

Augmenting Human Hazard Situational Awareness with Haptic Interface for Heterogeneous Autonomous Vehicles

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Abstract—As vehicle autonomy increases, human operators become more susceptible to distractions and a loss of situational awareness (SA) due to cognitive limitations. Rapidly enhancing human SA in hazardous situations is therefore critical for timely hazard perception and collision avoidance, particularly in human-vehicle teaming contexts that demand fast, accurate hazard reasoning. This study evaluates the efficiency of a low-cost vibrotactile interface for enhancing hazard SA of human operators when teaming with heterogeneous autonomous vehicles, including both ground and aerial autonomous vehicles. To do so, we evaluate the effectiveness of a vibrotactile interface in challenging time-critical scenarios considering adversarial attacks to better understand the cognitive constraints faced by human operators. Our quantitative analysis, based on the data collected from 39 participants, demonstrates that: (1) Haptic cues can significantly enhance human hazard SA across various metrics for the ground and aerial scenarios; (2) Perception of aerial attacks in a 3D environment is more challenging than ground risk perception. The dataset is publicly available at <https://github.com/YXING-CC/EEG-EMG-DATASET>.

Index Terms—Vibrotactile interface, Situation awareness, Human-Machine teaming, Autonomous vehicles.

I. INTRODUCTION

THE human cognitive attention shifts and distractions in autonomous vehicles (AVs) has emerged as a critical challenge in designing intelligent user interfaces [1]. Studies have shown that human attention can be diverted when transitioning from an active controller role to a passive observational one [2]. Prolonged periods of observation can significantly increase a human's mental workload, leading to diminished situational awareness (SA) and exposing human users to unforeseen dangers [3]. In the context of aerial vehicles, research has been conducted on remote and teleoperation interface design to enhance human-autonomy collaboration [4]. However, these studies typically focused on specific applications, such as military and professional uses [5]. A significant trend in commercial urban air transport is the increasing complexity of future Unmanned Aircraft System Traffic Management (UTM) systems, driven by the introduction of many autonomous and semi-autonomous unmanned aerial vehicles (UAVs) in the air [6]. Due to their sensitivity to environmental factors like wind and rain and the complexity of 3-dimensional (3D) path-planning, UAVs are expected to pose considerable challenges to UTM [7]. This will likely demand significant efforts from

remote and onboard human operators, such as those managing electric vertical take-off and landing aircraft (eVTOL) [8].

These challenges naturally call for advancements in human-computer interface (HCI) technologies that can rapidly enhance human SA to improve performance in anticipating and analysing future risks [9]. Collisions in both ground and aerial vehicles typically occur within seconds and can cause significant risks to human safety [10]. Therefore, HCI for time-critical situations must prioritize interaction speed and accuracy, where even a higher false positive rate could be helpful the alerts are swift and timely for SA recovery [11].

However, in time-critical scenarios, haptic feedback offers an additional channel to enrich audiovisual experiences and augment physical sensations in parallel [12]. Unlike vision and hearing, haptics is bi-directional, supporting both perception of, and response to, the environment [13]. It has been shown to assist visually impaired individuals and enhance user engagement [14]. A variety of studies have used haptic interfaces on joysticks, steering wheels, and seats, showing their effectiveness in conveying risks and assisting human operators [15]. However, these haptic interfaces also have limitations to communicate complex patterns or over complicated for public transportation systems [16]. As hazard SA augmentation becomes an increasing challenge in emerging 3D hybrid transport [17], it is important to develop efficient, yet low-cost, HCI technologies for human SA augmentation.

In this study, we argue that in scenarios where visual information is limited (e.g., remote UAV monitoring), visual attention is overloaded (e.g., drivers glancing at side displays), or auditory feedback is inefficient (e.g., verbal risk enumeration and), haptic feedback provides an effective complementary channel for conveying spatial hazard information. We aim to study a Haptic Sensing Field (HSF) which refers to a personalized sense of touch (a cognitive capability) that translates vibrotactile cues into the spatial locations of events (attacks). As illustrated in Fig. 1, the vibrotactile interface is designed based on publicly available component with minimal setup requirements. The contributions of this study are:

- We develop a novel cross-platform simulation environment to study human hazard SA dynamic and its augmentation with haptic interface. A low-cost yet efficient wearable haptic interface was designed.
- To the best of our knowledge, this study is the first to conduct human experiments in a unified environment considering the rare adversarial situation. The public dataset provides cross-platform benchmark.
- We explicitly analysed the impact of the haptic interface on human hazard SA augmentation across the two different scenarios. The lateral studies provide early evidence

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of the effectiveness of the haptic interface.

The reminder of this paper is organized as follows. Literature review is proposed in Section 2. The experimental setup and methodologies are discussed in Section 3. Section 4 provides the results analysis. Discussions are proposed in Section 5 and the paper is concluded in Section 6.

II. RELATED WORKS

A. Situational Awareness and Hazard Perception

Human SA is the ability to perceive, understand, and anticipate factors within a specific time and space. Endsley's model summarised SA into three levels: perception of environmental elements, comprehension of the situation, and projection of future states [18]. Detecting deficiency in SA and providing feedback to the user can help avert collisions and improve safety [19]. This is crucial for operators working alongside autonomous systems, where maintaining SA of dynamic environments is essential for rapid and informed decision-making. SA also plays a pivotal role in HCI, particularly in environments requiring complex decision-making and dynamic responses [20]. Meanwhile maintaining a high level of SA is essential to ensure operators can respond to changing scenarios [21].

B. General Applications of Vibrotactile Interfaces

Haptic feedback, especially through vibrotactile interfaces, is a promising tool for enhancing SA [22]. It has proven effective in safety-critical domains. For example, directional haptic cues help drivers detect pedestrian hazards more quickly and reduce collisions [23]. Short and high-intensity vibrations outperform auditory alerts by conveying urgency more effectively [24]. The bHaptic vest achieved over 95.6% accuracy in azimuth and elevation recognition with 6–8 real cues [25], though accuracy dropped significantly when combining real and illusory stimuli. A drone-guidance system for blind users demonstrated effective 3D object feedback [26], focusing on safe indoor settings with simple, linear feedback. Research has expanded beyond traditional hand-based interfaces, showing that vibrations on fingernails can convey emotions [27]. This highlights the potential of haptic cues for non-verbal, remote interaction. Lisboa et al. found that haptic alerts on forearms and shoulder blades outperformed glove-based feedback, especially under high vibration [28]. A 3D haptic system using head and waist actuators enabled spatial awareness of object depth and orientation. However, adding head-mounted devices can also increase cognitive load and pose safety risks [29].

C. Vibrotactile Interfaces in Ground Autonomy

Wearable devices with vibrotactile feedback offer numerous applications across AVs domains. Tactile cues have been shown to be intuitive of delivering information directly and specifically to the driver [30]. Presenting directional tactile cues can shift visual attention toward the cued side [31]. Vibrotactile on the torso convey spatial information by mapping stimuli to body coordinates. A 15-tactor linear array was used in [32] to examine horizontal directional mapping. While aligning the display across the torso supports natural spatial

perception, such designs may be impractical in scenarios like driving, where actuators are typically limited to the back.

In [32], 24 drivers tested seven haptic alerts on binary events. While confusion increased with more alerts, performance improved when cues were spatially distinct and mapped to intuitive responses. Our work extends the haptic interface design for more complex scenarios that involves simultaneous multi-directional hazards. [33] designed a haptic vest to assist users with navigation tasks in virtual reality (VR). While that study focused on steady-state navigation, our work extends this by encoding 3D spatial information into haptic cues to assess users' spatial SA in more dynamic and complex conditions.

In [34], 16 participants evaluated eight common non-directional warnings using a seat with three vibrotactile actuators on the back and thighs. The study focused solely on mode identification and did not explore spatial perception capabilities. [35] further investigated adaptive haptic feedback based on risk indicators like time headway. Their study showed that haptic protection systems increase steering resistance under risky conditions. While the study fails to consider wider directions of 3D space as proposed in this work.

D. Vibrotactile Interfaces in Aerial Autonomy

Early research with a tactile joystick interface was developed in [36] to simulating 32 directions across 360 degree range for UAV. However, the limitation of transferring 3D spatial information is significant. Alternative approaches have used haptic gloves or fingertip vibrators to convey quadrotor motion axes [37] and environmental disturbances like wind [38]. A more complex scenario involving human-swarm collaboration was also explored using a wearable hand interface [39]. While these studies offer lightweight vibrotactile solutions, they are limited to single or multiple drone control and do not address higher-risk situations or contextual threat feedback, as explored in our work. The AeroHaptix system enhances collision avoidance in remote drone operations by providing multidirectional feedback [40]. Results show that vibrotactile feedback improves workload management and SA. Our study builds on the prior work by introducing more complex scenarios, simulating real-world constraints where drones have limited view and face multi-directional threats.

Integrating gesture recognition and tactile feedback can improve control precision and reduce cognitive load [41]. [42] explores how tactile stimuli received on the skin are remapped into an allocentric coordinate for motor control. The results support the claim that remapping becomes more challenging in complex spatial transformations, as also quantitated in this paper. Current vibrotactile feedback design include develop more comfortable, user-friendly devices and conduct extensive field trials to validate the effectiveness of vibrotactile interfaces in real-world settings [22]. Studies in swarm robotics and VR indicate that the benefits of vibrotactile feedback can vary depending on the complexity of the task [43].

In summary, prior studies have focused on binary or low-complexity hazards (e.g., lane departure, single collision warning) using hand, seat, or steering-wheel actuators [34]. Others have addressed navigation or obstacle avoidance in simplified

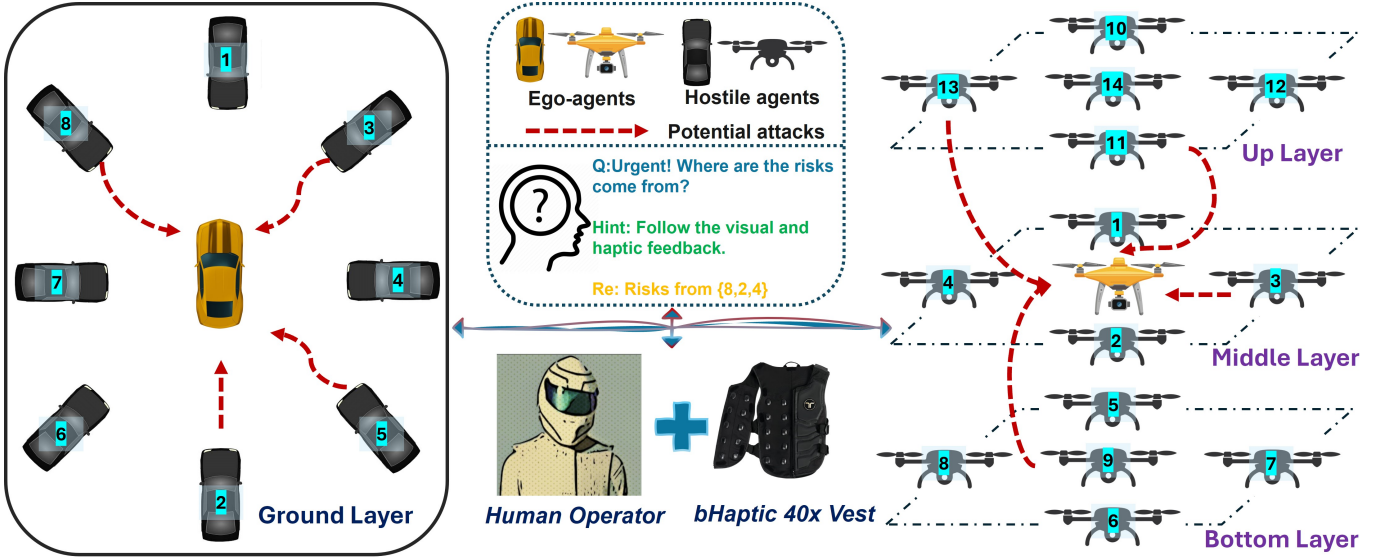


Fig. 1. Illustrations of the simulation environments. The left panel depicts a 2-dimensional ground scenario, while the middle panel highlights the task and haptic feedback. The right panel presents a 3-dimensional aerial scenario. The identity of surrounding vehicles indicates specific risk locations.

VR settings [33] or provided feedback for single UAV teleoperation tasks [40]. In contrast, this work introduces a unified torso-based interface across both ground and aerial domains, tested under multi-directional, adversarial hazard conditions.

III. EXPERIMENT DESIGN

A. Simulation Environment Design

In this study, we simulated time-critical ground and aerial scenarios in which adversarial risks could originate from any direction. For simplicity, we choose a certain directions and positions for ground and aerial scenarios as shown in Fig.1. Here, "Position" refers to horizontal risk locations, such as front, rear, left, and right, while "Direction" (used for the aerial scenario) pertains to vertical risk locations, such as top and bottom. The experimental platform were developed using Microsoft AirSim and Unreal Engine 4.27. Vehicle control programs were implemented in Python 3.9. An example of the user visualisation interface is shown in Fig.2. Participants faced a 48-inch monitor displaying the simulation environment. In the ground scenario, eight adversarial vehicles surrounded the ego vehicle and could initiate an attack. The ego vehicle autonomously drove for approximately 10 seconds before entering the attack zone (i.e., overtaking vehicle ID2 in Fig. 1). All adversarial vehicles were positioned 50 m from the center of the attack region. Four displays provided front, rear, left, and right camera views to support environmental monitoring. Once the ego vehicle surpasses the rear vehicle, participants are alerted by a 1-second sound stimulus. Up to three (random) adversarial vehicles will autonomously accelerate to 15m/s and drive straightforward toward the centre.

In the aerial scenario (3D space), vertical risk perception is as critical as horizontal risk perception. Accordingly, the left and right camera views were replaced with bottom and top views, positioned vertically on the right side of the display to clearly indicate direction and reduce spatial ambiguity. Unlike

typical UAV operations that rely on a single front-facing feed, this setup provided richer visual information to better simulate monitoring constraints while isolating the contribution of haptic feedback. 14 adversarial drones moved to predefined positions 50 m away (Fig. 1). The ego drone autonomously flew for approximately 10 s before entering the attack region, defined as the point at which its altitude exceeded the bottom rear adversarial drone. It then hovered while adversarial drones approached at 15 m/s. The compressed response window for the ground and aerial scenarios was chosen to model adversarial hazards, in contrast with normal takeover contexts where humans typically require 6–10 seconds for preparation and SA recovery from distractions [47].

For time recording, we record three critical timesteps, which are 1) program start time, 2) sound time (attack starts), 3) button pressing event indicating the participants are ready to report their perceived risks. A keyboard was positioned in front of the participants, allowing them to terminate the simulation. The adversarial vehicles were initiated sequentially by the program. Although the vehicles began moving within fractions of a second of one another, making the attacks appear nearly simultaneous to participants, the corresponding haptic cues were triggered in this initiation order. This design allowed us to evaluate not only whether participants detected the presence of multiple hazards but also whether they could discriminate against the correct order.

B. Haptic Interface Design with bHaptic40

The haptic interface was implemented using the bHaptics TactSuit X40 vest, which contains 40 actuators evenly distributed across the front and back. Haptic patterns were designed using the bHaptics Designer software. Back actuators were used to convey directional cues in both ground and aerial scenarios. For the ground mode, eight distinct directional patterns were implemented on the back panel. This design



Fig. 2. Experimental Setup Overview. (a) Overall experimental setup. (b) Ground Scenarios: The graph showcases the views from four cameras positioned at the front, back, left, and right. (c) Aerial Scenarios: This graph presents the drone's views from four cameras positioned at the front, back, top, and bottom. All cameras used in the setup have a 120-degree field of view to bring a holistic view for the observer.

followed established seat-based haptic warning conventions in automotive and aviation systems, enhancing ergonomic transferability. It also reduced perceptual overlap compared to activating both front and back simultaneously. In the aerial mode, we integrate two different patterns in the front region to denote the direction of risks from above or below. While this arrangement is not a pure egocentric mapping and may increase cognitive translation for front hazards, it reflects practical design trade-offs and ensures compatibility with existing control metaphors (e.g., seat, steering wheel, joystick). Moreover, this mapping was chosen to decouple vertical from horizontal channels and ensure clear allocation of spatial information. Future work will examine hybrid mappings that align more closely with egocentric principles. Each haptic pattern will last for one second, and the users are expected to experience up to three different vibrations continuously.

In the pilot study, vertical risk was conveyed using progressive vibration patterns moving from bottom to top or vice versa. While effective for single attacks, this approach caused confusion during simultaneous events due to overlapping cues across front and back actuators. Pilot testing highlighted the importance of simplicity in haptic design. Consequently, the formal experiments employed simple localized vibration patterns on the front and back panels to clearly indicate risk direction and position. In the experiment, no participant reported physical discomfort during the session. No vibration intensity adjustments were requested. After initial instructions, vibration locations were discriminable, and no sustained signal confusion was observed. Moreover, no participant reported

physical discomfort or fatigue during the session.

C. Procedure

Interested individuals registered and were assigned a unique identification code. Participants received an information sheet at least 24 hours prior to the experiment, and only those who signed the informed consent form were permitted to participate. Collected data included: (1) demographic information and prior AirSim experience; (2) timestamps of risk-confirmation button presses; (3) task questionnaire responses; and (4) Situation Awareness Rating Technique (SART) responses for self-assessed situational awareness. In addition, physiological signals including Electroencephalogram (EEG) and Electromyography (EMG) were recorded and available on the Github. These data were not analysed in the present study, as our scope was to establish behavioural baselines of haptic augmentation. Physiological analyses require dedicated preprocessing and modelling that will be addressed in future studies. The experimental process is clarified below:

Step 1: At the onset of the experiment, the research team will provide a detailed introduction to the tasks and expectations, addressing any questions from the participants.

Step 2: To familiarize participants with the haptic cues and establish the HSF, we iteratively activated stimuli corresponding to ground and aerial scenarios. Participants were instructed to track the cues and report discrepancies between perceived sensations and on-screen indicators. Calibration continued until participants demonstrated consistent understanding of the haptic patterns. This step ensured reliable detection of risks

using the vest. In practice, this calibration phase typically required 8-10 minutes for participants to consistently and reliably identify the generated patterns.

Step 3: In Phase 1, the experiment consisted of two conditions: Visual-only (VT) and Visual-Haptic (VHT). Each condition included two simulation trials for both ground and aerial scenarios. The order of VT and VHT was counterbalanced across participants (11 began with VT, 11 with VHT). The haptic vest was worn only during VHT. Participants could choose the order of ground and aerial scenarios, resulting in an approximately equal distribution of initial scenario selection. In Phase 2, a Single Haptic Trial (SHT) condition was added, in which visual input was totally disabled and only haptic cues were kept. Both scenario order and feedback modality order were counterbalanced across the 18 participants. Nine participants began with the ground scenario and nine with the aerial scenario. Modality sequences were evenly distributed among VT-VHT-SHT, VHT-VT-SHT, and SHT-VT-VHT.

Step 4: Each trial began with a pre-attack phase during which the ego vehicle or drone moved autonomously for approximately 10 s, allowing participants to observe the visual feeds and establish situational awareness. Upon entering the predefined attack zone, an auditory cue signaled the onset of adversarial attacks. Up to three adversarial agents then approached the ego platform, triggering corresponding haptic cues in the VHT and SHT conditions. Participants were required to (1) detect hazards, (2) determine their number, and (3) localize their positions. No strict time limit was imposed; participants pressed a key once confident in their assessment, ensuring that recorded response times reflected completed decision-making rather than intermediate deliberation.

Step 5: After each session, participants completed a task-specific questionnaire and the SART assessment. In Phase 1, each participant completed eight trials (2 conditions $\times$ 2 scenarios $\times$ 2 trials), with the full session lasting approximately 1–1.5 hours, including calibration, HSF training, formal trials, and self-report measures. In Phase 2, each participant completed 18 trials (3 conditions $\times$ 2 scenarios $\times$ 3 trials), with a total duration of 1.5–2 hours. To mitigate fatigue, 1-minute breaks were provided between trial blocks and 2-minute breaks between conditions, with extra pauses available upon request.

D. Participants

Data were collected in two phases: May–June 2024 (Phase 1) and June–August 2025 (Phase 2). Phase 1 included 22 participants (3 female), and Phase 2 included 18 participants (9 female), recruited from a local university without specific inclusion criteria. One participant in Phase 1 did not complete the study and was excluded from analysis. The mean age was 28.3 years (SD = 3.34; range 21–35). Six participants had prior AirSim experience (range 3–24 months), though none had experience with the present task; therefore, all were retained. Ethical approval (CURES/17468/2022) was obtained prior to the study. Participants were anonymized using numeric IDs, with identifying information removed after 28 working days.

E. Results Analysis

Prior to hypothesis testing, all performance metrics in Section IV below were examined for normality using the Lilliefors test and for homogeneity of variances using the Brown–Forsythe test. As most of the measures violated the assumptions of normality and equal variance, we employed the non-parametric Kruskal–Wallis (KW) test to evaluate group differences. Post-hoc pairwise comparisons were conducted using Dunn’s test with Bonferroni adjustment to control for multiple comparisons. This ensured that statistical conclusions were drawn from robust methods considering data distribution.

IV. PERFORMANCE EVALUATION AND RESULTS

In this section, we examine the influence of the haptic interface on risk perception, focusing on both accuracy and time metrics. The accuracy of risk perception is assessed using five primary metrics: Risk Detection Rate, Absolute Accurate Cases, Hit Rate, False Detection Rate, and Sequence Detection Rate. Additionally, we evaluate position-wise detection accuracy for both ground and aerial scenarios. For aerial scenarios, we also report on horizontal (position-wise) and vertical (direction-wise) detection accuracies to analyse how the haptic cues assist participants in perceiving risks from various directions. Regarding time metrics, we measure the Time-to-Decision (TTD), which is defined as the duration until participants halt the simulation and report their perceptions.

A. Risk Perception Accuracies

First, we evaluated the risk detection rate across both ground and aerial scenarios under conditions with and without haptic feedback. Risk detection rate is defined as the ratio as num_{est}/num_{tag} , where num_{est} is the reported number of risks and num_{tag} is the ground truth number of target, representing how many risks the participants can identify. As depicted in Fig. 3, the risk detection rate under conditions with haptic feedback are significantly higher than those without haptic feedback for both scenarios. Specifically, In the ground scenario, the Kruskal–Wallis test showed a significant effect of feedback condition on risk detection, $X^2(2, N = 246) = 38.05, p < 0.001$. Post-hoc analysis indicated that both the VHT condition (mean = 0.961, SD = 0.128) and the Haptic-only condition (mean = 0.952, SD = 0.123) produced significantly higher detection rates than the VT condition (mean = 0.783, SD = 0.271; $p < 0.001$ for both comparisons). No significant difference was observed between the VHT and SHT conditions. In the aerial scenario, feedback condition also had a significant effect, $X^2(2, N = 246) = 22.46, p < 0.001$. Detection rates were higher in both the VHT (mean = 0.917, SD = 0.162) and SHT (mean = 0.923, SD = 0.170) conditions compared with VT (mean = 0.778, SD = 0.256; $p < 0.001$ for both comparisons). As in the ground case, the two haptic-supported conditions did not differ significantly. Together, these results demonstrate that haptic feedback significantly improves risk detection in both ground and aerial tasks, while vision alone yields the lowest performance.

Second, given the reported attack agents $ID_{EstID} = [Est_1, \dots, Est_n]$ and the ground truth attack agents

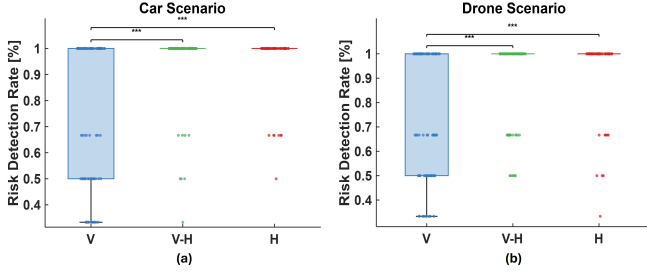


Fig. 3. Statistics of the risk detection rates for ground (a) and aerial (b) scenarios. V, V-H, H represent Visual-only, Visual-Haptic, and Haptic-only.

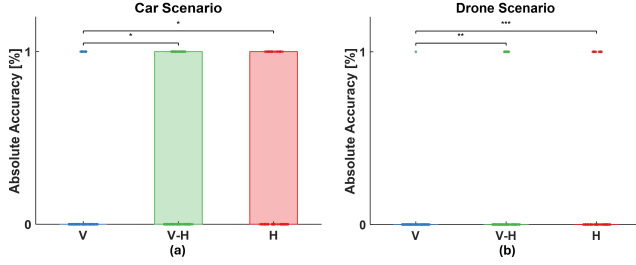


Fig. 4. Statistics of the number of absolute accurate cases for ground (a) and aerial (b) scenarios.

ID $GT_{ID}=[GT_1, \dots, GT_n]$, the absolute accurate is defined as $Est_{ID} = GT_{ID} \Leftrightarrow Est_1 = GT_1, \dots, Est_n = GT_n$. Here we reported the number of absolute accurate cases for the three modalities. Results are shown in Fig. 4. In the ground scenario, the Kruskal–Wallis test showed a significant effect of feedback condition, $X^2(2, N = 246) = 9.83$, $p = 0.007$. Post-hoc analysis revealed that the number of absolute accurate detections was higher in both the VHT condition (mean = 0.302, SD = 0.462) and the SHT condition (mean = 0.352, SD = 0.482) compared with VT (mean = 0.146, SD = 0.355; $p = 0.038$ and $p = 0.016$, respectively). No significant difference was found between the VHT and SHT conditions. In the aerial scenario, a similar effect was observed, $X^2(2, N = 246) = 16.28$, $p < 0.001$. Both VHT (mean = 0.146, SD = 0.355) and SHT (mean = 0.204, SD = 0.407) conditions produced significantly more accurate detections than VT (mean = 0.010, SD = 0.102; $p = 0.007$ and $p < 0.001$, respectively). Again, there was no significant difference between the two haptic-supported conditions. Together, these results indicate that haptic feedback could improve the precision of risk identification in both scenarios, while vision alone provides the lowest accuracy.

Third, the hit rate is defined as num_{ht}/num_{tag} , where num_{ht} is the number of correct identified risks (hits) from the participants, representing how many real risks have been observed (hit) by the participants. The results, as depicted in Fig. 5, indicate a substantial impact of the haptic interface on hit rate across both scenarios. In the ground scenario, the Kruskal–Wallis test showed a significant effect of feedback condition, $X^2(2, N = 246) = 38.48$, $p < 0.001$. Post-hoc analysis revealed that participants achieved higher hit rates in both the VHT condition (mean = 0.689, SD = 0.365) and the SHT case (mean = 0.713, SD = 0.349) compared

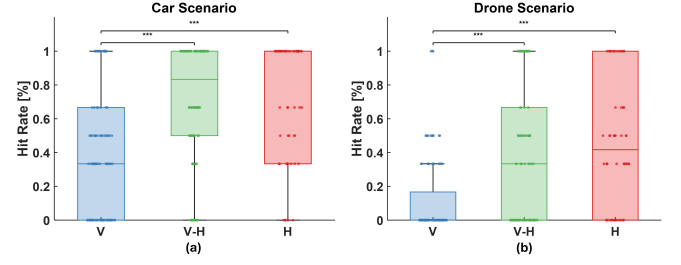


Fig. 5. Statistics of the hit rates for ground (a) and aerial (b) scenarios.

with VT (mean = 0.375, SD = 0.375; $p < 0.001$ for both). No significant difference was found between the two haptic-supported conditions. In the aerial scenario, a similar pattern is observed. The Kruskal–Wallis test again indicated a significant effect of feedback condition, $X^2(2, N = 246) = 34.79$, $p < 0.001$. Hit rates were significantly higher in the VHT case (mean = 0.356, SD = 0.402) and the SHT condition (mean = 0.460, SD = 0.384) compared with VT (mean = 0.123, SD = 0.238; $p < 0.001$ for both). No significant difference was observed between the VHT and SHT case. These results demonstrate that haptic feedback, markedly enhances the correct identification of risks in both ground and aerial tasks, while vision alone yields the lowest performance.

Fourth, the false detection rate is defined as num_{fd}/num_{test} , where num_{fd} is the number of false detections, representing the percentage of false detections over the entire reported detections. Statistical results are presented in Fig. 6. In the ground scenario, the Kruskal–Wallis test revealed a significant effect of feedback condition on false detection rates, $X^2(2, N = 246) = 9.30$, $p = 0.010$. Post-hoc analyses showed that participants in the VT condition (mean = 0.529, SD = 0.441) produced significantly more false detections than those in the VHT (mean = 0.373, SD = 0.357; $p = 0.039$) and SHT conditions (mean = 0.333, SD = 0.322; $p = 0.023$). No significant difference was observed between the two haptic-supported conditions. In the aerial scenario, the effect of feedback condition was even stronger, $X^2(2, N = 246) = 27.12$, $p < 0.001$. Participants in the VT condition (mean = 0.837, SD = 0.316) again exhibited significantly higher false detection rates than those in the VHT (mean = 0.640, SD = 0.407; $p < 0.001$) and SHT conditions (mean = 0.546, SD = 0.382; $p < 0.001$). As in the ground scenario, no significant difference was found between the VHT and SHT conditions. These results indicate that haptic feedback, whether alone or combined with vision, effectively reduces false alarms in both ground and aerial scenarios.

As attacks and the corresponding haptic cues are initiated sequentially during the experiment, the accuracy of detecting the sequence in which attacks occur represents another critical metric for evaluating the temporal efficiency of the haptic interface. Therefore, we also consider the sequence detection rate in this study. This metric explicitly measures participants' ability to correctly identify the order of risk events, providing further insights into the effectiveness of the haptic cues in enhancing SA during dynamic scenarios. Given a pair of estimated (reported) risks Est_{ID} and the ground truth risks

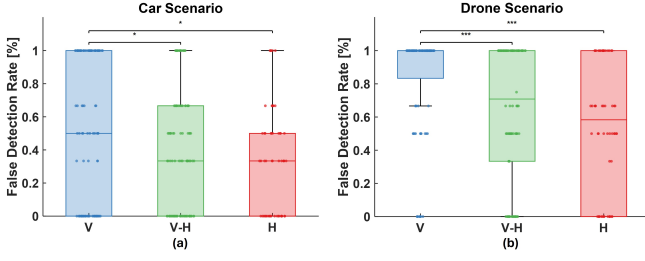


Fig. 6. Statistics of the false detection rates for ground (a) and aerial (b) scenarios.

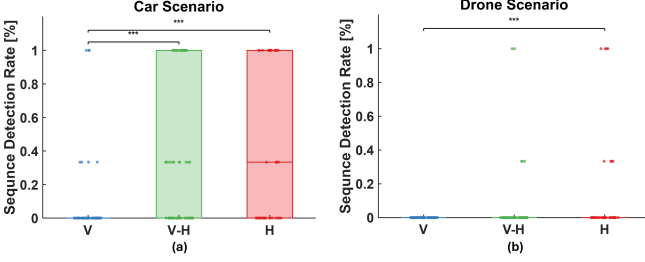


Fig. 7. Statistics of the sequence detection rates for ground (a) and aerial (b) scenarios.

Gt_{ID} , we evaluate the percentage of correct detected risk sub-pairs. Here, a sub-pair is a pair of elements (Est_i, Est_j) from Est_{ID} , where $i < j$, so the sub-pair subjects of Est_{ID} can be represented as: $P(Est_{ID}) = (Est_i, Est_j \mid i < j, 1 \leq i < j \leq n)$. Similarly, let $P(Gt_{ID})$ represents the pairs in Gt_{ID} that match the orders of pairs in $P(Est_{ID})$. Then, the number of matching Num_{MT} sub-pairs can be expressed as $\{(Est_i, Est_j) \in Est_{ID} \mid Est_i \text{ also appears before } Est_j \text{ in } Gt_{ID}\}$. In the end, we can evaluate how many sub-pairs in Est_{ID} also exit in Gt_{ID} with the same sequence as: $M(A, B) = \sum_{(Est_i, Est_j) \in P(Est_{ID})} \delta(Est_i, Est_j, Gt_{ID})$, where $\delta(Est_i, Est_j, Gt_{ID}) = 1$ if Est_i appears before Est_j in Gt_{ID} , and $\delta(Est_i, Est_j, Gt_{ID}) = 0$ otherwise.

As shown in Fig.7, in the ground scenario, the Kruskal–Wallis test revealed a significant effect of feedback condition on sequence detection rate, $X^2(2, N = 166) = 26.79$, $p < 0.001$. Post-hoc analyses showed that performance was significantly higher in both the VHT case (mean = 0.364, SD = 0.444) and the SHT case (mean = 0.453, SD = 0.474) compared with VT (mean = 0.070, SD = 0.227; $p < 0.001$ for both). No significant difference was found between the two haptic-supported conditions. In the aerial scenario, the Kruskal–Wallis test also indicated a significant effect of feedback condition, $X^2(2, N = 172) = 14.31$, $p < 0.001$. Post-hoc results showed that the SHT case (mean = 0.130, SD = 0.306) produced significantly higher sequence detection than the SHT (mean = 0.000, SD = 0.000; $p < 0.001$). No significant differences were observed between VT and VHT (mean = 0.050, SD = 0.194; $p = 0.196$) or between VHT and SHT ($p = 0.113$). These findings show that haptic cues enhanced participants' ability to perceive the temporal order of risks.

In summary, it is shown that the haptic interface can enhancing participants' hazard SA by improving hit rate and

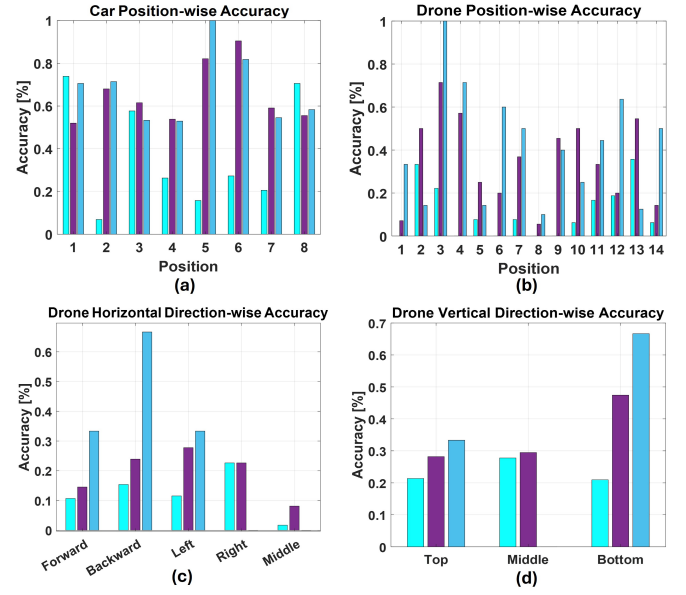


Fig. 8. Risk Detection Accuracy by Location, Position, and Direction (a) accuracy across eight specified locations for ground scenarios. (b) accuracy across fourteen locations for aerial scenarios. (c) horizontal position-wise risk detection accuracy. (d) vertical direction-wise risk detection accuracy.

reduced false detection rates. These findings highlight the value of haptic assistance in complex perceptual tasks.

B. Position-wise Risk Perception Accuracy

We assessed location-wise detection accuracy by categorising correct responses according to the attack locations in Fig. 1. Results for the ground scenario are shown in Fig. 8(a). With haptic feedback, detection performance improved markedly at locations 2, 4, 5, 6, and 7. In the VHT case, the highest accuracies occurred at location 6 (90.5%), location 5 (82.1%), and location 2 (68.0%), indicating that rear hazards that mapped to vibrotactile cues on the lower back were especially salient. The SHT case showed a similar trend, with its top performance at location 5 (100%), location 6 (81.8%), and location 2 (71.4%). Notably, SHT slightly outperformed VHT at several positions (1, 2, 5, and 8). By contrast, the VT case performed best at frontal locations 1 (73.9%), 8 (70.6%), and 3 (57.6%), but showed very poor detection at rear positions 2 (6.9%), 5 (15.8%), and 7 (20.6%). These findings confirm that while vision alone is sufficient for frontal hazards, haptic augmentation substantially enhances detection of rear hazards, which are otherwise difficult to monitor visually.

In the aerial scenario, risk detection proved more difficult than in the ground case, reflecting both the limited camera coverage under beyond-visual-line-of-sight conditions and the added complexity of the vertical dimension. The VT case was least effective, with participants frequently failing to identify hazards at key locations (1, 4, 6, 8, and 9). By contrast, the SHT condition supported accurate detection at locations 3 (100%), 4 (71.4%), 6 (60.0%), and 12 (63.6%), and overall outperformed both other modalities at eight positions (1, 3, 4, 6, 7, 11, 12, 14). The VHT condition achieved its best results at locations 2 (50.0%), 5 (25.0%), 9 (45.5%), 10 (50.0%), and

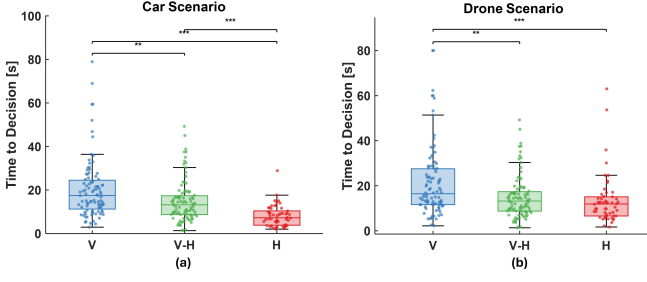


Fig. 9. Statistics of the Time-To-Decision analysis for the ground (a) and aerial (b) scenarios.

13 (54.6%). These results underscore the greater challenge of localising aerial risks relative to ground hazards, while showing the advantages of haptic cues at several directions.

Given the lower precision in the aerial scenario, the 14 attack locations were grouped into five horizontal positions (forward, backward, left, right, middle) and three vertical directions (top, middle, bottom), as shown in Fig. 8(c–d). Across both domains, the addition of haptic cues improved accuracy relative to VT, with the VHT condition outperforming visual baseline in every direction. The SHT condition revealed several notable advantages: forward detections reached 33.3% compared to 14.5% with VHT and 10.7% with VT; backward detections rose to 66.7%, representing a three- to fourfold improvement over the other modalities; and left-side accuracy reached 33.3% versus 27.8% (VHT) and 11.5% (VT). In the vertical domain, SHT produced the best performance for both top (33.3%) and bottom (66.7%) cues. However, the SHT mode introduced critical blind spots such as risks from the right side and from vertical middle positions.

In summary, the results show that the aerial scenarios, which require participants to detect risks in a 3D environment, present greater complexity, and challenge. This complexity persists despite the support provided by the haptic interface

C. Time-to-Decision Analysis

In this part, we assess the TTD in seconds to analysis the impact of the haptic interface on risk perception and decision-making speed. TTD is defined as the interval between the start of an attack and the moment participants press a key, signalling their readiness to report their perceptions. Statistical results are displayed in Fig. 9. In the ground scenario, the Kruskal–Wallis test indicated a highly significant effect of feedback modality on decision time, $X^2(2, N = 246) = 56.28, p < 0.001$. Post-hoc analyses showed that decisions were faster in the VHT condition (mean = 12.65 s, SD = 10.32) than in the VT condition (mean = 20.22 s, SD = 13.63; $p = 0.006$). Decision times were even shorter in the SHT case (mean = 8.10 s, SD = 4.88) compared with VT ($p < 0.001$). Moreover, participants responded significantly faster in the Haptic-only case than in the VHT condition ($p < 0.001$). These results indicate that haptic feedback substantially accelerated decision making in the car scenario, with the shortest times observed when participants relied on haptic cues.

In the aerial scenario, the Kruskal–Wallis test again showed a significant effect of feedback modality, $X^2(2, N = 246)$

= 19.29, $p < 0.001$. Post-hoc analyses revealed that decision times were shorter in both the VHT condition (mean = 14.88 s, SD = 9.56) and the SHT condition (mean = 13.59 s, SD = 11.15) compared with VT (mean = 20.58 s, SD = 62.91; $p = 0.004$ and $p < 0.001$, respectively). No significant difference was found between the two haptic-supported conditions ($p = 0.431$). Taken together, these results demonstrate that haptic feedback, whether presented alone or in combination with vision, reduces decision times in aerial tasks relative to vision alone. On average, however, decision times in the aerial scenario were longer than in the ground scenario, suggesting that participants required more time to make judgments in the aerial environment.

D. Inter-Individual Variability and Adaptation Effects

To examine individual adaptation patterns and potential short-term learning effects, we conducted participant-level analyses focusing on RDR, HR, and TTD. For each participant, performance changes between the VHT and VT conditions were computed as $\Delta = \text{VHT} - \text{VT}$. For RDR and HR, $\Delta > 0$ indicates improvement, whereas for TTD, $\Delta < 0$ indicates faster responses. To evaluate short-term adaptation, early and later trials within the VHT condition were compared (i.e., the first and second trials in Phase 1, and the first and final trials in Phase 2).

Inter-individual analyses revealed consistent benefits of haptic augmentation. In Phase 1, 76% of participants improved RDR and HR in the ground scenario (median $\Delta_{\text{RDR}} = 0.25, p < 0.01$; median $\Delta_{\text{HR}} = 0.33, p < 0.01$). Improvements were also observed in the aerial scenario in Phase 2, where 72–83% of participants improved accuracy metrics across scenarios (all $p < 0.01$). TTD analyses showed complementary effects. In Phase 1, approximately 70–76% of participants responded faster under VHT (median $\Delta_{\text{TTD}} \approx -4$ to -5 s), with significant acceleration in the ground condition. In Phase 2, time reductions were even more pronounced, with 78–89% of participants responding faster across scenarios (median $\Delta_{\text{TTD}} \approx -5$ to -8 s; $p < 0.01$). These findings indicate that haptic augmentation enhances both detection reliability and response efficiency for most operators.

Trial-to-trial comparisons within the VHT condition revealed no significant performance drift across repeated exposures in either phase (all FDR-corrected $p > 0.05$), and median trial differences were near zero. This suggests rapid familiarization following calibration and stable performance thereafter. Exploratory analyses further indicated no systematic performance differences attributable to gender or prior simulation experience, suggesting that the benefits of haptic augmentation are not restricted to specific user populations. These results demonstrate that variability across scenarios appears more closely related to intrinsic task complexity, particularly in 3D aerial contexts, than to learning effects or user background differences.

V. DISCUSSION

A. Haptic Interface for Time-Critical SA Augmentation

Experimental results show that an extra haptic interface could bring higher hit rates and lower false detection rates for

both ground and aerial scenarios. Additionally, risk detection rates improved to some extent with the use of haptic feedback. Our findings also highlight the challenges and limitations of haptic interfaces, as reflected by the relatively low absolute and sequence detection rates. As such, it may be practical to relax the criteria, such as evaluating detection accuracy based on broader categories like position and direction. However, enhancing 3D SA in complex environments remains challenging. This underscores the need for more efficient interface designs to support complex SA augmentation.

The reduced performance observed in 3D aerial scenarios can be attributed to several factors. First, our current haptic mapping requires cognitive translation, as horizontal directions were presented via back actuators and vertical cues via front actuators which may deviates from an egocentric mapping [25]. Second, spatial masking on the torso may limit users' ability to discriminate multiple simultaneous cues, consistent with prior findings on reduced tactile acuity in the torso [45]. Third, stimulus ambiguity arose when overlapping cues blurred together, producing confusion or extra ("hallucinated") reports. These explain why aerial conditions remained more difficult despite haptic support. In addition, the 3D haptic mapping may also increase mental workload due to the required spatial transformation between body-centred (egocentric) and environment-centred (allocentric) reference frames [50]. Research on directional cue alignment further suggests that performance degrades when spatial cues require cross-modal or frame-of-reference translation [56]. Therefore, future work will investigate more explicit vertical mapping strategies, including: (1) egocentric mappings where vertical cues are aligned with torso height [25]; (2) distributed mappings that combine front-back and vertical gradients to reduce cognitive translation [45]; and (3) multimodal encoding [56], where vertical information is reinforced via complementary channels.

Another concern is that improvements observed in the multimodal condition may simply reflect the benefit of having more cues, rather than the effectiveness of haptics itself. Thus, Phase-2 introduced a haptic-only condition. Results showed that Haptic-only performance was comparable to the Visual-Haptic mode. In some cases, such as faster decision times in ground scenarios and better sequence detection in aerial scenarios, Haptic-only even outperformed the multimodal condition. These findings demonstrate that the potential of the haptic interface extend beyond redundancy, highlighting its potential as a standalone modality.

B. Participants' Performance and Feedback

After the experiment, all participants agreed that combining both visual and haptic feedback was more helpful. However, more participants preferred haptic feedback in the aerial scenario due to the limitations of visual feedback. Specifically, in phase-1 18 out of 22 participants found the haptic interface more beneficial for the aerial scenarios compared to 14 participants for the ground scenarios. Only two participants considered visual feedback more useful for both the ground and aerial scenarios. Phase-2 experiment further valid this conclusion as 9 out of 18 participants prefer the haptic only

mode among the three modes, and 7 participants believe the visual-haptic mode are more helpful, leaving only two participants vote for the visual only mode. These findings suggest that the haptic interface can substantially complement visual feedback and serve as the primary interface in situations where visual feedback is limited or unavailable. However, it is also evident that the effectiveness of the haptic interface depending on the positions and directions from which risks originate, highlighting another constraint of this technology. A limitation is the overlap of different haptic signals, which frequently led to confusion among participants. These perception errors with the haptic interface underlines the importance of studying direction- and position-wise accuracy.

In this study, all participants without prior experience in similar task, suggesting that the observed performance gains with haptic support are achievable without extensive domain-specific training. Reaction times were largely concentrated within a similar temporal range across participants. No clear behavioural indication of tactile attenuation was observed, and no participants report diminished vibration detectability. Future deployment may benefit from structured onboarding protocols and adaptive cue calibration to accommodate individual spatial learning characteristics.

C. Intended Use Cases

While our study shows the promise of haptic interfaces, several real-world constraints remain. Latency between risk detection and actuation must be minimised, as small delays reduce usefulness in time-critical contexts [49]. False positives also risk undermining trust and increasing cognitive load, requiring a balance between sensitivity and reliability. User fatigue is another concern [47], since prolonged or intense vibrations may cause discomfort or reduced sensitivity. Further optimisation and field validation are needed before vibrotactile interfaces can be deployed in heterogeneous AVs systems.

It is important to note that the adversarial attack scenarios studied were intentionally designed to be safety-critical stress tests rather than replications of current routine operations. While such simultaneous rear and multi-directional attacks are unlikely in today's transportation settings, they are plausible in future city airspace cybersecurity and defence contexts, where heterogeneous AVs may be subject to coordinated adversarial threats. The proposed interface is designed as a cross-domain supervisory augmentation tool applicable to both training and operational contexts. In the near term, it can support training environments where operators safely practice hazard perception and decision-making under controlled but adversarial conditions, enabling scalable enhancement of situational awareness prior to real-world exposure. In the longer term, the same low-cost wearable system can be adapted for professional deployment as an operational aid in human-vehicle teaming [48]. Target domains include urban air mobility supervision [49], ground traffic safety monitoring [50], remote piloting of heterogeneous vehicle fleets [51], and specialist contexts such as search-and-rescue and defence operations [52]. While the present study focused on general operators with limited prior experience, future work will differentiate between civilian and

specialist users to assess domain-specific requirements and performance thresholds in high-stakes missions.

D. Limitations and Future Works

Considering the limitations, future longitudinal experiments could employ larger numbers of trials to more participants to ensure comprehensive exposure to all directions. Second, the studied adversarial experiments with physical AVs carry significant safety risks for both participants and devices, making high-speed collisions or multi-directional attacks ethically impractical to reproduce in the real-world. While this ensured experimental control and systematic manipulation of adversarial conditions, it reduces validity such as involving additional factors like environmental disturbances, hardware reliability, and communication delays. Moreover, as shown in Section IV. D, the observed inter-individual variability suggests that haptic perception and spatial mapping efficiency differ across users, even after calibration. This highlights the importance of personalized haptic interface design, where cue intensity and training protocols can be adapted to individual perceptual and cognitive characteristics. Thus, future work could explore adaptive calibration or learning-based personalization strategies to optimise haptic cue for different user groups [53].

Beyond haptics alone, future work will explore structured multimodal integration. For example, spatial audio can provide continuous directional context while haptic cues deliver discrete hazard alerts, enabling complementary encoding of urgency and location [54]. Coupling haptic feedback with gaze tracking may allow adaptive cue modulation based on the operator's current visual focus, reinforcing unattended regions and reducing redundant stimulation [55]. Such coordinated designs can distribute processing across sensory channels, enhance spatial richness, and mitigate overload in safety-critical supervisory tasks. Finally, practical constraints such as wearability and workflow integration must be considered. In this study, informal feedback suggested that perceived fatigue was more associated with task cognition rather than vest usage itself, and previous works with the same haptic interface also did not report significant discomfort or overload [56]. However, wearability and long-term comfort were not systematically evaluated in this study, which represents a limitation of the current work. A comprehensive assessment of long-term wearability, extended mission durations, and compatibility with domain-specific operational procedures will require dedicated ergonomic evaluation in future studies.

VI. CONCLUSION

To the best of our knowledge, this is the first study to evaluate the effectiveness of a haptic interface on human hazard SA in both ground and aerial scenarios. We propose a novel, unified design for a low-cost haptic interface within complex simulation environments and provide a comprehensive evaluation of the impact of haptic stimuli on risk perception accuracy, decision-making time, and brain dynamics. The findings reveal that: (1) Haptic cues significantly enhance risk perception accuracy across multiple metrics, including hit rate, false detection rate, and location-wise risk detection accuracy; (2)

Perception of aerial risks in a 3D environment is considerably more challenging than ground risk perception, as evidenced by lower absolute detection rates, sequence detection rates, and longer time-to-decision-making. The developed platforms, datasets, and pioneering studies presented here will support further in-depth analysis of time-critical human SA augmentation and the personalized design of multimodal interfaces incorporating visual, haptic, and brain-computer interactions.

While the present study focused on perceptual and decision-level SA, enhanced hazard detection is only one component of effective human-autonomy teaming as improved SA must ultimately translate into timely corrective actions. Future work will therefore extend the current framework to closed-loop control scenarios, where haptic cues not only support hazard recognition but also influence the accuracy, timing, and stability of subsequent manual interventions. Meanwhile, the ecological validity of this study is limited by its reliance on a controlled simulation environment. Future work should evaluate the interface in real-world settings, accounting for factors such as environmental noise, communication delays, and system uncertainties. It is also important to consider more realistic conditions, including multitasking, visual occlusion, and time-critical control demands, to assess robustness and operational transferability.

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Augmenting human hazard situational awareness with haptic interface for heterogeneous autonomous vehicles

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