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16. ABSTRACT
In this study, a driving simulator experiment was designed to assess driver distraction caused by roadside projects involving Unmanned Aerial Systems (UASs) and Under-Bridge Inspection Trucks (UBITs). The primary goals were to determine which scenario caused more distraction for drivers under various conditions, such as different UAS sizes, traffic densities, and traffic speeds. The analysis revealed the key parameters that significantly influence drivers' distraction levels, offering valuable insights into safer operational conditions for UAS and UBIT in the context of traffic safety. The following conclusions were made:

1. UBIT Scenario: In low and high traffic density conditions and at two different speeds of 25 and 60 mph, different traffic density and speed levels did not affect drivers' distractions in a statistically significantly different manner. Drivers consistently glanced at the UBIT regardless of these conditions.
2. UAS Scenarios: The size of the UAS, did not affect drivers' distractions in a statistically significantly manner. However, different traffic density and speed levels affected drivers' distractions in a statistically significantly different manner. Traffic speed significantly influences drivers' distractions when traffic density was high. There is a combined impact of traffic speed and density on driver distraction, emphasizing the need to carefully consider these factors when implementing UAS near roadways to minimize potential risks and enhance safety.
3. Comparison of UAS and UBIT: The comparison between UAS and UBIT revealed that UAS operations are safer than UBIT operations, causing substantially less driver distraction. UBIT operations were generally more distracting, with participants looking more at the UBITs.

In all cases, the mean TFD was well below the two-second threshold suggested in the literature as the maximum safe distraction duration. This indicates that although UBIT is more distracting than UAS, both types of distractions can be considered within acceptable limits.

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Caltrans Unmanned Aerial System (UAS)-Related Driver Distraction Research

Project Final Report

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EXECUTIVE SUMMARY

In this study, a driving simulator experiment was designed to assess driver distraction caused by roadside projects involving Unmanned Aerial Systems (UASs) and Under-Bridge Inspection Trucks (UBITs). The primary goals were to determine which scenario caused more distraction for drivers under various conditions, such as different UAS sizes, traffic densities, and traffic speeds.

Methodology

Eye movement/fixations and Electroencephalography (EEG) data were analyzed using data collected from 64 participants. Each participant experienced two scenarios for a total of 30–40 minutes of driving sessions, including normal driving (used as a control dataset) and a driving scenario involving UAS or UBIT operations. Using a combination of eye tracker and EEG modalities was an innovative aspect of this project. The eye tracker results were validated and verified with EEG data and the EEG data provided additional information and insights that would not have been possible using only eye tracker data.

Objectives

The study aimed to determine:

1. The extent of drivers' distraction caused by a UAS flying near their driving route, or as a result of the presence of UBIT.
2. A comparison of the levels of driver distraction under different operational conditions.

Results

The analysis revealed the key parameters that significantly influence drivers' distraction levels, offering valuable insights into safer operational conditions for UAS and UBIT in the context of traffic safety. The following conclusions were made:

1. **UBIT Scenario**: In low and high traffic density conditions and at two different speeds of 25 and 60 mph, different traffic density and speed levels **did not affect** drivers' distractions in a statistically significantly different manner. Drivers consistently glanced at the UBIT regardless of these conditions.
2. **UAS Scenarios**: The size of the UAS, whether small (DJI Mini 2) or large (DJI Matrice 600), **did not affect** drivers' distractions in a statistically significantly different manner. However, different traffic density and speed levels **affected** drivers' distractions in a statistically significantly different manner. Eye tracker data indicated that in UAS scenarios, traffic speed significantly influences drivers' distractions when traffic density was high. One EEG model also revealed that traffic speed was crucial factor when traffic density was low. Conversely, another EEG model found that only traffic density significantly affected drivers' distractions, with traffic speed having an insignificant effect. These findings underscore the combined impact of traffic speed and density on driver distraction, emphasizing the need to carefully consider these factors when implementing UAS near roadways to minimize potential risks and enhance safety.
3. **Comparison of UAS and UBIT**: The comparison between UAS and UBIT revealed that UAS operations are safer than UBIT operations, causing substantially less driver distraction. UBIT operations were generally more distracting, with participants looking more at the UBITs. The average total fixation duration (TFD) was 0.9 seconds for UAS and 1.4 seconds for UBIT.

In all cases, the mean TFD was well below the two-second threshold suggested in the literature as the maximum safe distraction duration. This indicates that although UBIT is more distracting than UAS, both types of distractions can be considered within acceptable limits.

1. INTRODUCTION

This research project aimed at comparing driver distractions caused by Unmanned Aerial Systems (UASs) to those arising from work zone-based road closures, where equipment like Under-Bridge Inspection Trucks (UBITs) are used. The primary goal was to evaluate the circumstances that lead to heightened driver distraction and to identify the most reliable and safe inspection tool for roadway/bridge engineering and construction purposes.

To achieve this objective, this report provides a comprehensive overview of existing research and methods on general driver distraction, specifically focusing on distractions caused by UAS and UBIT. It will also cover experimental design, driving simulator scenario development, participant recruitment, data collection, and data analysis. The most relevant study to the current project was led by the same principal investigator at San Diego State University (SDSU) in 2022 [1], where an exploration into UAS-based driver distraction was conducted using an eye tracker and a driving simulator. That study was limited in scope and focused solely on whether distraction would occur by conducting an experiment using a small human subject sample. Various scenarios involving different lateral distances, distinct weather conditions, different UAS locations, and diverse surrounding environments to investigate driver distraction across these conditions. The findings from that research suggested that the presence of UAS did result in some levels of driver distraction. However, it generally appeared to be a safe option for roadwork-related applications.

Building upon the previous study's findings, the researchers aimed to explore scenarios involving two different UAS sizes, small (DJI Mini 2) or large (DJI Matrice 600), and compare these with traditional roadwork methods, such as using UBIT in work zones which cause lane closures. This research investigated various conditions, including high and low traffic density, 25 and 60 mph traffic speeds, and different UAS sizes. Additionally, the study incorporated a new data modality by using an EEG headset to record brain signals, providing a more accurate assessment of potential distractions. Compared to the previous study, the study also increased the sample size to 64 participants. The results indicated significant differences between UAS and UBIT in causing distraction, with UBIT being more distracting to drivers. Traffic density and speed did not significantly impact distraction duration in UBIT scenarios, but they did have an effect in UAS scenarios. Also, the size of the UAS did not significantly impact distraction duration.

2. LITERATURE REVIEW

2.1 Driver Distraction

Driver distraction is a significant cause of traffic accidents and fatalities [2]. Driver inattention, including distraction, contributes to around 65% of safety-critical events [3]. Their cognitive and physiological states influence the ability of drivers to control their vehicles, making driver states crucial for automobile safety. The term "driver distraction" refers to taking attention away from tasks critical for safe driving to engage in a secondary, competing activity. According to the Multiple Resource Theory, secondary tasks that use the same resources as driving can decrease a driver's performance [4]. Two crucial resources for driving are the ability to visually perceive the road situation and the central processing power needed to understand and respond to situations. Secondary tasks requiring these resources, such as using a cell phone or a navigation aid, can distract drivers visually and cognitively, drawing their attention away from the road and competing with their ability to make driving decisions. Distraction can cause the driver's reaction time to slow down by up to two seconds, substantially increasing the risk of accidents. For example, visual distraction can reduce a driver's lateral control ability and time spent looking at the road.

The important role of drivers in the driving process is widely acknowledged, as it involves significant cognitive effort and attention from the operator's brain. Road traffic crashes cause approximately 1.3 million fatalities and 20 to 50 million non-fatal injuries each year, often resulting in long-term disabilities.

These injuries also result in significant economic losses for individuals, families, and nations, including the cost of treatment and lost productivity for those injured or affected by the crash [5]. According to the World Health Organization, road traffic crashes can cost most countries up to 3% of their gross domestic product. Moreover, according to the National Highway Traffic Safety Administration (NHTSA) in the USA, between 20% and 80% of crashes and near misses are due to driver distraction.

The quality of driving maneuvers can be significantly affected by poor driving conditions, such as distractions or drowsiness, and this can have catastrophic consequences for both the driver and passengers [6]. It is essential for drivers to remain alert and make accurate judgments while driving, as situations may arise that require quick and effective responses [7]. Thus, understanding driver behavior and optimizing driving performance is critical. Monitoring and regulating poor driving conditions and investigating dangerous driving behaviors have become crucial topics in road traffic safety. Distractions while driving can come from external stimuli in the environment, such as sights or sounds, as well as from internal factors like cognitive processes [8]. However, drivers have limited attention and must choose whether to focus on driving or distraction. Understanding the causes and effects of distraction on driving is crucial for improving road safety and developing advanced driver assistant systems.

The National Highway Safety Administration categorizes distractions in various forms, including auditory, biomechanical, cognitive, or visual distractions with visual distractions having the most significant impact [9], [10]. Auditory distraction involves diverting attention from the road by focusing on sounds, such as listening to the radio or engaging in conversations with passengers. Biomechanical distraction occurs when drivers remove their hands from the steering wheel, such as while eating, texting, or adjusting in-vehicle information systems (IVIS). Cognitive distraction involves mental shifting focus away from driving, such as daydreaming or engaging in conversations. Visual distraction arises when drivers take their eyes off the road, such as reading, watching videos, or using IVIS for navigation purposes. Moreover, in environments where drivers are visually distracted, their speed and lane position can be adversely affected. Studies have shown that drivers exhibit more significant variability in lane position and speed when confronted with roadside distractors, such as billboards, in comparison to road segments without any distractors [11]. These fluctuations in lateral position can potentially result in hazardous conflicts on the road [12]. However, most secondary tasks involve multiple forms of distraction, if not all, simultaneously [9], [13]. For instance, texting necessitates manual, visual, and cognitive distractions concurrently, with cognitive distraction being the most crucial factor [14].

2.2 UAS-Induced Driver Distraction

As the use of UAS or drones in construction continues to increase [15], it is important to understand how their presence may affect driver performance and safety [16]. One safety concern associated with UAS operating near roadways is the possibility of drivers being visually distracted by the UAS vehicle or its operators [17]. Driver diverting their attention from the road can significantly increase the risk of a crash, potentially doubling it [18]. The potential for cognitive distraction induced by drones, some drivers remain interested in observing the drone or its operators even after passing by [17]. Also, some drivers consistently observed the drone or operators for more than two seconds at least once. This finding is significant as glancing away from the forward roadway for two seconds or longer has been shown to double the risk of a crash or near-crash [19]. However, no significant difference was found in visual attention lasting over two seconds among the drone heights or the presence of operators [17]. The occurrence of multiple glances at a visual distraction presents a significant safety concern, as visually distracted environments have a detrimental impact on a driver’s ability to anticipate hazards [20], [21]. Even a brief diversion of attention away from the forward roadway at an inopportune moment can result in a critical safety incident [22]. Moreover, directing glances towards the drone, specifically, falls outside the driver’s peripheral view of the forward roadway where potential hazards like cyclists or pedestrians may be detected.

In the previous research conducted by the research team [15], a driving simulator experiment assessed driver distraction during roadside UAS operations. The study aimed to determine the extent of distraction caused by UAS flying near drivers and to explore variations in distraction under different operational conditions. Key findings revealed that factors such as UAS position, land use, and weather conditions significantly influenced distraction levels. Notably, when the UAS flew above the sides of the road, distraction remained below the maximum tolerable threshold, while positioning it above the road exceeded this threshold. The increased use of UAS in civil and construction applications brings efficiency but can also pose distractions to drivers, especially near roadways. These findings have implications for regulatory authorities tasked with ensuring safety and efficiency in UAS operations. The results of this research are valuable, and we will use its findings in our research as well.

On the other hand, few research studies specifically measure the potential visual distraction caused by UAS operations near roadways in different situations [15] and compare it with the distraction induced by the existing lane closure mechanisms. Therefore, it would be valuable to understand this phenomenon using a multi-modal analysis (i.e., collecting data from multiple sources) to investigate the effects of a construction UAS on driver performance. This study provides important insights into the potential risks associated with the use of UAS in roadway construction and maintenance activities and informs the development of strategies to mitigate these risks and promote safer driving practices [18]. Using multiple modalities in signal analysis can provide a more comprehensive and accurate understanding of cognitive and attentional states. It may be particularly useful in detecting and characterizing complex states like distraction. Therefore, future research in this area could explore the feasibility and potential benefits of utilizing a multi-modal approach for analyzing EEG and eye tracker signals in the context of distracted driving and UAS piloting. This could ultimately lead to developing more effective tools and strategies for preventing distracted driving and enhancing safety in UAS operations. Considering the potential distractions caused by UAS and their operators, it is advisable to establish research-based policies for circumstances in which UAS flies near roadways. Implementing such policies can contribute to creating safer roadway environments both presently and in the future.

The challenges and limitations mentioned earlier present excellent prospects for further exploration of this subject. All the studies referenced above focused solely on analyzing EEG signals, and only a few research studies have been conducted on a multi-modal analysis incorporating both EEG and eye tracker signals. Much research has proposed that combining information from multiple sensors could enhance distraction detection performance [23], [24].

2.3 Work Zone Lane Closure-Induced Driver Distraction

Work zones typically encompass controlled road sections undergoing construction or maintenance, whether stationary or mobile. Driving represents a multifaceted activity encompassing various physical (motor-related) and physiological (biological changes within the body) processes that operate concurrently. Numerous factors can influence the complexity of a driving situation, including the road’s geometry, traffic conditions, weather and lighting, and distractions [25], [26]. One Research [27] gained more profound insights into driver behavior within one of the most encountered geometrically constrained and visually intricate driving environments – work zones. Due to work zone complexity, including reduced speed limits, higher fines, and well-marked delineation, work zones are anticipated to have relatively few traffic incidents, according to the National Institute for Occupational Safety and Health (NIOSH). However, there has been a troubling uptick in fatalities [28] between 2015 and 2018, despite a consistent decline in work zone fatalities in the US from 2008 to 2014 (averaging 591 deaths). The recent increase brought the average number of work zone fatalities to 763 during that period, constituting approximately 2.1% of the overall national traffic fatalities tally of 36,560 [29]. This concern persists despite numerous educational campaigns and awareness initiatives by state departments of transportation. According to the Fatality Analysis Reporting System (FARS), inattention, tailgating, and speeding are among the leading driver-related factors contributing to these fatalities.

Research findings also indicate that the lateral position of a vehicle on the road can be influenced by gaze concentration, which refers to a phenomenon where drivers focus their attention on specific points of the roadway. In cases where drivers concentrate their gaze more toward the center of their lane, there is an observed improvement in lateral control [30], [31]. However, recent studies have introduced a more nuanced perspective, suggesting that lateral position variability may not be directly tied to gaze concentration but could instead be associated with increased mental workload [32], [33], [34], [35]. In an article [34], they proposed a direct link between mental workload, gaze concentration, and lateral variability. Nevertheless, their research findings revealed a weak correlation between the movement of the driver's gaze and the degree of lateral variability. Despite this weak correlation, exploring changes in gaze behavior can offer valuable insights into driver actions and overall awareness within work zones.

Based on the information provided earlier, it is evident that work zones and road construction activities can lead to driver distraction and an elevated cognitive workload. Therefore, it is imperative to delve deeper into this issue. This current research aims to conduct a comparative analysis between two scenarios. The first scenario involves a work zone where one lane is closed due to the presence of UBIT. The second scenario, in contrast, excludes UBIT and relies solely on UAS to perform their tasks. Hence, we can compare the safety of using UAS and UBIT in various situations by analyzing the data from these scenarios.

2.4 Evaluation of Driver Distraction Using Physiological Measures

Driver distraction is a significant cause of traffic accidents and fatalities. Their cognitive and physiological states influence the ability of drivers to control their vehicles, making driver states crucial for automobile safety. Physiological measures, such as heart rate data, skin conductance, and EEG, have been employed to detect distracted driving. However, research into skin conductance and heart rate showed that there was only a weak association between these measures and driver distraction [36]. Therefore, much research has been done on evaluating and detecting visual and cognitive distraction in drivers, with EEG-based experiments being beneficial for detecting cognitive distraction. Such research aims to study the relationship between EEG and distracted driving, the classification of distracted driving, the identification of different active areas of the brain during different interference tasks, and the prediction of the start and end times of distracted driving using EEG. Currently, research on cognitive distraction accounts for the most significant proportion, and experiments on distraction detection are primarily conducted in simulated driving environments. EEG activities related to interference events have become a focus of distracted driving research because experiments involve setting up various cognitive interference tasks.

Over the last three decades, EEG has proven to be one of the most effective methods for driver-state monitoring and human error detection [37]. EEG-based brain monitoring is a promising approach for driver state analysis, with many studies showing a significant correlation between EEG signals and driver performance. The researchers suggested that this approach could be used to develop real-time driver monitoring systems to detect and mitigate distracted driving behavior [37]. Many studies have been conducted to investigate different types of distractions and to explore methods for analyzing their impact on driver performance using EEG. However, there are some limitations and challenges in this area. According to one article, understanding methods for detecting distracted driving is a major challenge to improving traffic safety [38], and a driving simulation experiment is conducted to test the effectiveness of different methods, using various types of secondary tasks to induce distraction [39]. EEG data is recorded to measure changes in brain activity and determine the level of distraction [38], [40]. The researchers concluded that EEG data can be useful for assessing distractions' impact on driving performance. However, using advanced machine learning algorithms and state detection technologies based on EEG can significantly enhance road traffic efficiency and safety. This can be achieved by implementing advanced brain-controlled driving assistance systems or automated driving systems incorporating human brain cognitive decision-making and learning human driving behavior [41].

2.5 The Effects of Advanced Driver-Assistance Systems

An area that requires attention in future studies is examining the effects of advanced driver-assistance systems (ADAS) on driver distraction. Automated driving is viewed as an effective way to prevent traffic accidents caused by drivers who are unfit to drive. Presently, the development of automated driving systems does not factor in the impact of poor driving states on driving behavior, making it difficult to predict drivers' behavior in different conditions accurately. The Cooperative adaptive cruise control (CACC) system enhances traffic flow by allowing shorter time gaps and reducing driving workload through automated control. However, drivers must remain vigilant and monitor the system to respond to emergencies. Despite the potential performance benefits of reduced workload, studies have shown that drivers often engage in non-driving tasks and get distracted by on-board entertainment or off-road objects. When faced with emergency braking situations, these distractions lead to longer reaction times than manual driving. To facilitate the adoption of CACC in the real world, it is crucial to explore human- machine interface designs that improve driver engagement. Understanding the complex interaction between CACC system design, operations, and human behavior is essential [42].

Also, the findings from using Eye Tracking and EEG devices have provided evidence that the Adaptive Cruise Control (ACC) system impacts the workload and driver inattention, regardless of their experience level. As a result, they may divert their visual attention toward non-driving activities like texting, which can compromise the safety of other road users [43]. Under the ACC ON condition, drivers tend to rely on the system as a substitute for driving and divert their attention towards the car's interior, particularly the dashboard, to monitor the system's activation. As a result, this leads to distraction from the driving environment. Conversely, when the system is turned off (ACC OFF condition), drivers focus more on the road and traffic, focusing on the driving scene [44]. This trend was observed consistently throughout the test and in response to specific external events. Research has demonstrated that older drivers tend to be more cautious when utilizing ACC systems in hazardous situations [44], [45]. Surprisingly, the overall workload of experienced drivers who were accustomed to using ACC was higher than that of inexperienced drivers. This observation was supported by analyzing the drivers' brain activity (EEG) and partially funded by subjective measures. This phenomenon could be attributed to a learning process: while inexperienced drivers needed to familiarize themselves with the new automated system, experienced drivers, who were already acquainted with ACC in their vehicles, had to adjust their habits to adapt to a similar yet different system [44]. Consequently, the study observed higher instances of older participants disengaging the ACC, as they would brake whenever they observed the lead vehicle braking. This behavior indicates a certain level of caution or habitual response. According to a study [46], it was discovered that drivers experienced a decline in situation awareness for ACC or highly automated driving when they were distracted or engaged in secondary tasks, as compared to manual driving.

These findings highlight the distraction issue in relation to the emergence of (Advanced driver-assistance system) ADAS and provide further evidence that drivers tend to involve themselves in secondary tasks while relying on ADAS features. This behavior will persist or even increase as vehicle automation levels advance. When drivers are exposed to more capable automation systems that meet their expectations, they tend to trust these systems to handle driving tasks effectively. Furthermore, they may not always maintain sufficient alertness to regain control of the vehicle, when necessary, promptly. While ADAS features can enhance drivers' mental capacity and reduce their workload, it is crucial to ensure that drivers are educated about the limitations of these features and understand the potential consequences of becoming disengaged from the driving task [47], [48]. Hence, exploring the impact of employing ADAS driver distraction is imperative. Also, when there is the implementation of new systems, including automated ones, it is essential to provide training for users on their proper usage and interaction, and utilizing EEG can provide us with further insights and information regarding this matter [49].

2.6 The Two-Second Rule

Several studies have indicated that two seconds serve as a crucial threshold for diverting attention away from the road, beyond which the likelihood of safety-critical incidents escalates significantly. However, it is crucial to recognize that merely focusing on the road ahead does not necessarily imply driver attentiveness. Extensive evidence has demonstrated that the occurrence of "looked but failed to see" situations is a frequent contributing factor in road crashes [50], [51]. This phenomenon can be attributed to various aspects of mental workload arising from cognitive distraction [52]. Additionally, it is crucial to explore and investigate this aspect as well.

While previous research has examined driver performance during distractions, less attention has been given to the time required for performance recovery after a distraction. A study [53] aimed to address this gap by having participants engage in a 40-minute simulated drive with various distractions. Following each distraction, participants completed a visual Detection Response Task (DRT) to assess their resource availability and capacity to respond to hazards, along with continuous driving performance measures such as speed maintenance and lane position. The study analyzed recovery for 40 seconds following three types of distractions: cognitive-only, cognitive plus visual, and cognitive plus visual plus manual. In their research, each additional level of distraction resulted in slower DRT response times and increased speed variability during the first 0-10 seconds after the distraction. However, DRT accuracy was equally impaired across all conditions during the first 0-20 seconds after the distraction, while lane position maintenance was only affected when the distraction included a manual component. In another article [54], [55], they also used a DRT to measure recovery from cognitive distraction during real-world driving. They found that response times in the DRT were significantly elevated for 18 to 27 seconds after the distraction ended. This suggests that drivers may have limited awareness of the potential persistent consequences of distraction.

A limitation in many studies is that they only focus on a special number of volunteers or a particular age range or even gender to analyze the results in real-time [56]. For instance, one study only focused on young male drivers, and thus, future research should expand its scope to include more diverse and representative samples. [38]. In another article, it is suggested that a driving simulator experiment with an increased number of participants and signal types be conducted. Using a new multi-modality signal dataset will provide better opportunities to explore the effectiveness of different signals in detecting driver distraction. Also, future works will be required to expand the current studies by recruiting more subjects and considering demographic variables (e.g., age, gender, and occupational differences) [57]. Many previous studies did not account for individual differences in cognitive ability and driving experience, which may influence the effectiveness of the approach in real-world scenarios [58].

2.7 Detecting Visual Cognitive Distraction in Driving Using EEG Signals: Advantages and Challenges

EEG is a method of measuring the electrical activity or voltage differences between different brain areas, which occurs because of the flow of ionic currents during neuron communication. The use of EEG for communicating with computers was first proposed in the early 1970s, and since then, it has been used in diverse areas such as robotics, gaming, and neurofeedback. Brain-computer interfaces (BCIs) are increasingly used for real-time patient monitoring, neural prosthetics, affective computing, gaming, and security. EEG is commonly utilized to assess workload in the frontal cortex [59], [60] making cognitive distraction stimuli, such as math problems or auditory tasks, the most frequently used distractors in related literature.

EEG is a valuable tool for measuring the participant's mental state and can provide insight into the sensitivity of EEG in detecting cognitive distraction. There are different methods for detecting driver status, and it concludes that EEG signals are the most promising way to detect driver states due to their accuracy and intuitiveness. Many articles discuss different methods for detecting driver status, which includes vehicle-based, video-based, and physiological signals-based techniques. However, the most effective method is using neurophysiological measurements, particularly EEG signals, which can reflect the physiological activity of the human brain and are more accurate due to their strong immunity to artifacts. EEG signals have several advantages, including high temporal resolution, non-invasiveness, and low-cost properties, making them the "gold standard" for evaluating human cognitive state [61]. Furthermore, EEG is a simple and subject-acceptable method of obtaining data for driver state perception analysis [62], [63].

Choosing appropriate feature indicators is crucial for EEG-based studies, as signals can be extracted from various indicators. Distracted driving led to increased frontal theta and beta activities, and further analysis showed that the increase in frontal theta wave power could indicate the severity of distraction during actual driving [64]. In another article, they analyzed hemispheric data and identified the right frontal cortex as the most affected area during distracted driving, making the activation of this region a potential spatial indicator of driver distraction [65]. They also found that during distraction, there was higher coherence between frontal lobe electrode pairs and posterior brain regions. In contrast, in future work, they argued that distraction causes a reduction in overall theta wave activity in the occipital region [66]. In another article, it is said that theta and alpha power increases were reported in separate studies as indicators of cognitive load [67], while increases in theta and beta power were reported in another study [68].

Some researchers believe that driving distraction is typically the result of the interaction between multiple types of distractions. They explored the possibility of using a hybrid detection method that combines four commonly used measurement methods: driving performance measurement, driver physical measurement, driver biological measurement, and subjective reports [69]. They proposed a hybrid measurement method that combines physical and physiological measurements and found that this method had higher accuracy in detecting distraction than other methods [69]. In contrast to different detection methods that rely on external features, EEG-based detection can effectively identify all types of distraction and has an advantage in detecting cognitive distraction. This means that a single EEG device may detect mixed distractions, reduce the number of detection devices needed, and improve portability. On the other hand, biological measurements, such as EEG, can identify cognitive distraction by analyzing brain synchronization, but they are not as effective in detecting visual distraction since this type of distraction is primarily related to eye movements toward a specific location. Therefore, combining these complementary measures should yield a more precise assessment of visual cognitive distraction and its intensity.

Most studies on distraction detection concentrate on distinguishing between distracted and everyday driving. Distractions can have varying levels of complexity, meaning that some sources of distraction, such as deciphering a GPS map, can be more confusing than reading a simple signboard, even though both activities are considered competing tasks. Furthermore, some distractions, like looking at a GPS or reading a signboard, are necessary for driving, but the level of distraction can differ depending on the complexity of the source. Because the effects of distractions are expected to vary based on their level of complexity, it is essential to investigate and be aware of how different levels of distraction can affect driving performance to create a reliable detection method. To develop precise methods for detecting visual cognitive driving distraction, future research should consider a hybrid approach that combines physical measures, such as eye movement information, and biological measures, like EEG signals.

2.8 Enhancing distraction measurement in the presence of UAS: Benefits of multi-modal EEG and Eye Tracker

2.8.1 Utilizing Single EEG Signals and Eye Tracker Signals

A system based on a single sensor can provide users with comfortable interfaces while utilizing multiple sensors can enhance the system’s performance by integrating various distinct modalities [70]. Both EEG and eye tracker signals can be used to detect distraction [71], [72], [73], but they provide different types of information and have advantages and limitations. Among various sensors, EEG has demonstrated the ability to provide the most accurate information for classifying mental states [74]. EEG measures the brain's electrical activity and can capture neural responses related to cognitive processes, including attention and distraction [75]. EEG can detect changes in brainwave patterns associated with attentional states and cognitive workload, and it is sensitive to various brain activities and can provide detailed temporal information with high time resolution [76]. EEG signals directly capture neurophysiological signals correlated with alertness [77], [78]. However, it is less specific in identifying the exact source of distraction since it measures global brain activity rather than particular eye movements. As it directly reflects cortical activities, EEG is considered the primary physiological signal for analyzing mental states [79]. Additionally, EEG offers several advantages over other brain monitoring methods, including versatility, ease of setup, comfort, non-invasiveness, and safety [80], [81], [82], [83], [84]. Consequently, EEG has been extensively studied across various domains beyond mental state classification [85], [86], [87], [88].

On the other hand, EEG does have some limitations. One significant limitation is its susceptibility to noise, which biological or environmental factors can induce [89]. Common EEG artifact sources include eye blinks, muscle contractions, and electronic devices [90]. Furthermore, specific characteristics of EEG can vary from one individual to another [91]. To address these limitations, researchers have adopted a multi-modality approach by combining EEG with non-brain measures like eye tracker to improve the assessment of mental states and compensate for the shortcomings of EEG [92], [93], [94], [95], [96]. Moreover, an eye tracker measures the electrical potential generated by eye movements. It can directly capture eye movements, including saccades and blinks, closely related to attention shifts. The eye tracker is particularly useful for detecting eye movements associated with shifts in visual attention. Monitoring changes in eye movement patterns can provide a more direct measure of distraction-related to visual stimuli. One research [96] discovered that eye movements captured through eye tracker signals are reliable indicators for recognizing activity. The choice between EEG and eye tracker depends on the specific research or application context. If you are interested in monitoring general cognitive states and capturing broader aspects of distraction, EEG may be more appropriate. However, an eye tracker could be more suitable for focusing on visual attention and eye movement-related distractions.

2.8.2 Improving Distraction Measurement Utilizing Multi-Modal EEG and eye tracker

The experimental results presented in one study showed that fusing multiple modalities can lead to improved performance compared to using a single modality [94]. In this case, the fusion of eye tracker and EEG signals resulted in better vigilance estimation. The authors also found that eye tracker and EEG signals contain complementary information, meaning that each modality contributes unique aspects valuable for accurately estimating vigilance levels. The proposed approach could leverage each modality's strengths and enhance the overall performance by combining these two signal types.

Eye tracking [15] has played a significant role in driver attention research, providing insights into drivers' gaze behavior in different traffic environments and their distribution of glances during non-driving related tasks [97]. It has been particularly useful in classifying driver distraction based on gaze target analysis. However, eye tracking is limited as it can only objectively measure gaze direction. To gain a deeper understanding of why drivers look at specific locations, what visual information they acquire in the foveal region and peripherally, how the road environment and traffic situation influence their behavior, and how their expertise impacts their actions, it is necessary to move beyond simply counting the targets of foveated glances. [98]. While eye movement analysis has provided valuable insights into driver behavior, it is essential to recognize the fundamental limitations of using eye tracking to study driver attention and behavior. Firstly, eye tracker measures where and for how long individuals look in a particular direction or at a specific target, but it is not a direct measure of visual attention. Determining the purpose of a glance or the cognitive processing that occurs during the glance can be challenging. Additionally, there is no method to directly measure information acquisition through peripheral vision in real-world applications, despite evidence suggesting that drivers know more than what they directly fixate on. Peripheral input is thought to provide essential global and local information for driving.

Secondly, not all foveated information is necessarily processed by the driver. Sometimes, individuals may fail to notice or attend to important information even if it falls within their gaze. This phenomenon, known as "looked but failed to see" or inattentional blindness, highlights the limitations of relying solely on foveated information. Finally, it is essential to note that the absence of fixating on a specific object in the environment does not necessarily indicate a lack of awareness of that object [99]. An illustrative example is the behavior of distracted drivers who may not direct their gaze toward roadside billboards and fail to recognize them. However, their ability to operate the vehicle is less affected by distraction [100]. In this scenario, the information provided by fixating on the billboards is irrelevant to the primary driving task. The absence of fixation may suggest that the drivers have recognized the billboards but deliberately chose to ignore them. While there is currently no empirical testing of this hypothesis, one possible approach, among others, could involve conducting an EEG study to investigate whether billboards are actively suppressed in cortical areas when they are irrelevant to the driver's task. By examining brain activity, such a study could provide insights into the cognitive processes involved in perceiving and selectively attending to relevant stimuli while ignoring irrelevant information. Understanding driver attention requires a more comprehensive approach considering foveated and peripheral visual information [98], [101]. In conclusion, using multi-modal EEG and eye tracker for distraction measurement provides advantages over single psychology signal approaches. EEG captures neural responses related to attention and distraction, while an eye tracker directly measures eye movements associated with visual attention shifts. By combining these modalities, researchers can enhance the accuracy of vigilance estimation and improve overall performance in measuring distraction.

3. METHODOLOGY

3.1 Experimental Design

The driving simulator, a crucial tool in our experimental design, was used to create various driving scenarios. These scenarios were meticulously designed to engage participants and accurately measure driver distraction during encounters with UAS and UBIT.

3.1.1 Driving simulator

The experiment was conducted using a driving simulator setup. In this study, the employed driving simulator was the DriveSafety RS-250 simulator (Figure 1), located at the San Diego State University Smart Transportation Analytics Research (SDSU-STAR) Lab. This simulator was a fixed-base setup featuring an automatic transmission vehicle. Three front-display television screens were present to simulate the environment for the driver.

Figure 1. DriveSafety RS-250 simulator

3.1.2 Driving Simulator Scenarios Development

The scenarios were developed using HyperDrive software, integrating custom-designed tiles to simulate a diverse environment. These environments included suburban settings with streets with a speed limit of 25 mph and freeway/highway segments with a 60 mph limit, representing San Diego's urban and suburban landscape. To ensure unbiased distraction, participants were kept unaware of the presence of the UAS and UBIT before the driving simulation experience. This measure guaranteed that any distraction related to UAS and UBIT was natural, as participants did not anticipate encountering these objects.

This research examined visual distractions in these scenarios and the impact of various variables introduced in the subsequent section. During the scenarios, intervals of distraction, which combined various conditions, alternated with periods of undistracted driving. These distractions included visual and cognitive elements designed to elicit different patterns of brain activity. The scenarios featured driving in various conditions, programmed using the Tool Command Language (TCL), which is the programming language of the simulator integrated into the driving simulator software. The TCL script displayed the driver's speed at the bottom of the screen, providing a clear visual representation. Each scenario was divided into two sub-scenarios: low traffic density and high traffic density. The only difference between these sub-scenarios was the traffic density, while all other conditions remained consistent.

Before starting the first scenario, the researcher ensured that the EEG headset and eye tracker were correctly positioned. All electrodes of the EEG headset were placed, and the eye tracker was calibrated by having participants focus on various marks on the simulator monitors. Participants were then familiarized with the vehicle's mechanics and the virtual reality environment, and any susceptibility to motion sickness was identified.

Each scenario, including the variables and conditions involved, is described in detail in the following section.

Scenario 1: Normal Driving
This scenario was designed to establish a control group dataset. Participants engaged in uninterrupted driving for 5-6 minutes. The scenario was set in street and freeway/highway environments, with traffic speeds varying between 25 and 60 mph. No intentional distractions were introduced during this phase, ensuring participants' complete focus on driving. This scenario was instrumental in gathering baseline data for participants who were fully focused on driving and forming the control group dataset.

Scenario 2 and 3: Presence of UASs
In this scenario, UASs were displayed at different locations along the road. Driver distraction was evaluated under various conditions, which will be explained in the next section. Scenario 2 had low traffic density, and Scenario 3 had high traffic density. In these scenarios, participants had approximately 10-14 minutes to navigate the street and freeway/highway environments, and the traffic speed varied between 25 and 60 mph. Speed limit signs were strategically placed, and participants had to monitor their speed and adhere to the displayed limits. This allowed participants to navigate and respond to the UAS's dynamic presence and movements. The simulation incorporated specialized TCL scripts within the HyperDrive software to regulate the altitude of UASs, ensuring a consistent and fixed height is maintained throughout the scenario. Additionally, this simulation employed two distinct sizes of UAS (small and large), namely DJI Mini 2 and Matrice 600 (Figures 2 and 3), to investigate the effect of UAS size on potential distractions.

Figure 2. DJI Mini 2

Figure 3. Matrice 600

During the scenarios, participants encountered UASs randomly, introducing variations in their presence. For example, a small UAS was initially presented, followed by a larger one in the next position. In total, there were six positions featuring the presence of a UAS. Therefore, specific positions within the scenario featured only one of the UAS types. Figures 4 and 5 show snapshots of a scene in scenario 2, and to enhance visibility, there are two small drones. However, in the original scenario, there will be only one UAS at each position, showcasing the presence of UASs. Moreover, each UAS exhibited unique movements; for example, one may have had small movements opposite the traffic direction, while another maneuvered laterally across the road.

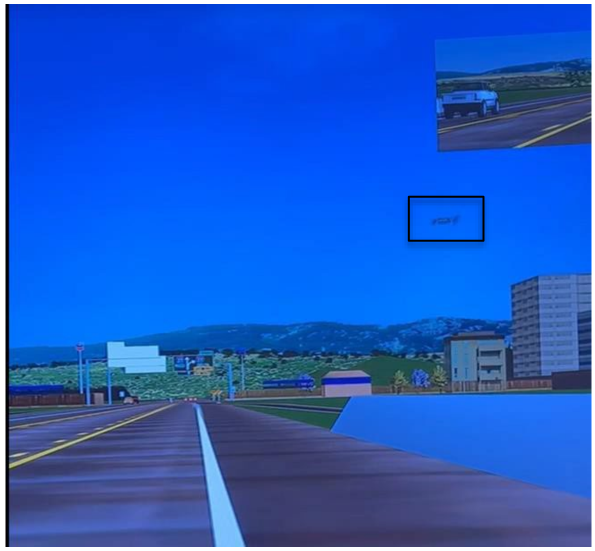

Figure 4. Demonstration of a large UAS presence

Figure 5. Demonstration of small UAS presence

Scenario 4 and 5: Presence of UBITs
This scenario involved UBITs and lane closures due to their presence, as illustrated in the real-world application depicted in Figure 6. Scenario 4 had low traffic density, and Scenario 5 had high traffic density. The participants were divided between these scenarios. The logistical setup in the scenario involving UBITs was similar to the UAS scenarios. Participants had approximately 10-14 minutes to navigate the street and freeway/highway environments where the traffic speed varied between 25 and 60 mph.

A segment of the road featuring a bridge has been selected to allow placement of the UBIT and simulate a construction zone. Participants encountered six construction areas with the presence of UBITs. Within the construction zones, dump trucks and construction workers were placed. Also, cones and barrels marked the boundaries of the construction zones. Before entering these zones, the appropriate signs were implemented, indicating to the driver their approach to a construction area and the closure of the shoulder due to the construction. This approach ensured a heightened level of realism in the simulation. Figures 7 and 8 show snapshots of a scene in scenarios 4 and 5, showcasing the construction zone and UBITs with their specific features at 25 and 60 mph traffic speed.

Figure 6. Real-world application of UBIT technology in a Construction Zone

Figure 7. Placement of UBIT and Construction Zone alongside a bridge, Traffic Speed: 25 mph

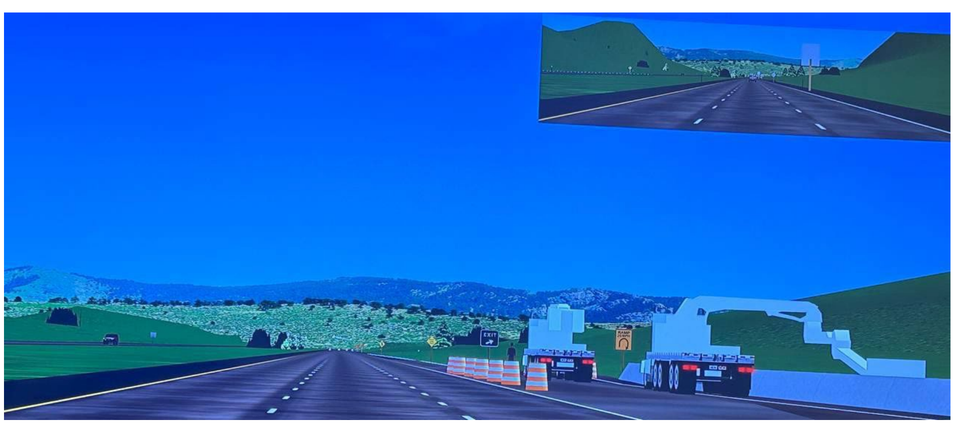

Figure 8. Placement of UBIT and Construction Zone alongside a bridge, Traffic Speed: 60 mph

3.2 Experimental Procedure

To capture the physiological and behavioral changes of distracted drivers and better understand instances of distraction, a comprehensive experiment was carried out in simulated driving situations using a driving simulator, as described in earlier sections. This section provides an overview of the data collection procedure and the following experimental design, where an eye tracker and an EEG headset were employed to capture detailed data from the participants.

3.2.1 Data Collection Systems

One of the participants' data collection modalities was the Pupil Core eye-tracking headset, designed by Pupil Labs [102]. This eye-tracker system is a wearable device like a pair of glasses, and it tracks participants' eye movements and what they look at. This device is equipped with a small front-facing camera capturing participants' perspectives while driving (referred to as the "world view"), along with two additional cameras on the sides to monitor their eye movements (Figure 9). The human eye serves two primary functions based on movement: fixation, signifying a steady gaze directed at a specific point, and saccades, representing the movement between fixations. The total fixation duration (TFD) was employed as a performance metric to assess the level of visual distraction across different independent variables. Each encounter with the UAS and UBIT was documented, including the count and duration of participants' fixation on each flying UAS and each UBIT.

In addition, the EPOC X 14 EMOTIV headset, a portable and non-intrusive data acquisition headband, was used to collect drivers' EEG signals (Figure 10). The headband is designed to be non-intrusive with little effect on drivers' behaviors. Previous studies have demonstrated that the brain region related to the driver's mental state is the occipital. Therefore, the electrodes will be placed on O1 and O2 by the International 10- 20 System. O1 and O2 in the International 10-20 System refer to standardized locations on the scalp for EEG electrode placement [103]. They specifically cover the left and right occipital lobes, which are essential for capturing brain activity related to visual processing. This system ensures consistency and facilitates data comparison in EEG studies. The sampling rate of this EEG device was 2048 SPS or Hz internal, which was its inherent or native sampling rate of the device. This oversampled data was extensively filtered to eliminate any potential traces of environmental electromagnetic interference. Subsequently, the data was down-sampled to 128 Hz. This process aided in reducing computational load, managing storage requirements, and ensuring compatibility with analysis techniques while retaining crucial information for analysis [104]-[116].

Figure 9. Pupil Core Eye Tracker

Figure 10. Emotiv EPOC EEG headset

3.2.2 Variables of the study

In this research, the utilized variables fall into two main categories: within-subjects and between-subjects variables. Within-subject variables refer to variables in which each subject experiences all the variable's levels during the study. On the other hand, between-subject variables involve each subject trying only one of the levels of the variable. The variables within the subject were the UASs' size and traffic speed in the UAS scenario and only traffic speed in the UBIT scenario. The between subject's variables were categorized as the presence of UAS or UBIT and traffic density (low or high). The levels for each variable are described below (refer to Tables 1 and 2).

Table 1: UAS Group, Variables, and Levels for Different UAS Scenarios

Variables	**Traffic Speed**	**UAS Size**
Levels	**1. 25 mph** **2. 60 mph**	**1. Small** **2. Large**

Table 2: UBIT Group, Variables, and Levels for Different UBIT Scenarios

Variables	**Traffic Speed**
Levels	**1. 25 mph** **2. 60 mph**

3.2.3 Participants

After evaluating different research methodologies and determining the optimal sample size based on variable orientation, calculations using G*Power indicated that 88 participants were required (refer to Appendix 1). G*Power is a statistical power analysis software that allows users to perform a range of statistical tests to determine the statistical power or sample size required for a given effect size (f)[1], significance level (α), and power level (β). It is commonly used in behavioral and social sciences and other research areas to plan studies, analyze power, and conduct priori and post-power analyses. G*Power aids researchers in making decisions regarding the design and execution of their experiments by providing valuable insights into statistical power and sample size determination.

Before starting the experiment, a Repeated Measures ANOVA, specifically a mixed-model ANOVA focusing on within-between interactions, was employed. This approach was chosen because the research included both within-subjects and between-subjects variables that needed to be examined. The determined size of the sample group was estimated by considering significance probability ($\alpha = 0.05$), statistical power ($1 - \beta = 0.95$), and the effect size ($f = 0.12$) that was derived from previous studies [117], [118], [119], [120]. Therefore, initially, it was determined that 88 participants were needed for this research.

The goal was to have a total of 100 participants. After enrolling 64 participants, the effect size was calculated based on the current data to verify the assumption about the initial effect size. The recalculated effect size, based on the standard deviation and mean of the data collected from each group [121], was found to be ($f = 0.3$). In studies involving groups with different sample sizes, the effect size can be computed by adjusting the standard deviation with weights corresponding to the sample sizes. This method is commonly called Cohen's *d* in the literature [122]. Based on the number of within- and between-subject variables and the new effect size, further recalculations indicated that 44 participants would be sufficient, with 22 participants needed in each UAS and UBIT group. This study ultimately included 64 participants, exceeding the required number.

[1] See Appendix 1 for more information on the justification for choosing the effect size.

4. DATA ANALYSIS

After developing the driving simulator scenarios and completing the experimental design, the next step was to update the institutional review board (IRB) approval considering the new methodologies adopted. The review and approval process took three weeks. Then, recruitment flyers were printed and posted around the campus, and recruiting the participants began. The participants should have been without mental illness or neurological diseases in the experiment. All participants should have had regular or corrected vision and normal auditory. A driving license and driving experience were required for each participant. The qualifications of each subject were verified, and informed consent was obtained before starting the experiment. They were briefed about the study's objectives, potential risks, and benefits and given a brief overview of the scenarios.

Then, the participants' data analysis was conducted using two modalities:

4.1 Eye Tracker:

Algorithms[2] were developed (refer to Appendix 2) for eye tracker data and were used to analyze the duration of eye fixations during potentially distracting events in each scenario. It determined how these fixation durations were influenced by traffic density, traffic speed, and the size of UAS (in the UAS scenario) and traffic density and traffic speed (in the UBIT scenario). The study aimed to understand the effects of various variables on drivers' visual attention and potential distractions by conducting an analysis of variance (ANOVA)[3] on eye fixation duration data. This analysis allowed researchers to determine the effect of different variables on driver distraction. This section describes the methodology employed to analyze the eye tracking data for the UAS and UBIT scenarios. Each UAS and UBIT scenario consisted of six events. In the UAS scenario, each event featured different traffic speeds and UAS sizes. For example, in the first event, the traffic speed was 60 mph, and the UAS size was small; in the second event, the traffic speed was 25 mph, and the UAS size was large. Also, in the UBIT scenario, each event had different traffic speeds. For example, in the first event, the traffic speed was 60 mph, and in the second event, the traffic speed was 25 mph. The duration of UBIT events and UAS events was approximately the same so that they could be compared reasonably. The traffic density variable was a between-subjects variable; in one scenario, traffic density was low and high was the other.

The data processing phase started with obtaining fixation information from the eye tracker software for each participant. This information was derived from a ".csv" file encompassing all their fixations, including each fixation's duration and each eye's x and y position throughout the scenario. Subsequently, fixations were categorized to include only those occurring during encounters with UAS and UBIT events. Fixations within each event were filtered to exclude instances where participants are looking ahead, at the middle of the road, or their speed, located at the bottom of the screen. Subsequently, the TFDs during each event were calculated. ANOVA tests were conducted on the TFDs. In the UAS scenario, the ANOVA test was employed for each UAS encounter to investigate the effects of traffic speed, traffic density, and UAS size on TFD. The UBIT scenario focused on the effects of traffic density and traffic speed at each UBIT encounter. The details of each algorithm for the UAS and UBIT scenario are explored in the next section.

4.1.1. UAS Scenario Method

The UAS scenario employed a machine learning method called K-Means clustering [123] to identify regions of interest (ROIs) in the fixation data. K-Means clustering partitions data into distinct groups (clusters) by minimizing the variance within each cluster, effectively grouping similar fixation points together. The primary goal was to cluster fixation points to determine the most relevant areas where the driver's attention was focused during specific events.

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[2] See Appendix 2 for the codes used for data analysis.

[3] See Appendix 3 for more details about ANOVA tests used in the study.

For this purpose, a file containing the time of each event for each participant based on their eye tracker data was used. Then, the time file for each participant is matched with its corresponding test data (UAS scenario) for analysis. The analysis involved filtering fixation data to include only those within specific event timeframes and extracting fixation data based on particular fixation coordinates (the approximate location of the UAS presence). In the UAS algorithm, K-Means clustering with two clusters was applied to the filtered data. The resulting clusters were labeled based on their y-coordinates, identifying the upper cluster as the ROI. This cluster's TFDs were then calculated to measure drivers' attention to specific areas, which was the presence of UASs in this scenario. This approach is efficient, easy to implement, and scalable, providing clear insights into drivers' focus and potential distractions. ANOVA tests were applied to determine which variables had a statistically significant impact on driver distraction in scenarios with UAS present in them; results are in Tables 7, 8, 9, and 10.

4.1.2. UBIT Scenario Method

The algorithm was designed to analyze eye-tracker data collected during UBIT scenarios, aiming to measure the duration of time participants focused on specific ROIs during predefined events. The initial attempt to use the same algorithm as in the UAS scenario failed to identify usable clusters. This failure was due to the uniformity and low variance in the fixation data within the UBIT scenario. Additionally, there was no significant difference in the y-coordinates to distinguish the UBIT event from the rest of the driving data. As a result, the algorithm could not effectively differentiate between the areas of interest in the UBIT scenario. To address this, an alternative method was needed to analyze and interpret the fixation data for UBIT events. Consequently, for each participant in the UBIT scenario, ROIs were manually specified for each event based on visual inspection (reviewed using world-view video recordings from the eye tracker) and predefined criteria using the fixations' normalized x and y coordinates. The approximate windows for each event were identified, and the corresponding ROIs were defined. The TFDs within the specified ROI for each event were calculated. Finally, ANOVA tests were applied to determine which variables impact driver distraction in UBIT scenarios, and the results are in Tables 11, 12, and 13.

4.1.3. Comparison Between UAS and UBIT Scenario

The final analysis compared the types of distraction (UAS and UBIT). For this comparison, all the UAS and UBIT scenarios data were gathered into a single file, and a new data frame was created. The ANOVA test was performed on this data frame to understand whether UAS or UBIT has a significant level of distraction. The results are shown in Table 6.

4.2 EEG Data

The first step of EEG data analysis was to synchronize the time of each event for the EEG data with the eye tracker data. Therefore, the times of each event in EEG data needed to be adjusted to align with the eye tracker's timestamps. Then, the raw EEG signal was preprocessed by limiting voltage changes to 30 microvolts between samples, referencing against an interquartile mean, and applying a high-pass filter with a 4 Hz cutoff to remove low-frequency noise. After these preprocessing steps, the data was transformed into different frequency bands such as alpha, theta, beta, and gamma. Transforming raw EEG signals into frequency bands like alpha, theta, and beta is essential because these bands correspond to different brainwave frequencies linked to various cognitive and physiological states. Analyzing these bands helps researchers understand and characterize brain activity more effectively. Focusing on specific frequency bands also reduces noise and artifacts from sources like muscle movements and eye blinks, thereby extracting meaningful information [124]. In applications such as brain-computer interfaces (BCIs) and neurofeedback, these frequency-based features improve the performance of machine learning models by providing more relevant and informative data.

For this reason, a Fast-Fourier Transform (FFT) converted the EEG data from the time domain into the frequency domain, and the data was normalized. Specifically, the Hanning window was multiplied by 2 (as the window reduces the amplitude of the Fourier transform by a factor of 2). The Hanning window is used in signal processing to reduce errors when analyzing signals like EEG data. Tapering in signal processing refers to gradually reducing the amplitude of a signal towards the beginning and end of the data segment. This smooth transition to zero at the edges helps to minimize discontinuities and reduce spectral leakage when performing frequency analysis, such as the Fourier transform. By tapering the signal to zero at the edges, the Hanning window smooths out the signal and minimizes boundary issues, leading to more accurate frequency analysis. This is important for studying brain activity, providing clearer and more precise frequency information. The Hanning window also helps maintain the main features of the EEG signal while reducing unwanted noise. After this, the output of the FFT was divided by window length. The mean of the data for each epoch/window was subtracted to remove the DC value, as it distorts the Fourier transform of the lower frequencies. Next, the four band frequencies—theta (4-8 Hz), alpha (8- 12 Hz), beta (12-25 Hz), and gamma (25-45 Hz)—were exported to a ".csv" file for further analysis. The data analysis focused on the theta, alpha, and beta bands, as these frequencies are known to show changes when a distraction occurs [125], [126], [127], [128].

In the next step, a comprehensive analysis was performed to detect anomalies during various driving scenarios. The code implemented an unsupervised autoencoder model based on Long-Short-Term Memory (LSTM) networks to detect anomalies in the input data. LSTM is a type of recurrent neural network well-suited for handling sequential data [129]. Being unsupervised means the model does not require labeled data for training; it learns to reconstruct the input data using only the data itself. The autoencoder consisted of an encoder, which compressed the input data into a lower-dimensional representation, and a decoder, which reconstructed the original data from this compressed representation. The model was trained on normalized features, and the reconstruction error (i.e., Mean Squared Error (MSE)) between the original and reconstructed data was calculated. Anomalies were identified when the reconstruction error exceeded a predefined threshold, indicating unusual patterns or distractions in the data.

The anomaly detection method works as follows. First, it started by loading control and test (UAS or UBIT scenario) data for each participant and their timing information for each event. Then, specific columns were selected from the training and test data based on predefined criteria. For instance, columns labeled 4-8 Hz were chosen when analyzing only theta. Columns with frequencies ranging from 4-8 Hz and 12- 25 Hz were selected when considering theta and beta. Similarly, for theta and alpha analysis, columns corresponding to frequencies of 4-8 Hz and 8-12 Hz were chosen. For a comprehensive analysis involving theta, alpha, and beta, columns spanning frequencies of 4-8 Hz, 8-12 Hz, and 12-25 Hz were selected. Subsequently, the selected features were normalized to ensure uniform scaling, promoting practical model training. Following normalization, separate neural network models were trained for each dataset to reconstruct the test data. Specifically, four distinct models (theta, theta, and alpha, theta, and beta, that, alpha and beta) were developed for each dataset based on the above feature extraction criteria. Once the models were trained, they were employed to reconstruct the input data, and the MSE between the original and reconstructed data was calculated. Anomaly detection was then executed by comparing the MSE to a predefined threshold. An anomaly was identified if the reconstruction error surpassed this threshold. After that, the algorithm aligns the EEG data with event timings to calculate the total distraction time for each event.

Finally, the ANOVA tests were used to detect the effects of each variable on the duration of the distraction using all four models to determine which model's results were more reasonable. The data analysis revealed that the theta model and the combined alpha and theta model produced better and more reasonable results, so those models were used. All these steps were done for UBIT and UAS scenarios. Employing two different models for EEG data was an effective approach to validating the method and ensuring its results were almost consistent. The result of the comparison using the alpha and theta model between the types of distraction is in Table 14. The results of the UAS scenario, using the alpha and theta model, are in Tables 15, 16, 17, and 18, and the results of the UBIT scenario, using the alpha and theta model, are in Tables 19, 20, and 21. The result of the comparison using the theta model between the types of distraction is in Table 22. The results of the UAS scenario, using the theta model, are in Tables 23, 24, 25, and 26, and the results of the UBIT scenario, using the theta model are in Tables 27, 28, and 29.

Overall, the results from both the eye tracker and EEG data were consistent, indicating that UBIT causes more distraction and longer TFD for drivers, regardless of traffic density and speed. While UAS size does not impact driver distraction, traffic density and speed influence distraction and TFD in UAS scenarios. Additionally, EEG data analyzed with different models provided valuable insights and details about driver distraction. For example, the eye tracker data analysis revealed no significant impact of traffic density on TFD. However, the EEG data analysis highlighted a significant finding: both traffic density and traffic speed significantly affect TFD.

5. RESULTS

One-way ANOVA tests were used to compare the type of distraction (UAS or UBIT) on drivers' TFDs. Additionally, one-way ANOVA tests were employed in the UBIT scenario to investigate the effect of traffic speed in low and high traffic density on drivers' TFDs. Two-way ANOVA tests were used to understand the effect of UAS size and traffic speed on TFD in low and high-traffic density scenarios.

A mixed ANOVA was used to analyze the data in the UAS scenario, where there were two within-subjects variables (size of UAS and traffic speed) and one between-subjects variable (traffic density). This allowed for the examination of the main effects of each variable as well as their interaction effects on the dependent variable. In the UBIT scenario, where there was one within-subject variable (traffic speed) and one between-subjects variable (traffic density), a mixed ANOVA was employed to determine how these variables impacted the dependent variable, considering their individual effects and interactions. Table 3 provides definitions of terms used in ANOVA test results.

Table 3. Parameters' definition

DF1	Degrees of Freedom (Between-Subjects) is the number of independent groups or levels minus one.
DF2	Degrees of Freedom (Within-Subjects) is the number of observations minus the number of groups.
SS	The sum of squares represents the total variability in the data.
MS	The mean square is the sum of squares divided by the respective degrees of freedom.
F value	The variable's mean square is divided by the error term's mean square.
p-unc	The p-value indicates the probability that the computed F-value would occur if the null hypothesis of no difference were true.
np2	Partial eta-squared measures effect size that indicates the proportion of variance accounted for by a particular effect.
eps	Epsilon, a correction factor, adjusts the violations of sphericity in repeated measures designs. It is used to compute adjusted degrees of freedom in the analysis.

5.1 Eye Tracker Results:

5.1.1 UAS Scenario

Based on the eye tracker data and one-way ANOVA test, Table 4 shows that the **type** of distraction (UAS or UBIT) has a statistically significant effect on TFD at the 95% confidence interval level (i.e., $p < 0.05$). A mixed ANOVA (Table 5) test between traffic density, speed, and interaction between them revealed that in the UAS scenario, **speed** significantly affects TFD (i.e., $p < 0.05$). Another mixed ANOVA (Table 6) test between traffic density, size, and interaction between them revealed that in the UAS scenario, size and traffic density do not significantly affect TFD (i.e., $p > 0.05$). A two-way ANOVA test (Table 7) between speed and size in a low-traffic density scenario revealed that speed and size do not significantly affect TFD (i.e., $p > 0.05$). However, in **high traffic density** (Table 8), **speed** significantly affects TFD (i.e., $p < 0.05$). This suggests that as traffic density increases, the traffic speed becomes an important factor influencing TFD, causing drivers to spend more time looking at UAS.

Table 4. UAS and UBIT, One-Way ANOVA Scenario Comparison

Source	DF1	DF2	F	p-unc	np2
Type	1	268	6.860322	**0.009315**	0.024959

Table 5. UAS Scenario, Mixed ANOVA Results, Traffic Density and Speed

Source	SS	DF1	DF2	MS	F	p-unc	np2	eps
TrafficDensity	0.268643	1	23	0.268643	0.069811	0.793965	0.003026	NaN
Speed	3.984942	1	23	3.984942	13.07015	**0.001455**	0.362354	1
Interaction	0.233485	1	23	0.233485	0.765805	0.390565	0.032223	NaN

Table 6. UAS Scenario, Mixed ANOVA Results, Traffic Density and Size

Source	SS	DF1	DF2	MS	F	p-unc	np2	eps
TrafficDensity	0.461551	1	23	0.461551	0.133639	0.718029	0.005777	NaN
Size	1.001924	1	23	1.001924	2.893932	0.102396	0.111761	1
Interaction	0.494055	1	23	0.494055	1.427016	0.244426	0.05842	NaN

Table 7. UAS Scenario, Two-Way ANOVA, Speed and Size, Traffic Density: Low

Source	SS	DF	MS	F	p-unc	np2
Speed	2.854322	1	2.854322	0.841378	0.362245	0.012222
Size	0.104487	1	0.104487	0.0308	0.861209	0.000453
Speed*Size	6.205439	1	6.205439	1.829197	0.180703	0.026195
Residual	230.6858	68	3.392439	NaN	NaN	NaN

Table 8. UAS Scenario, Two-Way ANOVA, Speed and Size, Traffic Density: High

Source	SS	DF	MS	F	p-unc	np2
Speed	8.394818	1	8.394818	5.598072	**0.020613**	0.070329
Size	4.383449	1	4.383449	2.923096	0.091511	0.038
Speed*Size	2.780024	1	2.780024	1.853855	0.177467	0.02444
Residual	110.9697	74	1.499591	NaN	NaN	NaN

Box plots were used to visualize the results, as shown in Figures 11 and 12. These plots indicate that traffic speed significantly impacts TFD. For example, the average TFD at 25 mph is higher than the average TFD of 60 mph. This is because drivers move slower at a speed of 25 mph, allowing them more time to focus on looking at UAS, thereby increasing the potential risk. Conversely, at 60 mph, drivers have less time to focus on UAS, reducing the risk. The figures also demonstrate that the size of the UAS does not affect TFD. The average TFD across all events remains below the two-second threshold for causing distraction and risk.

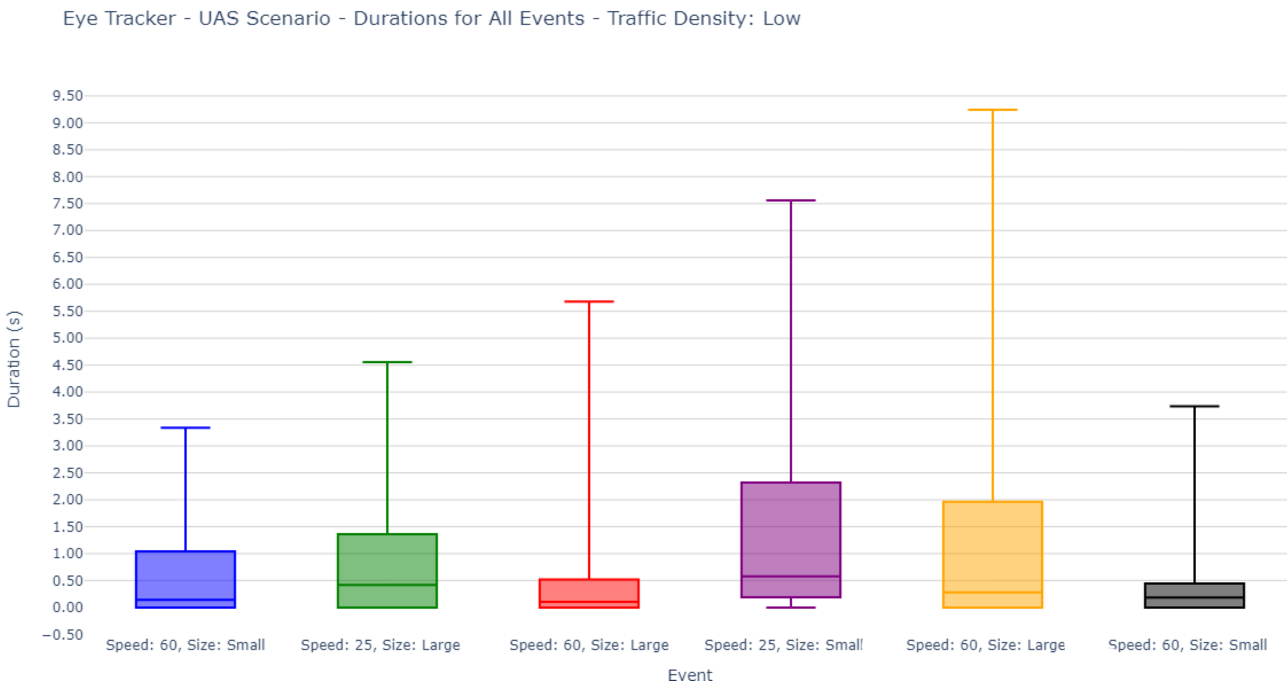

Figure 11. Duration (TFD) of Each Event in UAS Scenario, Traffic Density: Low

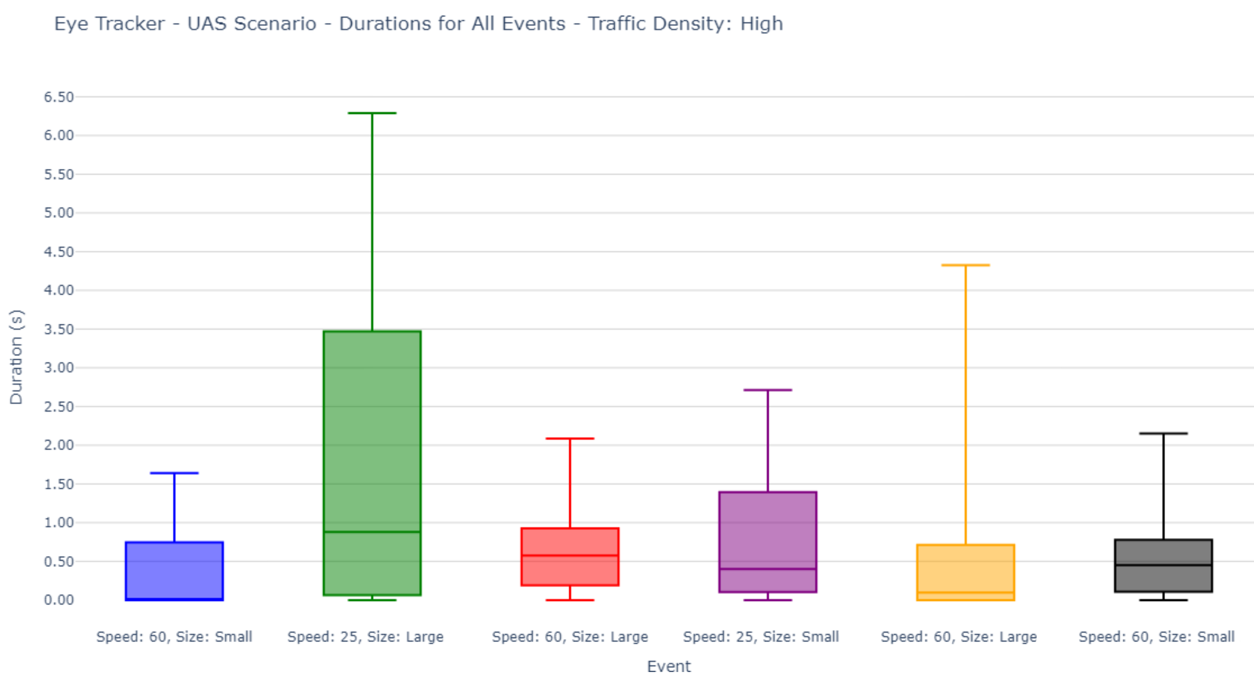

Figure 12. Duration (TFD) of Each Event in UAS Scenario, Traffic Density: High

5.1.2. UBIT Scenario

Based on the mixed ANOVA between traffic density and speed, in the UBIT scenario (Table 9), traffic density and speed do not have a statistically significant effect on TFD (i.e., $p > 0.05$). Based on the one-way ANOVA, when traffic density is low (Table 10) and high (Table 11), speed does not have a statistically significant effect on TFD (i.e., $p > 0.05$).

Table 9. UBIT Scenario, Mixed ANOVA Results

Source	SS	DF1	DF2	MS	F	p-unc	np2	eps
TrafficDensity	4.92689	1	18	4.92689	1.75970	0.20124	0.08905	NaN
Speed	3.47025	1	18	3.47025	1.87925	0.18727	0.09453	1
Interaction	0.09337	1	18	0.09337	0.05056	0.82461	0.00280	NaN

Table 10. UBIT Scenario, One-Way ANOVA, Speed and Traffic Density: Low

Source	ddof1	ddof2	F	p-unc	np2
Speed	1	40	2.177938	0.147831	0.051637

Table 11. UBIT, One-Way ANOVA, Scenario Speed, and Traffic Density: High

Source	ddof1	ddof2	F	p-unc	np2
Speed	1	76	1.620744	0.206869	0.02088

Box plots were used to visualize the results, as shown in Figures 13 and 14. These figures indicate that the average TFDs for UBIT are longer than the average TFDs for UAS. Additionally, traffic density and traffic speed do not significantly affect TFD and do not cause any notable differences. Also, the average TFD across all events remains below the two-second threshold for causing distraction and risk.

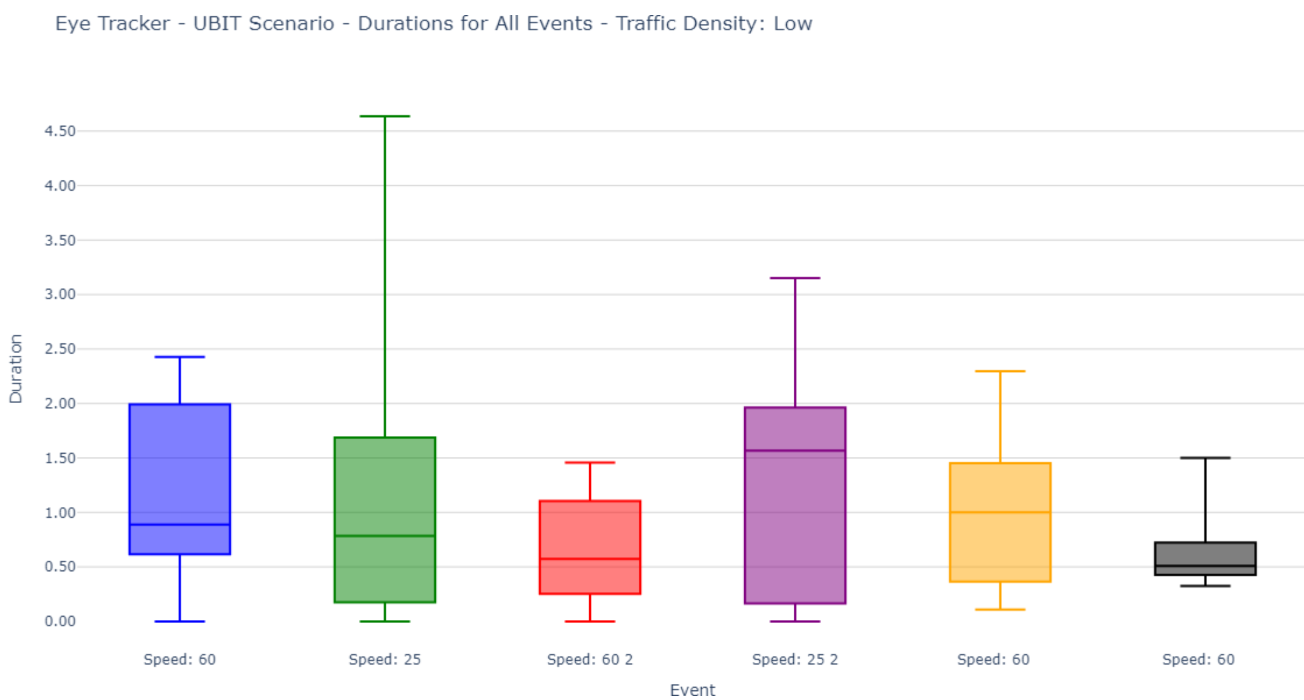

Figure 13. Duration of Each Event in UBIT Scenario, Traffic Density: Low

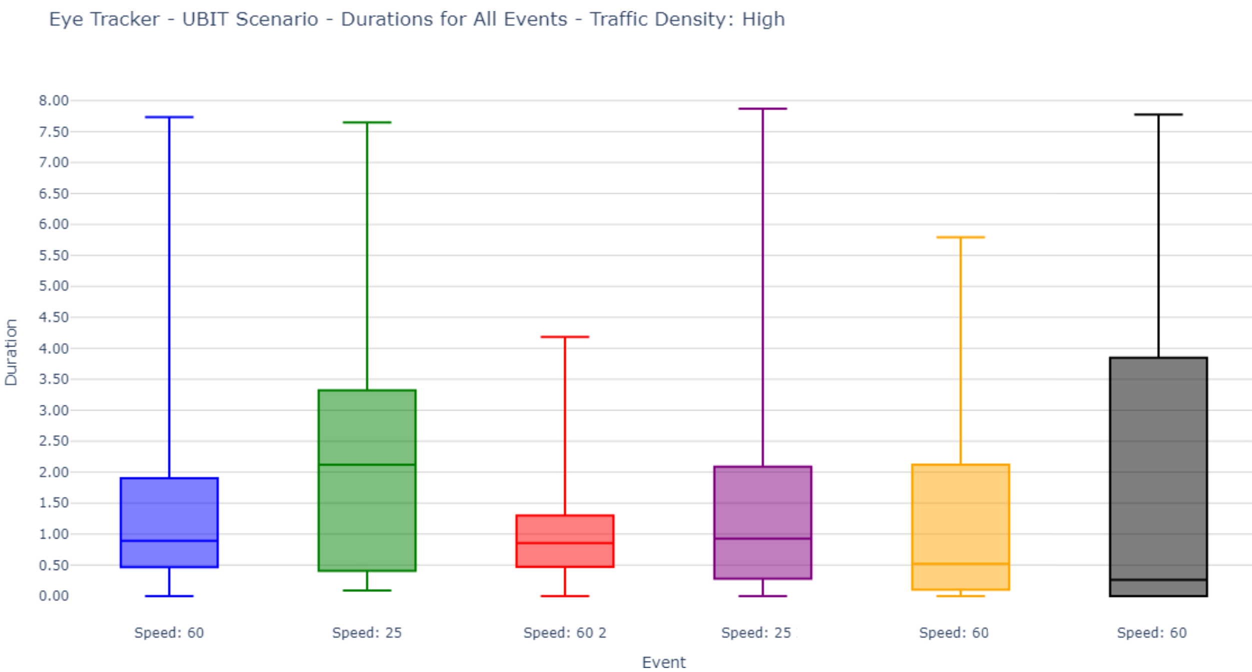

Figure 14. Duration of Each Event in UBIT Scenario, Traffic Density: High

5.2 EEG:

5.2.1 UAS Scenario, Alpha, and Theta Model

Based on the EEG data (using alpha and theta frequency bands) and one-way ANOVA test, Table 12 shows that the **type** of distraction (UAS or UBIT) has a statistically significant effect on TFD at the 95% confidence interval level (i.e., $p < 0.05$). A mixed ANOVA (Table 13) test between traffic density, speed, and interaction between them revealed that in the UAS scenario, **traffic density** significantly affects TFD (i.e., $p < 0.05$). Another mixed ANOVA (Table 14) test between traffic density, size, and interaction between them revealed that in the UAS scenario, size and traffic density do not significantly affect TFD (i.e., $p > 0.05$). A two-way ANOVA test (Table 15) between speed and size in a **low-traffic density** scenario revealed that **speed** has a significant effect on TFD (i.e., $p < 0.05$). This suggests that as traffic density decreases, the traffic speed becomes an important factor influencing TFD, causing drivers to spend more time looking at UAS. However, in high traffic density (Table 16), speed and size do not significantly affect TFD (i.e., $p > 0.05$). Also, the average TFD across all events remains below the two-second threshold for causing distraction and risk.

Table 12. UAS and UBIT Scenario Comparison

Source	DF1	DF2	F	p-unc	np2
Type	1	266	9.061033	**0.002908**	0.038548

Table 13. UAS Scenario, Mixed ANOVA Results, Traffic Density and Speed

Source	SS	DF1	DF2	MS	F	p-unc	np2	eps
TrafficDensity	0.95773	1	16	0.95773	6.064518	**0.025519**	0.274854	NaN
Speed	0.02124	1	16	0.021244	0.19197	0.66714	0.011856	1
Interaction	0.728811	1	16	0.728811	6.585702	0.02071	0.291587	NaN

Table 14. UAS Scenario, Mixed ANOVA Results, Traffic Density and Size

Source	SS	DF1	DF2	MS	F	p-unc	np2	eps
TrafficDensity	0.481731	1	16	0.481731	3.681888	0.073026	0.18707	NaN
Size	0.037768	1	16	0.037768	0.374761	0.549022	0.022887	1
Interaction	0.278248	1	16	0.278248	2.760998	0.116053	0.147167	NaN

Table 15. UAS Scenario, Two-Way ANOVA, Speed and Size, Traffic Density: Low

Source	SS	DF	MS	F	p-unc	np2
Speed	0.668256	1	0.668256	5.561969	**0.022306**	0.100104
Size	0.166486	1	0.166486	1.385685	0.244708	0.026966
Speed*Size	0.020811	1	0.020811	0.17321	0.679055	0.003452
Residual	6.007372	50	0.120147	NaN	NaN	NaN

Table 16. UAS Scenario, Two-Way ANOVA, Speed and Size, Traffic Density: High

Source	SS	DF	MS	F	p-unc	np2
Speed	1.331891	1	1.331891	3.17041	0.08106	0.059627
Size	0.781561	1	0.781561	1.860415	0.178686	0.035874
Speed*Size	1.563122	1	1.563122	3.72083	0.059424	0.069262
Residual	21.00502	50	0.4201	NaN	NaN	NaN

Box plots were used to visualize the results, as shown in Figures 15 and 16. The figures indicate that low or high traffic density and 25—or 60-mph traffic speed significantly affect TFD. However, the size of UAS does not significantly affect TFD. Also, the average TFD across all events remains below the two- second threshold for causing distraction and risk.

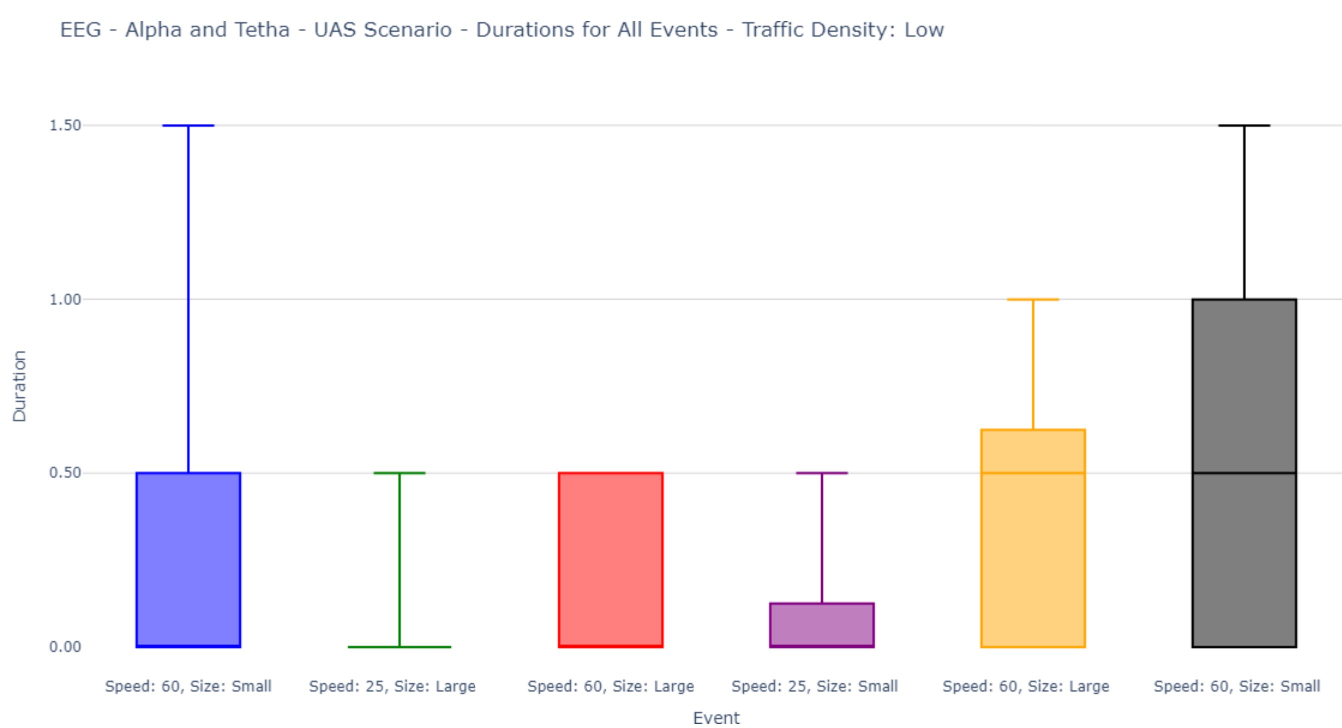

Figure 15. Duration of Each Event in UAS Scenario, Traffic Density: Low

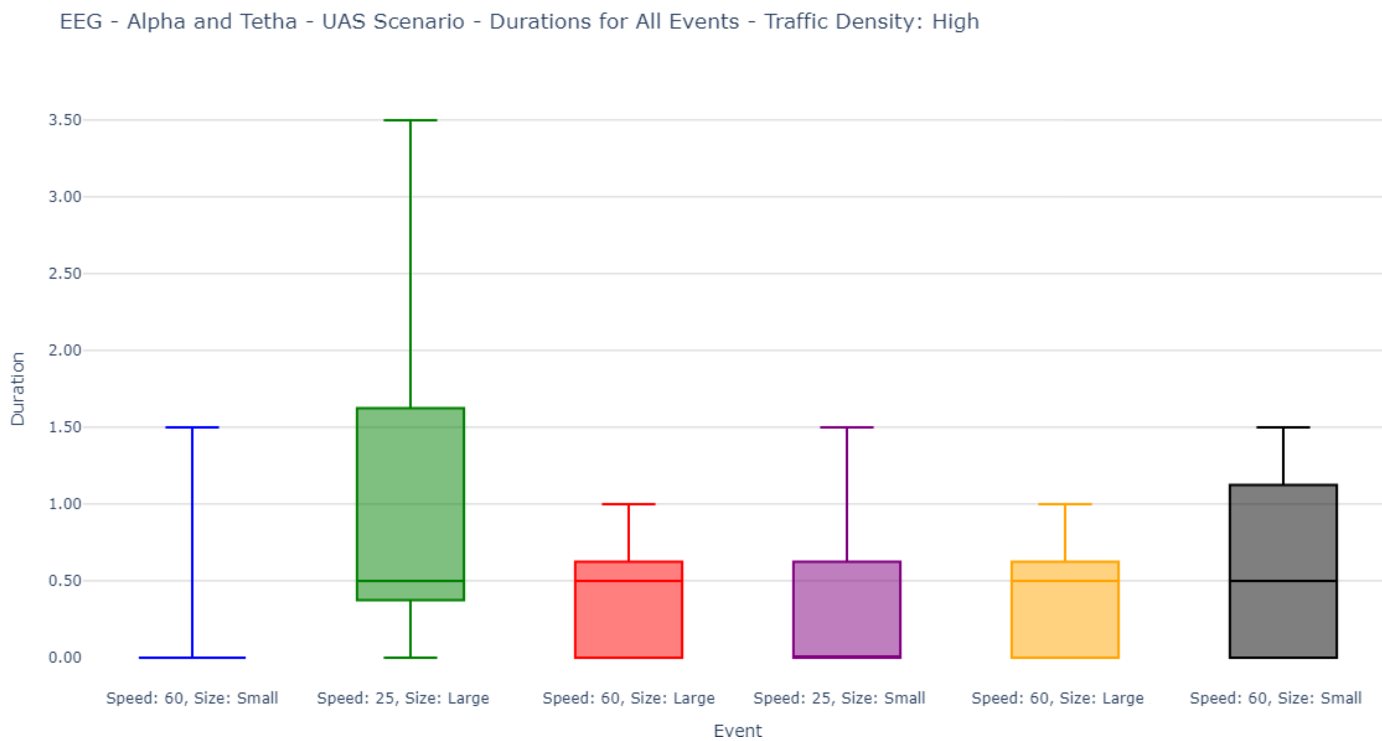

Figure 16. Duration of Each Event in UAS Scenario, Traffic Density: High

5.2.2. UBIT Scenario, Alpha, and Theta Model

Based on the mixed ANOVA between traffic density and speed, in the UBIT scenario (Table 17), traffic density and speed do not have a statistically significant effect on TFD (i.e., $p > 0.05$). Based on the one-way ANOVA (Tables 18 and 19), when traffic density is low and high, speed does not have a statistically significant effect on TFD (i.e., $p > 0.05$). Also, the average TFD across all events remains below the two-second threshold for causing distraction and risk.

Table 17. UBIT Scenario Speed and Traffic Density

Source	SS	DF1	DF2	MS	F	p-unc	np2	eps
TrafficDensity	0.056734	1	18	0.056734	0.331509	0.571901	0.018084	NaN
speed	0.156042	1	18	0.156042	1.094131	0.309402	0.057302	1
Interaction	0.039397	1	18	0.039397	0.276241	0.605591	0.015115	NaN

Table 18. UBIT Scenario Speed and Traffic Density: Low

Source	ddof1	ddof2	F	p-unc	np2
speed	1	52	0.079694	0.778834	0.00153

Table 19. UBIT Scenario Speed and Traffic Density: High

Source	ddof1	ddof2	F	p-unc	np2
speed	1	64	1.063463	0.306308	0.016345

Box plots were used to visualize the results, as shown in Figures 17 and 18. These figures indicate that the average TFDs for UBIT are longer than the average TFDs for UAS. Additionally, traffic density and traffic speed do not significantly affect TFD and do not cause any notable differences. Moreover, the average TFD across all events remains below the two-second threshold for causing distraction and risk.

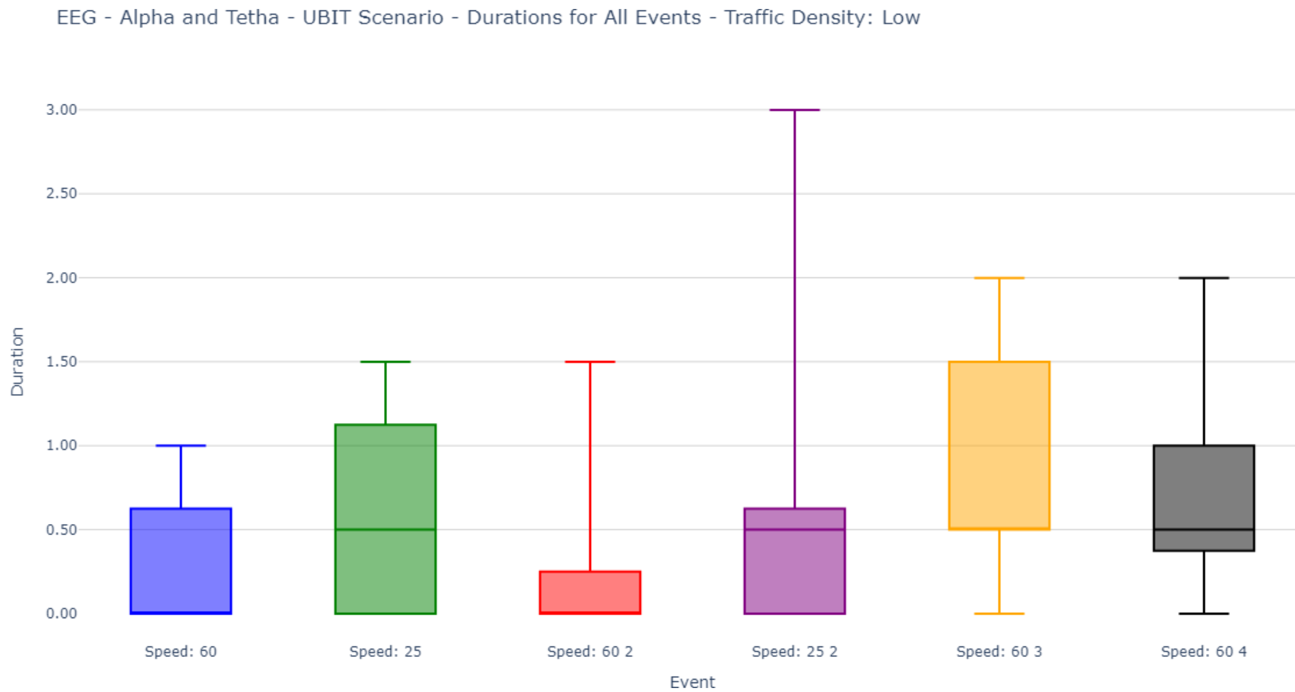

Figure 17. Duration of Each Event in UBIT Scenario, Traffic Density: Low

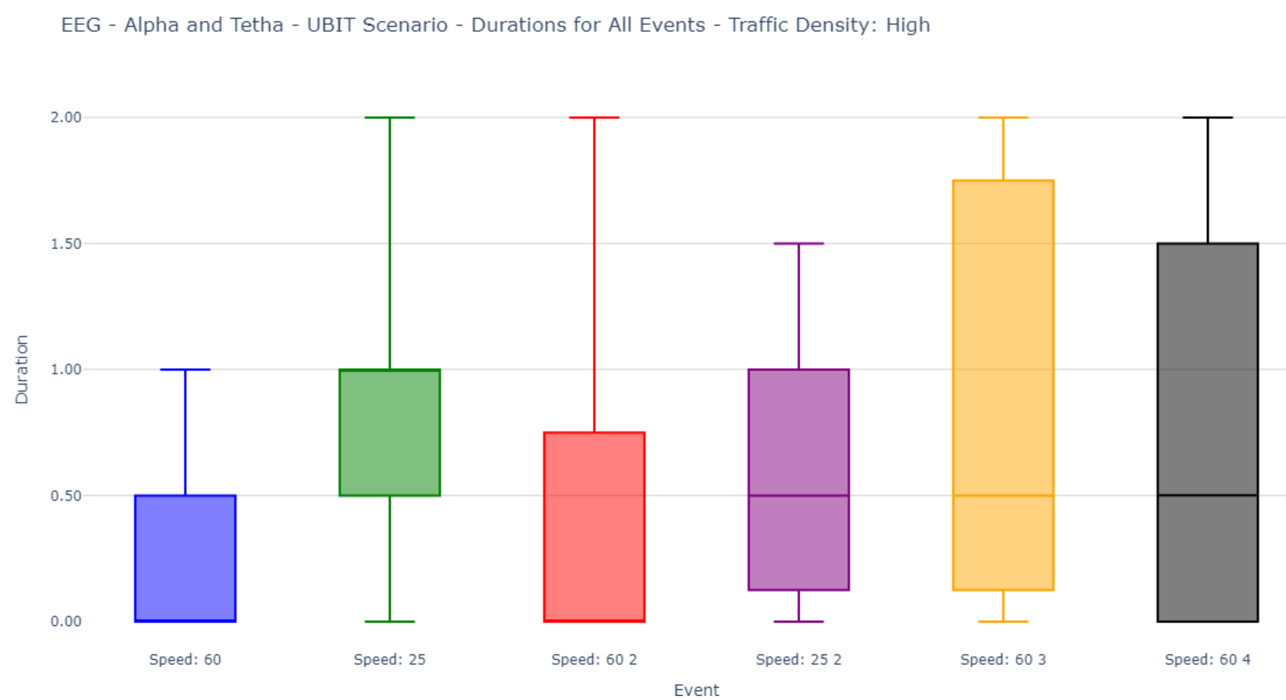

Figure 18. Duration of Each Event in UBIT Scenario, Traffic Density: High

5.2.3. UAS Scenario, Theta Model

Based on the EEG data (using theta frequency band) and one-way ANOVA test, Table 20 shows that the **type** of distraction (UAS or UBIT) has a statistically significant effect on TFD at the 95% confidence interval level (i.e., $p < 0.05$). A mixed ANOVA (Table 21) test between traffic density, speed, and interaction between them revealed that in the UAS scenario, **traffic density** significantly affects TFD (i.e., $p < 0.05$). Another mixed ANOVA (Table 22) test between traffic density, size, and interaction between them revealed that in the UAS scenario, **traffic density** has a significant effect on TFD (i.e., $p < 0.05$). A two-way ANOVA test (Table 23 and Table 24) between speed and size in a low and high-traffic density scenario revealed that none of them has a significant effect on TFD (i.e., $p > 0.05$). Also, the average TFD across all events remains below the two-second threshold for causing distraction and risk.

Table 20. UAS and UBIT Scenario Comparison

Source	DF1	DF2	F	p-unc	np2
Type	1	266	4.432861	**0.036357**	0.019237

Table 21. UAS Scenario, Mixed ANOVA, Speed and Traffic Density

Source	SS	DF1	DF2	MS	F	p-unc	np2	eps
TrafficDensity	0.877956	1	16	0.877956	6.617647	**0.020451**	0.292588	NaN
speed	0.097551	1	16	0.097551	0.845866	0.371383	0.050212	1
Interaction	0.156515	1	16	0.156515	1.357144	0.261108	0.078189	NaN

Table 22. UAS Scenario, Mixed ANOVA, Size and Traffic Density

Source	SS	DF1	DF2	MS	F	p-unc	np2	eps
TrafficDensity	0.648218	1	16	0.648218	6.570313	**0.020837**	0.291104	NaN
size	0.062432	1	16	0.062432	0.620689	0.442307	0.037344	1
Interaction	0.339909	1	16	0.339909	3.379309	0.084658	0.174377	NaN

Table 23. UAS Scenario, Two-Way ANOVA, Size and Speed, and Traffic Density: Low

Source	SS	DF	MS	F	p-unc	np2
speed	0.009249	1	0.009249	0.095786	0.758233	0.001912
size	0.166486	1	0.166486	1.72414	0.195155	0.033333
speed*size	0.083243	1	0.083243	0.862067	0.357622	0.016949
Residual	4.828098	50	0.096562	NaN	NaN	NaN

Table 24. UAS Scenario, Two-Way ANOVA, Size and Speed, and Traffic Density: High

Source	SS	DF	MS	F	p-unc	np2
speed	0.668258	1	0.668258	1.570995	0.215892	0.030463
size	1.040539	1	1.040539	2.446181	0.124119	0.046642
speed*size	1.685676	1	1.685676	3.962821	0.051995	0.073436
Residual	21.26864	50	0.425373	NaN	NaN	NaN

Box plots, shown in Figures 19 and 20, visualize the results. The results show that traffic density significantly affects TFD. The traffic speed and size of UAS do not significantly affect TFD. Moreover, the average TFD across all events remains below the two-second threshold for causing distraction and risk.

Figure 19. Duration of Each Event in UAS Scenario, Traffic Density: Low

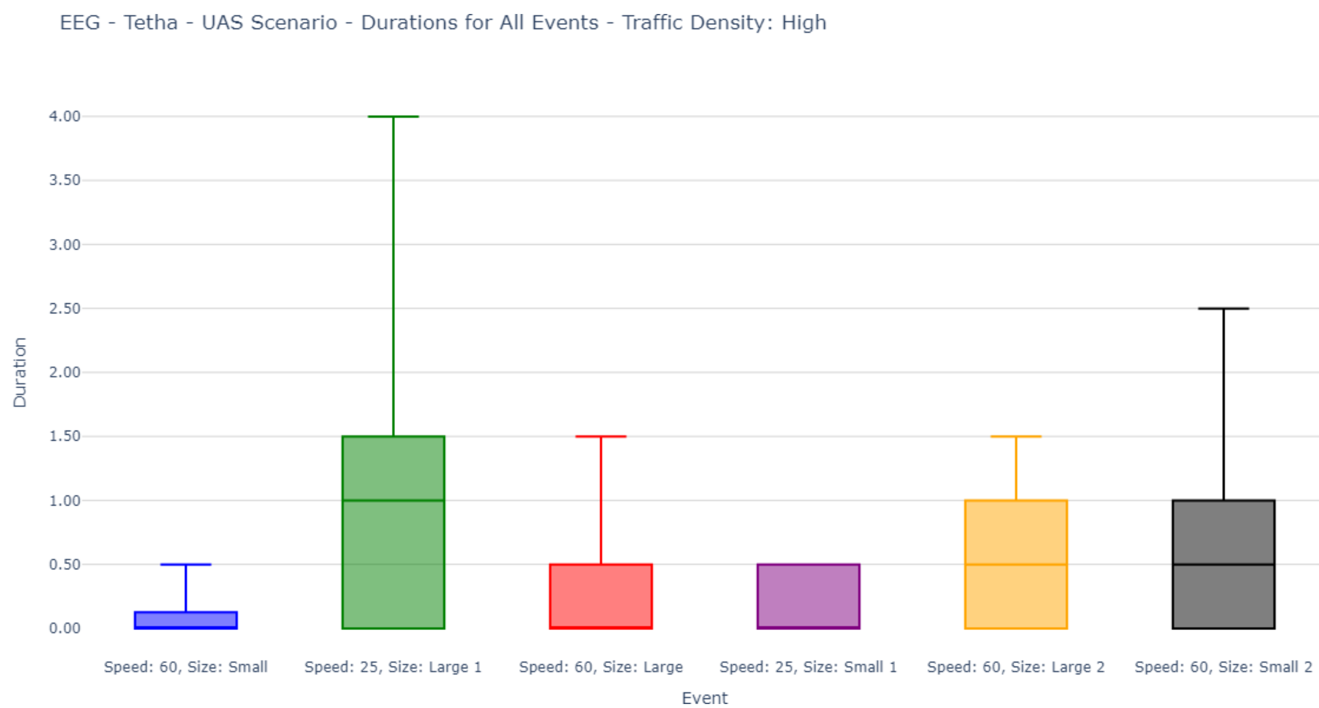

Figure 20. Duration of Each Event in UAS Scenario, Traffic Density: High

5.2.4. UBIT Scenario, Theta Model

In the UBIT scenario (Table 25), traffic density and speed do not have a statistically significant effect on TFD (i.e., $p > 0.05$). Based on the one-way ANOVA (Table 26 and Table 27), when traffic density is low and high, the speed does not have a statistically significant effect on TFD (i.e., $p > 0.05$). Also, the average TFD across all events remains below the two-second threshold for causing distraction and risk.

Table 25. UBIT Scenario Speed and Traffic Density, Mixed ANOVA

Source	SS	DF1	DF2	MS	F	p-unc	np2	eps
TrafficDensity	0.0371	1	18	0.0371	0.119544	0.733538	0.006598	NaN
speed	0.24392	1	18	0.24392	1.525855	0.232616	0.078145	1
Interaction	0.007989	1	18	0.007989	0.049973	0.825628	0.002769	NaN

Table 26. UBIT Scenario Speed and Traffic Density: Low

Source	ddof1	ddof2	F	p-unc	np2
speed	1	52	0.3747	0.543121	0.007154

Table 27. UBIT Scenario Speed and Traffic Density: High

Source	ddof1	ddof2	F	p-unc	np2
speed	1	64	1.260485	0.265754	0.019315

Box plots were used to visualize the results, as shown in Figures 21 and 22. These figures indicate that the average TFDs for UBIT are longer than the average TFDs for UAS. Additionally, traffic density and traffic speed do not significantly affect TFD and do not cause any notable differences. The average TFD across all events remains below the two-second threshold for causing distraction and risk.

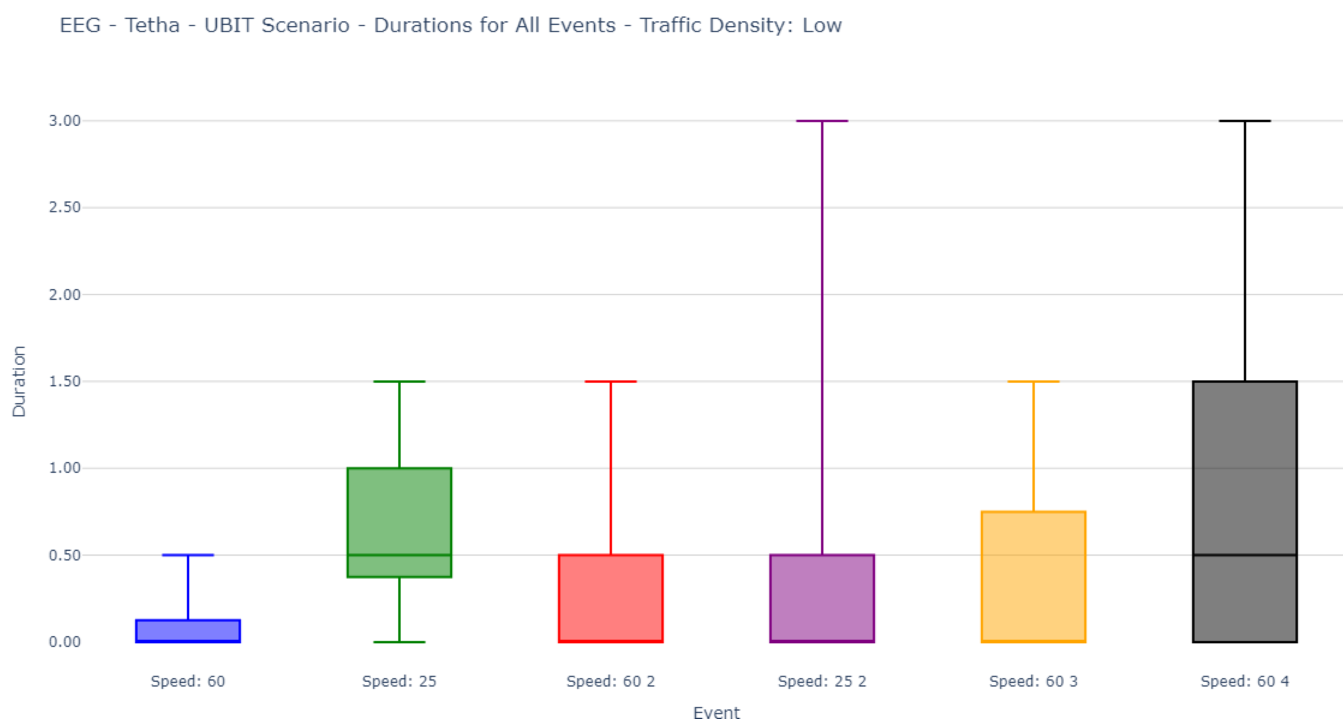

Figure 21. Duration of Each Event in UBIT Scenario, Traffic Density: Low

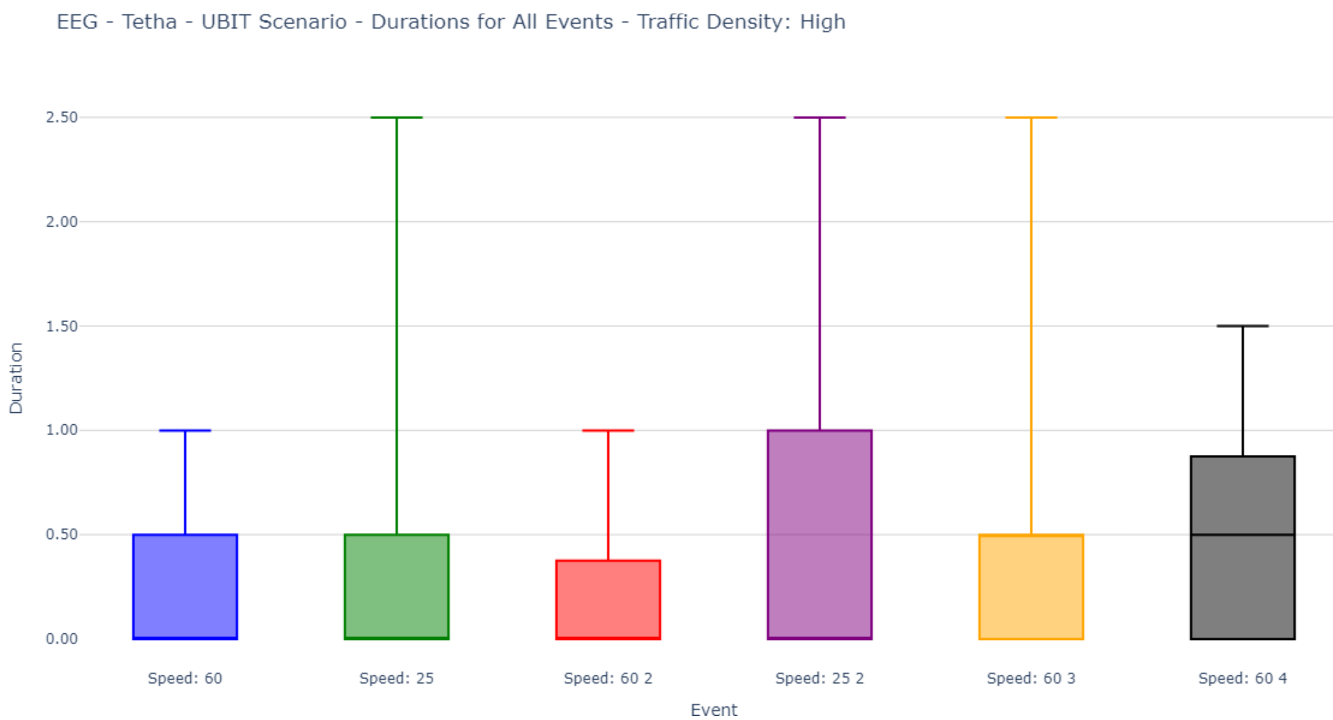

Figure 22. Duration of Each Event in UBIT Scenario, Traffic Density: High

6. CONCLUSION

The use of UAS in roadway and bridge inspection and construction projects is growing due to their efficiency and versatility. However, their presence near roadways raises safety concerns, particularly the risk of driver distraction. Drivers visually distracted by UAS can significantly increase the risk of crashes. Research has shown that drivers often continue to observe UAS even after passing them, with some glances lasting over two seconds—enough to significantly increase the risk of a crash. Despite these concerns, limited research has measured the visual distraction caused by UAS near roadways compared to existing lane closure mechanisms like UBIT. Previous research conducted by this research team assessed driver distraction during roadside UAS operations and found that UAS position, land use, and weather conditions significantly influenced distraction levels. Given the increased use of UAS in civil and construction applications, it is crucial to understand their potential to distract drivers and compare this to the distraction caused by traditional approaches involving UBIT. Work zones, typically associated with construction or maintenance, present complex driving environments that challenge drivers' attention and cognitive workload. Understanding which technology, UAS or UBIT, causes less distraction is essential for developing safer roadway practices. This research is critical for developing effective safety strategies, informing regulatory guidelines, and determining the safest approach to managing high-risk work zones, ultimately enhancing roadway safety and reducing accident risks.

This study's findings indicate that UAS is a safer option than UBIT because the average TFD for UBIT is longer and closer to the two-second safe threshold. Additionally, it was found that different traffic speeds and densities do not significantly influence the TFD for UBIT. However, when using UAS in different applications, it is important to consider different traffic densities and traffic speeds. This is because eye tracker data indicated that in UAS scenarios, traffic speed significantly influences TFD when traffic density is high. Two different EEG models revealed that traffic speed is also crucial when traffic density is low, while the third EEG model found that only traffic density significantly affects TFD, with traffic speed being insignificant.

These findings underscore the combined impact of traffic speed and density on driver distraction, emphasizing the need to carefully consider these factors when developing policies, standards, and guidelines for implementing UAS near roadways. For instance, frequent stopping and starting in high-traffic density scenarios increase drivers' chances of glancing around more frequently, leading to higher chances of noticing UAS operations. The increased number of vehicles and reduced speeds in these conditions inherently provide more opportunities for distraction. Conversely, in low-traffic density scenarios, slow-moving traffic still allows drivers more time to observe their environment, making UAS more conspicuous and increasing the likelihood of distraction. Whether the traffic density is high or low, slower traffic speeds tend to result in drivers spending more time observing UAS, thereby increasing the potential for distraction. This highlights the importance of considering traffic density and traffic speed when assessing the impact of UAS on driver distraction and roadway safety. Heightened awareness can significantly affect drivers' attention, driving performance, and reaction times. Therefore, understanding the interplay between traffic density, traffic speed, and the presence of UAS is essential for assessing the overall safety implications and making informed decisions about deploying UAS in various traffic conditions to minimize driver distraction and enhance roadway safety.

The novel approach of combining of eye tracker and EEG modalities in this study proved to be a groundbreaking advancement. First, it allowed the research team to validate the eye tracker results with EEG data. More importantly, the EEG data revealed crucial additional information and insights that would have been impossible to obtain with eye tracking alone. These profound insights are invaluable for policymakers and represent a significant leap forward in enhancing overall safety. Moreover, there are several areas where this study can be further expanded. For instance, investigating drivers' peripheral vision when they might not directly look at UAS or UBIT sources of distraction but notice them peripherally could provide valuable insights. This could be examined using EEG data. Additionally, there is a phenomenon where drivers may look at a source of distraction, as indicated by eye tracker data, but do not actually perceive it ("looked but failed to see") and hence do not get distracted. This cannot be fully understood through eye tracker data alone, and EEG data could help investigate this further. Finally, it is unclear how long drivers remain distracted by the source of distraction they saw but are no longer looking at, as they might still be thinking about it and thus remain distracted. This study could also be expanded to investigate other sources of distraction for drivers, such as static and digital billboards, which are significant sources of visual and cognitive distraction.

APPENDIX 1

At this stage, the decision regarding the effect size is provisional. The precise effect size cannot be definitively ascertained since the data required to calculate it accurately based on the collected participant data is currently unavailable. To address this uncertainty, a preliminary study will be conducted involving a limited number of participants (e.g., 10) available internally to the research team. This pilot study aims to collect data to estimate the correct effect size accurately. If the provisional effect size estimate is confirmed through the pilot study, confidence will be instilled for proceeding. However, if the pilot study reveals the need for an adjustment to the effect size, the necessary corrections will be made before the continuation of the main experiment. Conducting a pilot study is essential as it not only refines the research but also enhances the overall robustness and reliability of the project's outcomes.

The formula for calculating the sample size required for a repeated measures ANOVA with a between-within design can be complex and depends on several factors, including the effect size, desired power, significance level, and the specific design of a study (number of groups, measurements, etc.).

There are many different formulas for determining sample size. Here is one of the general formulas (refer to equation 1) that takes some of these factors into account:

$$N = \frac{2(Z_\alpha+Z_\beta)\sigma^2}{d^2} \qquad (1)$$

Where:

- N is the required sample size.
- z_a is the critical value for the chosen significance level α.
- z_B is the critical value for the desired power β.
- σ is the population standard deviation.
- d is the effect size.

However, this is a simplified representation, and statistical software like G*Power should be used for a more accurate calculation. G*Power and other statistical software typically use complex algorithms to calculate sample sizes for specific statistical tests, including repeated measures ANOVA with a between- within design. These algorithms consider various parameters, including the number of groups, measurements, within-subject correlations, effect size, desired power, and significance level.

The actual formula such software uses is not a simple, single equation like the general formula above. Instead, the software uses mathematical models and statistical tables to determine the required sample size based on the input parameters and the specific statistical test being performed.

Additionally, this formula (refer to equation 2) for between-within-subjects, repeated measures, and ANOVA closely resembles the calculations that G*Power might employ in its sample size estimation process.

$$N = \frac{f^2(j-1)(k-1)(1-\rho^2)^2}{MS_{error}(\frac{\alpha}{2}-0.5)^2} \qquad (2)$$

where:

- N is the sample size
- f^2 is the effect size (Cohen's f²) that want to detect, power analysis tool such as G*Power can be used to estimate the effect size.
- J is the number of repeated measures
- k is the number of levels of the between-subjects factor
- MS_error is the mean square error

- rho^2 (ρ^2) is the correlation between repeated measures. This can be estimated using the following formula (refer to equation 3):

$$rho^2 = \frac{(1 - \frac{SD\_between^2}{SD\_total})}{2} \quad (3)$$

where:

- $SD\_between$ is the standard deviation of the between-subjects factor
- SD_total is the standard deviation of the total variation

If there is no pilot study to estimate the correlation between repeated measures, rho^2= 0.5 can be used.

APPENDIX 2

All the codes used in this study are available at the following GitHub link:

https://github.com/zafzalikusha/Evaluation-of-UAS-and-UBIT-Drivers-Distraction-Using-Eye-Tracker-Data-and-EEG-Signals

The data and codes are private; you can request access by providing your email address.

APPENDIX 3

ANOVA (Analysis of Variance) is commonly used to compare the means of two or more groups. It determines whether different levels of categorical variables result in different means of a dependent variable across groups. ANOVA assesses whether the outcome variability is due to chance or the independent variables. There are several types of ANOVA tests: one-way, two-way, and mixed ANOVA. In this study one-way, two-way, and mixed ANOVA were used.

The conditions for conducting an ANOVA test which were met in this study include:

1. Independence: The observations within each group and between groups should be independent of each other. This means the data should not be paired or related.
2. Normality: The data within each group should be approximately normally distributed. This condition is particularly important when the sample sizes are small. For larger sample sizes, the ANOVA test is robust to deviations from normality.
3. Homogeneity of Variances: The variances among the groups should be approximately equal.
4. Continuous Dependent Variable: The dependent variable should be measured at the interval or ratio level, meaning it should be continuous and have meaningful intervals between values.

One-way ANOVA compares the means of independent groups to determine if a statistically significant difference between them involves a single independent variable with multiple levels. Two-way ANOVA examines the influence of two independent variables on a dependent variable. It can also evaluate the interaction effect between these variables, making it more complex by considering multiple factors and their interactions.

Mixed ANOVA combines elements of both within-subjects and between-subjects designs. It allows researchers to examine the effects of one or more independent variables, with at least one variable manipulated within subjects and at least one manipulated between subjects. In a mixed ANOVA, the within-subjects factor(s) typically involves repeated measures, where each participant is exposed to multiple conditions or levels of the independent variable(s). On the other hand, the between-subjects factor(s) involves different groups of participants experiencing different conditions or levels.

The primary advantage of mixed ANOVA is its ability to simultaneously address both within-subjects and between-subjects effects, thereby offering increased statistical power and efficiency. It allows researchers to examine the main effects of each independent variable and their interactions, including interactions between within-subjects and between-subjects factors.

The hypotheses tested in a mixed ANOVA are similar to those in other ANOVA designs. Specifically, the main hypotheses include:

1. The main effect of the within-subjects factor(s).
2. The main effect of the between-subjects factor(s).
3. The interaction between the within-subjects and between-subjects factors.

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