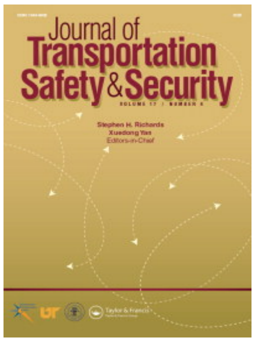

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ABSTRACT

Ensuring safety around roadway work zones is difficult which is evident by the fact that despite considerable safety measures, drivers and workers are still exposed to risks. An incomplete understanding of driver behaviors around work zones is one of the contributors to accidents and incidents, prompting the establishment of behavioral rules and a thorough assessment of driver awareness around work zones to enhance safety on roadways. Advancements in digital technologies combined with major developments in traffic simulation tools, including eye-tracking and the Car Learning to Act (CARLA) simulation platform, provides safe and realistic environments to virtually simulate diverse hazardous work zone scenarios to capture driver's behaviors without actually exposing them to real-world risks. This study presents a multi-module immersive car simulation and interactive driving platform to capture authentic driver reactions and behaviors around unstructured work zones, by leveraging eye tracking and VR technologies combined with the CARLA co-simulator. Two scenarios with three cases of roadway work zone configurations were implemented for conducting user studies, wherein driver awareness while traversing around work zones was assessed through gaze duration and fixation ratios. The findings indicate that drivers prioritize their attention on workers exhibiting risky behaviors over warning signs, with increased emphasis on these individuals despite signage existence. Warning signs enhanced the awareness of normal workers; however, in hazardous conditions, drivers' attention disproportionately diverted to risky workers, diminishing their focus on normal workers. Different driver awareness patterns observed based on how drivers were notified about work zones suggest that multi-type notification systems, such as dynamic digital displays, wearable devices for workers, and auditory alerts, with human notifiers at the center, be implemented to keep them aware of work zones and workers.

KEYWORDS

Roadway work zone safety; driver-worker interaction; driving simulator; VR; CARLA; eye-tracking

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1. Introduction

Ensuring safety on roadways, particularly in the presence of work zones, is a major challenge. Despite significant safety measures, the most recent annual crash data show 874 fatal work zone crashes and an average of 125 worker fatalities per year over the past decade, indicating that more effective safety measures are needed (National Work Zone Safety Information Clearinghouse, 2023). One impediment to achieving a complete situational understanding of safety in and around work zones is the lack of comprehensive and in-depth information on the behaviors of the main actors in these events, namely workers and drivers. To enhance work zone safety, it is crucial to focus on the awareness of both workers and drivers. Our previous research (Ergan et al. 2022) on using smartwatches to alert workers using VR-based traffic simulations highlights the importance of increasing workers' awareness. However, dangers in work zones also stem from drivers' behavior, underscoring the need to thoroughly understand their actions and then deploy appropriate traffic control measures. Considering that vehicles can be dangerous in roadway work zones, it is essential to better understand drivers' situational awareness and the impact of their interactions with workers in these environments. This requires innovative technologies to capture their behaviors in realistic settings.

Recent advancements in digital simulation and monitoring technologies have facilitated significant progress in understanding driver behavior and situational awareness in hazardous environments. Techniques such as virtual reality (VR), augmented reality (AR), and eye-tracking have been extensively used to create controlled environments for studying driver responses to various traffic scenarios, including work zones. For instance, VR platforms provide immersive simulations of road conditions, enabling researchers to capture driver behaviors under hazardous conditions without risking safety (Cheng et al., 2022; Zou & Ergan, 2021). Eye-tracking systems have been particularly effective in evaluating driver focus and fatigue, revealing valuable insights into visual attention allocation and the factors influencing driver awareness (Wang et al., 2019; Xu et al., 2018). However, while these studies highlight the efficacy of simulation technologies, they often fail to capture the dynamic and mutual interactions between drivers and workers in work zones. Moreover, existing research has primarily focused on static elements such as signage and cones (Vignali et al., 2019), neglecting the impact of worker behaviors—particularly risky ones—on driver attention. This gap underscores the need for a more comprehensive approach integrating dynamic worker behaviors and real-time driver reactions within a realistic simulation environment to develop targeted safety measures and interventions.

To address this need, we designed and implemented an eye-tracking-based co-simulation system that integrates a gaze recording system combined with VR-CARLA simulator and a racing wheel. This integrated system allows us to capture drivers' attention and driving behaviors effectively. This setup allows for time-stamped capturing of drivers' actions, perceptions, and reactions in realistic traffic simulations around virtual work zone environments. For capturing workers' driving behaviors around roadway work zones, we utilized full-body animations through the Unreal Engine within the CARLA simulator to simulate worker movements and interactions in real-time. This integration provides a holistic view of the human dynamics of drivers and workers in work zones, enabling the development of more effective safety measures and interventions.

By utilizing these advanced simulation tools, our goal is to improve safety in work zones by better understanding and addressing drivers' behaviors. The specific objective is to understand how drivers' awareness change (measured by their gaze movement) as they are exposed to variations in work zone design (e.g. unstructured with/without signage ahead of the work zone, whether signage is stationary or carried by workers) and variations in worker behaviors (e.g. whether workers are behaving safe or unsafe while working on construction tasks). To thoroughly explore the awareness levels of drivers navigating through or around work zones, we have developed three specific scenarios based on real-world cases. This study involves two scenarios, each comprising the same three cases to facilitate comparison. Case 1 (C1) involves an empty work zone without workers but with a delineation of the work zone area with traffic cones. Case 2 (C2) simulates a work zone enclosed with traffic cones and with two workers, one idling and another squatting while paving the asphalt. Case 3 (C3) introduces a more risky situation with one worker squatting inside the work zone doing the asphalt work and another idling outside of the work zone. The primary distinction between the two scenarios where these cases are implemented is the lack of/presence of a warning sign ahead of the work zone entrance: Scenario 1 (S1) lacks a warning sign, while Scenario 2 (S2) includes a warning sign positioned before the beginning of the work zone toward the incoming traffic. Traffic microsimulations have been integrated into the system *via* the CARLA town 10 map. To precisely gauge driver awareness, we employed a 50 mm radii circle to track participants' eye movements and areas of focus using eye-tracking glasses.

Using this platform, we designed user studies with drivers who would use this integrated platform while their driving behavior and eye movements (where they look, how long they look) were tracked. User studies with 20 participants capture drivers' reactions across the combinations of scenarios and cases. *Gaze duration* and *gaze fixation ratio* are used as metrics to analyze drivers' attention levels. Gaze duration measures the time spent looking at an object on the roadway, while gaze fixation ratio indicates the share of total fixations on that object. The contributions of this research are as follows:

- An eye-tracking integrated immersive driving simulator developed to capture drivers' attention around roadway work zones.
- Analysis of the impact of work zone configurations and worker behaviors on drivers' attention patterns using the data captured in user studies that leveraged the simulator.
- Identification of differences in drivers' attention levels when exposed to work zones with warning signs and those without, as well as between normal and risky worker behaviors, which potentially help policymakers in the design of work zone layouts.

2. Related works

2.1. Roadway work zone safety studies

Research on roadway work zone safety can be categorized into four key areas based on the technologies used and their focus: onsite real roadway studies, virtual reality (VR)-based studies, augmented reality (AR)-based studies, and Internet of Things (IoT)-based systems. These research streams vary in their emphasis on workers, drivers, or both, and collectively contribute to a broader understanding of safety in work zone environments.

Traditional studies conducted in real-world roadway work zones have provided valuable insights into safety issues, such as Mahmassani et al. (2013), and Bourne et al. (2010). These studies often focus on capturing driver behaviors or worker actions in live environments. For example, research in controlled field setups has demonstrated how temporary road signs and lane delineations influence driver responses (Lucas et al., 2008). Y. Ma et al. (2021) and Milardo et al. (2022) explore drivers' behaviors and emotions through the analysis of naturalistic driving data. However, such studies are inherently limited by their inability to safely replicate hazardous scenarios. Attempts to capture driver behavior in dangerous cases often expose participants to more than minimal risk, leading to ethical and logistical challenges. Furthermore, these studies generally offer limited control over environmental variables, making it difficult to isolate specific factors affecting driver and worker behaviors.

VR technologies have become powerful tools for simulating hazardous roadway scenarios in controlled and safe environments. By providing immersive experiences, VR allows researchers to study driver and worker behaviors under various work zone configurations, such as Chang et al.

(2020). For example, studies have demonstrated that VR platforms can replicate realistic traffic patterns and environmental hazards, enabling the collection of rich behavioral data for modeling driver reactions (Zou & Ergan, 2021). Beyond driver behavior, VR has been used to train workers in identifying and responding to potential hazards, with findings indicating significant improvements in situational awareness (Ergan et al., 2022). N. Kim et al. (2021) have also leveraged virtual reality and bio-signal monitoring to predict inattentiveness in construction environments, improving safety measures for workers and enhancing experimental control. Shayesteh et al. (2023) developed a platform for human-robot collaboration training on construction sites, utilizing virtual reality and biometric sensors. A deep learning-based architecture was applied to evaluate the safety performance of collaboration. However, the number of participants was only 15, which is insufficient to collect enough data points for data-driven training. While VR-based studies offer substantial benefits, including safety and control, the state-of-the-art research highlights gaps, such as the limited integration of real-time driver-worker interactions and the need for enhanced realism in traffic simulations (Reyes & Khan, 2010).

AR has gained traction for its ability to overlay digital information onto the real world, offering novel approaches to improving safety in work zones (Gong et al., 2024). Sabeti et al. (2024) demonstrates that haptic-visual AR warnings can significantly improve worker reaction times by effectively combining tactile and visual cues. Wearable innovations like the "Hapti-met" safety helmet integrate directional haptic feedback to boost workers' situational awareness, demonstrating promise in reducing accidents (Lordianto et al., 2024). However, AR systems are not limited to worker-focused applications. Some studies have explored AR solutions for drivers, such as heads-up displays (HUDs) that provide real-time hazard alerts, showing potential for improving driver attention and reducing collision risks in work zones. This dual applicability of AR underscores its versatility in addressing both worker and driver safety.

IoT technologies have further advanced work zone safety by enabling real-time monitoring and alerts (Sabeti et al., 2022). IoT-based systems, such as proximity warning solutions, utilize Bluetooth low-energy technology to alert workers when they are near heavy machinery, facilitating dynamic hazard assessment (K. Kim et al., 2023). These systems often integrate sensors and data analytics to enhance their effectiveness. While IoT has primarily focused on worker safety, its potential to improve driver awareness through vehicle-to-infrastructure (V2I) communication remains underexplored, presenting a promising avenue for future research. Moreover, Kanan et al. (2018) proposes an IoT-based autonomous system for worker safety in construction sites, emphasizing real-time alarming, monitoring, and positioning strategies. Utilizing components like wearable devices, directional antennas, RF wake-up sensors, and energy-efficient power systems, the framework addresses critical risks, including backovers and proximity hazards, ensuring safety through smart alerts and data-driven insights.

2.2. Driving simulator studies

Driving simulator research has extensively used eye-tracking metrics to assess driver attention and fatigue, uncovering significant insights into visual fixation patterns and behaviors in work zones; however, there are deficiencies in comprehending the effects of work zone configurations and hazardous worker behaviors, highlighting the necessity for immersive platforms such as VR and CARLA to enhance safety research in these areas.

A systematic literature review (Cheng et al., 2022) of 22 studies on eye-tracking techniques in construction safety revealed significant insights into visual attention allocation but highlighted the need for more realistic human-work zone interactions in future research. These studies have primarily focused on understanding how workers and drivers allocate their visual attention, providing valuable data on potential safety improvements. One notable study (Vignali et al., 2019) on the effectiveness of road work signs investigated the visual fixations of 29 drivers along rural roads. It revealed that drivers glanced equally at temporary and permanent signs but focused more on single-road work signs. This finding indicates that while drivers are aware of roadway work zone signage, the current design and placement may not be sufficient to fully mitigate unsafe behaviors. The study underscores the need for improved safety measures, as drivers' lack of attention in work zones poses significant risks to workers. Xu et al. (2018) demonstrated the potential of real-time driver fatigue detection using a head-mounted eye tracker and the D-Lab system, achieving 89% accuracy through the FKNN algorithm by identifying fixation duration and pupil area as key indicators, offering crucial insights for preventing work zone accidents. Wang et al. (2019) use RGB-D cameras for ongoing gaze zone assessment in actual driving scenarios, merging ICP-based head posture tracking with gaze estimate to improve safety monitoring, and effectively incorporating 3D gaze data for real-time driver attention evaluation.

Measuring human reactions can help evaluate drivers' attention, thereby improving road safety. The intelligent in-vehicle audio warning system by Duan et al. (2023) provides effective risk reduction for merging in roadway work zones, as demonstrated in a driving simulator experiment with 42 participants. It reduces merging risks, though its effectiveness declines with delayed warnings, and higher traffic density increases risks. The findings highlight its potential for enhancing roadway work zone safety and traffic management. Ezzati Amini et al. (2023) analyze driver behavior and safety-critical events in controlled environments. This study examines mobile phone distraction using eye-tracking and driving performance data from 58 participants, revealing altered gaze patterns and driving performance under distraction. However, there is a lack of similar research on drivers' attention in roadway work zone safety. Xu et al. (2023) explored eye movement analysis in driving behavior, particularly focusing on comparing left and right gaze bias and its impact under different driving rules. Research integrating human factors, motion perception, and environmental influences has demonstrated the potential for eye movement-based driving assistance systems. However, further work is needed on real-time eye tracking and intervention strategies to enhance roadway safety.

Visual attention in driving simulator studies is typically evaluated using metrics derived from eye-tracking data. Examples of these metics include fixation duration, which indicates the total time a driver fixates on a specific object or area, and is used to assess sustained attention (Vignali et al., 2019); fixation count, which measures the number of fixations within a specific area, and indicates the salience of an object or region (Xu et al., 2018); gaze transition matrix, a metric that maps the sequence of gaze shifts between regions of interest to analyze attention allocation strategies (Wang et al., 2019); heat maps, which captures visual representations of gaze density over specific areas, and is often used for intuitive understanding of attention patterns (Silvera et al., 2022); and pupil dilation, which is an indicator of cognitive load or emotional arousal, and is used to infer mental workload and stress levels during driving (Cheng et al., 2022). The integration of microsimulators such as SUMO, VR, and CARLA has opened new avenues for simulating and studying driver and worker behaviors in controlled traffic environments. For example, DReyeVR by Silvera et al. (2022) integrates VR driving simulation with CARLA-ROS and UE4-plugin-based eye tracking, providing a platform to study eye movements and driving behavior in a simulated environment. While DReyeVR offers a good introduction to the capabilities of combining VR with eye-tracking, it lacks extensive experiments and workload assessments, highlighting a gap in comprehensive studies that fully utilize this technology for work zone safety research. Kummetha et al. (2020) investigates how work zone configurations impact driver performance and gaze behavior, revealing gender-based differences in control and stability, with recommendations to reduce mental workload by adjusting barrier placement.

Although previous research has improved roadway work zone safety with the assistance of VR, AR, and IoT, most studies focus on the workers' perspective. However, the primary danger or threat comes from vehicles.

While some driving simulator studies measure drivers' attention to enhance roadway safety, there is still a lack of roadway work zone safety analysis from the drivers' perspective. The implications of work zone design layouts (e.g. with or without signage) or how risky worker behaviors in and around work zones affect driver attention have not been thoroughly studied. By utilizing the integrated and immersive driving platform developed, this study sheds light on drivers' attention patterns as these factors are altered in work zones.

3. Methodology

The system integration is accomplished through a series of implementations to facilitate bidirectional communication between system components (Figure 1). These implementations included (a) designing and implementing the eye-tracking/CARLA traffic co-simulation environment, (b) representing full body animation of workers, (c) integrating racing wheel hardware into the co-simulation environment, and (d) defining and implementing eye-tracking technology for capturing driver awareness while driving. Details of these implementations are provided below.

3.1. Representation of full body animation of workers in VR

CARLA, an open-source traffic simulator, provides a 3D immersive environment tailored for advanced autonomous driving research. It includes functionalities like sensor simulation and realistic urban settings control (Dosovitskiy et al., 2017). By integrating Unreal Engine (UE) 5.32, CARLA supports the creation of sophisticated virtual environments around

Figure 1. System components of the developed eye-tracking-based immersive driving simulator.

roadways, leveraging robust resources for designing realistic VR scenarios (Romero & Sewell, 2022).

Virtual reality technology enhances simulation realism through full-body animation, delivering an immersive experience to users. In this study, worker full-body animations were captured and integrated into the driver's perspective to replicate work zone scenarios. This approach significantly improves immersion while ensuring the fidelity of the animations. High-quality skeleton models of workers were sourced from Mixamo, incorporating two common animations: idling and squatting on the ground to perform tasks, shown in Figure 2. Additionally, we can design and produce more worker animations using Sony Mocopi motion capture sensors in conjunction with Maya and Unreal Engine software.

To address the challenges of simultaneous interaction between a driver and animated workers, which demands significant GPU resources, pre-built full-body animations were employed as the focus of the user study was on the drivers' attention only and not on the worker-driver interactions yet. These animations strike a balance between interaction quality and maintaining low latency. Vehicles typically pass swiftly through roadway work zones, requiring seamless and responsive simulation. By importing existing motion models into CARLA *via* UE5, the study reduced latency and rendering loads while maintaining a frame rate above 30 FPS. This ensured smooth and realistic driving experiences, prioritizing both worker and driver perspectives.

Full-body animations not only replicate physical work zone scenarios but also highlight the importance of workers' safety within these environments. By incorporating animated workers such as those crouching or idling beside work zones, the system achieves both immersion and efficiency in VR-based driver simulations. This integration provides a highly realistic simulation of roadway work zones while maintaining optimal performance for participants.

Figure 2. Pre-built full-body animations that are available in UE5 and implemented in scenarios. Left: worker animation squatting on the ground for pavement work. Middle: static worker mesh. Right: idling worker animation.

3.2. Integration of eye-tracking and hardware for capturing driver awareness while driving

To facilitate realistic human-driven vehicle interaction in the CARLA environment, we integrated a Logitech G29 racing wheel equipped with three pedals and calibrated it for precise vehicle control. Participants used this setup to navigate through a VR-CARLA co-simulation environment, with a Pygame interface enabling seamless interaction between the hardware and the CARLA system. The integration allows participants to control vehicles intuitively while observing the simulation on a display monitor, providing a practical setup for user experiments.

Drivers' awareness within the environment was captured using an integrated eye-tracking system. The Beam Eye Tracker tracked eye movement, while OBS Studio recorded the data and the driver's perspective. Figure 3 shows the integrated system and the screenshot of the driver's view containing the gaze tracking indicator. In road user safety research, eye-tracking metrics can vary depending on the user and/or scenario. These two metrics were selected for their frequent use in eye-tracking studies to capture attention distribution and situational awareness in dynamic driving environments, as validated by prior research (Jin et al., 2021; S. Ma et al., 2024). In Level 3 autonomous driving takeovers, gaze time on driving and non-driving tasks is a key measure of visual attention, given that non-

Figure 3. Gaze-tracking-based simulation environment with an integrated racing wheel. Top: set up and participant interactions with the simulation platform. Bottom: a view from the driver's perspective in the simulation.

driving tasks are inherent to Level 3 autonomy (Jin et al., 2021). Similarly, S. Ma et al. (2024) applied eye-tracking techniques to analyze bicyclists' behaviors, using fixation count, fixation duration, and saccades as key indicators of attention.

In the context of roadway work zone situations, we employed gaze duration and gaze fixation ratio to assess drivers' awareness of these work zones. Gaze duration denotes the time period from a driver's first glance of a work zone until the vehicle has completely traversed it. In Equation 1, the gaze duration is defined as the difference between t_p and t_f, where t_p represents the moment the driver traverses the work zone. t_f denotes the moment when the motorist first perceives the presence of a work zone. The gaze fixation ratio refers to the proportion of instances a driver focuses on a certain component relative to the overall number of fixations within the entire work zone region. The gaze fixation ratio quantifies the driver's attention allocated to normal workers, risky workers, and warning signs. In Equation 2, n_f denotes the quantity of fixations on a particular element of the work zone. N represents the aggregate number of fixations within the work zone. For annotation, we sample the gaze recording video at a rate of 10 frames per second, sufficient to capture variations in human consciousness.

$$Gaze\ \ Duration = t_p - t_f \tag{1}$$

$$Fixation\ \ Ratio = \frac{n_f}{N} \tag{2}$$

3.3. Implementation of work zone scenarios and cases to measure drivers' awareness

Using the Beam Eye Tracker and OBS Studio, we applied a 50 mm radius for the eye-tracking circle per participant to capture their visual attention. Each participant completed six trials covering two scenarios (S1 and S2) and three cases (C1, C2, and C3). The main distinction between the scenarios is the presence of warning signs: Scenario 1 (S1) lacks warning signs, while Scenario 2 (S2) includes a warning sign placed at the entrance of each work zone. Under each scenario, the three cases represent different work zone configurations, as detailed in Table 1.

The work zones were arranged in a staggered manner with sufficient separation to prevent overlapping visual attention between zones. The configuration was optimized to minimize the impact of roadway curves, ensuring consistency across trials. Figure 4 provides a visual depiction of the work zone setups.

Table 1. Details of work zone scenarios and cases.

ID	Scenario	Description	Key features
S1	Without warning signs	Work zones without warning signs	No advance notice to drivers about the presence of work zones
S2	With warning signs	Work zones with warning signs	Warning signs placed at the entrance of each work zone
C1	Empty work zone	Work zone without workers or equipment	Only traffic cones delineating the work zone
C2	Workers not exhibiting risky behaviors	Work zone with two workers both safe within the work zone	One idling and one performing a construction task
C3	Workers exhibiting risky behaviors	Work zone with risk-exposed workers	One worker within the work zone performing a construction task, and the other idling outside the work zone boundary

4. Experiments, analysis, and results

A user study was conducted with 20 participants aged between 23 and 40 (average age 28), including 13 males and 7 females, all possessing driver's licenses or permits. Although the user study included 20 participants, the main focus was on drivers' reactions around work zones, capturing their eye movements and the objects they fixated on. Given that each driver participated in six scenario/case combinations, with an average duration of 6.9 s per scenario, the resulting dataset was sufficiently large to analyze eye movements around work zones for statistical evaluation. An introductory overview of the experiment is presented to each participant at the beginning. They are directed to navigate through numerous roadway construction zones to drive realistically and avoid collisions with the work zones. Participants seeking to familiarize themselves with the driving system or steering wheel operation could practice in an environment without work zones. During the driving activity, all participants experienced consistent weather conditions set to a well-illuminated cloudy environment, which could be adjusted through the Python API if needed. Before the commencement of formal data collection, eye-tracking calibration is performed. The eye-tracking device employs a solitary webcam and BeamEye, a proprietary program. Calibration may require multiple repetitions to assure precision, particularly for individuals with significant myopia, astigmatism, or those utilizing blue light-blocking spectacles. During the driving activity, participants' gaze movement data is captured in video format, alongside real-time localization, velocity, acceleration, and inputs for steering, throttle, and braking. Upon conclusion of the experiment, participants filled out a questionnaire to offer ratings and feedback.

Our experimental framework has two scenarios, each containing three cases, as detailed in Table 1. Abbreviations will be utilized in the subsequent content: S1 denotes scenario 1, a work zone without warning signs,

Figure 4. Work zones implemented with scenarios (S) and cases (C). S1C1: empty work zone without warning sign; S1C2: two workers without risky behaviors in a work zone without a warning sign for work zone presence; S1C3: one worker without a risky behavior, one worker with risky behaviors in a work zone without a warning sign; S2C1: empty work zone with a warning sign; S2C2: two workers without risky behaviors in a work zone with a warning sign; S2C3: one worker without risky behavior, one worker with risky behavior in a work zone with a warning sign that marks the beginning of the work zone.

while S2 denotes scenario 2, a work zone equipped with warning signs. Case 1 (C1) depicts an empty work zone; Case 2 (C2) features two workers exhibiting normal behavior within the work zone, plus Case 3 (C3) comprises one worker demonstrating normal behavior inside the work zone and another worker displaying risky behavior idling outside the work zone.

Moreover, the data analysis on the collected data can be provided into two parts based on the metrics analyzed: gaze duration and gaze fixation ratio. Each trial has only one gaze duration per participant. However, gaze fixation ratios can vary. In this research, we aim to analyze the attention mechanism of drivers toward normal and risky behavior workers. Therefore, we calculated the gaze fixation ratio for normal workers under Scenario 1, Cases 2 and 3, and Scenario 2, Cases 2 and 3. Additionally, we analyzed the gaze fixation ratio for risky-behavior workers in Scenario 1, Case 3, and Scenario 2, Case 3.

4.1. Exploration of driver attention mechanisms

The drivers' attention mechanisms through an analysis of gaze duration data collected from user studies were examined, with the findings illustrated in Figures 5 and 6. Figure 5 presents a boxplot of duration times across six distinct work zone configurations, revealing that scenarios without warning signs (S1) exhibit higher median gaze duration and greater variability, particularly in the empty work zone case without workers (S1C1). This suggests that the absence of warning signs increases driver uncertainty, prompting heightened caution and longer attention durations.

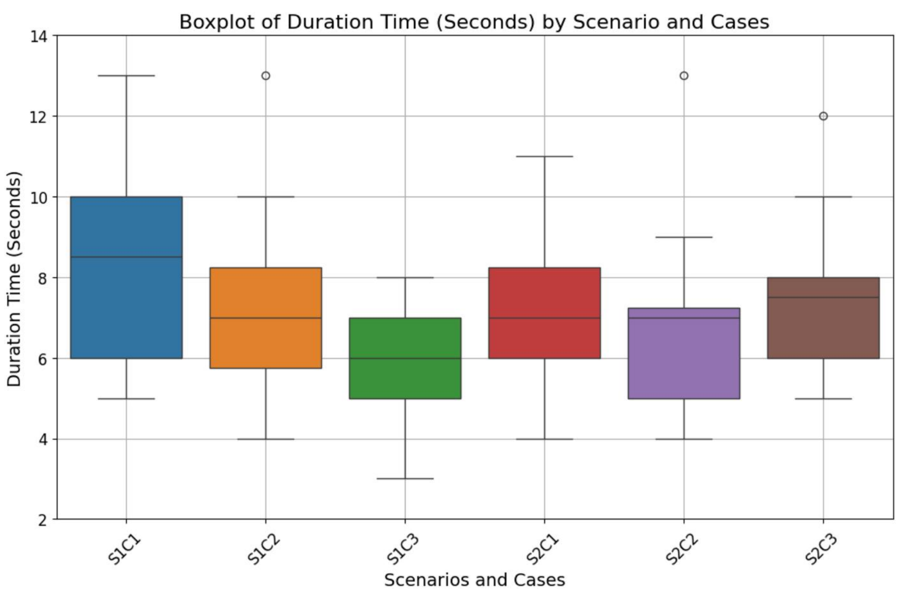

Figure 5. Gaze duration across the combinations of scenarios and cases.

In contrast, the presence of warning signs in Scenario 2 (S2) generally reduces variability in gaze duration, indicating that such signs effectively standardize driver behavior by providing clear cues about upcoming hazards. Notably, the case involving a risky worker outside the work zone in S2C3 shows an increased median gaze duration as compared to other S2 cases, highlighting that unexpected worker behavior significantly captures driver attention even in the presence of warning signs.

Figure 6 offers a granular view of individual participants' gaze durations time across all scenarios and cases through a heatmap visualization. This figure reveals substantial participant variability, and some drivers consistently exhibited longer gaze duration. For example, Participant P5 shows markedly longer duration time, especially in scenarios S2C2 and S2C3, which may reflect a higher level of caution or sensitivity to uncertain and risky conditions. Additionally, a learning effect is observed, as gaze duration tends to decrease in later configurations like S1C3 and S2C3, suggesting that repeated exposure to the work zone setups reduces cognitive load and allows for more efficient navigation. These findings underscore the complex interplay between environmental factors—such as warning signs and worker behavior—and individual driver characteristics in shaping attention mechanisms. They advocate for adaptive work zone designs that not only incorporate effective warning systems but also account for driver variability to enhance overall safety.

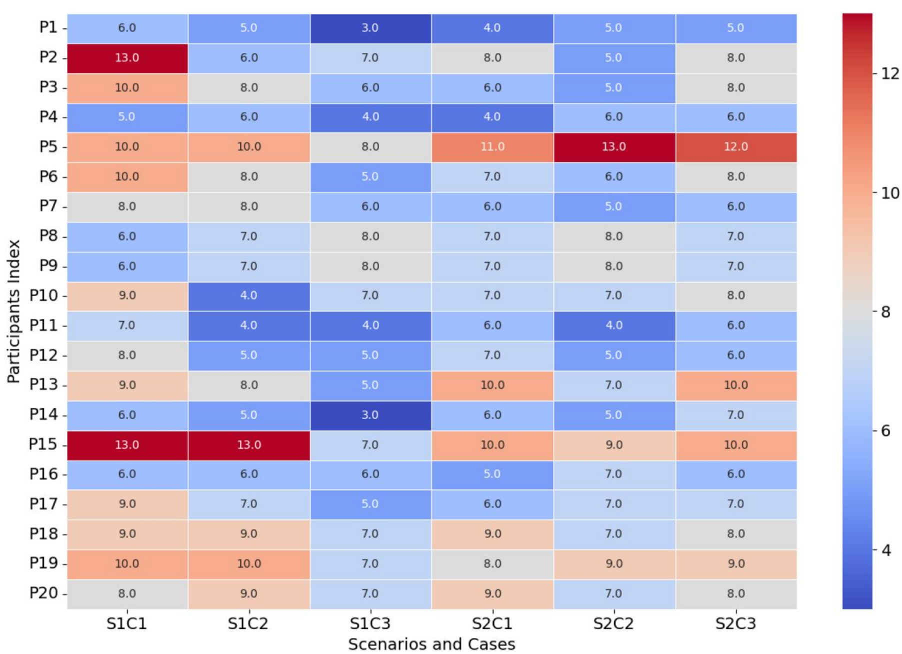

Figure 6. The heat map of gaze duration across participants and scenarios/cases.

The drivers' gaze fixation ratios on workers in various work zone scenarios and cases were also examined, with findings illustrated in Figures 7 and 8. Figure 7 presents boxplots of gaze fixation ratios across six scenario/case combinations. The results indicate that gaze fixation ratios for risk exposed workers (S1C3 and S2C3) are consistently higher than those for workers not exposed to risk (S1C2 and S2C2) across both scenarios. This suggests that drivers allocate more visual attention to workers exhibiting risky behaviors, regardless of the presence of warning signs. Additionally, the presence of warning signs in Scenario 2 slightly increases gaze fixation ratios for workers exhibiting no risky behaviors compared to Scenario 1, implying that warning signs may enhance driver awareness of workers in the work zone.

Figure 8 provides a heatmap of gaze fixation ratios for individual participants across all scenarios and cases, revealing significant driver variability. Some participants, such as P12 and P13, consistently exhibit higher fixation ratios on risky workers across all configurations, indicating a heightened sensitivity to perceived risk. Conversely, participant like P9 demonstrate lower attention to normal workers, which may reflect differences in risk perception or driving behavior. The heatmap also shows that participants generally allocate higher fixation ratios to workers in Scenario 2, particularly in risky configurations (S2C3), reinforcing the notion that warning signs increase overall attention toward work zone elements. Notably, some participants (e.g. P3 and P12) display unusually high fixation ratios in S1C3, suggesting individual differences in response to risk exposure.

Figure 7. Gaze fixation ratios across scenarios and cases.

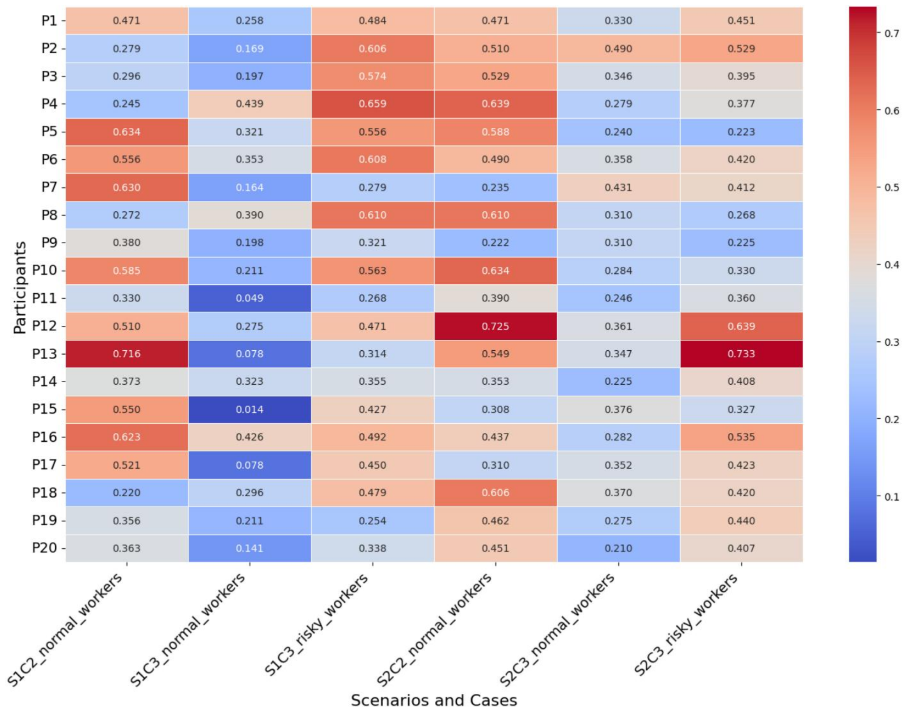

Figure 8. The heat map of gaze fixation ratio across participants and scenarios/cases.

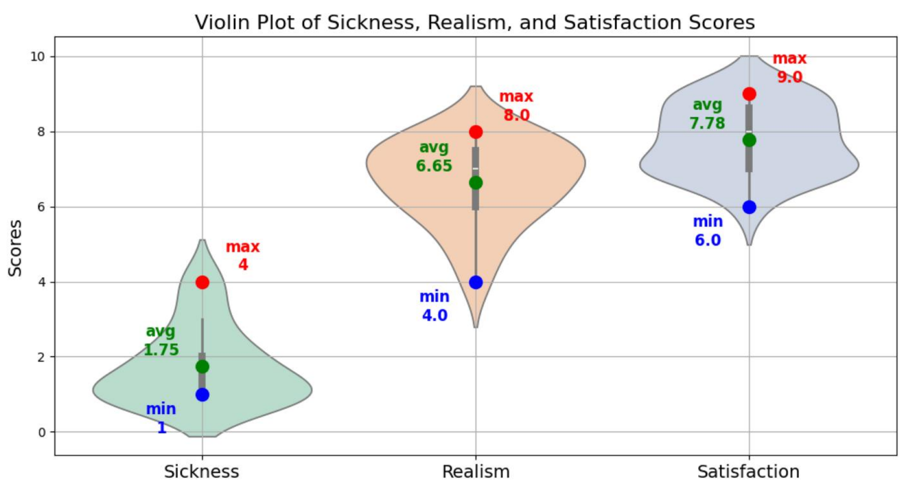

Figure 9. Scores of 3D motion sickness, realism, and satisfaction.

4.2. Impact of warning signs on drivers' awareness around work zones

The only difference between Scenario 1 and Scenario 2 is the existence/lack of warning signs at the beginning of work zones. This is to investigate the effect of warning signs on drivers' awareness around work zones when workers are exhibiting/not exhibiting risky behaviors. The hypothesis posits that the warning sign will affect drivers' attention, indicating that data from Scenario 1 should differ markedly from data in Scenario 2.

The paired t-test is the most suitable method to compare data in each group and analyze if they behave statistically significantly different. In our experiment, each driver must consistently navigate all work zone conditions, leading to dependent variables for each participant. The paired t-test is appropriate in this context as it compares measurements from the same subjects under varying settings, so effectively controlling for individual variability.

There are two pairs that can be used for validation: S1C2 and S2C2, S1C3 and S2C3. According to the paired t-test results in Table 2, drivers' attention on S1C3 safely behaving workers differs significantly from that on S2C3 safety behaving workers. Meanwhile, there is a significant difference in gaze duration between S1C3 and S2C3. Based on average values from Table 3, the average gaze duration for S2C3 is 7.60 s, which is higher than 5.90 s for S1C3. Additionally, the fixation ratio for S2C3 normal workers at 0.3211 is greater than that for S1C3 normal workers at 0.22954. However, there is no significant difference in attention paid to risky workers between the two scenarios, nor in attention paid to normal workers under safe conditions. Therefore, we can conclude that drivers pay more attention to normal workers under dangerous work zone conditions when a warning sign is present. Nevertheless, there is no significant difference in attention to risky workers, and the fixation ratios are comparably high, suggesting that drivers consistently pay more attention to risky behaviors regardless of the presence of a warning sign. However, further discussion is needed to solidify this conclusion. The differences between risky and normal behaviors will be covered in the next subsection.

4.3. Impact of workers' risk exposure on drivers' awareness around work zones

Besides the impact of warning signs, we are also interested in the influence of risky behaviors compared to normal behaviors. To achieve this goal, we should compare the differences between cases 2 and 3 in both scenarios. The hypothesis is that normal and risky workers receive the same level of attention from drivers. Three data sets can be used to validate this

Table 2. Statistical results of paired t-tests for Scenario 1 and Scenario 2.

Group 1	Group 2	T-Statistic	*p* Value
S1C2 normal workers	S2C2 normal workers	−0.6148	.5460
S1C3 normal workers	S2C3 normal workers	−2.6317	**.0164**
S1C3 risky workers	S2C3 risky workers	0.9140	.3722
S1C2 gaze duration	S2C2 gaze duration	1.2089	.2415
S1C3 gaze duration	S2C3 gaze duration	−4.7733	**.000132**

Bold text in the tables indicate statistically significant differences at 90% or above confidence level.

Table 3. Means and standard deviations (std) of gaze duration and gaze fixation ratios across cases.

Category	Scenario/case	Mean	Std
Gaze fixation ratio	S1C2 no signage and no risk exposing workers	0.446	0.148
	S1C3 no signage and no risk exposing workers (on task)	0.230	0.121
	S1C3 no signage and risk exposing workers	0.455	0.126
	S2C2 with signage and no risk exposing workers	0.476	0.137
	S2C3 with signage and no risk exposing workers (on task)	0.321	0.068
	S2C3 with signage and risk exposing workers	0.416	0.121
Gaze duration (s)	S1C1	8.4	2.26
	S1C2	7.25	2.27
	S1C3	5.90	1.59
	S2C1	7.15	1.93
	S2C2	6.75	2.01
	S2C3	7.60	1.70

Table 4. Multiple comparison of means (Tukey HSD, FWER = 0.05).

Group 1	Group 2	Mean diff	*p*-adj	Lower	Upper	Reject
(a) Scenario 1						
S1C2 normal	S1C3 normal	−0.216	0.0	−0.3191	−0.1128	**True**
S1C2 normal	S1C3 risky	0.0099	0.971	−0.0933	0.1131	False
S1C3 normal	S1C3 risky	0.2259	0.0	0.1227	0.329	**True**
(b) Scenario 2						
S2C2 normal	S2C3 normal	−0.1544	0.0003	−0.2423	−0.0664	**True**
S2C2 normal	S2C3 risky	−0.0594	0.2442	−0.1473	0.0286	False
S2C3 normal	S2C3 risky	0.095	0.0315	0.007	0.183	**True** .

Bold text in the tables indicate statistically significant differences at 90% or above confidence level.

hypothesis: attention to normal workers under safe work zone conditions, attention to normal workers under risky conditions, and attention to risky worker behaviors. We can perform the comparison in both scenarios 1 and 2. ANOVA is the ideal solution for cross-validating and comparing more than three groups. Duration time is not considered due to its units not aligning with the gaze fixation ratio. In scenario 1, the F-Statistic is 17.733, and the p value is 1.03×10^{-6}, indicating a significant difference between these groups. The Tukey HSD test is applied to compare differences between each group. Table 4(a) shows that the attention of Case 2 normal workers significantly differs from the attention of Case 3 normal workers. Also, Case 3 attentions on normal workers significantly differ from Case 3 attentions on risky workers. In scenario 2, the result of ANOVA shows an F-Statistic of 9.0697 with a p value of .00038. Table 4(b) indicates that the Tukey HSD test supports the same conclusions as scenario 1. From Table 3, the average data results show that S1C2 normal is 0.446, which is greater than S1C3 at 0.230; also, S2C2 normal is 0.476, greater than S2C3 normal at 0.321. The conclusion is that normal workers in safe conditions receive more attention than those in risky conditions, regardless of the presence of a warning sign. It is reasonable that risky workers draw more attention away from normal workers in the same work zone. The comparison data also supports this conclusion: S1C3 risky is 0.455, greater than S1C3 normal at 0.230; S2C3 risky is 0.416, greater than 0.321. Another conclusion is that workers exhibiting risky behavior always receive more attention, regardless of the presence of a warning sign.

4.4. Self-reports of participants on driving experience

Each participant was requested to complete a questionnaire and furnish comments and feedback regarding their experience. Users were asked to recall and report what they noticed during the driving experience. The most common responses, based on the number of mentions, included work zones (15 mentions), traffic lines (14 mentions), and the road surface ahead of the vehicle (8 mentions). For most VR-based simulators, motion sickness is a common issue due to low resolution, low frame rates, or a lack of haptic feedback. Realism is also crucial for user-based simulators to ensure high-quality data collection from users. Therefore, three scores were obtained, each ranging from 1 to 10. The initial score evaluated 3D motion sickness or any sensations of discomfort, with 1 signifying no discomfort and 10 denoting considerable discomfort. The second score assessed the realism of the driving system, where 1 signifies "not realistic at all," and 10 denotes "as realistic as driving on an actual road," and 10 also represents satisfaction with this driving experience. The result of scores is shown in Figure 9.

The findings indicated that individuals encountered minimal motion sickness, with an average score of 1.75 (on a scale from 1 to 4). Participants were assigned an average score of 6.65 for realism. Individuals with substantial video gaming experience frequently assigned lower realism values, as they favored higher frames per second rate. Several participants remarked on the diminutive dimensions of the Logitech G923 steering wheel, which fostered a perception of unreality. The key reasons for the diminished realism scores were these two aspects. The curve designs in the simulation were criticized for lacking smoothness; nonetheless, this was considered a minor concern as work zones were situated far from the curves.

Another aspect of input pertained to the density of work zones, which participants deemed excessively high in comparison to actual roadway configurations. This represents an area for enhancement in further endeavors. Several interviewees indicated a preference for more intricate traffic scenarios. This research concentrated on controlling variables to isolate the elements affecting drivers' consciousness, while future studies will incorporate several vehicles operating alongside the ego-vehicle. Consequently, no further automobiles were incorporated in the present user trials. Finally, participants reported comfort and satisfaction with the driving experience and their interaction with work zones, yielding an average satisfaction score of 7.78 out of 10.

5. Conclusions and discussion

This research involved the design and development of an eye-tracking-based driving simulator to record drivers' attention and responses. To investigate drivers' attention habits in work zone settings, we developed two scenarios, each comprising three cases, yielding six distinct types of work zones. The simulator documented the gaze trajectories of drivers while navigating through these work zones. An experiment with 20 participants was undertaken to assess the effect of warning signs in work zones and the influence of workers exhibiting risky behaviors on drivers' awareness and attention to other normal workers. Two metrics were employed to assess drivers' awareness: gaze duration, which quantifies the period drivers are aware of particular regions, and gaze fixation ratio, which indicates the frequency with which drivers see workers. The study revealed several key findings regarding driver attention in work zones. Workers demonstrating risky behaviors consistently garnered the most attention, regardless of the presence of warning signs, indicating heightened driver sensitivity to such actions. The placement of warning signs was found to enhance drivers' awareness of normal workers, particularly in risky work zone conditions, compared to typical work zone setups. However, in these risky conditions, drivers' focus was disproportionately directed toward workers exhibiting risky behaviors, resulting in reduced attention to normal workers relative to safer conditions. This study builds upon prior research by demonstrating that drivers' attention in short-term work zones is disproportionately focused on workers exhibiting risky behaviors, even when warning signs are present. These findings offer new insights into short-term work zone configurations and suggest that current interventions, such as warning signs, may not be sufficient to effectively mitigate attention diversion caused by risky worker actions. Unlike previous studies that primarily relied on aggregated crash data or static simulations, this research integrates real-time eye-tracking and VR-CARLA simulations to provide a more granular understanding of driver-worker interactions, highlighting the critical influence of worker behavior types on drivers' attention allocation beyond other factors evaluated. Policymakers should prioritize mitigating risky worker behaviors in work zones, as they disproportionately distract drivers from critical elements like warning signs and safely behaving workers. Targeted interventions such as worker training, wearable alert devices, and dynamic signaling are essential. Additionally, optimizing the placement and design of warning signs can improve drivers' situational awareness. These insights should guide the refinement of safety guidelines for short-term work zones, integrating worker behavior management and enhanced warning systems to reduce risks for both drivers and workers.

There are still some issues and shortcomings that need to be addressed as part of future research. First, the realism of the driving simulator needs to be further enhanced by providing a VR headset for an immersive driving experience. While the system is already quite realistic, it is essential to consider the potential for positive bias. Participants, knowing they are part of an experiment and being recorded, may behave differently, either performing better or not acting as naturally as they would under normal conditions. Moreover, this study does not analyze the interactions between parameters controlled in the experiments (e.g. the implications of worker hazardous/safe behaviors in relation to the presence or absence of warning signs), as they are not mutually exclusive. Future work should further examine these parameter interactions in different scenarios/cases and their impact on driver attention metrics. Additionally, integrating multimodal data could provide researchers with a more comprehensive understanding of drivers' awareness mechanisms during driving. For instance, including real-time data such as vehicle speed, acceleration, control inputs, and biometric measurements from drivers could make the analysis more robust and reliable. For future works, this platform and framework can be further developed and applied to work zone design, offering recommendations for improvements based on the findings and highlighting elements that are expected to enhance driver attention and safety.

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