Comparing 2-level and 3-level graded collision warning systems under distracted driving conditions

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

This study delves into a comprehensive exploration of driver performance by comparing the effects of a 3-level graded collision warning system with those of a 2-level graded system. Employing a within-between-subject design, the experiment seeks to unravel the impact of graded warning levels (2-stage and 3-stage) on driving performance in both normal and critical driving conditions. Forty participants were recruited to undergo precise testing within a controlled driving simulator environment.
The experimental setup involves dividing participants into two groups, each exposed to distinct collision warning paradigms. The first group experiences a two-level graded warning system, while the second group encounters a three-level graded warning system, structured based on Time to Collision (TTC) metrics. Each participant drove eight scenarios, including four normal and four critical scenarios. This strategic design allows for a comprehensive evaluation of the influence of warning system intricacies on various facets of driving behavior. The study encompasses an array of dependent variables, including eye-tracking data, wristband-derived physiological metrics, driver response times, and the incidence of collisions. This multifaceted approach ensures a holistic understanding of the drivers' reactions under different collision warning paradigms.

Results indicated that the 3-level graded system significantly reduced response times and collision frequencies compared to the 2-level system across both normal and critical driving conditions. Additionally, the 3-level system demonstrated better mitigation of driver distraction. While driving conditions did not significantly affect eye-tracking data, the warning level had a significant impact, with the 3-level system showing superior results. However, neither warning level nor driving condition significantly affected physiological data, including Electrodermal Activity (EDA), Heart Rate (HR) and Heart Rate Variability (HRV). Subjective evaluations highlighted the impact of collision warnings on driver performance, particularly in high-speed scenarios. Moreover, auditory warning modalities were preferred by a majority of participants.

These findings provide valuable insights for the development of advanced collision warning systems, emphasizing the importance of multi-level warnings and preferred warning modalities in enhancing driver safety and reducing collision risks in diverse driving environments.

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The successful completion of my master's work and this thesis has been made possible through the unwavering support of numerous individuals, without whom this journey would have been inconceivable.

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I extend my sincere appreciation to Dr. Barnett-Cowan and Dr. Bachmann for graciously accepting to be part of my thesis committee. Their insightful comments and constructive feedback greatly enriched the quality of this work, and I am truly thankful for their scholarly input. A special note of thanks is extended to the individuals who participated in this research. Their contribution has significantly enhanced the depth and breadth of this study.

I express my deep gratitude to my uncles, Amir and Abolfazl, for their unwavering support. Their encouragement and understanding have been a constant source of motivation, providing the emotional foundation necessary for the completion of this academic endeavor.

Lastly, I acknowledge using AI tools including Chat GPT and Grammarly to enhance the quality of my writing. They were useful in terms of offering advanced word replacements and modifying grammar issues. It helped me to improve clarity and coherence of my work. Nonetheless, it is worth noting that on occasion, these tools led to the generation of overly complex sentences, which required manual simplification.

Dedication

I dedicate this thesis to my beloved mother, whose unwavering love and selflessness have been my guiding light throughout this challenging academic journey. Her boundless support has been the cornerstone of my achievements, and I am profoundly grateful for the sacrifices she has made to see me succeed. This work is a tribute to her enduring strength, encouragement, and the immeasurable impact of a mother's love on the pursuit of knowledge.

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Chapter 1

Introduction

1.1 Background

The safety of our roads is a major concern in the modern world, with road collisions representing a significant and persistent threat to public safety. According to data from Transport Canada, there were 1,922 fatalities and 9,494 severe injuries resulting from motor vehicle accidents on Canadian roads in 2018 [1]. Disturbingly, distracted driving has emerged as a primary contributing factor to the increasing incidence of accidents [2]. In the past decade alone, fatalities resulting from crashes have witnessed an alarming 28% increase since 2005, underscoring the urgent need for effective countermeasures to address this growing threat [3].

Distracted driving occurs when drivers shift their focus from driving to other activities, causing a significant lapse in attention. [4, 5]. This diversion of attention profoundly impacts a driver's ability to perceive the dynamic driving environment, make timely decisions, and execute precise actions [6]. Distracted driving poses an increasing risk to traffic safety worldwide. Over the past approximately twenty years, it has been recognized as a significant contributor to pedestrian-vehicle collisions on a global scale [7]. As per the Canadian Automobile Association (CAA), driver distraction accounted for 16% of all documented motor vehicle accidents, 10% of fatalities, and 18% of injuries [8]. Nearly four million motor vehicle collisions are attributed to distracted driving annually in North America, with an upward trend happening [9].

The increase in electronic devices worsens this issue, amplifying concerns regarding distracted driving and its widespread impact on road safety. In this era of increasing reliance on technology, the alarming rise in distracted driving incidents calls for innovative solutions to identify and mitigate the risks associated with this dangerous behavior. The use of electronic devices while driving has become ubiquitous, and as a result, finding effective methods to counteract distracted driving is critical for ensuring public safety [10].

The driver's performance is directly influenced by their reaction [11]. The faster a driver can react to a potential hazard, the greater their chances of avoiding a collision. This critical emphasis on reaction time is rooted in the dual nature of cognitive and physical demands in the driving task. Cognitively, drivers must always monitor and interpret their environment, adeptly assess potential hazards, and make informed decisions accordingly [12]. Physically, drivers are tasked with responding promptly and accurately to sudden shifts in road or traffic conditions. Research has consistently shown that reaction time is influenced by factors such as fatigue and distraction [13, 14]. Drivers who are fatigued, or distracted, typically have slower reaction times, which can increase their risk of being involved in a collision. Therefore, it can be concluded that early detection and recognition of potential hazards is crucial to improve driver performance and reduce the risk of collisions.

In response to this matter, collision warning systems have emerged as promising technological interventions, designed to proactively alert drivers to potential hazards and save them precious moments for a more considered reaction. By providing drivers with an early warning regarding potential hazards, these systems hold the promise of augmenting reaction times and mitigating the risk of collisions. However, the effectiveness of these collision warning systems remains an area requiring further exploration and refinement.

1.2 Problem Statement

Despite advancements in collision warning systems, there remains a critical gap in understanding the comparative efficacy of two and three-level graded systems in enhancing driver performance under conditions of distracted driving.

Several studies have investigated the levels of warning in collision warning systems in terms of finding a balance between simplicity and better performance [5]. A system with fewer warning levels offers simplicity and ease of understanding for drivers, reducing cognitive load and potential confusion in critical moments. On the other hand, a system with more levels of warning, has the potential to enhance drivers' responsiveness by enhancing their understanding and confidence in the system [15]. Studies suggest that incorporating additional warning levels can widen the safety buffer, thereby offering an increased margin of safety [16, 17]. However, empirical evidence regarding their impact on driver behavior, physiology, and performance in simulated real-world scenarios is lacking.

Addressing this gap is essential for informing the ongoing research on road safety and optimizing the design and implementation of collision warning systems by gaining a deeper understanding of how these collision warning systems affect driver behavior, decision-making, and overall performance, to mitigate the risks associated with distracted driving, and providing a safer and more secure driving environment for all road users [5].

1.3 Research Objectives

The primary objective of this research is to investigate and compare the efficacy of a 3-level graded collision warning system against a 2-level graded system in enhancing driver performance across critical and normal driving scenarios [5]. By precisely examining driver behavior under distracted conditions in simulated scenarios, we seek to recognize the impact of the additional warning provided in the middle of the warning hierarchy (at TTC=12 s) in the 3-level system. The goal is to distinguish the potential advantages and drawbacks of these distinct warning systems under conditions of distracted driving, with the ultimate aim of contributing valuable insights to the ongoing research on road safety.

To achieve this, the study is designed with a within-between subjects approach, employing a robust methodology to generate empirical evidence. Participants engage in a simulated driving environment carefully crafted to replicate real-world scenarios, where they are exposed to potential distractions. The controlled nature of the simulation allows for a systematic investigation into how drivers respond to different collision warning systems under conditions that simulate the actual road environments. The simulated scenarios cover various driving situations, including normal and critical situations that demand more attention and rapid decision-making [5]. These conditions are not random; instead, they depend on the level of risk, the various potential hazards, and the amount of attention and caution demanded from the driver [5, 18, 19]. This diversity ensures a comprehensive evaluation of the warning systems across different potential real-world scenarios where distractions and collision risks may vary. Each participant experiences either the 3-level graded collision warning system or the 2-level graded system, providing a clear basis for comparative analysis. The study carefully collects data to unravel the intricate interplay between driver behavior and the warning systems employed. This data includes physiological responses measured through advanced wearable technology, eye-tracking data offering insights into visual attention dynamics, and performance metrics such as response times and collision frequencies.

In summary, this research aims to extend the current understanding of collision warning systems' impact on driver behavior, physiology, and performance. By addressing these objectives, the study aims to make a significant contribution to the field of road safety, providing a detailed perspective on the comparative effectiveness of two and three-level graded collision warning systems under conditions of distracted driving.

1.4 Thesis Organization

The remainder of the thesis is structured as follows:

1. Chapter 2 provides an overview of the relevant literature, focusing on topics such as driver distraction, collision warning systems, and driving performance. It synthesizes existing research to establish a foundation for the experiment and analysis.

2. In Chapter 3, the hypotheses are defined, and the experimental protocol is outlined. The methodological approach, experiment materials, experimental design, variables, driving scenarios, and secondary tasks are discussed in detail to provide insight into the experimental setup.

3. Chapter 4 presents the findings of the study, including analysis of driving simulator data, physiological data, eye-tracking data, and subjective evaluation results. Each finding is analyzed and interpreted to provide insights into the effectiveness of collision warning systems.

4. Chapter 5 discusses the implications of the findings, interprets their significance in the context of existing literature, and summarizes the conclusions drawn from the research. Additionally, it explores potential ways for future research in the field.

Chapter 2

Literature Review

2.1 Driver Distraction

Driving involves the simultaneous utilization of diverse cognitive, physical, sensory, and psychomotor skills, making it a complex task which needs driver attention [20]. Cognitive ergonomics views "attention" as a resource crucial for information processing, recognizing that stress and multitasking can disturb this resource, resulting in divided attention. [21, 22]. Recent driving studies have illuminated the pervasive impact of inattention on road safety, revealing that nearly 80% of crashes and 65% of near-crashes attribute inattention as a contributing factor [23]. Inattention occurs in various situations where the driver neglects the demands of driving, such as when a drowsy driver falls asleep. Inattention signifies a reduced focus on activities crucial for safe driving when there is no competing activity [24]. Driver inattention is broadly categorized into distraction and mental fatigue [25]. Distinguishing between the two is crucial; distraction involves explicit activities competing for attention, such as dialing a cell phone, while mental fatigue results in diminished capacity to attend to the roadway [24].

The distinction between distraction and mental fatigue takes center stage in several studies that interchangeably use distraction with workload. Workload, defined in terms of mental resources or the capacity for information processing dedicated to a task [26, 27, 28].

As the use of electronic devices while driving continues to increase, distracted driving is becoming an even greater concern. Young and colleagues [29] have identified three types of distraction sources, namely related to technology, not related to technology, and outside of the vehicle. Related to technology distraction includes the utilization of communication systems within the vehicle, such as mobile phones, texting, emailing, or using

GPS. Not related to technology distractions include activities like talking to passengers, eating, drinking, smoking, or attempting to navigate. These can cause multiple types of distractions, such as visual and cognitive distraction, and can increase the cognitive load on the main task of driving. Outside of the vehicle distractions involve visual and cognitive attention while driving, such as looking at events, people, or billboards. It is clear that distracted driving has a significant impact on road safety. These various distractions can impact drivers in different ways [30]. In recent decades, Advanced Driver Assistance Systems (ADAS) have promised improved driving performance and safety by assuming various vehicle control tasks. However, as these systems progressively assume more aspects of driving, drivers may transition into a more passive supervisory role or cause distraction. This raises concerns about the potential for increased engagement in non-driving-related activities, potentially undermining the expected safety benefits of ADAS [31, 32]. It has been explored in contexts such as baseline driving, driving with a single secondary task, and driving with two secondary tasks. Notably, heightened workload, particularly evident when managing two secondary tasks simultaneously, underscores the delicate balance required in allocating attentional resources during driving [33]. While driving, individuals must consistently distribute their attentional resources between both driving and non-driving tasks. Due to the automation of many aspects of the driving task through experience, drivers can often divide their attention among simultaneous tasks without significant consequences to driving performance or safety. However, under specific conditions, these adaptive behaviors may fail, leading to a notable decline in driving performance [20]. It is clear that driving safety is significantly affected by distraction. As environmental cues and task demands fluctuate constantly, drivers must make continuous decisions. Hence, if distraction by a competing task causes important cues to go unnoticed, situational awareness can be adversely affected [34].

Consequently, many studies have been done on driver distraction using a secondary task [35, 36, 37] and have shown engaging in secondary tasks unrelated to the safe operation of a vehicle can also impair the ability to predict hazards, identification of objects in the line of sight, decision Making, Situation Awareness (SA) and execution of a response in the driving environment [38]. These results highlight the importance of understanding the complex nature of driver distraction. This emphasizes the need for a closer look at collision warning systems in the following sections.

2.2 Collision Warning Systems

Distracted driving significantly contributes to vehicular accidents. In order to prevent a collision, the driver needs to recognize and address potentially dangerous situations. The effective handling of hazards is closely connected to the driver's capacity to accurately identify crucial situations, those that may lead to a collision without the driver's timely intervention. However, drivers frequently come across non-urgent scenarios situations that do not progress into immediate threats and consequently do not demand intervention from the driver [39]. Drivers who tend to overlook potential collisions could profit from a alarm system that issues alerts to forewarn them of an impending collision [40, 41, 42, 43, 44]. Such alerts can include notifying the driver of a braking vehicle in front (rear-end collision warning [39, 45, 16, 46, 47]), warning the drivers as they are beginning to depart from the road (road departure warning [48, 49, 50]) or lane-keeping support system [50].

The kinematic model is constructed with the aim of reducing collision risk through the optimization of Time Headway (THW), Space Headway (SHW), and TTC [51]. The effectiveness of collision warning systems is contingent upon two essential elements. Firstly, the system must encourage the driver to react in a timely and suitable manner. Secondly, minimizing annoyance linked to false alarms and gaining the trust of drivers are necessary for their acceptance of the system [52, 53]. If the alarms go off too often and too soon, the driver might find them annoying and may choose to ignore them or even turn off the device. Drivers tend to brake more swiftly when they receive early alerts, as opposed to situations where they drive without any assistance [54]. Nonetheless, there is a contention that warnings given too early in potential crash scenarios are often perceived as false alarms [55, 56]. In this situation, the system would not fulfill its intended purpose. When designing active systems, it is crucial to strike a balance and avoid alerting too soon while ensuring enough reaction time. This way, the driver has the necessary time and space to either prevent a collision or minimize its impact. [46].

Numerous studies have explored the impact of driving warning systems on driving performance, often using a secondary task to simulate distraction. Performance or functionality defines the actions of the automation, indicating the system's capability to assist the driver in avoiding collisions [39]. The development of an advanced collision warning system for vehicles is part of the collaborative efforts between automobile manufacturers and the National Highway Traffic Safety Administration to reduce the car crashes [57, 58, 59, 60, 61]. The mitigation strategies such as distraction warning systems, have shown a generally positive effect on driver performance [62], shorter driver reaction time [17], and improved drivers' headway estimation [63].

Additionally, some researchers have studied single-stage [43, 45, 64, 65] and graded

[51, 66, 67, 68, 69, 70, 71] warnings. A graded warning gives a signal that corresponds to the level of danger, like making the auditory signal louder as the driver gets closer to a lead vehicle. On the other hand, a single-stage warning only signals when the danger surpasses a certain level. Using a graded warning could improve how drivers respond by preparing them and increasing their comprehension and trust in the system [15]. Research indicates that graded warnings, specifically 2-level warnings, provide a greater safety margin compared to single-stage warnings [16, 17]. This suggests that warning systems with multiple levels of alertness might offer enhanced safety benefits, a crucial aspect to explore further in the context of distracted driving.

2.2.1 Warning Modalities

Another crucial feature of the interface that might impact how well the driver performs and accepts it is the sensory modality in which the warning is presented [16]. Collision warning systems utilize auditory, visual, and haptic cues. Human-Machine interfaces, requiring a delicate balance between driver acceptance and effectiveness in providing sufficient reaction time [40].

Various research studies have utilized visual [72, 73], auditory [10, 39, 50, 63] feedback, or combination of them [40, 16, 62]. Some studies have compared different warning approaches [16, 45], indicating the effectiveness of both visual and auditory interfaces [74].Among these, an auditory tone emerged as the most efficient modality [75]. However, auditory feedback is often found irritating, which may result in the abandonment of the system [66].

Other research results suggest that haptic alerts, like a vibrating, were perceived as less annoying and more appropriate [16] and had the shortest mean response time [45]. Haptic signals provide a potential and not extensively studied option compared to auditory warnings. These signals could potentially quicken response times and minimize irritation. Notably, kinesthetic cues based on torque showed faster reaction times than auditory signals [76], and vibrotactile cues improved reaction times to visual signals [77]. However, auditory strategies provided better benefits compared to visual strategies [62], suggesting that a combination of audio and haptic warning modalities might be the most effective strategy [78].

2.3 Driving Performance

Driving is a multifaceted activity, involving more than 1,600 distinct tasks across five behavioral tiers [79]. This requires drivers to simultaneously manage the vehicle, modulate speed and direction, navigate hazards, monitor progress towards their destination, and execute strategic choices such as route planning. driving behavior is predominantly goal-oriented, with drivers juggling various objectives (such as safety, speed, and fuel efficiency) that may occasionally be at odds with one another [80]. In response to these dilemmas, drivers assess the situation and manage their driving tactics accordingly. Consequently, this complex interplay of objectives and strategies in driving has spurred extensive research into driving performance [81, 82, 83].

Many techniques and metrics are available for assessing driving performance, such as longitudinal control indicators like speed and headway, lateral control criteria including vehicle positioning and steering wheel control, metrics for measuring response times, evaluations of gap acceptance, analyses based on eye tracking, and various workload assessment methods, which are categorized into subjective assessments, physiological evaluations, and performance-based analyses [84].

In our study, we assess driver performance utilizing a range of metrics: driver response time, eye movement measures, physiological assessments, and subjective evaluations.

2.3.1 Driver Response Time

Response time refers to the duration required for a driver to notice and react to unforeseen circumstances [85]. Response time metrics are gaining popularity due to their correlation with accident risk. Various measures, such as missed events, incorrect responses, reaction time, and reaction distance, can be analyzed. As intelligent communication technologies grow, a significant safety issue arises from the potential for increased response times, thereby hindering drivers' ability to promptly respond to potential dangers [86]. The ability of drivers to detect and react to unexpected incidents is often hindered by distractions within the vehicle, especially from complex devices. Numerous studies have demonstrated that a distraction like using phones while driving leads to increased response times [87, 88, 89, 90, 13]. Additionally, research has investigated how demographic factors like age and gender affect response times in distracted conditions. Studies showed that both older and younger drivers have slower reactions when they are distracted [91, 92].

2.3.2 Eye Movement Measures

The employment of eye-tracking technology in driving simulator experiments has gained popularity, yet it is crucial to acknowledge several inherent challenges that necessitate careful consideration. Techniques such as analyzing fixations, saccades, pupil positioning, and smooth pursuit movements are instrumental in detecting visual and cognitive distractions. Fixations represent moments when the gaze remains relatively static, with the location and duration of these fixations shedding light on the direction of attention and the depth of information gathered from the observed point [93]. Saccades, characterized by rapid eye movements transitioning between points of fixation, facilitate the shift in gaze. Conversely, smooth pursuits are observed when the gaze follows a moving object, like a car passing by, enabling the stabilization of the object's image on the retina for continuous perception despite its motion relative to the observer. Within the driving domain, smooth pursuits play a crucial role in capturing data from the evolving road scene. Both fixations and smooth pursuits can reveal the extent to which cognitive distractions impact drivers' visual information intake [94].

2.3.3 Physiological Responses

The physiological assessment of workload is grounded in the empirical observation that heightened mental demands elicit more pronounced physical responses from the body [95]). This approach to measuring workload focuses on the continuous monitoring of the body's physical reactions. Most research focuses on five physiological areas to measure workload: cardiac activity, respiratory activity, eye activity, speech measures, and brain activity. Cardiac metrics include heart rate, variability in HR, EDA, and blood pressure, offering insights into the heart's response under varying levels of mental exertion. Respiratory analysis involves tracking the volume of air inhaled and the frequency of breaths, reflecting changes in breathing patterns associated with different workload levels. Eye measures primarily cover horizontal eye movements, the rate of blinking, and the duration of eye closures, although additional, less conventional indicators also exist. Speech measures assess workload through parameters such as pitch, speaking rate, volume, and variations in voice quality, including jitter and shimmer. Brain activity is typically gauged using electroencephalography (EEG) or electro-oculography (EOG), tools that provide a window into the neurological responses to workload [96]. Physiological metrics are acknowledged for their precision [97] and consistency [98]. Numerous research studies have portrayed physiological metrics as credible means for assessing the cognitive state of individuals [99]. Also, EDA has a extensive track record of being utilized as an indicator of attention and arousal [100]. Research showed that higher values of HR and EDA while driving indicate greater mental demand and increased attention [101].

2.3.4 Subjective Evaluation

The assessment of workload levels on a subjective basis employs rankings or scales to gauge the perceived workload of an individual. These subjective measures of workload predominantly rely on an intermittent format of question-and-answer responses to various workload intensities. Subjective workload assessment is categorized into two primary scale types: unidimensional and multidimensional scales [96]. Unidimensional scales, recognized for their simplicity and ease of use, do not require complex analysis methods. These scales focus on a single aspect of workload measurement, often resulting in greater sensitivity compared to their multidimensional counterparts [102]. To capture an individual's perceived mental workload, a variety of straightforward subjective scales have been developed, finding application especially within the driving context. Prominent scales include the NASA-Task Load Index (TLX), the Rating Scale Mental Effort (RSME), the Situation Awareness Global Assessment Technique, and the Driving Activity Load Index (DALI) [96].

2.4 Gap in the Literature

While existing literature has extensively examined the impact of 2-level graded warnings on driving performance compered to single stage warnings, there remains a notable gap in understanding the effectiveness of 3-level graded warnings. Previous studies have consistently demonstrated that 2-level graded warnings yield superior results in terms of enhancing driving performance. However, the specific contribution and potential advantages of a three-level graded warning system, particularly one that introduces an additional level before the initial warning, are yet to be comprehensively explored.

In our research, we seek to address this gap by undertaking a comparative analysis between two-level and three-level graded warnings. Our focus is on evaluating whether the inclusion of an extra warning level, strategically positioned between two other levels, can yield further improvements in driving performance. By investigating the differences between these warning configurations, we contributed valuable insights that extend the current understanding of collision warning systems.

In this study, we aim to compare 2-level and 3-level graded warning to see if adding another level which will be added before the first level and makes the warning start earlier, can make a better impression on driving performance. Moreover, this study investigates collision warning systems, specifically examining the potential benefits and drawbacks of 2-level and 3-level graded warnings under distracted driving conditions. As we explore this area, we expect uncovering new perspectives that could influence the design and implementation of future collision warning systems, ultimately enhancing overall road safety [5].

The following chapter provides a detailed account of the methodology and experimental design employed in our study. Additionally, it elucidates the technical specifications of the equipment used, laying the foundation for a rigorous and comprehensive investigation.

Chapter 3

Human Experiment

3.1 Hypothesis and Overview

This study investigates the impact of warning level variations, specifically comparing the effectiveness of 2-level and 3-level graded collision warning systems under distinct driving conditions, namely critical and normal scenarios. The investigation is particularly relevant in the context of drivers concurrently engaged in secondary tasks, a common occurrence in real-world driving scenarios.
Critical driving conditions:

H_0 (Null Hypothesis): There is no significant difference in driving performance within the 2-level and 3-level graded collision warning systems across critical driving conditions.

H_A (Alternative Hypothesis): The 3-level system results in better driving performance compared to the 2-level system across critical driving conditions.
Normal driving conditions:

H_0 (Null Hypothesis): There is no significant difference in driving performance within the 2-level and 3-level graded collision warning systems across normal driving conditions.

H_A (Alternative Hypothesis): The 3-level system results in better driving performance compared to the 2-level system across normal driving conditions.

The rationale behind these hypotheses lies in the need to explore whether the introduction of an additional warning level (three-level system) brings about measurable improvements in driving performance, particularly when drivers are faced with critical or normal driving conditions. The examination of both scenarios adds depth to our understanding of how these warning systems operate under varying levels of stress and complexity.

As we embark on this empirical investigation, the subsequent sections outline the methodology employed, detailing the experimental design, participant recruitment, and the specific parameters considered. Additionally, the instrumentation and technical aspects of the experiment are thoroughly expounded upon to ensure transparency and reproducibility in our research endeavors.

3.2 Methods and Materials

3.2.1 Participants

For this research, 40 participants were recruited through targeted emails sent to both current students and alumni of the University of Waterloo. Prior to recruitment, G*Power 3.1.9.7 [103] was used to determine the number of participants. The parameters used for the 'ANOVA: Repeated measures, between factors' statistical test were $\alpha = 0.05$, statistical power of 1-β = 95%, effect size f = 0.51 as it is considered to be a large effect [104], 2 groups, 4 measurements and 0.5 correlation among repeated measures. It was calculated that a minimum of 34 participants would be required to detect significant effects. However, to enhance the reliability and accuracy of the study, and considering the potential for participant dropouts, a sample size of 40 participants was chosen. This decision ensures a sufficient margin to accommodate any unforeseen circumstances and increases the robustness of the study's findings.

Participants were included from the age group of 23-44 years, with the majority falling within 25-34 range. However, to ensure representation across a broader age spectrum, four participants aged 23 (in the age group of 18-24) and two participants aged 35-44 were evenly distributed across the groups assigned to 2-level and 3-level warning systems. Gender distribution was also carefully balanced, with an equal number of male and female participants in each group. This stratification aims to neutralize any potential confounding effects related to age and gender on participants' performance. Regarding driving experience, participants were required to possess a valid Canadian driver's license and have at least one year of driving experience. To assess whether driving experience significantly differed between the two groups, a t-tests was conducted, comparing the mean years of driving experience for participants assigned to the 2-level and 3-level warning systems. The t-test results yield a t-statistic of approximately -0.83 and a p-value of about 0.41. This p-value indicates that there is not a statistically significant difference in driving experience between the two groups with different levels of warnings. Thus, the difference in driving

Table 3.1: Analyzed sample demographics

Demographics	Participants (n=40)
Age	
Minimum-Maximum	23-44
Gender n(%)	
Female	18 (45%)
Male	22 (55%)
Driver's license n(%)	
*G**	14 (35%)
*G2***	26 (65%)
Driver's experience (years)Minimum-Maximum	1-17
Mean (SD)	6.85 (4.92)

*G: In Ontario, the G license is a fully unrestricted driver's license [105].
**G2: part of the Ontario graduated licensing system's Level Two, grants holders the ability to drive independently, with certain conditions [105].

experience between participants receiving 2-level and 3-level warnings is not statistically significant at 0.05 significance level.

Clear or corrected vision, achieved through contacts, was a prerequisite for participation. Exclusion criteria were established to ensure the safety and well-being of participants. Individuals with a history of vertigo or motion sickness were excluded due to their heightened susceptibility to simulator sickness, which could potentially compromise the integrity of the experimental results.

The final participant count stood at 40 individuals. The gender distribution included 18 females and 22 males. Each participant devoted approximately 60 minutes to the study, receiving a remuneration of $20 for their time and contribution.

Ethical considerations were paramount, and the study obtained clearance (ORE # 45394) from the University of Waterloo Office of Research Ethics. The experimental procedures strictly adhered to the approved protocols to guarantee the ethical conduct of the research.

3.2.2 Procedure

To ensure clarity and transparency in the experimental process, participants were thoroughly briefed on the study's purpose, benefits, procedures, and anticipated duration

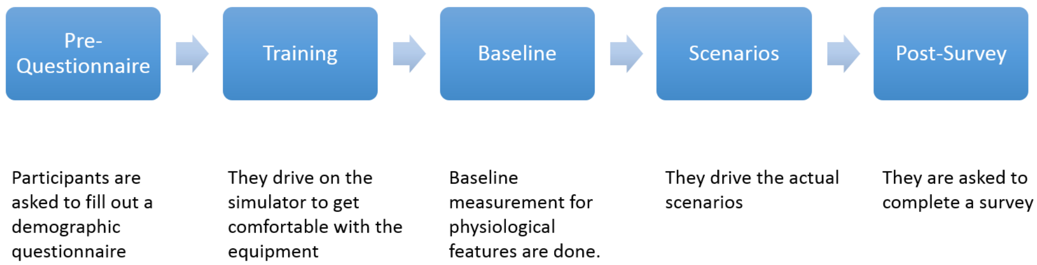


Figure 3.1: Experimental flow for each participant

through remote communication. Only those who willingly chose to participate provided their informed consent by signing a consent form before the commencement of the study. A demographics questionnaire (refer to Appendix A) was then administered, capturing essential information such as age, driving experience, and any prior encounters with motion sickness.

Prior to initiating the main experiment, participants engaged in a training scenario using a car simulator. This simulation replicated a suburban road environment devoid of traffic but featuring multiple turns. The training session lasted between 5 to 15 minutes and ended when the participant announced they were ready. The purpose of this exercise was to familiarize participants with the simulator's operation and ensure a baseline level of proficiency. Throughout this training phase, participants wore a physiological sensor to collect baseline data including EDA and HR data. Following the training, participants were outfitted with an eye-tracker, which underwent calibration concurrently with the physiological sensor. The experimental procedure is illustrated in Figure 3.1.

The main experimental phase involved participants navigating through eight distinct road scenarios, described in the following sections. Each scenario was precisely designed to represent various driving environments and speed limits. All scenarios were approximately of equal length, and vehicle parameters, including speed, throttle, steer and brake data were closely monitored throughout the trials. Following the completion of these scenarios, participants were invited to share their insights and experiences through a post-questionnaire survey (refer to Appendix B). This survey served as a crucial component of the post-experiment data collection, capturing subjective perspectives and feedback from the participants.

The meticulous execution of these procedures aimed to provide a robust foundation for analyzing the impact of warning level variations on driving performance under critical and normal driving conditions.

3.2.3 Apparatus

For the comprehensive assessment of driver behavior, this research harnessed information from diverse sources, employing a multifaceted approach that incorporated physiological data, eye-tracking technology, and vehicle kinematics. The experimental setup involved a driving task wherein participants were directed to follow specific instructions and adhere to traffic regulations. All experiments took place in a closed room devoid of windows, ensuring a controlled environment. The lighting within the room remained consistent throughout the experiments, with only the experimenter and the participant present.

The controlled environment, free from external distractions, ensured that the data collected were reflective of the participants' responses to the experimental conditions. To prioritize participant comfort and ethical considerations, participants were explicitly informed that they retained the right to halt the experiment at any point based on their comfort level with the equipment. This emphasis on participant agency contributes to the ethical conduct of the study and helps establish a trusting relationship between the experimenter and the participants.

The following equipment was used for this study:

1. Carla Driving Simulator: Carla is a simulator for driving research that is open-source, offering freely accessible digital assets such as urban layouts, buildings, and vehicles. The simulation platform allows for flexible customization of sensor suites and environmental conditions. [106].It is shown in Figure 3.2.

2. E4 Empatica wristband: This inconspicuous physiological monitoring device records data on HR at 1Hz, EDA at 4Hz, a 3-axis accelerometer at 32Hz, skin temperature at 4Hz and Inter-Beat interval (IBI) [107]. The wristband can wirelessly connect to any computing device through Bluetooth, for real-time data transfer. It is shown in Figure 3.3.

3. AdHawk MindLink: This wearable eye tracking device has a listed glance direction accuracy of 1 degree and its tracking field of view of 40×25 degrees. The eye cameras operate at a sampling rate of 60-500 Hz. Also, the front camera has a resolution of 1280×720 pixels [108].It is shown in Figure 3.4.

4. Dayton Audio Tactile Transducer Mini Bass Shaker and Nobsound Mini Power Amplifier: This mini base shaker has been installed on the driver's chair to provide vibration for haptic warnings. For the haptic warning, a sound with a 40 Hz frequency was played through the shaker using the amplifier. No sound could be heard; it only produced vibrations. They are shown in Figure 3.5.

Figure 3.2: Driving simulator

Figure 3.3: E4 Empatica wristband, Source: [107]

Figure 3.4: AdHawk MindLink Eye tracker, Source: [109]

[a]

[b]

Figure 3.5: a) Dayton Audio Tactile Transducer Mini Bass Shaker, Source: [110] b) Nobsound Mini Power Amplifier, Source: [111]

3.3 Experimental Design

The experimental design employed in this study was a mixed factorial design (2×2) incorporating two key factors: the number of warning levels (2 levels versus 3 levels) as the between-subjects independent variable and the driving condition (critical versus normal) as the within-subjects independent variable. The experiment aimed to study the interactions between the warning system variations and driving conditions, providing a comprehensive understanding of their combined impact on driving performance [5].

Each participant navigated through all eight scenarios, ensuring a comprehensive exposure to diverse driving conditions. To eliminate the potential influence of scenario repetition on driving behavior, no participant encountered a repeated scenario. Each scenario was characterized by a specific speed limit, which was clearly communicated through simulation signboards and verbally announced before the commencement of each drive. This approach aimed to standardize the experimental conditions, providing a consistent basis for evaluating the impact of warning levels under varied driving circumstances.

The utilization of this mixed factorial design allowed for a detailed exploration of the interplay between warning levels and driving conditions, contributing to the depth and validity of the study's findings.

3.4 Variables and Metrics

The dependent and independent variables adopted are summarized in Table 3.2. These variables aim to capture diverse aspects of driver behavior and response under varying warning levels and driving conditions.

The data collected for this study were analyzed using a combination of descriptive statistics and Analysis of Variance (ANOVA). Descriptive statistics were employed to summarize the characteristics of the variables under investigation. These included measures such as mean, standard deviation, and range to provide a comprehensive overview of the data distribution. ANOVA was utilized to examine the relationships between the independent and dependent variables. This statistical technique allowed for the comparison of means across multiple groups, providing insights into any significant differences or relationships present in the data.

3.4.1 Independent Variables

The primary independent variable is the Number of Warning Levels, manipulated as a between-subjects factor. Participants are exposed to either a 2-level or 3-level graded collision warning system, allowing for a comparison of their driving performance under these different warning configurations.

The second independent variable is the Driving Condition, manipulated as a within-subjects factor. Participants navigate through scenarios representing both critical and normal driving conditions, enabling an exploration of how warning levels interact with different driving complexities.

3.4.2 Dependent Variables

1. Response Time: A driver's response time, comprises two components Perception Reaction Time (PRT) and Maneuver Time (MT). PRT is the duration it takes for the driver to recognize the necessity for a reaction based on road conditions, determine the suitable maneuver (such as stopping the vehicle in the case of a rear-end collision), and commence the maneuver by releasing the accelerator and applying the brake pedal [112]. MT, alternatively referred to as movement time, represents the time required to execute the maneuver, including decelerating and bringing the vehicle to a halt [113]. The duration it takes for a driver to notice and react to unexpected situations is a critical metric, holding significance for roadway system designers and often playing a crucial role in litigation arising from motor vehicle accidents [85]. Response time, measured in seconds, serves as a key dependent variable, providing insights into the efficacy of warning systems in facilitating timely responses.

2. Number of Collisions: The number of recorded collisions during driving serves as a crucial metric for evaluating warning effectiveness. This metric encompasses collisions with obstacles and instances of driving off the road, offering a comprehensive assessment of the system's ability to prevent or mitigate collisions.

3. EDA and HR: Collected from the E4 Empatica wristband, EDA and HR values offer insights into participants' physiological responses. These responses are particularly relevant, as driver distraction can influence physiological features [114, 115]. Monitoring EDA and HR provides a glimpse into the physiological impact of warning systems on driver arousal and stress levels.

Table 3.2: Overview of dependent and independent variables

Construct	Type of variable	Unit
Number of warning levels	Independent variable	Count
Driving condition		Normal / Critical
Response time	Dependent variable	Seconds
Collision frequency		Count
Pupil position		degree
HR		bpm
HRV		Seconds
EDA		Micro-Siemens (μS)

4. HRV: HRV is a measure of the variance in the duration between successive heartbeats. It is calculated from the IBI time series data, collected from the E4 Empatica wristband. There are different ways in which to calculate HRV using IBI: time-domain analysis, frequency-domain analysis, and non-linear analysis [116, 117, 118]. In this study, time-domain analysis is chosen and calculated by computing the SDNN of IBI, employing a custom Python script designed for this particular analysis.

5. Pupil position: Obtained through the eye tracker, eye data and pupil position can capture visual attention patterns. Given that driver distraction can significantly affect visual features, this variable allows for an in-depth analysis of how warning systems influence participants' visual attention during the driving scenarios.These variables collectively form a comprehensive set of metrics, providing a rich dataset for evaluating the multifaceted impact of warning levels on driving behavior. The subsequent chapters elucidate the analysis and interpretation of these variables, providing insights into the complex interplay observed during the experimental investigation.

3.5 Driving Scenarios

The driving scenarios constitute a pivotal component of this experimental investigation, providing a realistic and varied backdrop to evaluate the impact of warning levels on driving performance. The comprehensive overview of these scenarios is presented in Table 3.3, highlighting the intricacies embedded in the experimental design.

Table 3.3: Driving scenarios

Scenario No.	Condition	Scenario Description
Scenario 1	Critical	Foggy city, an obstacle on the road, high traffic volume
Scenario 2		Foggy highway, an obstacle on the road, high traffic volume
Scenario 3		City, an obstacle on the road, rainy night, high traffic volume
Scenario 4		Highway, an obstacle on the road, night, high traffic volume
Scenario 5	Normal	City with an intersection without a traffic light in the daytime
Scenario 6		City with an intersection without a traffic light and an obstacle
Scenario 7		City with an obstacle on the road in the daytime
Scenario 8		Highway with an obstacle on the road in the daytime

3.5.1 Scenario Composition

In total, there are 16 distinct driving scenarios, strategically divided into two groups: 8 scenarios featuring 2-level graded warnings and another 8 scenarios incorporating 3-level graded warnings. Participants were randomly assigned to one of these groups, ensuring a balanced distribution of participants across the different warning configurations. Each participant engaged in a total of 8 driving scenarios, further evenly distributed into 4 instances of normal driving conditions and 4 instances of critical driving conditions.

Participants operated a manual vehicle, traveling at 90 km/h on a three-lane highway and at a speed of 30 km/h on an urban non-highway road. Moderate pre-planned traffic conditions were maintained in all scenarios to simulate real-world driving conditions. Adding an element of distraction, participants were engaged in a secondary task during each scenario, mirroring the challenges of multitasking while driving.

3.5.2 Normal Driving Conditions

Scenarios unfolding under normal driving conditions presented a scenario mirroring ideal circumstances. These conditions included clear weather, optimal visibility, stable road conditions, and a moderate traffic flow. Participants encountered situations such as negotiating an intersection lacking a traffic light or maneuvering through a road blocked by an obstacle which is a crashed car, demanding a complete stop from the driver. The normal scenarios are shown in Figure 3.6.

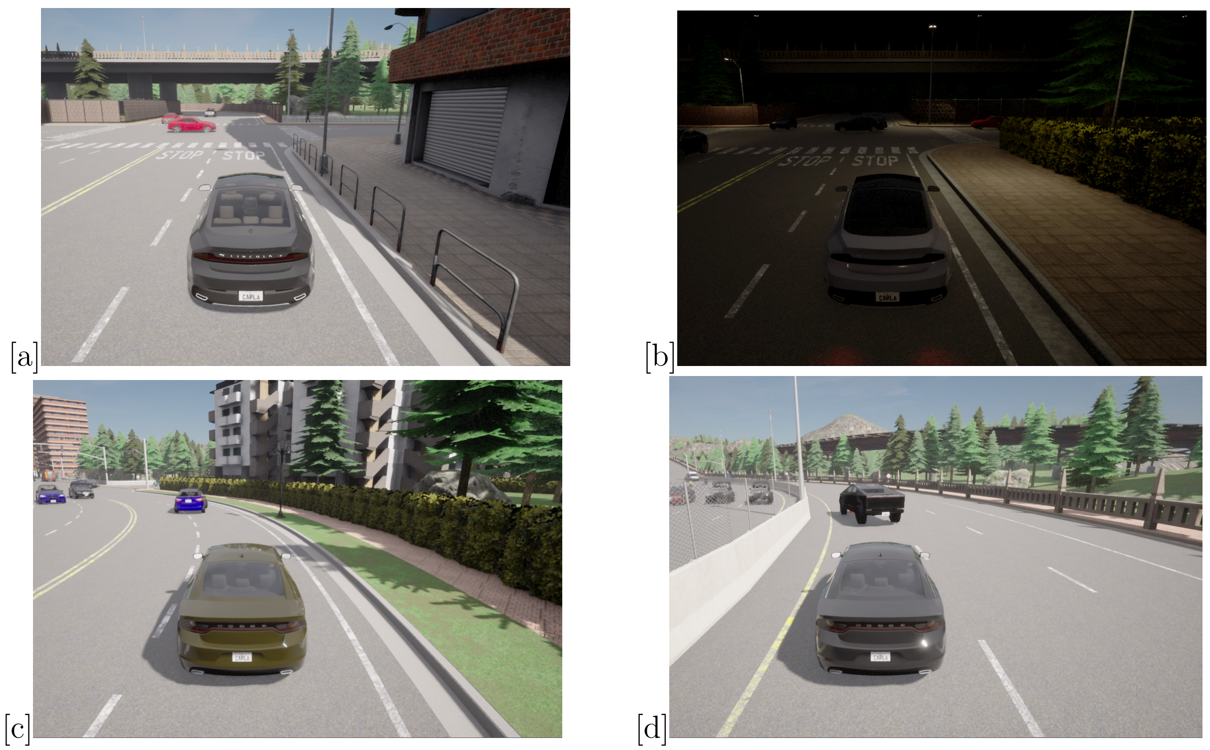
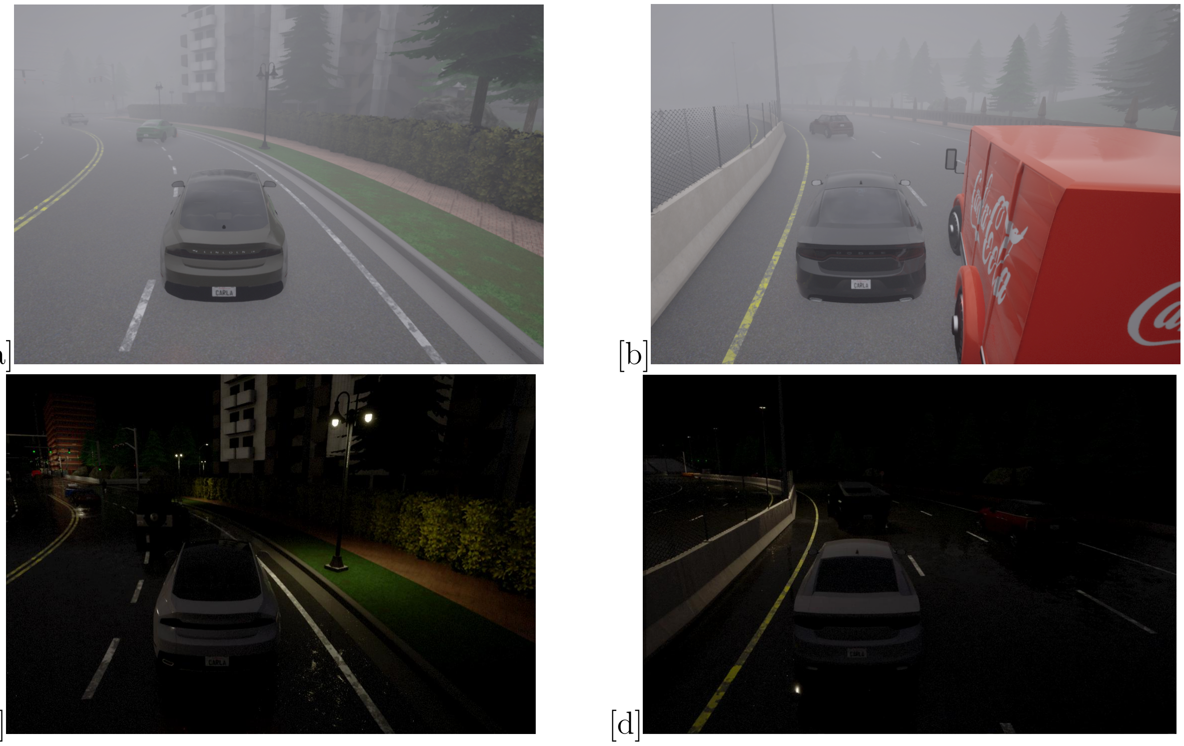


Figure 3.6: Normal Scenarios: a) City with an intersection without a traffic light in the daytime b) City with an intersection without a traffic light and an obstacle c) City with an obstacle on the road in the daytime d) Highway with an obstacle on the road in the daytime



[a] [b] [c] [d]

Figure 3.7: Critical Scenarios: a) Foggy city, an obstacle on the road, high traffic volume b) Foggy highway, an obstacle on the road, high traffic volume c) City, an obstacle on the road, rainy night, high traffic volume d) Highway, an obstacle on the road, night, high traffic volume

3.5.3 Critical Driving Conditions

Conversely, critical driving conditions injected an additional layer of complexity into the scenarios. Challenges included navigating higher traffic volumes demanding rapid decision-making, driving during rainy nights, and contending with foggy weather that significantly diminished visibility. An obstacle strategically placed in these scenarios posed a considerable challenge, with participants able to identify it only when in close proximity. To avert a collision, drivers had the option to either reduce speed or come to a stop within their current lane or swiftly switch to another lane. The scenario order was counterbalanced across subjects to mitigate any potential sequence biases. The critical scenarios are shown in Figure 3.7.

Table 3.4: Overview of warning timeline

Warning Type	Warning level	Warning threshold	Warning modality
2-Level	Level 1	TTC=20	Visual
	Level 2	TTC=5	Visual + Haptic + Auditory
3-Level	Level 1	TTC=20	Visual
	Level 2	TTC=12	Visual + Haptic
	Level 3	TTC=5	Visual + Haptic + Auditory

3.5.4 Warning Issuance

Warnings were strategically issued based on TTC values. The TTC stands as one of the most commonly utilized safety metrics, serving as an indicator of crash risk [46]. It signifies the duration until a potential collision between two vehicles would have transpired had their courses and speed differentials remained constant [119]. In the 3-level graded warning scenarios, warnings were triggered at specific TTC values with varying modalities. Initially, a visual warning in the form of an alert message "Warning" was displayed on the screen when TTC reached 20 seconds. Subsequently, at TTC=12 seconds, both visual and haptic warnings were simultaneously introduced, providing a dual sensory alert to the driver. Finally, at TTC=5 [119] seconds, a comprehensive warning comprising visual, haptic, and auditory elements was activated, aiming to maximize driver attention and response. Each warning modality persisted for a duration of 3 seconds.

Similarly, in the 2-level graded warning scenarios, warnings were also issued based on TTC values. At TTC=20 seconds, a visual warning identical to the one in the 3-level scenario was presented. Subsequently, at TTC=5 seconds, the comprehensive warning consisting of visual, haptic, and auditory elements was deployed. As in the 3-level scenario, each warning modality persisted for 3 seconds. These are summarized in Table 3.4.

One of the primary goals of our experiment was to examine not only the efficacy of warning systems in alerting drivers to potential hazards but also to closely monitor changes in driver performance and physiological responses. Given this focus, we deliberately chose TTC thresholds that provided extended warning times well beyond what would typically be encountered in real-world driving scenarios. By selecting higher TTC values, we aimed to create longer time margins, allowing for more comprehensive observation and analysis of driver behavior and physiological responses. This approach enabled us to capture subtle variations in performance and physiological indicators, which may not be as readily observable in shorter time frames.

In the event that drivers did not react to the warnings, no additional actions were triggered, allowing the scenario to continue without interruption. After successfully navigating past the obstacle or intersection, participants continued to manually drive for an additional 30 meters, marking the conclusion of each scenario. This design element aimed to simulate a seamless transition back to regular driving conditions after encountering a potential hazard or critical situation.

The arrangement of these driving scenarios allows for an examination of how different warning levels affect driver behavior in different driving conditions. Subsequent section will explain more about the secondary task.

3.6 Secondary Task

In the realm of realistic driving scenarios, sometimes drivers are not consistently focused on the primary driving task due to engagement in non-driving-related secondary activities. Engaging in secondary tasks that divert drivers' attention from the road ahead [120, 121] can diminish their visual scanning abilities [122] and escalate cognitive strain, posing heightened risks [123]. In a 2006 study analyzing findings from a 100-car field test [124], it was revealed that nearly 80% of all accidents and 65% of near-accidents occurred when drivers diverted their gaze away from the road shortly before the event. As a result, the inclusion of a standardized secondary task becomes imperative to simulate the attentional demands placed on drivers in experimental settings. To authentically replicate such scenarios, participants undertook the Surrogate Reference Task (SuRT) [125], carefully integrated into the experimental design.

The SuRT , a well-established driver distraction task, was chosen to mirror real-world attentional demands. Participants received thorough practice in adherence to ISO Standards for the task, ensuring familiarity before engaging in the primary experimental scenarios. The task was presented on a 14-inch laptop notebook, offering a standardized platform for task execution.

Participants were instructed to perform the secondary task during driving scenarios at their own pace, with an emphasis on completing as many tasks as possible while prioritizing safety. The SuRT involves a visual search and manual input task, where participants identify a larger (target) circle among circles of the same size (distractor) using the left and right keypad buttons. The difficulty level of the task can vary, ranging from easy to hard, depending on the size difference between the target circle and surrounding circles. Target and distractors are presented as white circles against a black background, with correct selections indicated by a green flash and incorrect ones marked with red.

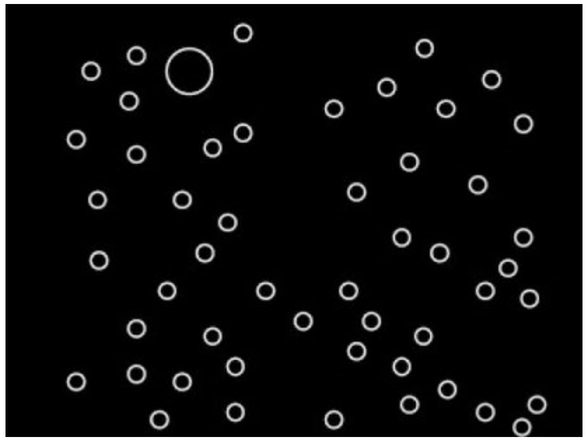


Figure 3.8: SURT interface with distractors and target

For this experiment, the easy version of the SuRT task was employed, aligning with the manual driving requirements [126]. Figure 3.8 visually represents the interface of the DominionSURT software [127] , a crucial component of this study's secondary task execution.

The incorporation of the SuRT as a secondary task within the experimental framework provides a detailed understanding of how attentional demands impact driving performance. In the subsequent chapters, the analysis of collected data, interpretations, and insights derived from the interplay between the primary driving task and the secondary task is expounded upon, shedding light on the intricate dynamics of distracted driving, derived from this experimental framework.

Chapter 4

Data Analysis and Results

4.1 Driving Simulator Data

In this chapter, we embark on a comprehensive analysis of the collected data, focusing on descriptive statistics to provide a clear overview of the dataset. Additionally, we use a 2×2 mixed ANOVA which is a statistical test, to explore the effects of different warning levels and driving conditions on our dependent variables. This analysis will be conducted using the Python programming language.

4.1.1 Response Time

Each participant underwent eight scenarios, each lasting around 2 minutes. Using Carla's recorder function, all scenarios were initially captured. The simulator produced diverse data such as speed, throttle, brake, steering commands, and collision events. The response time of the drivers was extracted from both the eye-tracker video data and the simulator data. It represents the duration taken by the driver to perceive and react to unforeseen situations [85]. The descriptive statistics of the driver response time is presented in Table 4.1. Furthermore, Figure 4.1 illustrates the comparison between different warning levels and driving conditions.

A two-way repeated measures ANOVA was conducted, to test the effect of the warning level (2-level, 3-level) between-subjects factor, and the driving condition (normal, critical) within-subjects factor on driver response time.

Table 4.1: Descriptive statistics of the driver response time

Warning Type	Condition	Driver Response Time		
		Mean	SD	Median
2-Level	Critical	2.81	0.22	2.77
	Normal	2.23	0.22	2.24
3-Level	Critical	2.21	0.32	2.16
	Normal	1.8	0.23	1.7

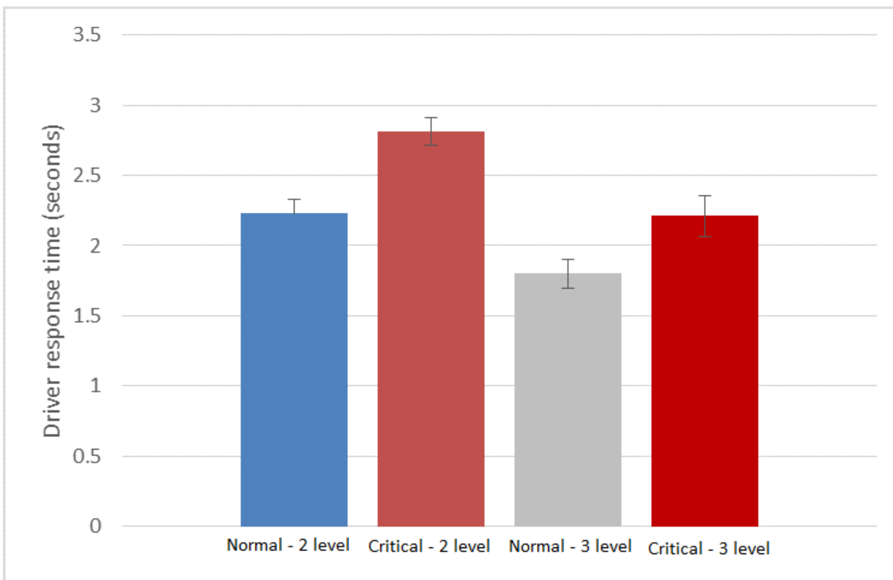


Figure 4.1: Analysis of driver response time (s) for 2-level and 3-level warning under normal and critical driving condition

Table 4.2: ANOVA table for driver response time

Variable	df	F-value	p-value
Warning level	(1,19)	51.544	< 0.0001
Driving condition	(1,19)	148.1534	< 0.0001
Interaction between Warning Level and Driving Condition	(1,19)	4.0899	0.0574

Table 4.3: Descriptive data for number of collisions

Warning Type	Condition	Number of Collisions	Total
2-Level	Critical	10	17
	Normal	7	
3-Level	Critical	5	7
	Normal	2	

According to the Table 4.2, there is a significant effect of the warning levels and the driving condition on driver response time. However, the interaction effect between the warning system and driving condition on response time is not statistically significant.

4.1.2 Collision Frequency

There was a total of 24 collisions that occurred in the driving scenarios (see Table 4.3). 17 participants collided with the hazard in 2-level warning scenarios (10 in critical and 7 in normal driving condition), while this number was 7 for 3-level warning scenarios (5 in critical and 2 in normal driving condition).

4.2 Physiological Sensor Data

Various factors influence driving behavior, encompassing traffic conditions and diverse driver characteristics such as age, emotional state, and aggressiveness. The influence of mental state and stress significantly affects driver behavior, particularly at intersections. Stress levels are gauged using physiological indicators like HR and skin conductance, also known as EDA [128]. These signals, detectable by sensors, are employed in this research.

The study's measurements were obtained using the E4 Empatica wristband worn by participants, both before the experimental drive (baseline data) and during their driving sessions with the simulator, using a button on the wristband.

4.2.1 EDA

The EDA values are compared with the baseline data for 2-level and 3-level warnings in normal and critical driving conditions, shown in Table 4.4 and Figure 4.2 to Figure 4.5.

Table 4.4: Descriptive statistics of the driver's EDA

Warning Type	Condition	Mean	SD
2-Level	Baseline	1.11	1.23
	Critical	2.03	0.37
	Normal	1.78	0.33
3-Level	Baseline	0.57	0.44
	Critical	1.16	0.36
	Normal	1.53	0.25

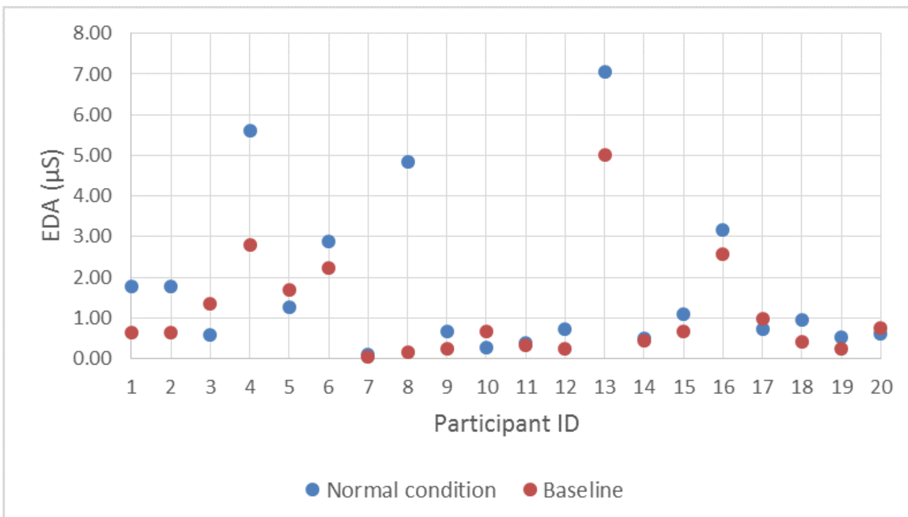


Figure 4.2: Analysis of EDA for 2-level warning for baseline and under normal driving condition

In 2-level warning group, there are instances where the EDA response under critical conditions peaks significantly above the baseline, suggesting episodes of higher stress or arousal. For most participants, EDA responses under critical conditions seem to be slightly above the baseline. However, most EDA responses in normal conditions tend to stay close to the baseline levels. In 3-level warning group, EDA responses are mostly consistent with the baseline. Also, it is observed that the 2-level system may elicit slightly higher EDA responses in both conditions compared to the 3-level system.

The EDA values are also compared between warning levels and driving conditions in Figure 4.6. For the 2-level warning system, the median EDA response for the critical condition is slightly higher than for the normal condition. However, for the 3-level warning

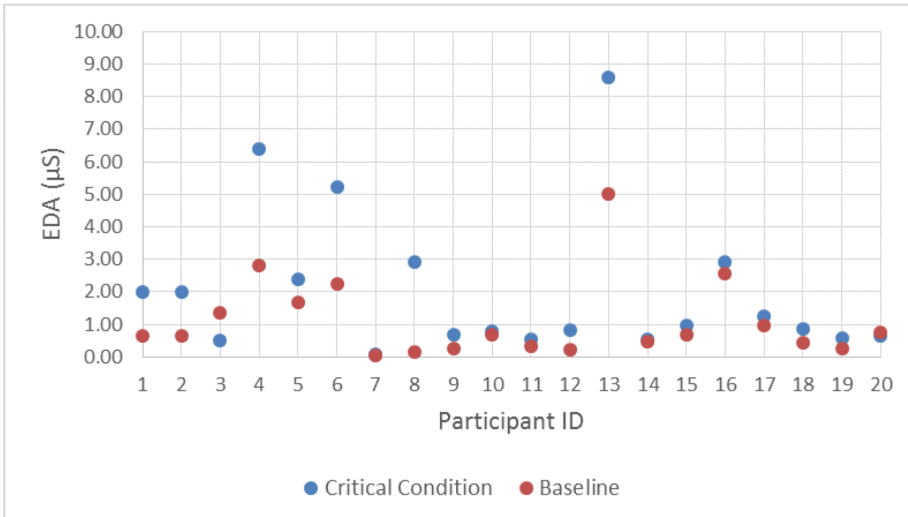


Figure 4.3: Analysis of EDA for 2-level warning for baseline and under critical driving condition

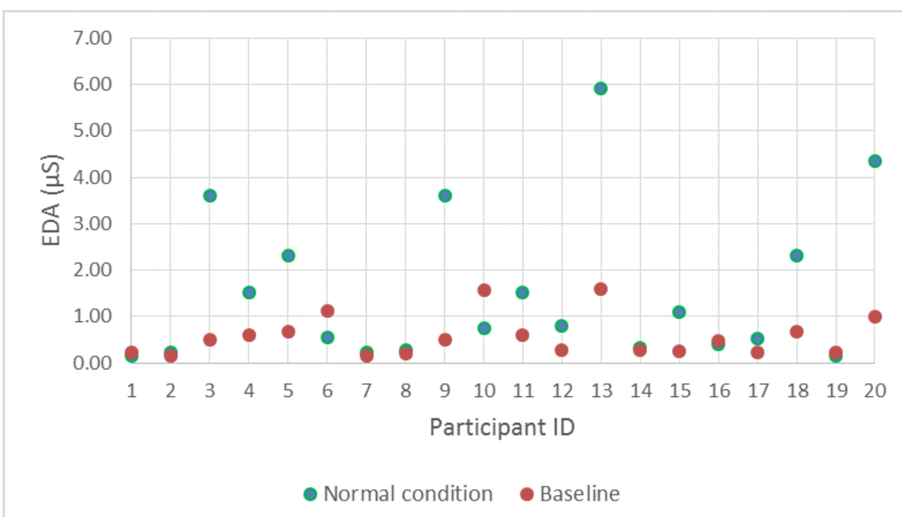


Figure 4.4: Analysis of EDA for 3-level warning for baseline and under normal driving condition

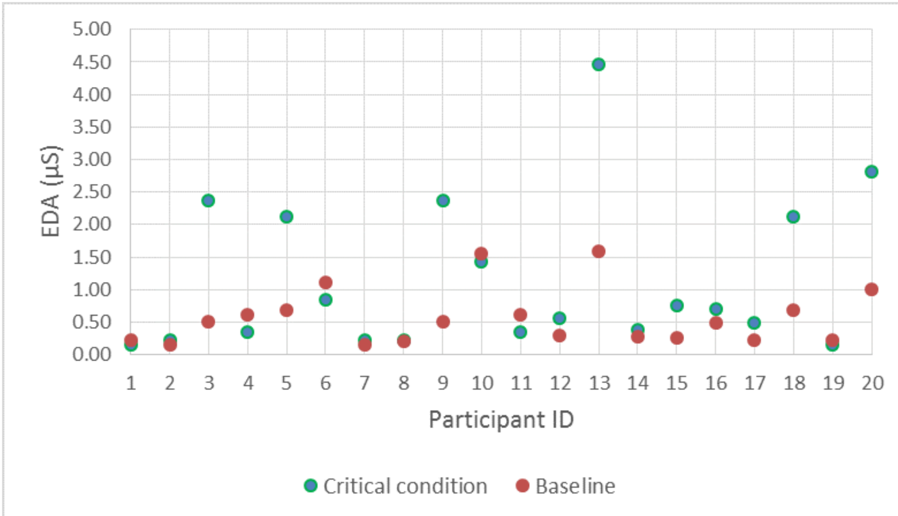


Figure 4.5: Analysis of EDA for 3-level warning for baseline and under critical driving condition

system, the median EDA response for the critical condition is slightly lower than for the normal condition. Although, the difference is not as pronounced. Furthermore, there are several outliers in both conditions for the 2-level warning system. In contrast, there are fewer outliers in the 3-level warning system.

Given the divergent results observed, we conducted a two-way ANOVA to assess the significance of the factors on EDA responses. According to Table 4.5 which provides ANOVA results of test condition EDA, the p-value for the warning system level effect is approximately 0.249, indicating that there is no significant difference in mean EDA between the 2-Level and 3-Level warning systems across all conditions. Similarly, the p-value for the condition effect is approximately 0.621, suggesting that there is no significant difference in mean EDA between Normal and Critical conditions across all participants. Furthermore, the p-value for the interaction effect is approximately 0.018, suggesting that there is a significant interaction effect between the condition and warning system level on mean EDA. It suggests that the effectiveness of the warning system in influencing EDA differs depending on the driving condition.

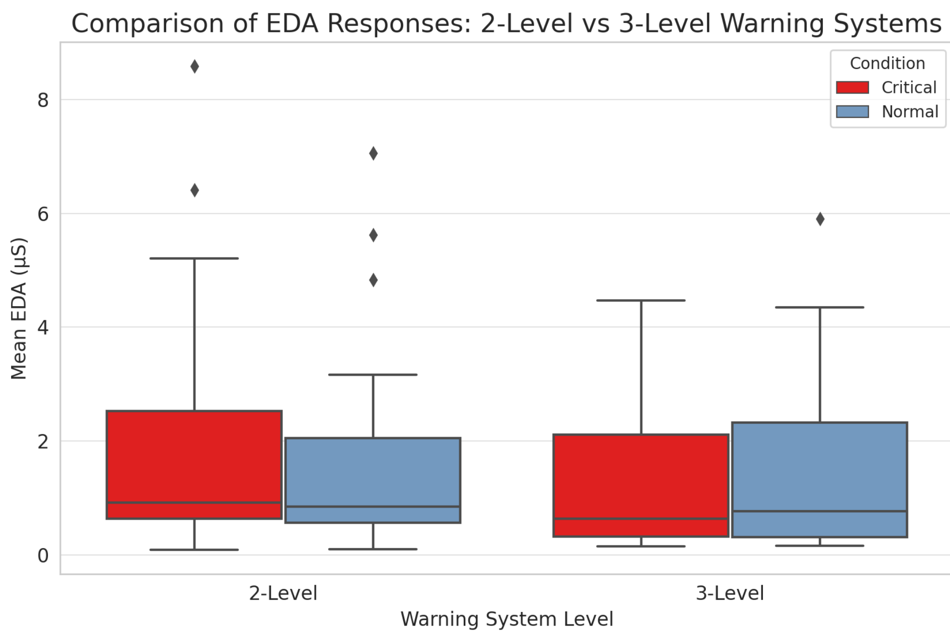


Figure 4.6: Analysis of EDA for 2-level and 3-level warnings, under normal and critical driving condition

Table 4.5: ANOVA table for driver EDA

Variable	df	F-value	p-value
Warning level	(1,19)	1.4113	0.249
Driving condition	(1,19)	0.2525	0.621
Interaction between Warning Level and Driving Condition	(1,19)	6.746	0.018

Table 4.6: Descriptive statistics of the driver's HR

Warning Type	Condition	Mean	SD
2-Level	Baseline	76.75	5.8
	Critical	77.97	5.7
	Normal	77.25	7.37
3-Level	Baseline	76.5	6.41
	Critical	79.64	6.52
	Normal	77.19	8.64

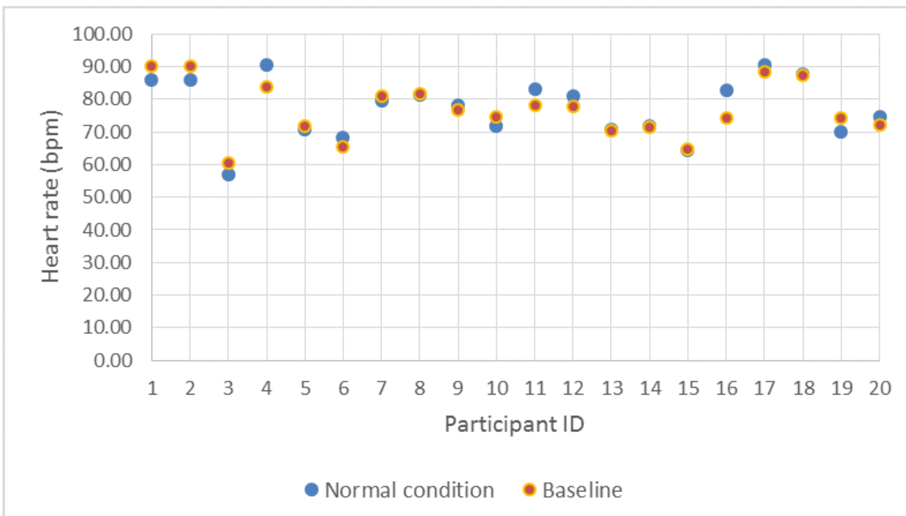


Figure 4.7: Analysis of HR for 2-level warning for baseline and under normal driving condition

4.2.2 HR

The HR values are compared with the baseline data for 2-level and 3-level warnings in normal and critical driving conditions, shown in Figure 4.7 to Figure 4.10.

The Table 4.6 indicates that, on average, participants' HR during both critical and normal driving conditions were close to or slightly above their baseline HR across both warning systems. This indicates a subtle variation in HR in response to the driving experiment conditions. However, in 3-level warning systems, participants' HR is higher than baseline in both driving conditions.

The HR values are also compared between warning levels and driving conditions in

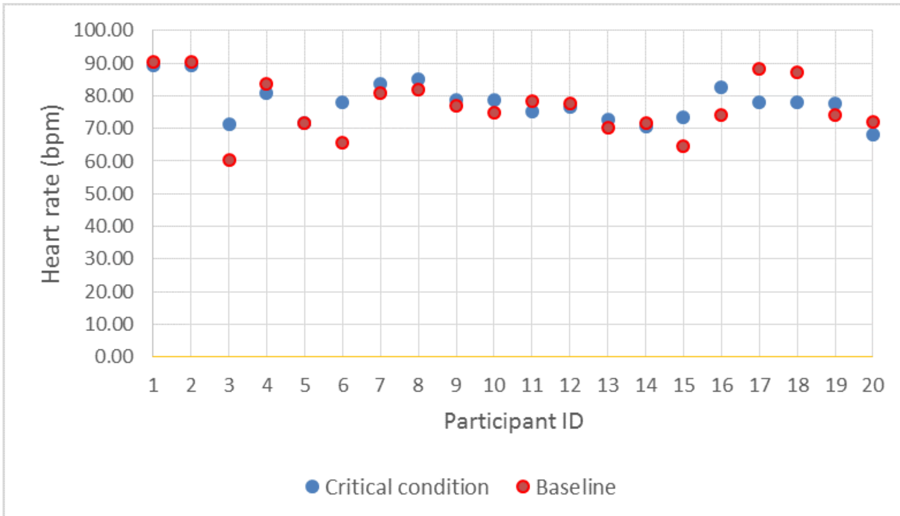


Figure 4.8: Analysis of HR for 2-level warning for baseline and under critical driving condition

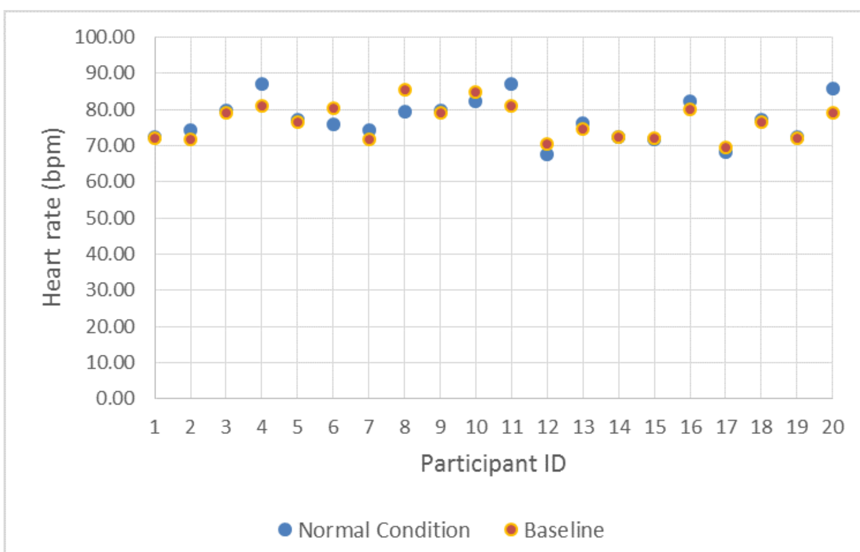


Figure 4.9: Analysis of HR for 3-level warning for baseline and under normal driving condition

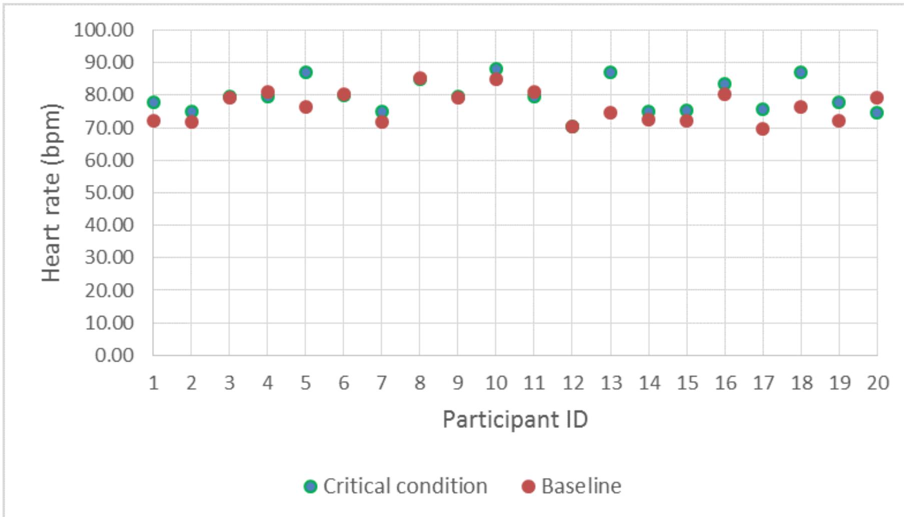


Figure 4.10: Analysis of HR for 3-level warning for baseline and under critical driving condition

Table 4.7: ANOVA table for HR

Variable	df	F-value	p-value
Warning level	(1,19)	0.0487	0.828
Driving condition	(1,19)	0.0899	0.768
Interaction between Warning Level and Driving Condition	(1,19)	0.0487	0.828

Figure 4.11. The box-plot illustrates that there does not seem to be a dramatic difference in the central tendency (median) of heart rates between 2 and 3-level warnings for critical driving condition. However, in the 2-level warning system, the median heart rates for normal conditions appear to be slightly higher than other conditions. The range of heart rates is also similar between the two warning levels, which implies that the extremities of heart rate responses do not change much between warning levels, except for the 2-level normal scenarios which showed a wider range.

Additionally, a two-way ANOVA was conducted to assess the significance of the factors on HR values. According to Table 4.7, the results showed that there is no significant effect of the warning level, driving condition or interaction effect between warning level and driving condition on the HR mean.

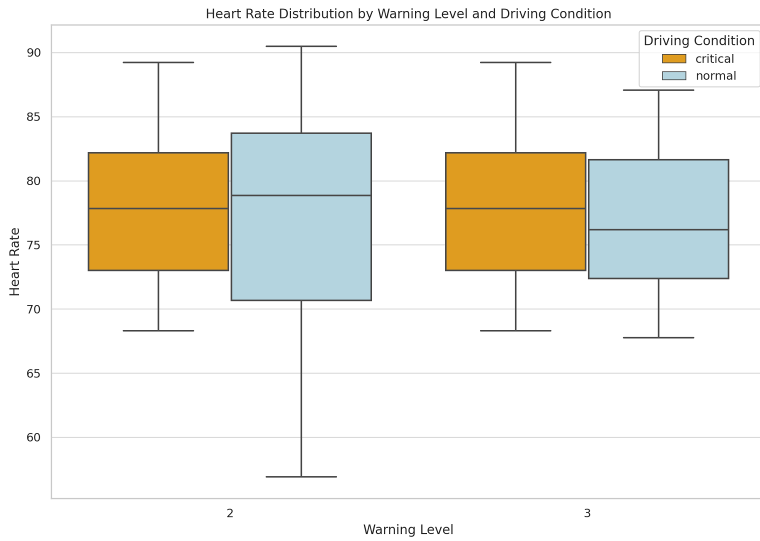


Figure 4.11: Analysis of HR for 2-level and 3-level warning under normal and critical driving conditions

4.2.3 HRV

As we couldn't extract useful findings from HR data, an analysis was conducted on the HRV data as well. The 2-level and 3-level group HRV values are compared in normal and critical driving conditions, shown in Figure 4.12 and Figure 4.13. Analysis indicates that, on average, 2-level warning group had slightly higher HRV values compared to 3-level warning group in both normal and critical driving conditions.

Additionally, a two-way ANOVA was conducted to assess the significance of the factors on HRV values. According to the results shown in Table 4.8, the results showed that there is no significant effect of the warning level, driving condition or interaction effect between warning level and driving condition on the HRV mean, as the P-value is more than 0.05.

4.3 Eye Data

As eye data, encompassing gaze and pupil position data [129], can provide valuable insights due to the visual distraction, they were collected using the Adhawk eye tracker worn by

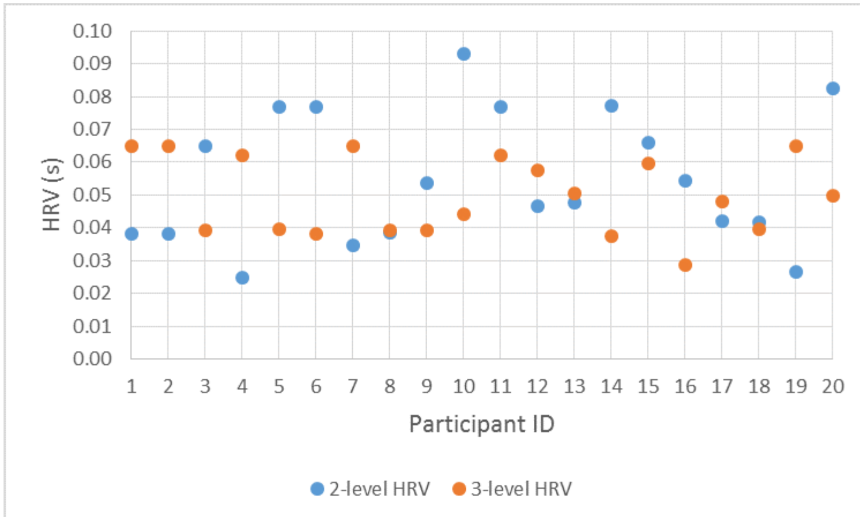


Figure 4.12: Analysis of HRV for 2-level and 3-level warning under normal driving condition

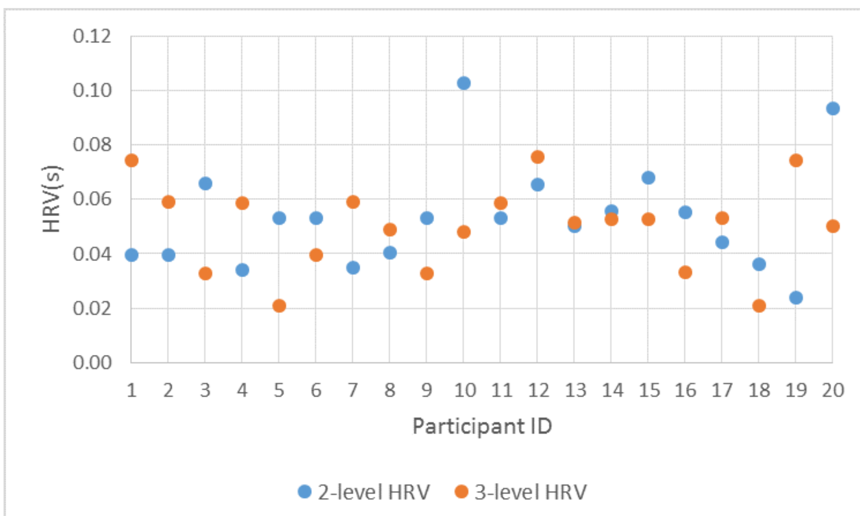


Figure 4.13: Analysis of HRV for 2-level and 3-level warning under critical driving condition

Table 4.8: ANOVA table for HRV

Variable	df	F-value	p-value
Warning level	(1,19)	1	0.331
Driving condition	(1,19)	0.75	0.398
Interaction between Warning Level and Driving Condition	(1,19)	0.7879	0.387

Table 4.9: ANOVA table of pupil position for warning level factor

Variable	df	F-value	p-value
Pupil_Pos_X_Right	1	14.24	0.0027
Pupil_Pos_Y_Right	1	103.11	< 0.0001
Pupil_Pos_X_Left	1	23.90	0.0004
Pupil_Pos_Y_Left	1	0.11	0.05

Table 4.10: ANOVA table of pupil position for driving condition factor

Variable	df	F-value	p-value
Pupil_Pos_X_Right	1	1.06	0.3243
Pupil_Pos_Y_Right	1	0.46	0.5089
Pupil_Pos_X_Left	1	1	0.3369
Pupil_Pos_Y_Left	1	0.52	0.4853

participants in this study.

A two-way ANOVA was conducted to understand the significance effects of the warning level and driving condition on the pupil position. According to F-value and p-value showed in Table 4.9, there is a significant effect of the warning system type on the mean pupil position, suggesting that the mean pupil position differs significantly between the 2-level and 3-level warning systems. However, the driving condition (Critical vs. Normal) does not have a significant effect on the pupil position at the conventional 0.05 significance level (Table 4.10). Additionally,the interaction effect is not significant, indicating that the difference between the 2-level and 3-level warning systems on the pupil position does not depend significantly on whether the driving condition is critical or normal (Table 4.11).

In our analysis of distraction from eye data, we compared baseline pupil position data for each participant, representing their pupil position when focusing on the monitor while

Table 4.11: ANOVA table of pupil position for interaction between warning level and driving condition

Variable	df	F-value	p-value
Pupil_Pos_X_Right	1	1.34	0.2696
Pupil_Pos_Y_Right	1	0.83	0.3814
Pupil_Pos_X_Left	1	0.07	0.8007
Pupil_Pos_Y_Left	1	0.1	0.7519

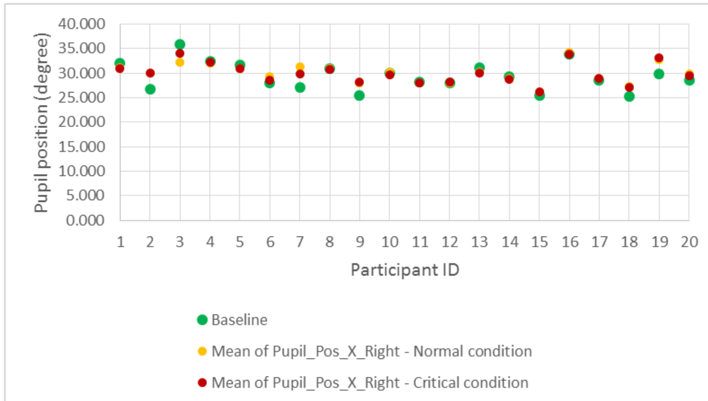


Figure 4.14: Comparing mean pupil position during 2-level warning normal and critical scenarios and baseline pupil position

Table 4.12: Difference Between Mean Pupil Position During Scenarios and Baseline Pupil Position

Warning type	Normal condition	Critical condition
2-level Warning	1.364	1.147
3-level Warning	1.248	1.077

driving, with the mean pupil position during both critical and normal scenarios (Figure 4.14 and Figure 4.15).

The proximity of this mean to the baseline indicates the participant's level of focus on driving and degree of distraction. The difference between the mean pupil position during scenarios and the baseline was calculated and presented in Table 4.12. The smaller difference observed in the 3-level warning group compared to the 2-level warning group in both normal and critical driving conditions.

4.4 Subjective Evaluation

At the end of the experiment, each participant was tasked with completing a comprehensive survey aimed at gauging the workload and their perceptions of the warnings provided. The survey covered various aspects, including the clarity of the warnings, the level of annoyance experienced, the perceived effectiveness of the warnings, and preferences regarding different modalities. Participants were encouraged to express their feedback and insights on these

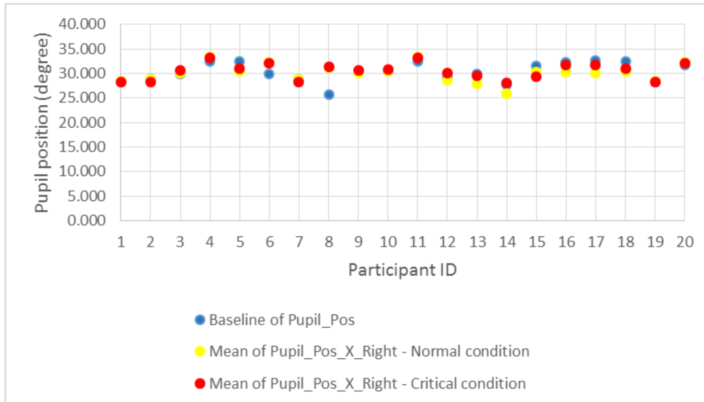


Figure 4.15: Comparing mean pupil position during 3-level warning normal and critical scenarios and baseline pupil position

key dimensions to provide a well-rounded evaluation of their overall experience during the experiment.

The survey results provide valuable insights into their effectiveness and areas for improvement. The results revealed that 80% of participants identified the critical highway scenarios as the most demanding and risky, highlighting the increased necessity for effective warnings under high-speed conditions. Conversely, 88% considered the normal city scenarios as lower risk and less demanding. A substantial majority found the warnings to be clear, with 52.5% rating them as very clear and 35% as clear, demonstrating that the warnings were generally well-understood. Moreover, 93% of participants felt that the warnings positively influenced their refocusing on driving, and 88% reported an improvement in driving performance, especially during highway scenarios. However, the feedback also pinpointed challenges, notably that 37.5% of participants found one of the warnings to be distracting or annoying at times, suggesting that while the warnings were clear, their presentation or modality may have impacted the participants' driving experience negatively.

Additionally, the preference for warning modalities varied among participants, with 45% favoring auditory and 25% preferring haptic warnings, emphasizing the need for customizable warning systems to accommodate individual preferences.

Regarding the challenge posed by secondary tasks, 48% of participants found them to be demanding, indicating a significant portion experienced an increased cognitive load. Yet, a considerable number rated these tasks as neutral or not challenging, suggesting variability in participants' capacity to manage additional tasks alongside driving.

Chapter 5

Discussion and Conclusion

5.1 Discussion

This study compared 2-level and 3-level collision warning systems under both normal and critical driving conditions, particularly when the driver is distracted by a secondary task.

The insights gained from the previous chapter provide us with an understanding of the variables influencing the driver performance. Statistical analysis has been conducted to determine whether to retain or reject the null hypotheses.

5.1.1 Response Time

The descriptive statistics presented in Table 4.1 reveal notable differences in response times between the two warning systems. In critical driving conditions, participants subjected to the 3-level warning system exhibited a mean response time of 2.21 seconds, whereas those under the 2-level warning system had a mean response time of 2.81 seconds. Similarly, in normal driving conditions, participants in the 3-level warning group demonstrated a mean response time of 1.8 seconds, compared to 2.23 seconds for those in the 2-level warning group. These findings suggest that the 3-level warning system consistently outperformed the 2-level system in terms of response time across both critical and normal driving conditions. This reject our null hypotheses (H_0) and supports our alternative hypotheses (H_A), indicating that the 3-level system indeed led to better driving performance compared to the 2-level system.

Furthermore, the analysis highlights the influence of driving conditions on response time. Participants faced with critical driving scenarios exhibited longer response times compared to those in normal driving conditions, irrespective of the warning system employed. This observation aligns with existing literature, which suggests that reduced visibility and increased traffic volume, attention, and cognitive load associated with critical driving situations can impede reaction times [130, 131, 132, 133].

The interaction effect between warning levels and driving conditions, while not statistically significant, is noteworthy. Although the difference in response time between the two warning systems varied across driving conditions, the magnitude of this difference did not significantly change. This implies that while the warning level influences response time, its impact remains consistent regardless of the driving context.

5.1.2 Collision Frequency

As depicted in Table 4.3, participants in the 2-level warning group experienced a higher number of collisions compared to those in the 3-level warning group. Specifically, in critical driving conditions, 10 collisions occurred among participants in the 2-level warning group, while only 5 collisions occurred among those in the 3-level warning group. Similarly, in normal driving conditions, participants in the 2-level warning group experienced 7 collisions, whereas only 2 collisions occurred among those in the 3-level warning group. These findings suggest that the 3-level warning system was more effective in reducing the frequency of collisions compared to the 2-level system across both critical and normal driving conditions. This reject our null hypotheses (H_0) and aligns with our alternative hypotheses (H_A), indicating that the 3-level system indeed led to a lower number of collisions compared to the 2-level system.

Additionally, the analysis underscores the influence of driving conditions on collision frequency. Participants in critical driving scenarios experienced a higher number of collisions compared to those in normal driving conditions, regardless of the warning system employed. This observation is consistent with the heightened cognitive load, and reduced visibility, associated with critical driving situations, which can weaken driver performance and elevate the risk of accidents or crashes. [134, 135, 136, 137].

5.1.3 EDA

The descriptive statistics presented in Table 4.4 showed interesting patterns in EDA responses between baseline and driving conditions. In the 2-level warning group, participants generally exhibit higher EDA responses under critical driving conditions, indicated by peaks above the baseline. This suggests increased stress or arousal levels [138] when faced with potential hazards or critical situations. Conversely, EDA responses in normal driving conditions tend to remain closer to baseline levels, indicating relatively lower stress levels during routine driving tasks. Furthermore, participants in the 3-level warning group exhibited higher EDA values in both normal and critical driving conditions compared to the baseline, indicating increased stress or arousal levels in response to the driving experiment conditions. However, the 3-level group showed slightly higher EDA responses in normal driving conditions compared to critical ones.

The boxplot (Figure 4.6) analysis further explores the differences in EDA responses between the two warning systems under different driving conditions. It is observed that the 3-level system has a more consistent EDA response between critical and normal conditions, whereas the 2-level system shows more variability. The median EDA response for the normal condition is higher in the 3-level system compared to the 2-level system, which might suggest that the additional level of warning in the 3-level system engages participants more even during normal driving conditions. Moreover, the critical condition elicits a higher median EDA response than the normal condition for 2-level warning systems. This could indicate that the critical driving scenarios with 2-level warnings might have been more engaging or demanding in terms of attention, leading to higher arousal as measured by EDA. However, participants showed unexpectedly opposite results in 3-level warning group. Finally, there are several outliers in both conditions for the 2-level warning system, indicating that some participants had EDA responses that were notably different from the rest. In contrast, there are fewer outliers in the 3-level warning system, suggesting more consistent responses among participants.

The results of the 2-way ANOVA provide insights into the significance of warning system levels and driving conditions on mean EDA responses. The p-value for the warning system level effect indicates that there is no significant difference in mean EDA between the 2-level and 3-level warning systems across all conditions. Similarly, the p-value for the condition effect suggests no significant difference in mean EDA between normal and critical conditions. This results fail to reject the null hypotheses (H_0) that there is no significant difference in driving performance within the 2-level and 3-level graded collision warning systems across normal and critical driving conditions. However, the significant interaction effect between warning level and driving condition on mean EDA indicates that the relationship between these factors is not straightforward. This highlights the importance of considering the combined influence of warning systems and driving conditions on drivers' physiological responses.

5.1.4 HR

The comparison of HR values between baseline and driving conditions reveals subtle variations in participants' physiological states during the experiment. Across both 2-level and 3-level warning systems, participants generally exhibit HR values close to or slightly above their baseline HR during critical and normal driving conditions. This indicates a modest increase in heart rate in response to the driving experiment conditions.

The boxplot (Figure 4.11) analysis further explores the differences in HR responses between the two warning systems under different driving conditions. The central tendency (median) of HR values does not show significant differences between 2-level and 3-level warning systems for critical driving condition. Similarly, the range of HR values remains consistent between the two warning levels, indicating similar physiological responses across warning systems, except for 2-level normal condition. Within 3-level warning system, the median HR values for critical and normal conditions are comparable, with a tendency towards higher median HR in critical conditions. However, it showed opposite results in 2-level warning system with a higher median in normal condition.

The results of the two-way ANOVA provide insights into the significance of warning levels and driving conditions on mean HR values. The lack of significant effects for warning level, driving condition, or their interaction suggests that these factors do not have a pronounced impact on participants' HR responses during the driving scenarios. This indicates that the differences observed in HR values between warning levels and driving conditions are not statistically significant.

Analyzing the physiological data shows that adding another level to collision warning systems has not a significant effect on driver's stress levels.

5.1.5 HRV

The analysis of HRV data was conducted to reveal intriguing insights into the physiological responses during different driving conditions. Despite encountering challenges in deriving meaningful conclusions from HR, we extend HRV data analysis for a deeper examination of autonomic nervous system dynamics. The comparison between 2-level and 3-level warning groups under both normal and critical driving conditions, as illustrated in Figure 4.12 and Figure 4.13, unveiled noteworthy trends. It was observed that, on average, participants in the 2-level warning group exhibited slightly higher HRV values than those in the 3-level warning group across both driving conditions.

Furthermore, a rigorous statistical analysis was conducted to evaluate the significance of various factors influencing HRV values. Employing a two-way ANOVA methodology enabled a comprehensive assessment of the impact of warning level, driving condition, and their interaction effect on HRV means. As delineated in Table 4.8, the results of the analysis suggest that there is no statistically significant effect of warning level, driving condition, or their interaction on HRV means. This inference is substantiated by the observation that the computed P-values exceed the conventional threshold of 0.05, indicating a lack of significant differences attributable to these factors.

5.1.6 Eye Data

A driver must gather visual information from various locations. A significant portion of the cognitive effort involved in comprehending the surrounding environment is dedicated to predicting its near-future state [139, 140]. This holds especially true for the road environment, where making predictions with reasonable chances of success is feasible [141]. Pupil position data provide insights into the visual focus and cognitive engagement of drivers during the experimental driving scenarios [142]. The comparison of mean pupil position between 2-level and 3-level warning systems reveals significant differences, as indicated by the results of the two-way ANOVA. Specifically, the mean pupil position differs significantly between the two warning systems, suggesting that drivers may exhibit distinct patterns of visual attention and cognitive processing [143] based on the number of warning levels presented.

In contrast to the significant effect of warning system type, the driving condition (critical vs. normal) did not show a significant effect on pupil position. This suggests that drivers' visual attention, as reflected by pupil position data, may not vary substantially between critical and normal driving conditions within the context of this study. The non-significant interaction effect between warning level and driving condition indicates that the difference in mean pupil position between 2-level and 3-level warning systems is consistent across both critical and normal driving conditions. This suggests that the impact of warning system complexity on driver visual attention and cognitive load remains relatively consistent regardless of the driving context.

Additionally, the comparison of mean pupil position during scenarios with baseline pupil position data, which is the pupil position when the driver is looking to the monitor and is focused on driving, provides insights into driver distraction. The smaller difference observed in the 3-level warning group compared to the 2-level warning group (Table 4.12). This indicates that participants in the 3-level warning group were less distracted and more focused on driving. This reject our null hypotheses (H_0), and aligns with our alternative hypotheses (H_A), suggesting that the additional warning levels may have helped maintain driver attention and reduce cognitive distraction, contributing to improved performance.

5.1.7 Subjective Evaluation

The subjective evaluation component of the study offers valuable insights into participants' perceptions of the warning systems and their overall driving experience. The survey results reflect participants' recognition of the varying levels of risk and demand across different driving scenarios. The majority identifying critical highway scenarios as the most demanding and risky aligns with expectations, highlighting the importance of effective warnings in high-speed environments where the margin for error is reduced. Conversely, the perception of normal city scenarios as lower risk and less demanding underscores the need for context-sensitive warning systems that adapt to different driving environments.

The positive ratings for the clarity and effectiveness of the warnings indicate that participants generally understood and appreciated the warnings provided during the driving scenarios. The high percentage of participants who felt the warnings positively influenced their refocusing on driving and improved driving performance underscores the potential benefits of collision warning systems in enhancing driver attention and responsiveness, particularly in critical situations.

Despite the overall positive feedback, a notable proportion of participants found certain warnings to be distracting or annoying at times. This highlights a crucial consideration in warning system design: the balance between providing clear alerts and avoiding undue distraction or annoyance. The variation in preference for warning modalities further emphasizes the importance of customizable systems that cater to individual user preferences and mitigate potential negative effects on driving experience.

The survey results regarding secondary task demands offer insights into participants' multitasking abilities and the impact of concurrent cognitive tasks on driving performance. The finding that nearly half of the participants found secondary tasks demanding suggests the presence of increased cognitive load, which can potentially affect driving performance and safety. However, the variability in participants' perceptions of task difficulty underscores the complex interplay between individual factors and task characteristics in determining cognitive workload.

5.2 Conclusion

In this study, we investigated the effectiveness of 2-level and 3-level graded collision warning systems under different driving conditions, namely critical and normal scenarios. Through a combination of objective data analysis and subjective evaluations, we aimed to gain insights into the performance and usability of these warning systems in real-world driving contexts.

The objective data analysis revealed significant findings regarding driver response time, number of collisions, physiological responses (such as electrodermal activity and heart rate), and eye data (including pupil position). Overall, the results indicated that both warning systems had a measurable impact on driving performance, with variations observed across different driving conditions. Notably, the 3-level warning system showed promising outcomes, particularly in reducing response time and mitigating collisions under critical driving conditions.

The subjective evaluation provided insights into participants' perceptions of the warning systems, their clarity, effectiveness, and potential areas for improvement. While participants generally responded positively to the warnings and acknowledged their influence on driving behavior, challenges such as distraction and variability in task demands were also identified. These findings underscore the importance of designing warning systems that strike a balance between providing clear alerts and minimizing distraction.

In conclusion, this study contributes to our understanding of the effectiveness and usability of different levels of collision warning systems in enhancing driver safety and performance. By integrating objective data analysis with subjective evaluations, we have gained valuable insights into the complex interplay between warning system design, driver behavior, and driving context. Moving forward, continued research in this area is essential to further refine warning system designs and ultimately improve road safety for all drivers.

5.2.1 Implication

The findings of this study have several implications for the design and implementation of collision warning systems in real-world driving scenarios. By understanding the factors that influence driver behavior and perception, future iterations of warning systems can be tailored to better meet the needs and preferences of users. This includes considering 3-level graded warnings, exploring customizable warning modalities, and refining algorithms to adapt to dynamic driving environments.

5.2.2 Limitations

It is important to acknowledge the limitations of this study. While efforts were made to simulate controlled driving scenarios, the findings may not fully generalize to all real-world driving situations. As the research took place in a lab-based low-fidelity driving simulator, it may not accurately mirror real-world conditions. During the practice sessions, some participants initially remarked that the Logitech G29 steering wheel and pedals felt distinct from the real vehicles they have driven. Additionally, the acceleration behavior in the CARLA software diverged from that of a real vehicle, as releasing the accelerator pedal would swiftly bring the speed to zero. Consequently, participants had to apply additional effort to sustain their speed [126]. Moreover, the implementation of a supervised simulator experiment, coupled with the utilization of wearable sensors, is expected to influence driver performance differently when contrasted with a naturalistic study [144, 145]. Furthermore, the absence of Area of Interest (AOI) analysis limits the depth of understanding of participants' gaze patterns and inhibits direct comparisons with existing literature.

Another limitation of this study is the age distribution of the participants, which predominantly skewed towards younger individuals. The recruitment process primarily targeted university students and alumni, resulting in a sample that predominantly represents a younger demographic. Consequently, the study lacks representation from older drivers, which limits the generalizability of the findings across age groups. The absence of older participants prevents a comprehensive understanding of how age-related factors, such as cognitive decline or differing reaction times, may influence the effectiveness of collision warning systems.

5.2.3 Future Work

Future research stemming from this study could explore deeper into several key areas to advance the understanding and effectiveness of collision warning systems, particularly focusing on 3-level graded warnings. One avenue for future work involves the adoption of high-fidelity simulators to enhance the accuracy and reliability of data and results. High-fidelity simulators offer more advanced features and realistic driving scenarios compared to conventional simulators, providing a more immersive and authentic driving experience for participants. By leveraging these technologies, researchers can collect more detailed data on driver behavior and performance, leading to deeper insights into the efficacy of collision warning systems.

Another important consideration for future studies is the recruitment of participants from a broader age range to address the limitation of predominantly young participants in this study. Actively recruiting older drivers would ensure a more representative sample and enhance the applicability of the study's findings to diverse driver populations.

Additionally, investigating the integration of artificial intelligence and machine learning techniques could pave the way for the development of adaptive warning systems. These systems would be capable of learning from real-time driving data to tailor warnings to individual drivers' preferences and situational contexts, thereby maximizing their effectiveness.

Furthermore, as semi-autonomous and autonomous vehicles become increasingly prevalent, future research could explore the interoperability of collision warning systems with these advanced technologies. Understanding how collision warning systems can complement semi-autonomous and autonomous driving features could lead to synergistic advancements in overall safety and user experience. By addressing these avenues for future research, scholars can contribute to the ongoing evolution and improvement of collision warning systems, ultimately enhancing road safety for all drivers.

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APPENDICES

Appendix A

Questionnaires

The questionnaires filled by the participants before starting the experiment are given below-

Demographic Questionnaire

Participant's Code:

Please indicate your gender:

- Male
- Female
- Prefer not to say

Prefer to self-identify: __________

Please select the category that indicates your age:

- 18-24
- 25-34
- 35-44
- 45-54
- 55-64
- 65 or above

Do you possess a valid Canadian G2 or G Driver's License?

- Yes
- No

Do you have at least one year of driving experience?

- Yes
- No

Are you susceptible or have a history of motion sickness?

- Yes
- No

Appendix B

Surveys

The surveys filled by the participants after finishing the experiment are given below-

Post-Experiment Survey

Participant code:

Dear Participant,

Thank you for participating in our driving distraction study. Please read each question carefully and select the response that best reflects your experience and opinions. Your honest responses will contribute to the improvement of road safety and warning technologies.

If a question does not apply to you or if you are unsure, you can skip it.

- Did you feel that the warnings were clear and easy to understand?

  Very Clear ☐ Clear ☐ Neutral ☐ Unclear ☐ Very Unclear ☐

- Were there any specific warning modalities (visual, haptic, auditory) that you found annoying or distracting?

☐ No

☐ Yes, ____________

- Did you feel that the warnings improved your driving performance and safety?

☐ No
☐ Yes

- How challenging did you find the secondary task while driving?

  Challenging ☐ Neutral ☐ Not Challenging ☐

- Did the warnings influence your decision to refocus on driving?

☐ No
☐ Yes

- How important did you think it was to return to driving after receiving different warning signals?

  Important ☐ Neutral ☐ Not Important ☐

1

- Please rate each scenario in terms of the urgency and risk level you experienced during the experiment (1-10, 1: very low risk – 10: very high risk)

Scenario 1 & 2 & 3 & 7: City map with an obstacle ___________

Scenario 4 & 8: Highway with an obstacles ___________

Scenario 5 & 6: Intersection without traffic lights ___________

- Were there any specific scenarios where you felt the warnings were particularly helpful or not helpful?

☐ No
☐ Yes, ____________

- Which type of warnings did you find more acceptable?

☐ Visual
☐ Haptic
☐ Auditory

Appendix C

GenAI Documentation

GenAI Documentation

Platform: ChatGPT

DATE	CONVERSATION LABEL	PROMPT	RESPONSE	ACTION
20-02-2024	sophisticated Warning System Advancement	Improve the writing: Choosing between fewer or more warning levels in collision systems has been always a question. It is important to balances simplicity with better performance.	The debate between fewer levels of warning versus more levels of warning in collision warning systems underscores a delicate balance between simplicity and better performance.	Final sentences I used in the document: Several studies have investigated the levels of warning in collision warning systems in terms of finding a balance between simplicity and better performance.
		Paraphrase this: Driver distraction is the voluntary or involuntary diversion of attention from the primary driving tasks not related to impairment where the diversion occurs because the driver is performing an additional task and temporarily focusing on an object, event, or person not related to the primary driving tasks.	Distracted driving, in essence, manifests as a critical form of attention lapse wherein drivers divert their focus from the primary task of driving to engage in secondary activities.	Final sentences I used in the document: Distracted driving occurs when drivers shift their focus from driving to other activities, causing a significant lapse in attention.
		Improve the writing: By studying how collision warning systems influence driver performance and decision making, we aim to improve and customize these systems further.	By gaining a deeper understanding of how these collision warning systems affect driver behavior, decision-making, and overall performance, we aspire to pave the way for the development of more sophisticated and tailored warning systems.	Final sentences I used in the document: Addressing this gap is essential for informing the ongoing research on road safety and optimizing the design and implementation of collision warning systems by gaining a deeper understanding of how these collision warning systems affect driver behavior, decision-making, and overall performance, to mitigate the risks associated with distracted driving, and providing a safer and more secure driving environment for all road users.
		Improve the writing: This study aims to compare two types of collision warning systems: one with 2 levels and another with 3 levels, to understand their effectiveness better.	The focus of this study is to delve into the nuanced dynamics of collision warning systems, specifically comparing the efficacy of two distinct approaches: a 2-level graded warning system and a 3-level graded warning system.	Final sentences I used in the document: The primary objective of this research is to investigate and compare the efficacy of a 3-level graded collision warning system against a 2-level graded system in enhancing driver performance across critical and normal driving scenarios.

DATE	CONVERSATION LABEL	PROMPT	RESPONSE	ACTION
		Improve the writing: This study compares a 3-level graded collision warning system to a 2-level one in real-world driving conditions to see which works better. For this purpose, this study use simulated driving situations, examining both critical and normal driving conditions.	The goal of this study lies in a deliberate and systematic examination of the comparative effectiveness of a 3-level graded collision warning system against a 2-level graded counterpart. This investigation extends beyond the realm of mere theoretical scrutiny, delving deep into the crucible of both critical and normal driving conditions.	Final sentences I used in the document: The controlled nature of the simulation allows for a systematic investigation into how drivers respond to different collision warning systems under conditions that simulate the actual road environments. The simulated scenarios cover various driving situations, ranging from normal driving to critical situations that demand more attention and rapid decision-making.
		Improve the writing: These differences aren't random; they're based on the risk level, potential hazards, and how much attention and caution the driver needs.	The distinctions between these conditions are not arbitrary; rather, they pivot on the level of risk, the array of potential hazards, and the requisite degree of attention and caution demanded from the driver.	Final sentences I used in the document: These conditions are not random; instead, they depend on the level of risk, the various potential hazards, and the amount of attention and caution demanded from the driver.
		Improve the writing: As we explore this new area, we expect to find insights that can shape future collision warning systems, making roads safer.	As we delve into this unexplored territory, we anticipate uncovering new perspectives that could influence the design and implementation of future collision warning systems, ultimately enhancing overall road safety.	Final sentences I used in the document: As we explore this area we expect uncovering new perspectives that could influence the design and implementation of future collision warning systems, ultimately enhancing overall road safety.
		Improve the writing: This multi purpose experiment design aimed to examine how different warning systems and driving conditions interact, helping us understand how they affect driving performance.	This intricate design aimed to scrutinize the nuanced interactions between the warning system variations and driving conditions, providing a comprehensive understanding of their combined impact on driving performance.	Final sentences I used in the document: The experiment aimed to study the interactions between the warning system variations and driving conditions, providing a comprehensive understanding of their combined impact on driving performance.