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Optimizing sound alerts for traveler information systems: Insights from a driving simulator and eye tracking study

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ABSTRACT

Traveler information apps provide drivers with timely alerts about crashes, work zones, and road closures, using accurate, agency-reported data to enhance safety. This study evaluates the effectiveness of different types of road incident alerts in enhancing driver responses using a driving simulator, eye-tracking glasses, and a questionnaire. This study assesses driver reaction and perception behavior through a combination of recorded driving performance and eye movements, while also gathering participant feedback on the most effective alert types. The findings revealed that alerts providing comprehensive information such as incident notifications, distance to the incident, and actionable instructions were most effective in eliciting quick driver responses and improving safety, particularly when delivered two miles in advance of the incident. These types of alerts had a significantly faster response period compared to other types of alerts analyzed. Eye-tracking data indicated that simpler alerts, such as those with only incident information, could also help drivers maintain focus on the road and reduce decision-making complexity. Survey results supported these findings, showing a clear preference for alerts with detailed information, including distance and recommended actions. This study also identified the preferred optimal alert timing as being at least two miles before the incident in high-speed interstate roadway conditions. These findings emphasize the importance of clear, actionable alerts in traveler information systems and highlight opportunities for optimizing alert timing and simplicity to improve driver safety.

1. Introduction

Traveler information systems offer recommendations to assist motorists in making well-informed travel decisions by considering factors such as weather, crashes, road closures, or traffic congestion (Zhang et al., 2022). This information is disseminated through various channels, including television, email, radio, text messages, 511 websites, and mobile applications (Robinson et al., 2018). Many transportation agencies have worked towards making 511 traveler information systems into mobile applications for easier access (Morris et al., 2014). 511 traveler information apps differ from commercial navigation apps, such as Google Maps, Apple Maps, and Waze, as they do not offer turn-by-turn navigation. Instead, their primary focus is on providing specific alerts to support better decision-making during trips (Morris et al., 2014). The information delivered through 511 traveler information apps is typically more

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accurate and timelier because the incident alerts are sourced directly from various official agencies. This contrasts with commercial navigation apps, such as Google Maps or Waze, where information is often crowd-sourced from drivers on the route, which can sometimes result in the data being delayed in their connection to drivers, or information inaccuracies in reporting (Nedkov & Zlatanova, 2012). Despite their advantages, the adoption of highly accurate traveler information system apps remains relatively limited, as many drivers continue to prefer commercial navigation apps (Higgins et al., 2013). These commercial apps, while convenient, can provide less reliable information and may also pose safety risks by increasing visual distractions during driving (Morris et al., 2014).

Although technological advancements have introduced various traffic management methods, such as alerts and notifications in navigation apps, these tools can also present challenges. While they provide valuable warnings about congestion, crashes, and road closures, the alerts themselves can cause distractions and create safety risks for drivers (Tarqui et al., 2013). The growing number of collision and lane-change alerts in vehicles, combined with navigation app notifications, makes it increasingly difficult to design alert systems that effectively convey road issues while minimizing driver distraction (Nees & Walker, 2011). Various types of sounds are used in in-vehicle technologies and navigation apps, including auditory icons, earcons, environmental sounds, musical tones, pure tones, sonification, spearcons, speech, and spindex (Nees & Walker, 2011). However, most common alerts are limited to chimes, beeps, tones, and speech, as investigated in several previous studies (Barrow & Baldwin, 2010; Capallera et al., 2023; Jeon, 2019; Nees & Liebman, 2023; Nees & Walker, 2011). Much of the existing research has focused on driver responses to in-vehicle alert systems, with less attention given to how drivers react to alerts from navigation apps (Nees & Walker, 2011).

Publicly-funded traveler information applications bear a greater responsibility than proprietary apps to ensure user safety by integrating designs that actively minimize distractions (Morris et al., 2014). Furthermore, these apps must comply with state-specific hands-free laws by incorporating designs that prioritize user safety. However, limited research exists on how traveler information apps should be designed to ensure that the alerts provided to drivers are safe and effective. A key challenge lies in the fact that these apps primarily target residents of a specific state who are familiar with local roads and primarily seek updates on incidents or changes affecting their usual routes. As a result, these apps prioritize delivering timely and relevant incident notifications over navigation guidance, ensuring drivers receive critical updates without unnecessary distractions. Given gaps in knowledge of best practices within in these systems, this research aims to identify effective methods for designing successful traveler information mobile applications. Specifically, this study focuses on determining the types of alerts, notification sounds, and timing that are most likely to prompt appropriate responses from drivers.

This research addresses critical gaps in the design of alert systems for traveler information applications, with the goal of enhancing driver safety. Unlike prior studies that primarily focus on in-vehicle alert systems (Lewis et al., 2014; Nees & Walker, 2011) or takeover requests in automated vehicles (Wu et al., 2018; Yoon et al., 2019) where reaction times are extremely short and alerts are designed for immediate interventions. This study examines alert strategies suited to traveler information apps, which operate in different temporal and contextual conditions. Furthermore, while commercial navigation apps do utilize alerts, their protocols are not publicly disclosed, and their primary focus is on minimizing travel time through rerouting rather than delivering consistent, safety-focused information. In contrast, traveler information apps are designed to inform users of real-time incidents and disruptions, with an emphasis on timely, relevant, and non-distracting alerts tailored to familiar routes. This study aims to provide a guideline to design alerts for such systems.

This research addresses critical aspects of alert system design in traveler information applications with the goal of enhancing driver safety and app usability. Specifically, our study focuses on three primary objectives: 1) identifying alert messages that effectively capture the attention of drivers, ensuring they result in prompt and appropriate responses in real-time situations, 2) determining the optimal timing for delivering alerts to maximize driver engagement and responsiveness without causing distractions or overload, and 3) investigating strategies to foster long-term user adoption and retention of the app, ensuring that drivers continue to engage with the system over extended periods.

To achieve these objectives, the study employed a comprehensive methodology combining driving simulation, eye-tracking technology, and user questionnaires. Driving simulation scenarios provides a controlled environment for studying real-time drivers' reactions to different alert types and timings, while eye-tracking technology allows for precise measurement of attention allocation and response patterns. User questionnaires provide valuable insights into subjective experiences, preferences, and potential barriers to adoption. Through this multi-faceted approach, the research offers actionable, evidence-based recommendations for the design and implementation of alert systems that can significantly enhance driver safety, user satisfaction, and overall app effectiveness.

2. Literature review

The literature review offers an in-depth examination of existing research on alert types in driving systems, emphasizing their effectiveness, usability, and associated challenges. It further explores the application of various methods and equipment used in this study.

2.1. Alert types

Several types of sounds, including auditory icons, earcons, environmental sounds, musical tones, pure tones, sonification, spearcons, speech, and spandex, are used in different alert systems for drivers (Nees & Walker, 2011). However, in the context of driving systems, most of the alerts used consist of chimes, beeps, or tones along with speech, as documented in numerous studies (Barrow & Baldwin, 2010; Capallera et al., 2023; Jeon, 2019; Nees & Liebman, 2023; Nees & Walker, 2011). The effectiveness of auditory alerts in driving contexts has been widely explored, with various studies comparing the response times and perceived effectiveness of different auditory tones and speech messages. Research by Kiefer et al. (1999) demonstrated that auditory tones such as beeps, chimes, and horns elicited shorter reaction times in drivers, indicating that these sounds are more immediately noticeable. However, these tones could also be perceived as irritating and could cause confusion, as they lack explicit meaning about the nature of the associated risk (Campbell et al., 1998). In contrast, speech-based auditory warnings, while generally resulting in longer response times (Graham, 1999), were identified as a more effective means of conveying detailed information to the driver (Campbell et al., 2004). Further studies have also investigated the integration of various auditory displays, such as speech, spearcons, and earcons, in driving simulators designed for takeover requests in automated vehicles. These studies found that auditory cues, especially speech and earcons, improved driver alertness in situations requiring a handover of control from automated driving systems (Chai et al., 2024; Nees et al., 2016; Richie et al., 2018). Specifically, speech-based alerts were the most effective and favored by participants, whereas spearcons were ranked least preferred (Jeon, 2019). These findings suggest that while speech-based messages may take longer to process, they offer superior clarity and are more likely to enhance driver awareness.

Moreover, studies have shown that the design of auditory alerts must consider both precision and frequency. Campbell et al. (2007) emphasized that effective auditory alerts should be infrequent and concise to avoid desensitization and frustration. Their study also concluded that excessive repetition or frequent false alarms can undermine driver trust in the system and hinder response to genuine warnings. In speech-based alert systems, studies have shown that the duration of the message also plays a crucial role in driver processing time, with shorter messages generally preferred (Campbell et al., 2004). Introducing a tone before a speech message has also been shown to have no positive impact and may even result in increased response times (Campbell et al., 2004). Design guidelines for auditory alerts recommend an intensity range between 20 and 30 dB, with a maximum amplitude of 90 dB (COMSIS, 1996), ensuring that alerts are sufficiently audible without causing discomfort or distraction.

2.2. Application of alerts in driving simulator and eye tracking studies

Driving simulators and eye tracking systems have been extensively used to understand drivers' responses to alerts. Several studies have confirmed the reliability of driving simulator experiments by comparing the results with real-world driving scenarios (Wynne et al., 2019; Yao et al., 2019). These studies have consistently shown similar behaviors, supporting the validity and effectiveness of driving simulators in studying driving behavior. Wu et al. (2018) investigated the impact of auditory warning characteristics from a forward collision alert system on driver's avoidance behavior in a driving simulator scenario. Analyzing data from 192 participants, the findings revealed that warning alerts significantly reduced collision rates and improved reaction times. In another driving simulator study (Gray, 2011), the effectiveness of looming auditory warning signals was compared with other types of auditory warnings. Results showed that veridical looming (i.e., sounds that get louder over time, creating the impression of an object moving closer to the listener) and car horn warnings had significantly faster brake reaction times and higher accuracy, suggesting the superiority of looming auditory warnings ineffectively warn drivers about impending collision risks. Results from Maltz & Shinar's (2004) study indicated that speech alerts were reported as more helpful than either the tone or visual interfaces. An experiment with 135 licensed drivers assessed the effects of an in-vehicle collision avoidance warning system (IVCAWS) on driver performance, showing that the system led to safer headway maintenance.

Driving simulator studies have often been used to analyze takeover alerts in Advanced Driver Assistance System cases. Petermeijer et al. (2017) found that in cases of conditionally automated driving systems, auditory and tactile takeover requests resulted in faster reactions compared to visual requests, irrespective of the non-driving task (i.e., reading, calling, or watching a video). Richie et al. (2018) explored various auditory displays for takeover situations in automated vehicles, focusing on the potential of spearcons and found that speech, especially speech in a masculine voice, and a beep demonstrated faster reaction times than spearcons. Other studies related to driver's response to smartphone-based warning systems using driving simulators have also been conducted. These studies indicated an increased awareness of drivers due to these alerts (Dumitru et al., 2018; Starkey et al., 2020).

Eye tracking studies have consistently played a crucial role in assessing the efficacy of various alert systems, often in conjunction with diverse driver metrics. Coupling eye tracking with driving simulators has been instrumental in investigating age-related differences in perceiving in-vehicle signs at intersections (Caird et al., 2008). It also evaluates the effectiveness of red light violation warnings (Banerjee et al., 2020), and examines how auditory and visual alerts impact the gaze behavior of older drivers during left turn movements (Bassani et al., 2023) both before and just after entering intersections. In terms of analyzing effectiveness, several metrics have been investigated in previous studies. Specifically, in driving simulator studies with eye tracking, several metrics have been applied, including accuracy of action, perception reaction time, speed, rate of acceleration/deceleration, brake reaction time, gaze analysis, eye movement analysis, fixation count percent, fixation duration, and gaze variability, to analyze effectiveness of different alert systems (Banerjee et al., 2020; Bassani et al., 2023; Caird et al., 2008; Capallera et al., 2023; Jeon, 2019).

Most of the research in this area to date has focused on benchmarking driver responsiveness to in-vehicle alert systems, with limited attention given to investigations that aim to understand how drivers respond to different mobile application alerts that can aid in driving tasks. Previous research underscores the importance of well-designed alerts featuring proper auditory cues, concise length, non-repetitive frequency, and precise information (Campbell et al., 2004, 2007; COMSIS, 1996). Yet, the understanding of the best approach to convey auditory alerts from mobile apps, especially during the driving task, remains limited. Utilizing driving simulators in conjunction with eye-tracking technology holds meaningful potential to determine the optimal parameters for auditory alerts in such systems. Thus, this study investigates the best practices for an effective auditory alert protocol that communicates clear, concise, and accurate information to drivers from app-based traveler information systems.

2.3. Methodology

This study investigated optimal alert type and timing that may be used in different traveler information system apps. The complete study methodology consisted of three distinct steps and utilized a driving simulator, eye-tracking technology, and a questionnaire to understand driver preferences.

2.4. Experimental setup

To evaluate driver responses to alert systems in a controlled environment, this study utilized the RDS-100 Desktop Driving Simulator developed by Realtime Technologies (FAAC, 2025). This simulator offers a compact yet capable platform for mid- to high-fidelity simulation, making it well-suited for behavioral research and human factors studies. The hardware setup included a dedicated high-performance simulation computer, three 32-inch HD monitors arranged to provide an immersive 150-degree forward field of view, a force-feedback steering wheel, a responsive pedal set, and a basic 2.0 audio system to deliver auditory cues such as alert sounds. A dedicated operator workstation was employed to control the simulation sequence in real time. Fig. 1 provides a visual representation of the driving simulator setup used in this study.

The base scenario for the study was designed in Internet Scene Assembler, which provided a flexible platform to build realistic freeway environments, including detailed roadway geometry, signage, and visual symbols commonly encountered in real-world driving. This base scenario served as the foundation for further customization. Introducing experimental variables, SimCreatorDX was used to program and integrate complex driving maneuvers, including the timed deployment of incident alerts at specified distances from the crash site, the presentation of crash scenarios, and the simulation of dynamic traffic conditions in both directions. SimCreatorDX also allows precise control of environmental variables such as lighting and weather. Each maneuver was timed and geospatially mapped to correspond with the structure of the experimental design, ensuring consistency across participants and trials. This allowed the research team to assess driver performance in reacting to different types and timings of alerts under realistic driving conditions.

In addition to the driving simulation, the study incorporated eye-tracking to analyze visual attention. Argus eye-tracking glasses (Argus Science LLC, 2025) were employed to capture real-time eye movement data throughout each scenario. The simulator was synchronized with the eye-tracking hardware through embedded maneuvers that flagged the exact locations where alerts were issued and when a crash occurred. Eye movement data including fixations, saccades, and gaze patterns were analyzed using iMotions software (iMotions, 2022), a widely used platform for multimodal behavioral research.

This integrated setup provided a comprehensive framework for examining the effectiveness of alert systems in traveler information applications. The RDS-100 system has been used in previous studies to assess driver behavior and has demonstrated reliability in capturing performance and attentional measures (Brooks et al., 2025; Wei et al., 2024; Yamani et al., 2024).

2.5. Study design

The study was conducted in three distinct phases. Following University of Arizona Institutional Review Board approval of the developed protocol, an intention-to-participate form was publicly distributed to announce the study and invite eligible participants to register. Participants were recruited across the University of Arizona campus and throughout Pima County using flyers and via email. Potential participants were directed at a Qualtrics link to indicate their interest in participating. During this phase, sociodemographic information, including age, gender, race, education level, and other relevant factors, was collected from potential participants. Based on this information, a subset of individuals was selected and formally invited to participate in the study.

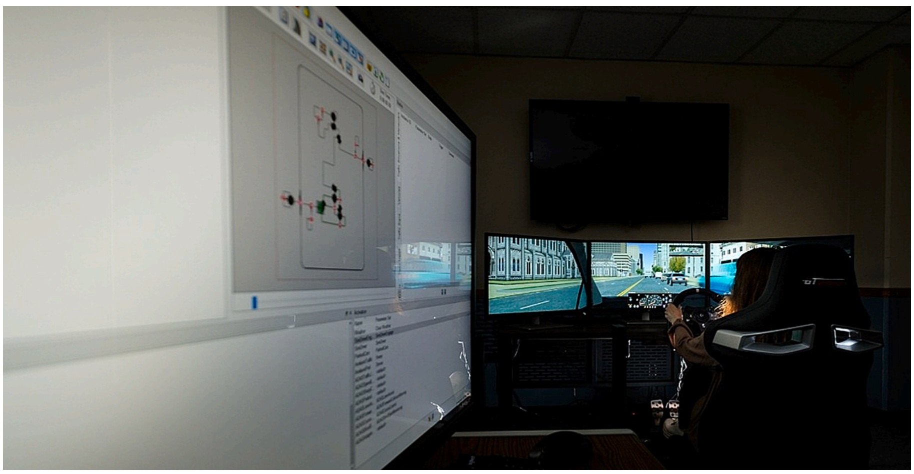

Fig. 1. The RDS 100 Driving Simulator used in this study located at the University of Arizona.

The driving simulator study included eight primary scenarios and a dummy scenario and further used a Latin square design to control order effects. A Latin square design uses a matrix with an equal number of rows and columns, where each condition appears exactly once in every row and column, ensuring that all conditions are evenly distributed across positions so as to remove any order effects (Richardson, 2018). A power analysis was conducted using G*Power (Faul et al., 2007, 2009) to determine the appropriate sample size for the repeated measures design used in this study. The analysis assumed a medium effect size ($f = 0.25$), an alpha level of 0.05, a power of 0.95, and a correlation among repeated measures of 0.6, yielding a minimum required sample size of 28 participants. However, the study employed a balanced Latin Square design across eight primary scenarios, which necessitates a sample size that is a multiple of the number of scenarios to ensure proper counterbalancing. Based on this design requirement, a minimum of 32 participants was needed. This sample size also aligns with prior literature, which has consisted of at least four repetitions per condition for adequate statistical power in driving simulator studies with limited in-study variables (Ryan et al., 2020). To further account for potential dropouts, simulator sickness, or data loss, a total of 40 participants were recruited. Eligibility criteria included being between 18 and 64 years of age and holding a valid driver's license.

In the second step, participants provided informed consent and completed an 8 to 10-minute test drive to familiarize themselves with the driving simulator's functionality. They were told to drive as they normally would and were not given details for the purpose of the study. Furthermore, the test drive differed significantly from the actual driving scenario design, taking place in a downtown city environment, to avoid potential bias from learning the scenario design ahead of time. Following the test drive, participants were equipped with eye-tracking glasses, which were then calibrated to ensure accurate data collection. Each participant subsequently completed nine driving short (less than three minutes each) scenarios, randomized using a Latin square design to mitigate potential biases from learning effects or fatigue. These nine included the eight intended to study the variables, and the one dummy scenario, described in the next section. The Latin square design ensured that each condition appeared in every starting position. Further details of these scenarios and the study designs are described in the following sections.

In the third phase upon completing the scenarios, participants completed a questionnaire to indicate their preferences for different types of alerts. Participants were not informed of the specific objectives of the study prior to the simulation; they were instructed only to drive as they normally would while adhering to all traffic laws, to ensure natural driving behavior throughout the experiment. After completing all simulation scenarios and post-study questionnaires, participants were then debriefed regarding the purpose and goals of the study. Lastly, participants were compensated financially for their time.

2.6. Scenario baseline

To ensure consistency and reliability in the analysis of driver responses, a baseline scenario was developed to standardize key driving conditions across all experimental scenarios. The baseline scenario provided a controlled environment against which the effects of different alert types, timings, and strategies on driver behavior could be systematically evaluated. Establishing a standardized baseline was critical for minimizing variability introduced by external factors, ensuring that observed differences in driver behavior could be attributed solely to the experimental factors being analyzed. The baseline scenario was intentionally designed to mimic typical driving conditions with the following features:

Traffic Conditions: The driving lane ahead of the participant remained clear of vehicles to eliminate the influence of vehicle interactions or congestion on driving behavior. Overall, traffic density was maintained at exceptionally low to low levels in the opposing direction, simulating an environment with minimal external stimuli.

Speed Limit: A posted speed limit of 75 miles per hour was displayed at the beginning of each scenario as well as throughout the scenario, providing participants with a consistent speed reference throughout the experiment. This is the standard speed limit on Arizona interstates, which were the base conditions of this experiment.

Roadway Characteristics: The roadway consisted of a divided two-lane configuration in each direction, designed to replicate interstate highway geometry.

Environment: Scenarios were set in a rural area characterized by minimal visual distractions, such as buildings or dense vegetation. The simplicity of the environment was created to reduce potential confounding factors, such as unexpected visual stimuli.

Weather and Lighting Conditions: Clear weather conditions were simulated to remove the influence of adverse weather on driving performance. All scenarios took place during the daytime to provide consistent lighting and visibility.

These baseline conditions were applied uniformly across all scenarios to create a stable reference point for comparison. By controlling environmental and contextual factors, the baseline ensured that differences in driver performance could be attributed directly to the experimental variables under investigation, such as the type, timing, and distance of alerts.

2.7. Alerts

Four different alert types were evaluated at two different distances (i.e., an alert sent out at two miles, or an alert sent out at one mile prior to the incident scene) making the total number of alerts eight. The findings from the literature review led to the selection of only speech-based alerts for this study, as they were identified as the most preferred and least confusing type of alert compared to other options. The selection of one mile and two miles as alert distances was based on common practice observed in commercial navigation applications, such as Google Maps (Google Maps, 2025), Apple Maps (Apple, 2025), and Waze (Waze, 2025), which typically issue alerts at these distances in similar driving contexts. These apps generally provide alerts at or before the 2-mile mark, with Waze typically issuing them around the 1-mile distance. These distances were further reviewed in consultation with professionals from the Arizona Department of Transportation (ADOT) who oversee the AZ511 system (ADOT, 2024). They confirmed that the reported distances align with both the operational capabilities and strategic interests of the alert system integrated into their application. The literature review identified that most secondary crashes occur within 0.5 miles of the primary crash (Goodall, 2017; Wang et al., 2019), underscoring the importance of issuing alerts at greater distances to provide drivers with adequate time to respond and prevent further incidents. As a result, a 0.5-mile alert distance was not chosen for this study for investigation. Furthermore, given the lack of established literature specifically addressing optimal alert distances for incident management, an open-ended question was included in the post-survey questionnaire to gather feedback on alternative alert distances, and these responses are discussed in the study.

A crash scene was selected as the incident scene for all alerts, aligning with real applications of a traveler information system application. Along with the eight alert scenarios, a dummy scenario was also evaluated. Unlike the other scenarios in the study, the dummy condition did not include any crash events or alert notifications and represented a baseline roadway environment. This control scenario served three primary purposes: first, to establish baseline driving behavior in the absence of experimental interventions; second, to reduce the likelihood of participants forming expectations about the timing or presence of alerts; and third, to identify potential anticipatory behaviors indicative of learning effects. To maintain counterbalancing and to reduce order-related biases, the dummy scenario was embedded within the Latin square design, consistent with practices in simulation research (Ryan et al., 2020). The study used a combined design featuring within-subject and between-subject factors. All examined variables are displayed in Table 1.

The alerts were played through the driving simulator's speakers to mimic in-vehicle systems. Each driver participated in nine different scenarios with some scenarios requiring action, while some not requiring any action. The eight primary driving scenarios were divided into two distinct groups based on crash location. The first group of scenarios, 1A, 1C, 2A, and 2C, positioned crashes adjacent to the right traffic lane, requiring lane changes only from participants who began in the right lane, while those in the left lane could continue unimpeded. The second group of scenarios, 1B, 1D, 2B, and 2D, mirrored this design with crashes on the left side, necessitating lane changes from left positioned participants.

Table 2 provides the details of the driving scenarios assessed in the study. The messages in alert types 1A and 2A provided precise information about the exact location of the incident. Alert types 1B and 2B were the shortest alerts evaluated, simply notifying drivers that there might be a crash ahead without additional details. Alert types 1C and 2C enhance the notification messaging by informing drivers of a crash ahead and including the distance to the crash. Lastly, alert types 1D and 2D provide the most detailed information, combining the notification of a crash ahead messaging with the distance to the crash and an action statement advising drivers to stay in a specific lane, either left or right.

3. Scenario order

The study employed a Latin square design to systematically counterbalance the order of driving scenarios across participants, controlling for potential order effects (Fitzpatrick et al., 2016; Lee et al., 2021; Rodriguez et al., 2016). This design ensured balanced representation of each scenario across all possible presentation orders. To address learning effects arising from repeated exposure, both the starting lane position (left vs. right) and crash scenario location (left vs. right) were incorporated as between-subjects factors. Participants were systematically assigned to specific starting lanes to maintain experimental control while introducing necessary variability in driving contexts. Table 3 presents the scenario order for each participant. "L" and "R" indicates the left and right lane from which each of the participant started, respectively.

3.1. Driving simulator study framework

All scenarios were based on the same design, consisting of a 5-mile (approximately 8,000 m) stretch of highway, with the crash scene located at the 3.86-mile (6,200-meter) mark. In four of the scenarios, alerts were triggered 2 miles (1.86-mile mark/3,000 m) prior to the crash, while in the remaining scenarios, alerts were activated 1 mile (2.86-mile mark/4,600 m) before the crash.

All scenarios were ordered using a factorial structure using Latin square design that incorporated variations in alert timing (1 mile vs. 2 miles) and alert type. To mitigate learning effects and reduce participant anticipation, starting lane positions were alternated between the left and right lanes across different scenarios. The crash location also varied, with scenarios 1A, 1C, 2A, and 2C featuring crashes on the right shoulder, and scenarios 1B, 1D, 2B, and 2D placing the crash on the left shoulder. Scenarios were randomized for each participant to eliminate potential order effects or systematic bias. This comprehensive design ensured a balanced distribution of conditions and minimized the likelihood that participants could predict either the timing or location of upcoming crash events, thereby supporting a more accurate evaluation of driver responses. A One-way Analysis of Variance (ANOVA) along with Tukey's Honestly Significant Difference (HSD) post-hoc test (Lane, 2010) was applied to understand if the reaction time and reaction distance across the scenarios were significantly different. A linear mixed effect model was also modeled to understand differences in reaction time and

Table 1
Within-subject and between-subject factors.

Design Factor	Variable	Levels
Within-Subject	Alert distance	2 miles, 1 mile
	Alert speech	Location, only incident, incident with distance, incident with distance and action
Between-Subject	Crash location	Left lane, right lane
	Starting lane	Left lane, right lane

Table 2
Driving scenarios with label.

Scenario	Starting Lane (Between-Subject)	Crash Position (Between-Subject)	Auditory Alert (Within-Subject)	Distance from Crash when Alert Occurred (Within-Subject)	Action
1A	Left	Right	Crash on [Location Details]	2 miles	No action required
	Right				Move from right lane to left lane
1B	Left	Left	Crash ahead		Move from left lane to right lane
	Right				No action required
1C	Left	Right	In 2 miles, there is a crash		No action required
	Right				Move from right lane to left lane
1D	Left	Left	In 2 miles, there is a crash, stay right		Move from left lane to right lane
	Right				No action required
Dummy	Left	None	None	1 mile	No action required
2A	Left	Right	Crash on [Location Details]		No action required
	Right				Move from right lane to left lane
2B	Left	Left	Crash ahead		Move from left lane to right lane
	Right				No action required
2C	Left	Right	In 2 miles, there is a crash		No action required
	Right				Move from right lane to left lane
2D	Left	Left	In 2 miles, there is a crash, stay right		Move from left lane to right lane
	Right				No action required

reaction distance considering individual variability. An example of the crash scenario on the left shoulder is shown in Fig. 2.

3.2. *Eye tracking framework*

Eye-tracking data was recorded using Argus ET eye-tracking glasses. Prior to each session, the glasses were carefully calibrated to align with the participant's pupils and eye movements, ensuring accurate tracking of gaze direction during each scenario. The eye-tracking system was integrated with data from the driving simulator using APIs, providing seamless synchronization. This allowed for the precise identification of the moments and locations when alerts were triggered, correlating them with the corresponding eye movements and visual focus points recorded by the simulator.

The eye-tracking glasses captured several key metrics, including gazes (i.e., the general direction of focus), fixations (i.e., periods when the eye remains stationary at a specific point), and saccades (i.e., rapid eye movements between fixations). These metrics were analyzed to explore their relationship with driver perception and other factors critical for interpreting driving behavior. In all scenarios, three main Areas of Interest (AOIs) were considered for analysis: (1) the speedometer, (2) the rearview mirror, and (3) the driving direction, with a primary focus on eye tracking behavior related to the driving direction. The analysis categorized the data into three distinct phases: (1) before the alert, (2) from the alert until just before the crash scenario, and (3) at the crash location. Fig. 3 illustrates these three AOIs.

This study examined various eye-tracking metrics to assess participants' visual attention during the task, including dwell time, time to first fixation, revisit count, saccade count, and peak velocity. Dwell time, which measures the percentage of duration a participant fixates on an Area of Interest (AOI), was investigated alongside time to first fixation, which calculates the average time in seconds from the start of an AOI to the participant's first fixation on it. The revisit count quantified how often a participant revisited a specific AOI, while the saccade count reflected the average number of rapid eye movements made within an AOI. Peak velocity measured the maximum speed of the eye during a saccade. These metrics were analyzed to uncover patterns of visual engagement and attention allocation throughout the scenarios.

3.3. *Post-study questionnaire*

At the conclusion of the study, participants completed a post-study questionnaire to provide feedback on their experiences with the alerts. The questionnaire was divided into two sections: an alert-specific evaluation and an investigation of general driving preferences. In the first section, participants provided feedback on the four alerts. Using a 5-point Likert scale, participants rated each alert based on their helpfulness, clarity, ease of understanding, suitability in duration, and the adequacy of the information provided. These responses allowed for the identification of trends and preferences in how different alert types influence the driving experience.

The second section gathered contextual data, including participants preferred alert distances, whether they lived in urban, rural, or suburban areas, and their familiarity and frequency of the use of traveler information apps. The questionnaire was administered digitally using Qualtrics.

Table 3
Sequence of driving scenarios for each participant.

Participant Number	Scenario Number and Order								
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
1	1AL	1BR	1DL	2BR	2DL	Dummy	2CL	2AR	1CL
2	2CL	1CR	2DL	2AR	1DL	Dummy	1AL	2BR	1BL
3	2BL	Dummy	1BL	2AR	1AL	1CR	1DL	2CR	2DL
4	1DL	2DR	1AL	2CR	1BL	1CR	2BL	2AR	Dummy
5	2AL	1CR	Dummy	2CR	2BL	2DR	1BL	1DR	1AL
6	1BL	1AR	2BL	1DR	Dummy	2DR	2AL	2CR	1CL
7	2CL	2DR	1CL	1DR	2AL	1AR	Dummy	1BR	2BL
8	Dummy	2BR	2AL	1BR	1CL	1AR	2CL	1DR	2DL
9	1DL	1AR	2DL	1BR	2CL	2BR	1CL	Dummy	2AL
10	1CL	2AR	2CL	Dummy	2DL	2BR	1DL	1BR	1AL
11	1BL	2BR	1AL	Dummy	1DL	2AR	2DL	1CR	2CL
12	2DL	2CR	1DL	1CR	1AL	2AR	1BL	Dummy	2BL
13	Dummy	2AR	2BL	1CR	1BL	2CR	1AL	2DR	1DL
14	1AL	1DR	1BL	2DR	2BL	2CR	Dummy	1CR	2AL
15	1CL	2CR	2AL	2DR	Dummy	1DR	2BL	1AR	1BL
16	2BL	1BR	Dummy	1AR	2AL	1DR	1CL	2DR	2CL
17	2DL	1DR	2CL	1AR	1CL	1BR	2AL	2BR	Dummy
18	2AL	Dummy	1CL	2BR	2CL	1BR	2DL	1AR	1DL
19	1AL	1BR	1DL	2BR	2DL	Dummy	2CL	2AR	1CL
20	2CL	1CR	2DL	2AR	1DL	Dummy	1AL	2BR	1BL
21	2BL	Dummy	1BL	2AR	1AL	1CR	1DL	2CR	2DL
22	1DL	2DR	1AL	2CR	1BL	1CR	2BL	2AR	Dummy
23	2AL	1CR	Dummy	2CR	2BL	2DR	1BL	1DR	1AL
24	1BL	1AR	2BL	1DR	Dummy	2DR	2AL	2CR	1CL
25	2CL	2DR	1CL	1DR	2AL	1AR	Dummy	1BR	2BL
26	Dummy	2BR	2AL	1BR	1CL	1AR	2CL	1DR	2DL
27	1DL	1AR	2DL	1BR	2CL	2BR	1CL	Dummy	2AL
28	1CL	2AR	2CL	Dummy	2DL	2BR	1DL	1BR	1AL
29	1BL	2BR	1AL	Dummy	1DL	2AR	2DL	1CR	2CL
30	2DL	2CR	1DL	1CR	1AL	2AR	1BL	Dummy	2BL
31	Dummy	2AR	2BL	1CR	1BL	2CR	1AL	2DR	1DL
32	1AL	1DR	1BL	2DR	2BL	2CR	Dummy	1CR	2AL
33	1CL	2CR	2AL	2DR	Dummy	1DR	2BL	1AR	1BL
34	2BL	1BR	Dummy	1AR	2AL	1DR	1CL	2DR	2CL
35	2DL	1DR	2CL	1AR	1CL	1BR	2AL	2BR	Dummy
36	2AL	Dummy	1CL	2BR	2CL	1BR	2DL	1AR	1L
37	1AL	1BR	1DL	2BR	2DL	Dummy	2CL	2AR	1CL
38	2CL	1CR	2DL	2AR	1DL	Dummy	1AL	2BR	1BL
39	2BL	Dummy	1BL	2AR	1AL	1CR	1DL	2CR	2DL
40	1DL	2DR	1AL	2CR	1BL	1CR	2BL	2AR	Dummy

Fig. 2. Example of a crash scenario as visualized in the driving simulator.

4. Results

The results obtained from the driving simulator, eye-tracking equipment, and questionnaire are outlined below. The first subsection presents the demographics of the participants, followed by results from the driving simulator, eye tracking analysis, and questionnaire.

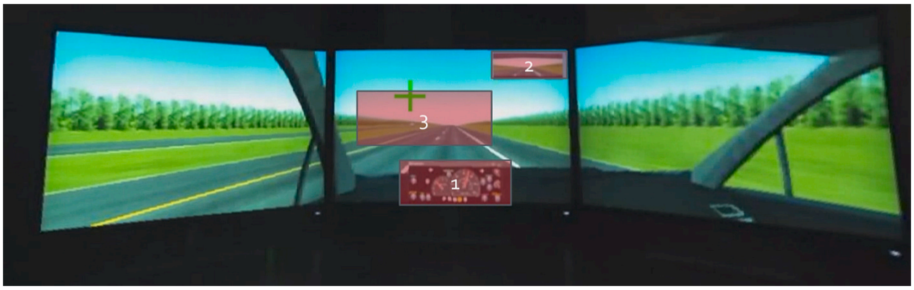

Fig. 3. The three Areas of Interest (AOI) analyzed in this study.

4.1. Demographic overview of study participants

As shown in Table 4, a total of 40 participants took part in the study, with an equal gender distribution: 20 men and 20 women. Gender was self-reported by participants. To ensure demographic relevance and consistent representation, participants were grouped into five age categories using 10-year bins based on U.S. Census age groupings. Specifically, 12 drivers (30 %) were aged 18–24 years, 11 drivers (27.5 %) were aged 25–34 years, 8 drivers (20 %) were aged 35–44 years, 4 drivers (10 %) were aged 45–54 years, and 5 drivers (12.5 %) were aged 55–64 years. A greater proportion of younger drivers (ages 18–34) was observed, comprising 57.5 % of the sample. Nonetheless, a balanced distribution of driving experience was maintained across all age groups. This age-binning approach is consistent with prior driver behavior research (AAA Foundation for Traffic Safety, 2018; Ryan et al., 2019; Singh & Perel, 2003). This allowed for a more in-depth gathering of age data compared to wider age group bins (Richard et al., 2005).

In terms of racial and ethnic diversity, the participant sample consisted of 40 % Non-Hispanic White individuals, 17.5 % Hispanic or Latino individuals, 25 % Asian individuals, 10 % Black or African American individuals, 5 % American Indian or Alaska Native individuals, and 2.5 % Middle Eastern or North African individuals. This diverse composition aimed to reflect the broad sociodemographic makeup of the United States, enhancing the generalizability of the study's findings across various ethnic and racial groups. Regarding driving experience, participants exhibited a wide range of experience levels: 5 % had less than one year of driving experience, 25 % had 1–3 years, 30 % had 4–6 years, 5 % had 7–10 years, and 35 % had more than 10 years.

4.2. Driving simulator results

The results from the analysis of the driving simulator are discussed below. Two unique metrics are presented: reaction time and reaction distance. The results provide insights into the performance and behavior of drivers, in addition to the questionnaire.

4.3. Reaction time

The reaction times for the eight scenarios are illustrated in Fig. 4. Reaction time is defined as the duration from the moment an alert is triggered to the point at which the driver initiates an appropriate response to the alert.

In scenarios where a driver made multiple lane changes following the alert, the reaction time was measured as the time difference

Table 4
Sociodemographic characteristics of participants.

Category	Variable	Percentage
Gender	Male	50 %
	Female	50 %
Age Group	18–24 years	30 %
	25–34 years	27.5 %
	35–44 years	20 %
	45–54 years	10 %
	55–64 years	12.5 %
Race	Non-Hispanic White	40 %
	Hispanic or Latino	17.5 %
	Asian	25 %
	Black or African American	10 %
	American Indian or Alaska Native	5 %
	Middle Eastern or North African	2.5 %
Driving Experience	Less than 1 year	5 %
	1–3 year	25 %
	4–6 year	30 %
	7–10 year	5 %
	More than 10 years	35 %

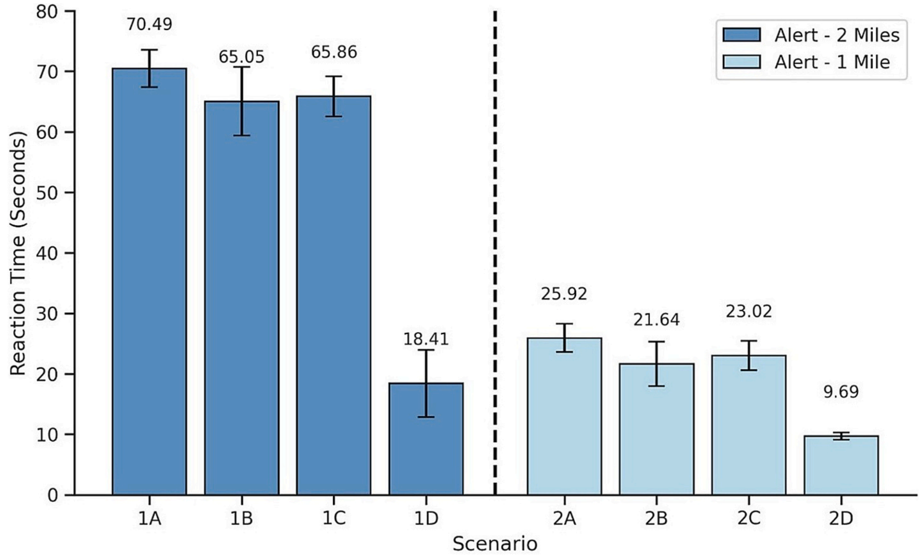

Fig. 4. Reaction time associated with the different alerts. The values indicate the mean reaction time.

between the alert and the final lane change before the crash scenario occurred. For instances where only a single lane change was made, the reaction time was calculated as the time interval between the alert messaging and the moment of that lane change.

The reaction time data across the eight scenarios shows notable trends in driver responses to alerts at different distances from the incident. For alerts given two miles before the incident (scenarios 1A, 1B, 1C, and 1D), reaction times varied, with a minimum of 18.41 s in scenario 1D and a maximum of 70.49 s in scenario 1A. Scenarios 1D and 2D, which included detailed information like crash location and action instructions (e.g., "stay left/right") in the alert messaging, showed the fastest response times, suggesting that more informative alerts lead to quicker reactions. The 1-mile before the incident scenario with the alert messaging that indicated the location and action information (i.e., scenario 2D) had the shortest reaction time of 9.69 s.

4.4. Reaction distance

The reaction distance data for the eight scenarios are illustrated in Fig. 5. Reaction distance refers to the distance a driver traveled from the moment an alert was triggered until they took the proper lane change action, to be in the opposite lane of the incident. In scenarios where a driver made multiple lane changes, the reaction distance was measured as the distance traveled from the alert to the final lane change before the crash scene. For single lane changes, it was calculated as the distance from the alert message to the moment

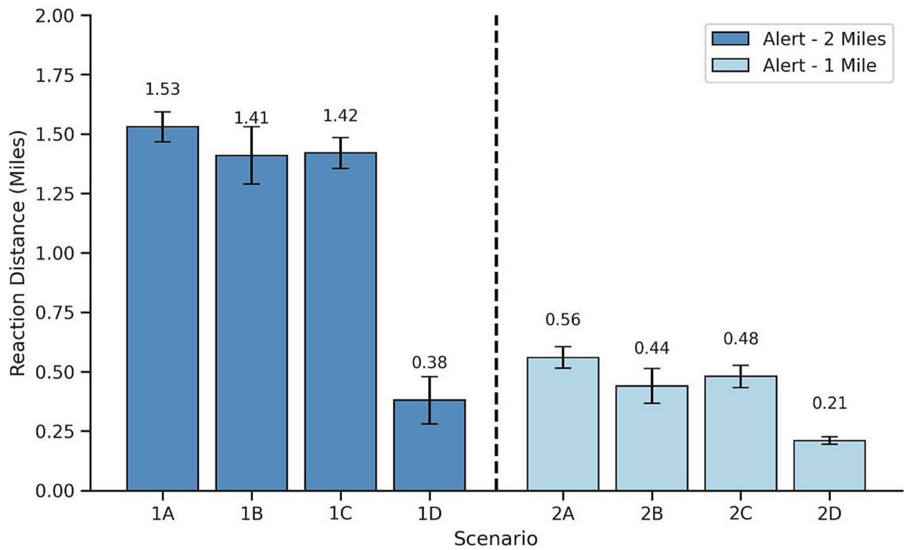

Fig. 5. Reaction distance for the different alerts evaluated. The values indicate the mean reaction time.

of that lane change.

The reaction distance across the eight scenarios revealed trends related to the distance of the alert from the incident. For alerts triggered two miles before the incident (scenarios 1A, 1B, 1C, and 1D), reaction distances range from 0.39 miles in scenario 1D to 1.54 miles in scenario 1A. Scenario 1D, which encompassed more detailed alert information (i.e., crash location and action instructions) had the shortest reaction distance, suggesting that more specific alerts lead to quicker driver responses. For alerts triggered one mile before the incident (scenarios 2A, 2B, 2C, and 2D), reaction distances were shorter, with scenario 2D at 0.21 miles being the shortest. Scenarios 2A and 2C had longer distances, at 0.56 miles and 0.48 miles, respectively.

4.5. Gender differences in reaction time and response distance

The analysis of reaction time and reaction distance data for male and female participants, as shown in Fig. 6, revealed notable gender differences. Across most scenarios, female drivers exhibited faster reaction times compared to male drivers. Specifically, in scenarios 1C, 2A, 2B, 2C, and 2D, female drivers consistently responded more quickly than male drivers. However, in scenario 1A and 1B, male drivers had a slightly faster reaction time than female drivers.

In scenario 1D, the gender difference in reaction time was more pronounced. Female drivers responded on average in 10.7 s, whereas male drivers took significantly longer, with a reaction time of 27.3 s.

4.6. Average position along the route

Fig. 7 presents the average vehicle position across all drivers for each experimental scenario, analyzing how alert timing and

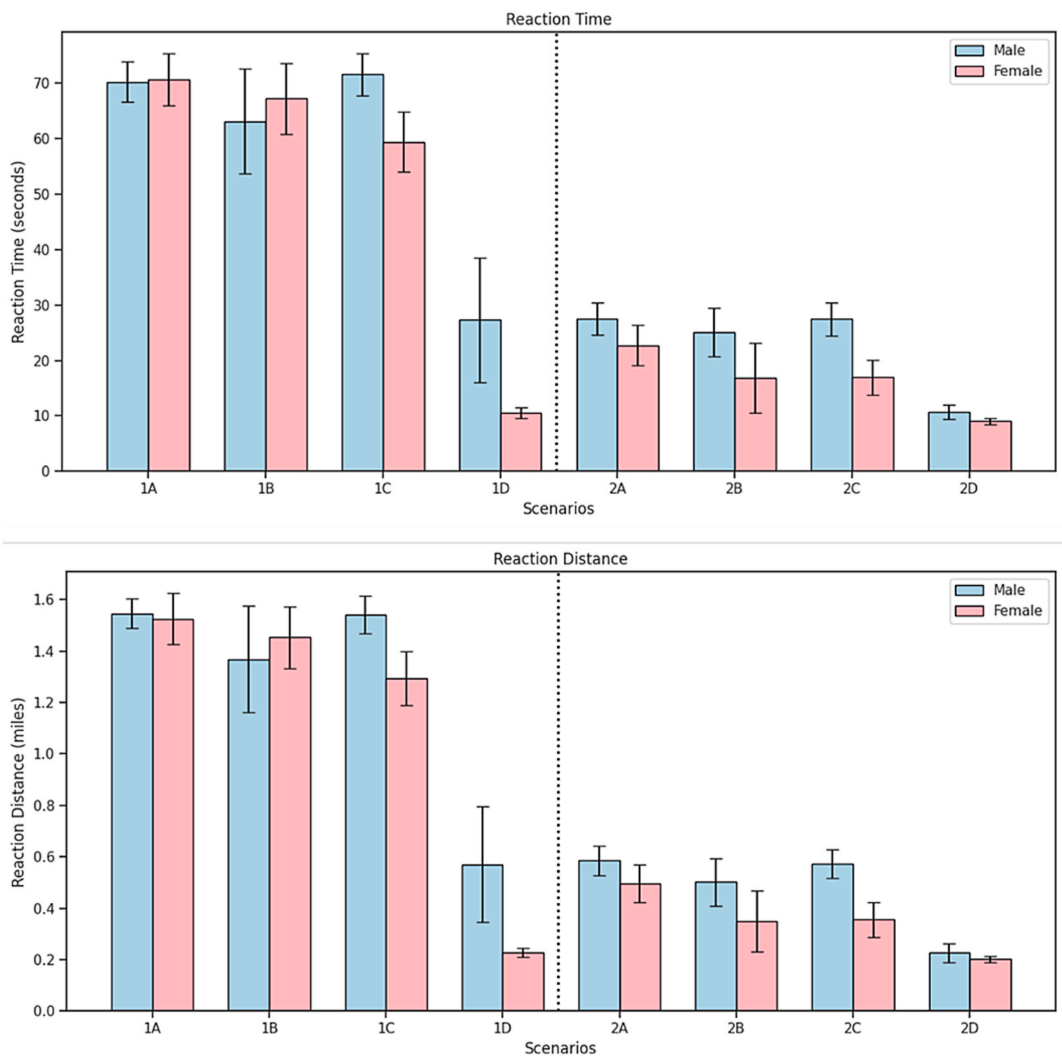

Fig. 6. Reaction time (Top) and reaction distance (Bottom) across scenarios for male and female drivers.

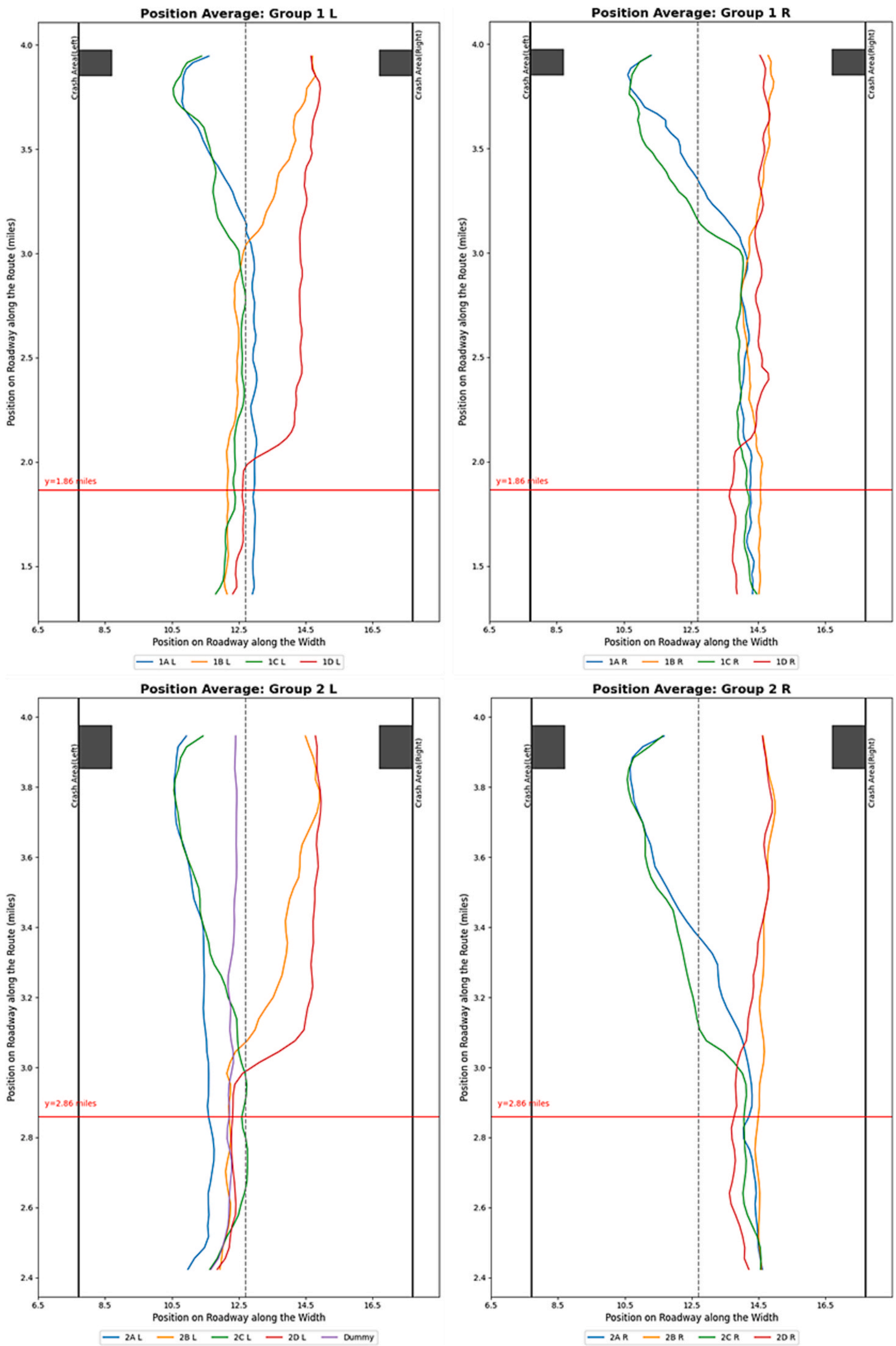

Fig. 7. Vehicle position and distance at which drivers on average changed lanes for the alerts evaluated.

starting lane position influenced driving behavior. Scenarios are grouped based on the timing of the alert: Scenario Group 1 issued notifications two miles before the crash, while Scenario Group 2 provided alerts one mile before the incident. The initial lane of travel is also considered, with "L" indicating the left lane and "R" indicating the right lane. The earliest reaction is seen for Scenario D (marked in red). The dummy scenario (marked in purple) where no alerts were presented exhibit on average no lane changes. Comparison of scenarios A through C showed similar response timing patterns, although Scenario C (including distance information) prompted marginally quicker reactions indicating that providing distance might evoke slightly earlier reaction. These findings highlight the significant influence of alert timing, distance and content, with distance and action-specific notifications proving most effective.

5. Statistical analysis

Two statistical approaches were used to analyze participants' response behavior across alert scenarios. First, a One-Way ANOVA was applied to assess differences in reaction time and distance across the four scenarios. Post-hoc comparisons were conducted using Tukey's HSD test to identify specific group differences. Given the within-subject design, a Linear Mixed-Effects Model (LMM) was also employed, with random intercepts for participants and fixed effects for scenario and gender. This allowed us to account for individual variability and assess potential demographic interactions.

5.1. *ANOVA with Tukey's HSD*

A One-way Analysis of Variance (ANOVA) along with Tukey's Honestly Significant Difference (HSD) was applied to understand if the reaction time and reaction distance across the scenarios were significantly different. The ANOVA test revealed a significant effect, prompting a post-hoc analysis using Tukey's Honest Significant Difference (HSD) test to identify specific group differences. Tukey's HSD compares all possible pairs of group means while controlling the family-wise error rate.

For the two-mile scenarios, the ANOVA results indicate a significant difference in reaction distance across the four scenarios (F-statistic (3,83) = 37.388, p-value < 0.001). Tukey's HSD post-hoc test further highlights these differences. Scenarios 1A and 1B did not show significant differences in reaction distance compared to 1C, as their mean differences were small and not statistically significant ($p > 0.05$). However, significant differences were observed between scenario 1D and all other scenarios (1A, 1B, and 1C), with scenario 1D having lower reaction distances. These differences are confirmed by large negative mean differences and p-values of less than 0.001. This suggests that scenario 1D stands apart with a significantly shorter reaction distance, whereas the other three scenarios exhibit comparable performance. For the one-mile scenarios, the ANOVA results indicate a significant difference across the four scenarios (F-Statistic (3,78) = 10.675, p-value < 0.001) while scenario 2D stood out as the scenario with statistically significant differences in reaction distance. Similar results were observed in reaction time, where reaction time was found to be significantly different in scenarios 1D and 2D. Table 5 presents the results from the Tukey HSD post-hoc test.

5.2. *Linear mixed effect models*

A linear mixed-effects model was employed to predict reaction distance, measured in miles, based on various scenarios and participant gender. This model incorporated both fixed effects, representing the influence of scenarios and gender, and a random intercept to capture individual variability across participants. By including random effects, the model effectively accounts for differences in baseline reaction distances among individuals. The strength of this modeling approach lies in its ability to simultaneously estimate the overall effects of scenarios and gender while considering the correlation of repeated observations within each participant. Parameters in the model were estimated using the Restricted Maximum Likelihood (REML) method, which offers robust and unbiased

Table 5
Results from the Tukey HSD post-hoc test.

Metric	Scenario 1	Scenario 2	Mean Difference	P value
Reaction Distance (meters)	1A	1B	−203.93	0.75
	1A	1C	−179.97	0.68
	1A	1D	−1843.14	0.00*
	1B	1C	23.9596	0.99
	1B	1D	−1639.21	0.00*
	1C	1D	−1663.1702	0.00*
	2A	2B	−187.06	0.40
	2A	2C	−120.39	0.59
	2A	2D	−553.08	0.00*
	2B	2C	66.67	0.94
	2B	2D	−366.02	0.02*
	2C	2D	−432.70	0.00*
Reaction Time (seconds)	1A	1B	−5.44	0.82
	1A	1C	−4.62	0.79
	1A	1D	−52.08	0.00*
	1B	1C	0.82	0.99
	1B	1D	−46.64	0.00*
	1C	1D	−47.45	0.00*
	2A	2B	−4.28	0.66
	2A	2C	−2.90	0.77
	2A	2D	−16.23	0.00*
	2B	2C	1.38	0.98
	2B	2D	−11.95	0.01*
	2C	2D	−13.33	0.00*

* Statistically significant at the 95 % confidence level

estimates by properly accounting for the estimation of fixed effects.

Table 6 depicts the goodness of fit measures for the mixed effect model for reaction distance. The R^2 values indicate a strong model fit. The marginal R^2 (0.7548) reflects the proportion of variance explained by the fixed effects alone, while the conditional R^2 (0.7985) includes both fixed and random effects, suggesting that the model accounts for a substantial amount of the variance in reaction distance.

The results from the mixed effect model for reaction distance are shown in Table 7. The fixed effects results from the linear mixed-effects model show that scenario 1A, serving as the reference category, has a baseline reaction distance of 1.475 miles ($p < 0.001$). Scenarios 1B and 1C exhibit minimal negative effects on reaction distance (−0.106 and −0.111 miles, respectively), but these results are not statistically significant ($p > 0.05$). In contrast, scenarios 1D, 2A, 2B, 2C, and 2D show significant negative impacts on reaction distance. Scenario 1D results in a decrease of 1.122 miles ($p < 0.001$), while scenario 2D has the most substantial negative effect at −1.296 miles ($p < 0.001$). Scenarios 2A-2D are all about 1 mile shorter than scenario 1A, which suggests that they would typically require a shorter reaction distance. Interestingly, even though scenario 1D represents a longer scenario, the reaction distance is shorter compared to the shorter-distance scenarios 2A-2C, where no action statement is given, suggesting that the inclusion of an action statement might facilitate quicker reactions. Additionally, the gender coefficient for males is 0.125 miles ($p = 0.037$), indicating a slight but statistically significant difference in reaction distance, with males generally exhibiting a longer reaction distance than females.

In terms of random effects, the model also accounts for variability across participants. The group variance is estimated at 0.016 (Std. Err. = 0.034), showing that there is some between-participant variability in reaction distance, though the random effect is small.

Another mixed effect model was developed to understand variability in reaction time across scenarios and gender. This model included both fixed effects, reflecting the impact of scenarios and gender, and a random intercept to account for individual differences among participants. Table 8 depicts the goodness of fit for the mixed effect model for reaction time. The R^2 values for the reaction time model are slightly lower than for the reaction distance model, indicating that the fixed effects explain about 73 % of the variance in reaction time, and with random effects, the model explains about 79 % of the variance.

Table 9 presents the results from the mixed-effects model predicting reaction time. The findings closely mirror those from the reaction distance model. Scenario 1D which includes crash location, distance information, and an action statement produces a significantly shorter reaction time ($p < 0.001$) compared to the baseline scenario that only provides crash location. The gender effect, though marginally significant ($p = 0.062$), suggests that males tend to react slightly slower than females, with a coefficient of 5.784 s.

The model also included random intercepts to account for variability between participants. The estimated group-level variance was 50.539 (Std. Err. = 1.855), indicating substantial individual differences in reaction times. Compared to the reaction distance model, the higher random intercept variance in the reaction time model reflects greater variability across participants in how quickly they responded. This suggests that participants differed in their baseline driving speeds or responsiveness, independent of the scenario presented.

5.3. Eye tracking results

The eye tracking results are summarized in this section. The results presented include the following: time to first fixation, dwell time, dwell count, revisit count, saccade count, and peak velocity. These eye tracking metrics provide an indication to driver's perception and behavior.

5.4. Time to first fixation for AOIs

Fig. 8 presents the trends in time to first fixation (TTFF) across nine scenarios, categorized by the alert type and the areas of interest (driving direction, speedometer, and rearview mirror). The driving direction represents drivers looking ahead in the area they will be driving soon. In scenarios with alerts, the TTFF for the driving direction AOI decreased notably compared to the dummy scenario, suggesting faster responses to visual cues related to the driving direction AOI when alerts are present. Scenarios with more specific alerts (e.g., crash location and action instructions, scenarios 1D and 2D) showed lower TTFF values, indicating faster reactions.

In scenarios 2A, 2B, and 2C (all with alerts triggered 1 mile before the crash scene), TTFF values for the driving direction AOI were moderate, indicating drivers started to focus on the direction of travel in anticipation of the incident. The speedometer and rearview mirror AOIs also exhibited higher TTFF values for the rearview mirror than for the driving direction AOI. In scenario 2D, TTFF for the

Table 6
Goodness of fit for linear mixed effects model for reaction distance.

Statistics	
Number of Participants	40
Number of Observations	168
Constant Log Likelihood	−155.7572
Final log likelihood	−46.4976
Marginal R^2	0.7548
Conditional R^2	0.7985

Table 7
Estimation results of the linear mixed-effects model predicting reaction distance (in miles), with parameters estimated using REML.

	Coefficient	Std. Error	z-stat	p-value
Intercept	1.475	0.062	23.699	0.000
Scenario 1A	Reference			
Scenario 1B	−0.106	0.097	−1.097	0.273
Scenario 1C	−0.111	0.075	−1.467	0.142
Scenario 1D	−1.122	0.088	−12.751	0.000
Scenario 2A	−1.017	0.078	−12.955	0.000
Scenario 2B	−1.085	0.099	−10.954	0.000
Scenario 2C	−1.067	0.076	−13.974	0.000
Scenario 2D	−1.296	0.083	−15.594	0.000
Gender: Female	Reference			
Gender: Male	0.125	0.060	2.083	0.037
Group Var	0.016	0.034		

Table 8
Goodness of fit of linear mixed effects model for reaction time.

Statistics	
Number of Participants	40
Number of Observations	168
Constant Log Likelihood	−797.7421
Final log likelihood	−665.1082
Marginal R^2	0.7277
Conditional R^2	0.7884

Table 9
Estimation results of the linear mixed-effects model predicting reaction time (in seconds), with parameters estimated using REML.

	Coefficient	Std. Error	z-stat	p-value
Intercept	67.446	3.094	21.797	0.000
Scenario 1A	Reference			
Scenario 1B	−3.927	4.701	−0.835	0.403
Scenario 1C	−4.347	3.643	−1.193	0.233
Scenario 1D	−50.537	4.261	−11.861	0.000
Scenario 2A	−46.389	3.790	−12.239	0.000
Scenario 2B	−48.150	4.790	−10.052	0.000
Scenario 2C	−48.251	3.687	−13.088	0.000
Scenario 2D	−59.087	4.022	−14.691	0.000
Gender: Female	Reference			
Gender: Male	5.784	3.103	1.864	0.062
Group Var	50.539	1.855		

driving direction AOI was relatively low. In the dummy scenario without an alert, TTFF values for all three areas were higher, particularly for the driving direction AOI, indicating potentially slower focus on critical driving cues without an external alert.

5.5. Dwell Time, revisit count, saccade count and peak velocity

To understand driver perception and concentration after the different alerts were triggered, four different eye-tracking metrics were analyzed: dwell time (in percentage), revisit count (in frequency), saccade count (in frequency) and peak velocity (in degrees per second). Table 10 presents these analyzed metrics from the eye-tracking data.

The analysis of the eye-tracking metrics across the eight scenarios provides valuable insights into how drivers allocate their attention and respond to different types of alerts, particularly in relation to the timing of the alert (i.e., issued two miles versus one mile before the incident). Dwell time is a key indicator of how long drivers maintain focus on specific AOI. Group 1 scenarios (1A, 1B, 1C, 1D), where alerts were issued 2 miles before the incident, generally exhibited higher dwell times compared to Group 2 (2A, 2B, 2C, 2D) scenarios, where alerts were issued 1 mile before the incident. Scenario 1B had the highest dwell time of 75.5 %, suggesting that drivers in this scenario spent the most time focusing on the driving direction AOI after receiving the alert. In contrast, Group 2 scenarios showed slightly lower dwell times, with scenario 2D with a dwell time of 64.96 %.

Revisit count was another key metric that indicates how often drivers shift their attention away from the driving direction AOI and

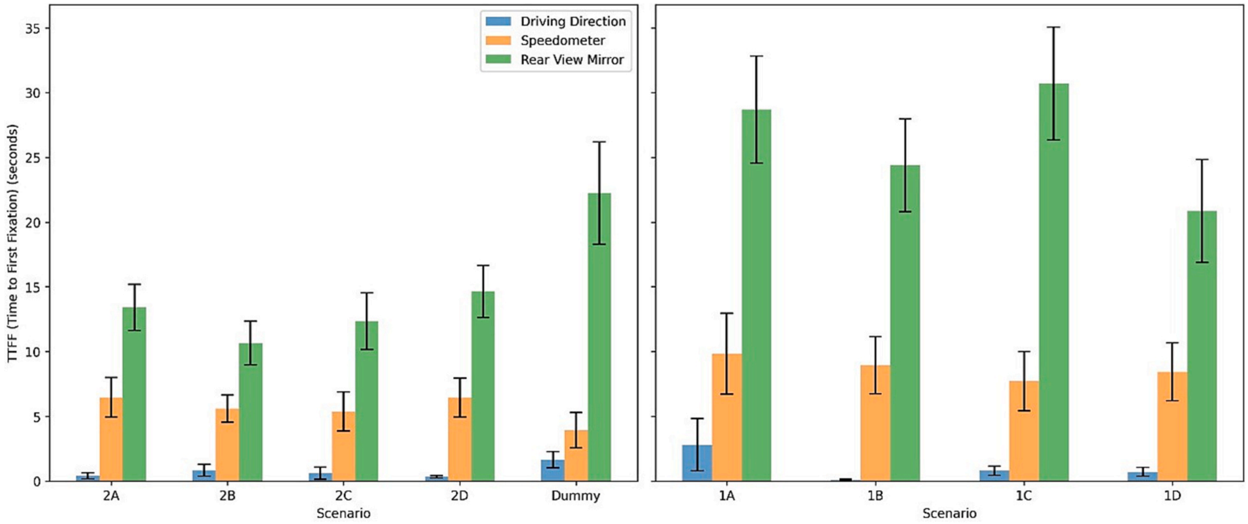

Fig. 8. The average time taken by participants to develop their first fixation at the three AOIs for the nine scenarios.

Table 10
Average eye-tracking metrics analyzed across scenarios including metrics for males and female participants.

Scenario	Dwell Time			Revisit Count			Saccade Count			Peak Velocity		
	All	**Male**	**Female**	**All**	**Male**	**Female**	**All**	**Male**	**Female**	**All**	**Male**	**Female**
1A	61.17	64.93	57.59	18.41	20.74	16.2	42.05	40.53	43.5	52.98	51.83	54.06
1B	75.5	75.15	75.85	15.88	17.05	14.7	51.02	48.35	53.7	54.6	55.99	53.2
1C	64.43	68.53	60.14	20.8	22.57	18.95	41.83	43.14	40.45	54.52	53.35	55.75
1D	67.13	67.51	66.75	19.98	20.75	19.2	44.25	44.35	44.15	54.7	55.57	53.84
2A	63.99	67.91	59.89	9.51	9.71	9.3	22.68	23.81	21.42	54.67	56.31	52.86
2B	63.73	61.96	65.58	9.32	10.48	8.1	19.54	22.19	16.75	54.62	59.05	49.96
2C	64.61	67.02	62.08	9.07	9.29	8.85	20.1	21	19.15	55.14	56.62	53.59
2D	64.96	66.8	62.92	10.22	10.81	9.58	19.48	18.1	21	52.19	52.84	51.47

return to it. In Group 1 scenarios, scenario 1C showed the highest average revisit count of 20.8, while scenario 1B had the lowest average revisit count (15.88). In Group 2 scenarios, scenario 2C had the lowest average revisit count at 9.07, while scenario 2D had the highest at 10.22. The relationship between dwell time and revisit count suggests that drivers with higher dwell times are more focused on the task at hand, while higher revisit counts reflect more exploratory behavior, where drivers shift attention between different areas of interest (e.g., speedometer, rearview mirror) before refocusing on the road. The saccade count, which measures the number of rapid eye movements between different AOIs, emphasizes the differences in visual exploration across scenarios. Scenario 1B had the highest average saccade count (51.02), indicating that drivers in this scenario engaged in more scanning and exploration behavior. In Group 2 scenarios, scenario 2A, had highest average saccade counts (22.68), while scenario 2D had the lowest average saccade count (19.48) indicating that drivers may explore their potential visual area less when provided with an action statement. It is important to note that comparisons between Group 1 and Group 2 scenarios cannot be made directly for the revisit and saccade counts as the duration of time drivers spent in the moments after the alert differed due to the difference in mileage ahead of the incident when the alert was triggered.

Finally, the average peak velocity, which measures the average speed of eye movements during saccades, ranged between 52.19 deg/s (in scenario 2D) and 58.56 deg/s (in scenario 1B). The average peak velocities in Group 1 scenarios were slightly higher, indicating that drivers in these scenarios were making faster eye movements and hence higher searching behavior. In contrast, Group 2 scenarios had slightly lower peak velocities, with scenario 2D being the lowest.

The analysis of eye-tracking metrics across driving scenarios revealed largely comparable patterns between male and female participants. As shown in Table 10, the mean values for dwell time, revisit count, saccade count, and peak saccade velocity were generally similar across both genders, with only slight variations. For instance, dwell time and saccade count remained consistent in most scenarios, and differences in peak velocity were often marginal. These findings align with the results of the Welch's t-tests, which indicated that most gender differences were not statistically significant, suggesting broadly equivalent visual attention behavior between males and females across the simulated driving tasks.

However, there were a few notable exceptions. In scenario 2B where only a crash alert was given 1 mile before the crash, female participants demonstrated significantly lower revisit counts and lower peak saccade velocities compared to male participants. Specifically, the revisit count for female participants was 8.10, compared to 10.48 for male participants, and the peak saccade velocity was 49.96 for female participants versus 59.05 for male participants. These differences were statistically significant, with $t(38) = 2.34$, $p = 0.025$ for revisit count, and $t(38) = 3.30$, $p = 0.002$ for peak saccade velocity. This suggests that in this scenario, female participants engaged in fewer repeated fixations and exhibited slower saccadic eye movements, potentially indicating an increased focus in the driving direction.

5.6. Questionnaire

The questionnaire was designed to gather feedback on the alerts, focusing on drivers' perceived helpfulness, clarity, ease of understanding, duration, and adequacy of information. The participants were also asked about their preferences regarding their preferred distance to receive alerts. The findings are summarized in this section.

5.7. Feedback on alert types

Fig. 9 illustrates the responses of the survey on the alert types, revealing distinct preferences among drivers regarding the format and content of the alerts. Responses were weighted so that higher values reflect stronger agreement and thus, stronger preference while lower values indicate disagreement or lower preference. The results suggest that drivers prefer alerts that are clear, are concise, and contain actionable information, such as the distance to the crash and specific lane guidance.

Alerts that included the distance of the crash along with an action statement garnered the most positive responses, with participants finding them most helpful, clear, and easily understandable over other three alert options. Alerts indicating the crash distance along with the notification of crash also received strong ratings, indicating that distance alone can be effective in cases where action statements may be more difficult to provide, potentially due to action complexity.

Alerts that provided minimal information, such as crash notification, received more mixed feedback, with some participants finding them unclear or lacking sufficient detail. On the other hand, the alert, which included highly specific location-based information, received negative responses. While a few participants found it helpful, many others reported it to be less helpful and less easy to understand, highlighting that too much detail can overwhelm drivers and hinder their ability to respond quickly in a dynamic driving situation.

Considering the overall responses to the five questions—helpfulness, clarity, duration, adequacy of information, and distraction, the data consistently indicated that alerts with clear and actionable instructions were the most positively rated. In contrast, alerts with specific locations received the lowest ratings.

5.8. Preferred alert distance

Out of the 40 participants, 30 (75 %) preferred receiving incident alerts two miles ahead, 9 (22.5 %) favored a one-mile warning, and 1 (2.5 %) selected a three-mile warning. These results indicate that most participants find a two-mile alert time optimal, providing sufficient time to assess the situation and make adjustments without causing distraction. The preference for a one-mile warning suggests that some participants may feel this distance does not offer enough preparation time, while the small preference for a three-mile warning reflects a desire for even more lead time. Overall, these results suggest that an alert time of at least two miles strikes the right balance for high-speed, interstate situations.

6. Discussion

This study investigated driver responses to various alert types and their effects on reaction time, reaction distance, eye-tracking behavior, and subjective preferences. The findings provide valuable insights into how alert design and timing influence driver performance and perceptions, with several notable implications for improving transportation safety systems.

The analysis revealed that alerts with detailed and actionable information were most effective in reducing both reaction time and reaction distance. This was evident in scenarios 1D and 2D, where drivers exhibited the fastest response times and shortest reaction distances. These findings align with existing literature (Chang et al., 2008; Noyes et al., 2006) suggesting that clear and concise speech based alerts enhance driver understanding and decision-making under time-sensitive conditions. Notably, alerts with minimal information, such as crash notifications without action guidance, were less effective, as observed in scenarios 1A and 2A. This highlights the importance of providing not just the notification but also appropriate details that drivers can easily interpret and act upon. This result aligns with previous literature which indicated that the best utility value lies in messages with information such as distance and lane instruction (Yang et al., 2024). Still, it is noted that there is a scarcity of literature focusing on the specific content that should be delivered in speech-based alerts. This study offers valuable insights that can assist in guiding the design of future alert systems.

Additionally, this study identified gender differences in reaction times, with female participants generally responding faster than male participants in most cases. This difference may be attributed to the fact that males typically exhibiting riskier driving behaviors compared to females (Rhodes & Pivik, 2011) and females are relatively safer drivers.

Eye-tracking data provided deeper insights into driver attention allocation and visual behavior in response to different alerts. Scenarios with more detailed alerts (i.e., 1D and 2D) resulted in lower time-to-first fixation for critical areas of interest, indicating faster recognition and prioritization of key driving cues. These alerts also had reduced saccade counts and revisit counts, suggesting that drivers may have been less likely to engage in exploratory scanning and were more focused on the driving direction in these situations (Mahanama et al., 2022). Conversely, scenarios with less informative alerts (e.g., 1A and 2A) showed higher TTFF and saccade counts, reflecting delayed and more scattered visual attention.

Driver feedback from the questionnaire corroborated the objective findings, with participants favoring alerts that provided clear,

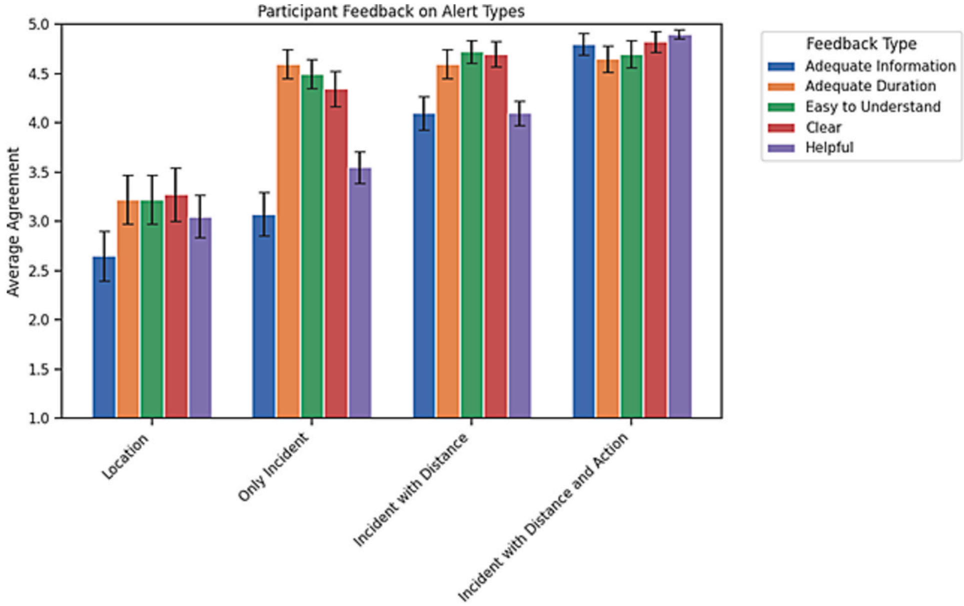

Fig. 9. Participant feedback on the four different alert types analyzed.

concise, and actionable information. Alerts that included both crash distance and action guidance were rated highest in terms of helpfulness, clarity, and adequacy of information. However, alerts with excessive detail, such as highly specific location-based instructions, received mixed responses. While some participants found them helpful, others reported feeling overwhelmed or distracted. This suggests that overly complex alerts may hinder driver comprehension and performance, particularly in high-stress situations which is similar to what is seen in current literature (Nees et al., 2016).

The findings also suggest that drivers prefer alerts delivered at a suitable distance from the incident. Alerts issued two miles before the crash (i.e., group 1 scenarios) provided drivers with sufficient time to process the information and plan their response, resulting in improved performance. While previous research (Yang et al., 2024) has indicated that shorter time intervals may also be effective for delivering alerts within urban environment, the amount of research examining this aspect of alert timing remains limited to date.

The findings of this study provide valuable insights into the development of improved traveler information system applications. The results emphasize the importance of designing alert systems that deliver clear and actionable guidance, such as instructions for lane changes or speed adjustments, to improve driver response and enhance safety. Additionally, the timing of alerts plays a critical role; while alerts delivered at longer distances from incidents are effective, they must be carefully balanced to avoid overwhelming drivers with excessive information. Striking this balance between timing and content is essential for optimizing alert performance. Moreover, the study highlights the need to account for demographic differences, including gender-based variations in response behavior, to inform the creation of adaptive or personalized alert systems that accommodate diverse user needs and preferences. These insights can guide future advancements in traveler information systems to improve overall traffic safety and driver experience.

The study has a few noted limitations. First, the participant pool did not include young drivers (under 18 years of age) or old drivers (over 64 years of age), which may limit the generalizability of the findings to these age groups. Older drivers were not recruited in this study to avoid drivers who may have a higher likelihood of simulator sickness. Secondly, to minimize confounding effects from traffic, the driving simulation was conducted without any traffic in the driving direction of participants. While this allowed for a focused analysis of driver responses to the alerts, it may not fully represent real-world driving conditions. Future studies could build on these findings by exploring how the most effective alert type identified in this study performs in traffic conditions and considering how these factors might affect driver behavior. Additionally, this study was limited to a single alert prior to the incident and at distances of 1 mile and 2 miles. Future research could investigate the impact of receiving multiple alerts over the course of the driving experience as well as different distances, which may provide additional insights into how alert timing influences driver responses. Lastly, the experimental design incorporated multiple safeguards to account for learning effects, including Latin square design counterbalanced scenario presentation, dummy scenario inclusion, and between-subjects lane assignment. However, repeated exposure to similar driving situations could potentially lead to some behavioral adaptation, despite these controls.

7. Conclusions

This study evaluated the effectiveness of different types of alerts in enhancing driver responses, utilizing a driving simulator, eye-tracking glasses, and a questionnaire. A study protocol was created where driver reaction behavior was recorded through driving simulator, while perception behavior was recorded using eye-tracking glasses. At the end of the experimental study the participants provided feedback on what might be the most effective alerts for traveler information systems.

Several findings were revealed in this study. First, the results demonstrated that alerts providing comprehensive information specifically the incident notification, distance to the incident, and actionable instructions were most effective in eliciting quick driver responses, improving both reaction time and overall driving safety. These alerts led to faster driver reactions and more effective decision-making, particularly when delivered two miles in advance of the incident. Eye-tracking data further revealed that simpler alerts, such as those containing only incident information, could also be beneficial in some situations by helping drivers maintain focus on the road ahead and reducing decision-making complexity. While these alerts may not offer as much situational awareness, they can still be effective in specific contexts where less detail is required.

The survey results supported these findings, with participants expressing a clear preference for alerts that included both crash information and specific action instructions. Additionally, most drivers preferred receiving alerts at least two miles ahead of the incident, indicating that timely alerts are critical for optimal response. The results indicate that the best type of alert that could be used is the one that provides a notification on an upcoming incident, including the distance the driver is from the incident and what action may be taken to minimize incident impacts of the driver to create a safer situation.

In conclusion, this study offers valuable insights into the design of road incident alerts for traveler information systems, highlighting the importance of clear, actionable information while also acknowledging the effectiveness of simpler alerts in certain contexts. While the study primarily focuses on traveler information apps, the findings have broader applicability and could inform the design of alerts in other navigation apps as well. By striking a balance between the level of detail and ensuring their timely delivery, alert systems can better assist drivers in making safer, more informed decisions while driving.

8. Research data and data statement

The data investigated in this research cannot be shared due to the confidentiality of the human subjects' data, as per the approval of the Institutional Review Board protocol at the University of Arizona.

9. Study approval

The study was reviewed and approved by an Institutional Research Board (IRB) at the University of Arizona and was found to be compliant with all regulations, ethical standards, and institutional policies.

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CRediT authorship contribution statement

Saquib M. Haroon: Analysis, Investigation, Methodology, Visualization, Writing - Original Draft. **Elizabeth Smith:** Investigation, Formal Analysis. **Alyssa Ryan:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The data that has been used is confidential.

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