2.4 User experience

IM had significant effects on the following four UEQ factors: attractiveness (F(1, 29)=5.83, p=0.022, η^2=0.17); dependability (F(1, 29)=40.27, $p<0.001$, η^2=0.58); perspicuity (F(1, 29)=15.83, $p<0.001$, η^2=0.35); efficiency (F(1, 29)=56.09, $p<0.001$, η^2=0.66). In contrast, TD had no significant main effect on any UX factors. Fig. 10 shows the values of the above factors. The integrated interaction increased these factors by 0.4 to 1.2 points on the 7-point scale, which indicated a more attractive and dependable user experience for drivers while increasing their perspicuity and efficiency. The results also showed a significant effect of IM on participants' trust (F(1, 29)=19.50, $p<0.001$, η^2=0.40). The trust score was 5.32 (SD=1.23) with the integrated interaction and 4.38 (SD=1.29) under the baseline ($p<0.001$). No significant interaction effects were found between IM and TD for any user experience factors.

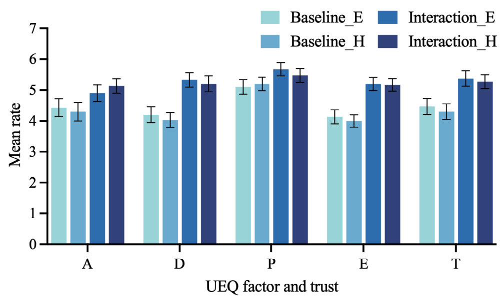

Fig. 10 Mean values for UEQ factors and trust ($p<0.05$) in different conditions. E means easy task while H means hard task. A: attractiveness; D: dependability; P: perspicuity; E: efficiency; T: trust. Error bars indicate the standard errors of the means

3.2.5 After-driving survey

In the interviews from Study 2, 24 out of 30 participants indicated that under hard NDRT conditions, compared to easy NDRT, their attention was much more likely to be completely absorbed in the NDRT, leading to frequent instances where they were unable to detect risks in the traffic. This situation made them feel unsafe, so they would consciously switch their attention between the traffic and the typing task, although this behavior disrupted the continuity and efficiency of their NDRT. However, with the integrated airflow and surround sound interaction, they could engage in NDRTs with greater peace of mind and feel in control, as one participant stated: "I could feel the traffic situation around me, even while focusing on typing." Participants unanimously agreed that this interaction method did not disturb their NDRT execution but actually enhanced their travel experience.

4 Discussion

Our work investigated the effects of surround sound and airflow on drivers' SA performance and NDRT efficiency. This section focuses on three aspects: (1) how conveying attributes of road users and vehicle behaviors contributes to SA reconstruction, (2) the effect of peripheral interaction methods on enhancing NDRT efficiency, and (3) the practical value of our peripheral interaction approach.

4.1 Conveying attributes of road users and vehicle behaviors to reconstruct drivers' situation awareness

Previous studies have demonstrated that information on road users or vehicle behaviors could help drivers reconstruct SA (Liu et al., 2023; Colley et al., 2024; Kim et al., 2024a). Our work found similar results and further investigated their differences. The results of Study 1 supported that conveying road user information helps drivers understand the traffic situation, and that conveying intended behaviors enables drivers to anticipate automated system responses to road user behaviors. Previous research primarily conveyed this information in a static form without variation (Wang MJ et al., 2017; Yang J et al., 2022). We further established a coding method that achieves dynamic situational information by adjusting the information presentation based on changes in road users' positions and risk levels. The information coding method aligns with those of Karatas et al. (2020) and Shi JL et al. (2024). They found that drivers could identify targets more rapidly when information was dynamically presented rather than relying on metaphors or static indicators. In quickly changing traffic scenarios, these attributes promote drivers' understanding of traffic and potential risks.

Our findings suggest that information on road users and vehicle behaviors complements each other. This finding aligns with previous research showing that providing both how and why information leads to better performance compared to providing "why only" or "how only" information (Koo et al., 2015; Zhang YW et al., 2023). In our work, road user information serves as the causal basis for understanding vehicle behaviors, allowing drivers to comprehend not only what the vehicle will do but also why it takes such actions. This comprehensive understanding appears to improve drivers' SA performance. Taking the above findings together, we recommend that practitioners integrate road user information and vehicle behavior cues when designing interaction systems for drivers, as these two types of information complement each other effectively.

Participants in Study 1 reported that vehicle behaviors conveyed by airflow helped them focus on traffic scenarios and predict attributes of road users, increasing SA-U by 15% compared to baseline. Participants also demonstrated better SA-O performance with vehicle behaviors conveyed by airflow than road user information conveyed through surround sound. We believe that this reveals a more efficient logic of information delivery. The surround sound provides raw details about the environment, requiring the driver to identify and interpret them from scratch. In contrast, the vehicle's behavioral intent conveyed by airflow acts as a highly summarized "event summary." This "summary" is highly effective because it ingeniously activates and leverages the driver's own expertise and inferential abilities. Upon receiving a high-level cue about the vehicle's intent, the driver is instinctively and rapidly prompted to search for the cause of that behavior. This reveals a design implication: it may be cognitively more efficient to provide a high-level summary of how the vehicle is responding to the environment rather than raw information on the environmental details. This approach utilizes the driver's own inferential abilities to effectively reconstruct SA.

4.2 Leveraging peripheral interaction methods to enhance drivers' NDRT efficiency

Few studies have investigated how interactions designed for SA reconstruction affect drivers' NDRT efficiency. NDRT represents a key benefit offered by L3 automated driving, and research shows a general increase in NDRT efficiency while using automated driving systems (Hungund and Pradhan, 2023). However, inappropriate timing and interaction methods of requests may degrade drivers' NDRT performance and increase stress (Wintersberger et al., 2018). When drivers must abruptly cease their NDRT, they often rush to complete it, leading to errors and reduced performance.

While recent research on NDRT efficiency predominantly relies on visual displays (Schartmüller et al., 2021; Ding et al., 2024), our results indicate that airflow and surround sound interactions can facilitate significant improvements in drivers' NDRT efficiency. These modalities appear to reduce workload by utilizing sensory channels that are less occupied during NDRT, allowing for more efficient information processing. Besides, participants noted that information from auditory and airflow interaction is distinct and easily discernible without causing perceptual interference. Accordingly, participants driving with the integrated interaction could type more Chinese characters per minute. Some of them stated that although they could not observe the traffic around them while typing, they could feel the road users and the vehicle's intended behaviors, making them less out of control and more focused on completing typing tasks. Moreover, this facilitation effect was found to be more pronounced in high-difficulty task conditions, suggesting that these interaction methods may be particularly valuable when cognitive demands are elevated.

Our work provides empirical evidence for applying the peripheral interaction theory to automated driving. In our study, the NDRT constitutes the center of attention, primarily engaging the driver's visual and cognitive resources.

Theoretically, a disruptive attention-switching process would result in a performance trade-off between SA and NDRT. Our airflow and sound interactions were designed to be processed with little attention by utilizing distinct and less-loaded sensory channels. Through brief familiarization, our specific auditory icons and airflow patterns are flagged by the brain as high-relevance signals. Consequently, while the driver focuses on the NDRT, their brain can pre-attentively monitor this information stream. When one of these flagged signals appears, it automatically and bottom-up captures the driver's attention, pulling it from the periphery to the center. Our results confirm the effectiveness of this approach, showing that drivers could effectively utilize these peripheral cues to build a mental model of the traffic environment and then seamlessly return their focus to the NDRT. This efficient attentional capture—rather than a strenuous and top-down-managed switch—explains the synergistic improvement observed in both SA and NDRT performance, which contradicts the expected theoretical trade-off. This indicates that the interaction is fluid and efficient, thereby providing empirical evidence for applying the peripheral interaction framework's core principles in a driving context.

Our auditory icons were particularly effective as they enabled intuitive associations between sound effects and road user categories (Fagerlönn et al., 2015; Isherwood and McKeown, 2017), allowing drivers to distinguish between three categories of road users accurately. Additionally, the results showed that auditory icons compressed into three rhythms were perceived as understandable and attractive. Some research also indicated that the compressed auditory icons prompted driving performance over other auditory warnings (Song et al., 2022; Chai et al., 2024). However, we employed only a 5.1-channel sound system with four speakers to deliver the auditory icons. Limited by the current apparatus setup of surround sound, the resolution of sound source localization was constrained, which partially affected the spatial separation between sound sources. Loudspeakers with variable directivity and higher-order loudspeakers with multiple radiation modes can improve surround sound recognition in enclosed rooms (Poletti et al., 2012). If the prototype physically presents the trajectory of sounds by more speakers, its sense of direction will be clearer (Müller et al., 2014). Applying these methods in the future may help deliver more distinct auditory information.

The airflow-based behavioral communication draws on the concept of Vection, which is typically defined as the embodied illusion of self-motion in the absence of real physical movement through space (Riecke et al., 2023). Vibration stimulation has been widely utilized as a tactile interface designed to enable human motion perception (Kooijman et al., 2022, 2024; Shi JL et al., 2024). However, studies have identified that participants' sensation of Vection decreases when sensory cue conflicts occur (Greenlee et al., 2016). Such vibration-based methods may create conflicts with the natural vibrations caused by driving, making them less ideal for in-vehicle applications. Airflow, as an emerging approach for inducing Vection, provides a promising method for conveying motion-related information and creating a consistent virtual motion experience (Seno et al., 2011; Riecke et al., 2023; Cai et al., 2025). It creates a direct sensory experience that complements auditory perception without introducing conflicts with existing in-vehicle sensations. Users can perceive both the self-body's motion and the environmental air's condition, improving their performance (Deligiannidis and Jacob, 2006; Kurosawa et al., 2018).

Our work provides insights for interaction design in automated driving. The advanced sound dampening in modern vehicles creates a paradoxical situation: while it isolates the driver from the outside world, muffling environmental sounds and eliminating the sensation of air drag, this same quiet and controlled cockpit makes subtle internal interactions easier to detect and interpret. This controlled environment provides an opportunity to deliver critical environmental information in a more refined and information-rich manner. In this case, the integrated auditory and airflow interaction emerges as a spatial interface (Wang JM et al., 2024), which allows drivers to perceive information more intuitively by drawing upon their existing driving experience and keeps drivers in the loop (Kim et al., 2024b). Specifically, our findings suggest that (1) interactions that utilize surround sound and airflow have the potential to improve NDRT efficiency without compromising safety in an enclosed and stable cockpit like our simulated context, and (2) interactions that mimic natural environmental cues may require less workload and processing demands, leaving more cognitive resources available for NDRT.

4.3 Practical value of peripheral interaction in road traffic safety

Our work enhances drivers' SA performance and NDRT efficiency during automated driving. The results of Study 2 showed that the integrated interaction of airflow and surround sound reduced the workload of reconstructing SA and performing NDRT under different task difficulties. The integrated interaction also improved drivers' experience of participating in NDRT and driving. We were concerned that the surround sound might be too loud and that the airflow could cause skin discomfort, potentially affecting the driving experience. Fortunately, the results indicated that participants found these interactions attractive and dependable.

The concept of interacting with drivers before the takeover aligns with the two-stage takeover method, which separates the process into monitoring requests and takeover requests (Ma et al., 2021; Xu LL et al., 2022). Participants mentioned that such early interaction allows for a deeper understanding of the automated driving situation, reducing the shock caused by sudden alerts. Besides, explaining the intended behavior positively influences trust and a sense of control in automated driving (Detjen et al., 2021; Zhang YW et al., 2023; Zhang TR et al., 2024), which has also been proven in our studies. An important consideration is that repeatedly issuing monitoring requests without subsequent takeover requests may decrease drivers' vigilance and takeover readiness (Ma et al., 2021). Therefore, future iterations of the first-stage interaction strategy should be carefully designed to maintain drivers' vigilance and readiness for potential takeover situations.

Our peripheral interaction methods are designed in alignment with key functional safety principles of ISO 26262, particularly concerning the human–machine interface (HMI) (ISO, 2018). The standard mandates that safety-critical information be presented without creating new hazards, such as driver distraction or information overload. Our design addresses this in two ways: (1) minimizing sensory competition—leveraging surround sound and airflow to deliver critical situational information without competing for the driver's visual resources, which are often occupied by NDRTs in L3 automated driving (This adherence to using appropriate sensory channels helps prevent information overload and distraction); (2) supporting driver readiness for control—a core goal of ISO 26262 is to ensure that the driver is in a position to safely control the vehicle, for which a high level of SA is a fundamental prerequisite. Our studies demonstrate that our interaction methods enhance driver SA. By building this critical cognitive foundation before a control transition is imminent, our methods support the conditions necessary for maintaining vehicle controllability and preparing the driver for a safe state transition.

4.4 Limitations and future work

First, we must acknowledge the limitations of a driving simulator. While ensuring a controlled environment, it lacks the full sensory complexity of real-world driving, such as the inertial feeling of acceleration and steering. This missing sense of motion is a crucial physical cue for SA reconstruction. Furthermore, our designed interactions could face real-world interference from factors not present in the simulation, such as an open window or the vehicle's climate control system, potentially diminishing their clarity. The airflow in our prototype acted as an advanced reminder, and its effectiveness would likely be enhanced when paired with the physical sensation of real motion. Note that in our two studies, each participant drove for 70 min, which exceeds the average driving time of 61.3 and 60.2 min per person reported by the AAA Foundation for Traffic Safety from 2020 to 2022 (Tefft, 2022; Steinbach and Tefft, 2023). This suggests that drivers might not be irritated by such interactions during most daily trips. However, this study did not assess the effects of long-term exposure, leaving questions unanswered regarding potential driver habituation, the performance in diverse traffic scenarios, and the risk of annoyance during prolonged and multi-hour journeys. These simulator-based studies do not constitute a formal compliance assessment under ISO 26262's Automotive Safety Integrity Level (ASIL) procedures. Future work should integrate these peripheral modalities into system-level safety validation processes to assess their implications for certified functional safety. Another methodological limitation of our study is the use of the SAGAT freeze-probe technique. Although we implemented a mitigation measure, we acknowledge that the frequent interruptions likely influenced the cognitive flow of the typing task, thus potentially affecting the NDRT efficiency metrics. Future work could employ less obtrusive measures, such as eye-tracking, to naturally assess the interplay between SA and NDRT performance. In conclusion, our findings must be interpreted with caution, and future on-road studies are essential to validate efficacy and user acceptance of these peripheral interactions in real-world conditions.

Second, our work has currently measured only the impact of two interactions on drivers' SA, while the effect on takeover performance remains unclear and will be further clarified in subsequent studies. Takeover performance, measured by metrics such as reaction time and the quality of vehicle control after resuming manual command, is the most direct indicator of a driver's ability to handle critical events. Therefore, a crucial next step for future research is to conduct studies that explicitly measure takeover performance to validate the real-world safety impact of our peripheral interaction methods.

Third, the generalizability of our findings is limited. Our participant sample was relatively homogeneous, consisting primarily of young university students recruited from our campus. This demographic is often considered the primary target audience and early adopters for automated driving systems (Nordhoff et al., 2018; Cheng et al., 2021), which lends relevance to our findings for this key user group. Nevertheless, this demographic may not be representative of the general driving population, as the perceptual, cognitive, and technological acceptance patterns of older or more experienced drivers may differ. Moreover, we employed only a visually and cognitively demanding typing task as NDRT. While this choice provided a rigorous test case for our interaction methods, other types of in-vehicle activities remain to be investigated. Future work should evaluate our interaction methods with larger and more diverse participant samples across a broader spectrum of NDRTs, such as an auditory-based phone call.

This work has potential for future extensions. Currently, we focus on visual NDRT as the target task. However, other NDRT may occupy auditory or tactile resources and have a heavier cognitive load. For such tasks, incorporating information across additional modalities may provide a more effective means of in-car interaction (Wang MJ et al., 2020; Colley et al., 2021b). In the future, it will be essential to analyze the type of NDRT in which the driver is engaged and adjust the interaction modality to provide information accordingly. Additionally, information such as traffic lights, weather, and road icons can be presented. Other problems with the current prototype, mentioned earlier, such as the selection of sound effects, also need to be solved step by step in future work. As a follow-up to this research, it is necessary to incorporate specific takeover information when exceeding the operational design domain. Future research should explore the effects of these interactions on takeover performance. Additionally, the impact of long-term use of these interactions and their effectiveness in real-world driving conditions should be examined.

5 Conclusions

This study investigated the effects of leveraging peripheral interactions (airflow and surround sound) on drivers' SA performance and NDRT efficiency. Study 1 indicated that the single interaction of airflow and surround sound effectively delivered their encoded information, with their integration yielding the best performance in SA. Study 2 demonstrated that the integrated interaction helped drivers perform better in terms of SA performance and NDRT efficiency under hard tasks. Peripheral interaction approaches significantly enhanced drivers' performance on NDRT, reduced drivers' perceived workload, improved user experience, and increased trust in the automated system. Our work provides insights into achieving a balance between NDRT participation and SA reconstruction in L3 automated driving systems, supporting the design of effective and user-centered in-vehicle interactions.

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Author contributions

Hanfei ZHU contributed to conceptualization, methodology, software, validation, formal analysis, investigation, writing—original draft, and visualization. Wei XIANG contributed to conceptualization, methodology, resources, writing—review and editing, supervision, and funding acquisition. Yifu ZHANG contributed to software, investigation, writing—original draft, and visualization. Ziyue LEI contributed to software and visualization. Lingyun SUN contributed to supervision, resources, and funding acquisition.

Conflict of interest

All the authors declare that they have no conflict of interest.

Compliance with ethics guidelines

Our study ensured the privacy and confidentiality of all data used and was approved by the Ethics Committee of Zhejiang University for the ethical review of research projects (No. 2024097).

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declaration on the use of generative AI tools

During the preparation of this work, the authors used ChatGPT and Gemini to improve language. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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