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Modeling the Impact of Connected and Automated Vehicles on Driving Behaviors and Safety: A Driving Simulator Study

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MODELING THE IMPACT OF CONNECTED AND AUTOMATED VEHICLES ON DRIVING BEHAVIORS AND SAFETY: A DRIVING SIMULATOR STUDY

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ABSTRACT

MODELING THE IMPACT OF CONNECTED AND AUTOMATED VEHICLES ON DDRIVING BEHAVIORS AND SAFETY: A DRIVING SIMULATOR STUDY

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Connected vehicles (CVs), equipped with advanced sensors, can communicate safety messages to drivers. Automated vehicles (AVs), designed with the ability to automate safety-critical control functions, will redefine the traditional role of drivers. This dissertation aims to investigate the impact of connected and automated vehicles (CAVs) on driving behaviors and safety outcomes using data from driving simulator experiments. More specifically, the research objectives include:

1. Modeling the impacts of CVs on driving aggressiveness and situational awareness in highway crash scenarios.
2. Modeling the impacts of CV technologies on driving behaviors and safety outcomes in highway crash scenarios under diverse weather conditions, including clear and foggy weather.
3. Understanding the factors influencing driver safety performance within CAV technology during safety-critical events that necessitate driver takeover.

Structural equation modeling (SEM) was utilized to examine the interrelationships among the use of CV warnings, psychological factors including aggressiveness and situational awareness, driving behavior, weather conditions, safety outcome, and other variables. Random effects logit models were developed to understand the contributing factor to CAV drivers' takeover performance in safety-critical events. Results showed that the proposed CV warnings significantly

reduced aggressiveness and increased situational awareness, contributing to improved safety especially on a horizontal curve. Foggy weather had an overall negative impact on safety on a horizontal curve, despite that it increased drivers' situational awareness. Additionally, CV warnings could notably improve the drivers' takeover performance in safety-critical events.

The insights gained from this dissertation are crucial in shaping the development of advanced driving assistance systems and automated driving systems. that seamlessly integrate psychological factors. They underscore the importance of customization based on weather conditions and location-specific factors. Moreover, this study provides valuable insights into improving human-machine interactions of CAV systems in safety-critical events, ultimately contributing to safer roads.

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CHAPTER 1

INTRODUCTION

1.1 Background

Traffic crashes are responsible for 1.35 million deaths yearly (World Health Organization [WHO], 2018). According to a report by Blincoe et al. (2023), the United States experienced a record high of 36,500 fatalities resulting from motor vehicle crashes in 2019, which also incurred a total economic cost of $339.8 billion. The trend continued in 2020, with fatal crashes increasing by 6.8% to reach a new peak of 38,824 in the last decade as reported by the (National Center for Statistics and Analysis (2022). There is no doubt that one of the significant factors leading to traffic crashes is driving behavior. Over the period of 1999 to 2019, there was a reduction in fatal crashes and fatality rates, which can be attributed to various factors. Among these factors, improved driver behavior played a significant role (Blincoe et al., 2023). On the other hand, risky driving behavior can exacerbate the safety performance (Park et al., 2019a). Therefore, it crucial to fully understand driving behavior to create a safe and efficient traffic environment that can reduce crashes (Zhenlong Li et al., 2021). To achieve this, it is also essential to investigate the psychological factors such as driving aggressiveness and situational awareness (Dong et al., 2022) that affect driving behavior to obtain an overall acceptable driving safety performance. The term “psychosocial factors” is commonly employed in studies on driving behavior (Disassa & Kebu, 2019; Murugan et al., 2007). Irwin P. Levin et al. (1977) defined psychological factors as intervening variables connecting system, user, and environmental characteristics to observable behavior. They refer to mental and emotional characteristics that influence an individual behavior and perception in carious situation, including driving scenarios.

Connected and automated vehicles (CAVs) have a great potential for enhancing driving safety via changing driving behaviors. Connected vehicles (CV) are equipped with advanced sensors and can communicate with other vehicles, infrastructure, and devices. CV environment is an emerging system that has the potential to control and improve driving behavior by exchanging real-time traffic information which leads to better traffic safety and operation (Son et al., 2020). Advanced CV alerts are likely to reduce the impact of unforeseeable abnormal events on drivers' behavior and enhance overall safety performance. Further, the past few years have seen a remarkable advancement in the of automated vehicle (AV) technology. This is apparent from the proliferation of corporations that are actively engaged in the development of automated and self-driving capabilities, as well as the growing number of research initiatives, demonstrations, and trials of the technology in real-world scenarios (Felix et al., 2021). AVs are those in which at least some aspect of a safety-critical control function (e.g., steering, braking) occurs without direct driver input. Avs are envisioned to drastically enhance traffic safety by eliminating crashes caused by human errors. The role of human drivers regarding how they interact with AVs will be completely redefined.

1.2 Research Motivation

Previous literature has recorded an advanced level of progress in understanding the crucial role of CV technologies under certain traffic and weather conditions (Theriot, 2017; Yang et al., 2020; Adomah et al., 2021). In particular, some driving safety studies have focused on the effect of CV environment on drivers' behavior and situational awareness during clear and the adverse weather conditions (Ali et al., 2020; Khoda Bakhshi et al., 2021). Nevertheless, only a few studies have investigated the impact of warning/advisory messages on driving behavior in the light of danger of secondary crashes that might occur as a result of an earlier primary crash. To the best of the author’s knowledge, some real-world scenarios, where drivers do not have a freeway road exit (e.g., a rest area) located right before the primary crash and under clear weather conditions, are not investigated yet. In addition, the reduced visibility and turbulent traffic flow caused by adverse weather conditions, such as fog, can affect driving behavior in a negative way (Zhibin Li et al., 2014). To mitigate these effects and enhance safety outcomes, advanced alerts provided by CVs may be a promising solution. However, it is currently unclear whether CVs are effective in highway crash scenarios across varied weather conditions, as there is limited research in this area.

As AV technology rapidly advances, it becomes increasingly crucial to explore how AVs may influence driving behavior and the various factors impacting driver safety performance. This exploration should align seamlessly with the pace of technological advancements. According to Fang et al. (2022), the percentage of AVs on the road is expected to increase as AV technology continues to develop. This makes it increasingly important to further explore the potential impact of AVs on driving behavior and safety performance, as some studies have already highlighted (Rodrigues et al., 2022). In particular, several studies integrated the connectivity with AV as an attempt to understand the influence of CAV system on the driving behavior and safety outcomes (Fang et al., 2022; Chityala et al., 2020). Chityala et al. (2020) conducted research on the impact of CAVs on drivers' behaviors during merging scenarios on the ramp and freeway. The study found that drivers were willing to accept shorter headway gaps as the number of CAVs on the road increased. Fang et al. (2022) conducted a microscopic study and found that the incorporation of CAVs would result in a negative impact on traffic performance. However, the literature reveals a substantial gap in our understanding of the implications of AV and CAV technology on factors influencing drivers' safety performance during safety-critical events, especially in scenarios involving highway merging and intersections. Therefore, further research is necessary to address this gap and develop a more comprehensive understanding of how these technologies can be integrated into the transportation system safely and effectively.

Driving behavior needs to be deeply investigated and explored by rigorous statistical models to measure psychological factors affecting driving behavior directly or/and indirectly and to evaluate the interrelationships between all exploratory indicators. Using only descriptive analyses or hypothesis tests is insufficient to reveal the complex interrelationships between observed variables and the latent psychological factors. A wide range of previous studies have conducted driving simulator experiments; however, only few used advanced statistical models to best accommodate the collected data and make reliable inferences. Further, effective variable that can obtain insight in exploring driving behavior needs to be included. Along with observed variables (i.e., a speed, an acceleration, a lane offset, and a steering angle), traffic conflict an essential variable in evaluating driving behavior is not sufficiently employed.

1.3 Objectives

The overarching goal of this dissertation is to model the impact of CAV technologies on driving behaviors and safety outcomes using advanced statistical methods and data collected from driving simulator experiments. More specifically, the following research objectives will be achieved:

Research Objective I: Model the impact of CV warning messages on psychological factors such as aggressiveness and awareness under highway crash scenarios and how those psychological factors can affect driving behaviors.

Research Objective II: Model the influence of CVs on safety outcomes via changing driving behaviors in adverse weather conditions (e.g., foggy weather). Understand the interrelationship between the application of CV alerts, driving behaviors, aggressiveness, situational awareness, weather conditions, and other factors.

Research Objective III: Investigate how various factors impact the safety performance of drivers within CAVs, particularly during safety-critical events, employing networked driving simulators. Specifically, the study will focus on CAVs with Level 2 and 3 automated driving systems (ADS) and involve conducting multiple experiments in various highway and intersection settings.

1.4 Apparatus

A high-fidelity driving simulator (Realtime Technologies RDS - 1000) at Old Dominion University (as depicted in the top-left part of **Figure 1)** was utilized to conduct the driving simulator experiment. The simulator has three degrees of freedom motion (pitch, roll, and yaw) and provides a virtual testbed that closely replicates the real-world driving environment. As illustrated in **Figure 1**, the control station consists of the Host Computer, Center Channel, and SimObserver. The Host Computer serves as an interface to administer the simulator, run the main software, provide an access to the Center Channel system, and save driving experiments. The Center Channel is used to create the experiment from scratch and store the profiles of the experiment such as the driving behavior of the ambient traffic, a wide variety of engine sounds, and alert/warning messages. As shown in **Figure 2,** SimObserver is able to capture data and video recordings in real-time at a rate of 60 Hz, in four synchronized views (main, front, side, and bottom) of each driving scenario along with collected driving data simultaneously. As a part of the software suites, SimDriverDX can enable researchers to develop driving experiments with the desired scenarios. Data Distillery can be utilized to replay captured videos, look into data spreadsheets, and create graphs of any desired variables.

Studying multi-driver crashes in great detail is a task that most driving simulator laboratories are not capable of achieving (Schwarz et al., 2017). To enable synchronized driving scenarios in which two drivers could interact in the same virtual driving environment, a desktop driving simulator (RDS-100, Realtime Technologies) as illustrated in the right side of **Figure 1** was used in addition to the high-fidelity driving simulator (RDS-1000, Realtime Technologies) mentioned previously. The ODU's distributed driving simulator environment presents a unique opportunity to explore the new and largely uncharted area of interactive driving behaviors within CV and AV scenarios, as well as a wide variety of road geometries such as highway and signalized and non-signalized intersections.

Figure 1. Networked driving simulator environment at Old Dominion University

Figure 2. Four synchronized views on SimObserver

1.5 Research Framework

CVs and AVs are rapidly emerging technologies that have made significant progress in the last decade. However, there are still insufficient studies on understanding the influence of these technologies on driving behaviors and safety outcomes through utilizing advanced statistical methods. In an effort to address this research gap, this dissertation outlines three related driving simulator studies, each of which contributes a crucial building block to the overall structure of the dissertation.

The research framework of the proposed dissertation is presented in **Figure 3**. The subsequent section provides a literature review focused on the impact of CVs on driving behavior and safety outcomes, AVs, and CAVs, adverse weather conditions, traffic conflict points, as well as a few articles that have adopted SEM. To address Research Objective I, Chapter 3 provides a detailed examination of a driving simulator study that investigates the impact of CVs on psychological factors such as driving aggressiveness and situational awareness. In Chapter 4, the main objective is to fulfill Research Objective II, which involves investigating the impact of CVs on driving behavior and safety outcomes in various weather conditions. Finally, to achieve Research Objective III, Chapter 5 explores the factors impacting drivers' safety performance within CAVs during safety-critical events, including highway merging and intersection scenarios.

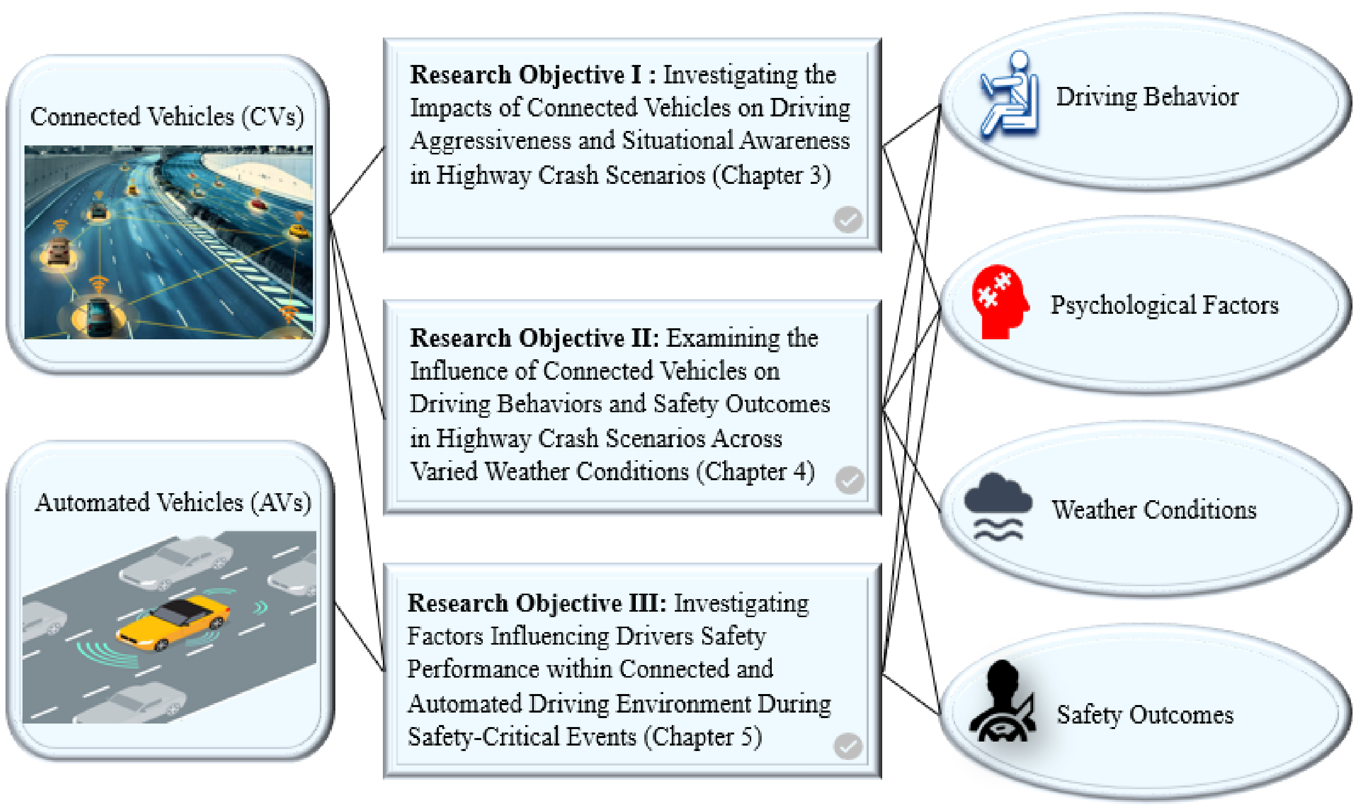


Figure 3. Research framework

CHAPTER: 2

LITERATURE REVIEW

This chapter comprises of five sections. The initial section presents an overview of the literature on CV technology, emphasizing its possible impact on driving behavior and safety performance. The section describes various driving simulator experiments featuring diverse driving scenarios. The second section delves into AV technology, covering its definition, classification, and recent research. Additionally, the section discusses CAV and its potential influence on driving behavior and safety. The third section provides a summary of studies conducted on the impact of adverse weather conditions on driving behavior and safety, as well as the potential role of CVs in mitigating these effects. The fourth section highlights studies that have explored the occurrence of traffic conflicts and their contribution to better understanding driving behavior and safety performance. Finally, the last section presents studies that have used structural equation modeling (SEMs) and summarizes their rigorous approach in evaluating complex relationships.

2.1 Connected Vehicles

Previous studies have conducted driving simulator experiments to explore the impact of CVs on psychological factors such as drivers' aggressiveness and situational awareness (Gugerty, 2011; Wang et al., 2019; Fitzpatrick et al., 2017). Li et al. (2018) found that drivers' awareness with CV notifications applied, in the work road environment, significantly outperformed non-CV scenarios. Acceptable values and ranges, which led to a safer driver's performance, for variables such as deceleration rate, lane changing, and speed were reported in the forward alert messages.

24 participants were involved in a driving simulator experiment to assess the visual fidelity impact on driving performance, gaze behavior, and subjective discomfort survey (Leeuwen et al., 2015).

To evaluate the driving performance, dependent variables, e.g., the average and standard deviation of absolute lane deviation, speed, and the percentage of steering wheel steadiness, were utilized. The results showed that speeds and steering in the high-fidelity phase were observed to be more than low fidelity. Situational awareness is acknowledged to be a viable variable to identify driving performance (Alyamani & Kavakli, 2017). Khoda Bakhshi et al. (2021) concluded in their driving simulator study that CV warning messages on slippery horizontal curves can decrease the prospect of curve segment crashes. The study reported that the CV led to enhanced situational awareness and a reduction in aggressive driving behavior. Yang et al. (2020) carried out a microscopic simulation and modeling framework study to test the CV, V2V, and its influence on secondary crashes. It was stated that the connectivity can improve the situational awareness and aggressive behaviors of motorists, which ended up in a meaningful enhancement of highway traffic safety. Adomah et al. (2021) investigated the ability of CV forward warnings on Interstate-80 (I-80) to enhance the drivers' behaviors in the work zone locations. According to the results of the driving simulator experiment, it was found that the situational awareness of vehiculars has been improved leading to a better performance assessment of CV in work zone areas. Theriot (2017) developed a driving simulator test bed of a four-lane arterial highway scenario to examine the role of the CV system under blind spot warning (BSW) and do not pass warning (DNOW) to improve traffic safety performance. It was highlighted that the CV safety applications with a market penetration (MP) of 50% would increase the situational awareness of drivers and as a result a significant safety enhancement. Drivers who are prone to abnormal traffic conditions (e.g., traffic congestion induced by primary crashes) may be more suscptible to turbulent driving behaviors and lack of situational awareness. Zhao et al. (2021) found that the CV application was able to improve driving safety by inducing drivers to be more cautious on the road and enhancing driving behavior.

Osman et al. (2015) conducted a driving simulator experiment with CV applications and classified 30 participants into aggressive and non-aggressive drivers. It was found that warning messages induced aggressive drivers to enhance their traffic safety by raising their time to collision (TTC). Li et al. (2020) recruited 25 participants in a driving simulator experiment to assess the traffic congestion possible effect on driver behavior on the post-congestion roads. Performance measures such as steering angle, lane offset, speed, and longitudinal acceleration were collected, and the results suggested that under such circumstances, the driver's behavior tended to be more aggressive (e.g., higher speed, acceleration rate, and lane changing increase) along with the deterioration of the situational awareness.

The effectiveness of CV technology in highway crash scenarios has been studied to a less extent. Secondary crashes are a significant category of highway crashes and it has been found that every elven primary crashes that occur, there is one additional secondary crash that is caused as a result (Yang et al., 2013). Gaweesh et al. (2021) investigated the impact of CV environment in alleviating the potential safety risk of secondary crashes. 23 participants completed the driving simulator experiment with CV and non-CV scenarios. It was reported that the CV system was able to reduce variation and the mean of driving speed. Upon receiving alerts, participants selected to take a detour option rather than heading to the primary crash location. Although the article provided a valuable result, it is not always the case that such a detour is available at the occurrence of the primary crash; therefore, such a crash scenario needs to be assessed and further studied. Similarly, Son et al. (2020) designed driving simulator experiments to assess driving behavior on secondary crash danger by adopting the CV technology. The authors recruited 26 drivers with an age group from 21 to 33 years to be involved in this study. Data was obtained, speeds, accelerations, and brake forces, to be utilized in data analysis models such as t-test, MANOVA, and ANOVA tests. It was reported that in general, the CV system has positively influenced hindering the risk of secondary crashes. Furthermore, a microscopic traffic modeling and simulation framework was carried out by Yang et al. (2017) to measure the influence of CV vehicle-to-vehicle (V2V) on secondary crashes' imminent risk. It was revealed that the hazard of secondary crashes can be remarkably decreased when adopting CVs. In summary, the literature showed that CV technology could positively influence traffic safety performance by altering driving behavior. However, a few studies have highlighted the role of CV in rectifying driving behavior under highway crash scenarios and the majority of them lack the development of rigorous statistical models to measure latent psychological factors (e.g., aggressiveness and situational awareness) and capture the interrelationship between CV alerts, driving behavior, psychological factors, and other factors. Thus, in this study, we design a driving simulator experiment under highway crash scenarios to gain further insights into the impacts of CVs on psychological factors and driving behavior. The SEM is a powerful tool as it can concurrently conduct the measurement and structural models and reveals the direct and indirect relationships between variables.

2.2 Automated Vehicles

As autonomous driving technology advances, the burden of responsibility increasingly rests on the autonomous system rather than the human driver, thereby reducing the workload of the latter (Hofbauer et al., 2020). The classification system established by the Society of Automotive Engineers (SAE) delineates vehicle automation into six distinct levels. Specifically, Levels 3 to 5, denoted as the Automated Driving System (ADS), represent the pinnacle of automation, signifying their capacity to function autonomously during driving operations (SAE International, 2018). Nevertheless, at Level 3, it is noteworthy that driver intervention is required when the operational design domain (ODD) system encounters a failure, and this automated vehicle possesses mechanisms for returning control to a human driver under specific circumstances. Conversely, Level 0 (entailing no driving automation), Level 1 (emphasizing driver assistance), and Level 2 (involving partial automation) necessitate the active participation of the driver in vehicle operation, accompanied by the concomitant responsibility for their actions (SAE International, 2018). This spectrum, ranging from Level 0 to Level 2, encompasses a spectrum of driver assistance features, encompassing rudimentary functionalities like cruise control and extending to sophisticated attributes such as traffic jam assistance, lane centering, and parking assistance.

CAVs are an emerging technology that have garnered the attention of researchers and inspired them to conduct studies to investigate and explore their potential impacts. An appropriate level of human behavior integration is vital for the successful deployment of CAV applications, particularly during the early stages when CAVs and human-driven vehicles will interact and coexist on the same roadways in a mixed traffic environment (Ahmed et al., 2022).

Ahmed et al. (2022) underscore the critical significance of effective communication in the context of CAVs. The study implemented by (Peng et al., 2023) aimed to investigate the influence of CAV technology on the gap acceptance behavior of vehicles at unsignalized intersections. The researchers developed a driving simulator experiment. The analysis of the experiment's results revealed that CAVs with a smaller car-following distance on a minor road are more likely to accept gaps or lags aggressively, resulting in a decrease in the critical gap and an increase in the acceptance probability. Conversely, a shorter car-following distance for CAVs leads to longer platoons and shorter gaps on a major road, ultimately reducing the acceptance probability. In various driving simulator studies, researchers have employed a networked simulator capable of accommodating multiple drivers. (Schwarz et al., 2017; Abdelgawad et al., 2016; Sadraei et al., 2020). Two or more driving simulators are linked by a local network so that operators of all simulators can share the same driving environment. This allows researchers to conduct more realistic driving scenarios, such as analyzing the impact of CAV systems on driving behavior while involving two drivers simultaneously. The distributed driving simulators provide a controlled and safe virtual testing environment for this type of research. With a multi-driver simulator, researchers can investigate driver interaction and evaluate the effectiveness of new cooperative Intelligent Transportation Systems (ITS), in addition to addressing broader research questions related to driver behavior (Oeltze & Schießl, 2015). In a recent study conducted by Yue et al. (2021), a multi-driver simulator system was used to evaluate how the merging algorithms employed CAVs affect the driving behavior of human-driven vehicles on the main roadway. The goal of this investigation was to assess the impact of CAV merging algorithms on human-driven vehicle behavior and to validate these algorithms using realistic driving behavior. The authors analyzed four distinct merging algorithms, including the reference trajectory-based merging algorithm and the social-psychology-based merging algorithm. While these algorithms showed promising results during initial simulation studies, the study found that their effectiveness varied significantly when realistic driving behavior was introduced into the experiment. In their recent study, Park et al. (2019b) utilized networked driving simulators to evaluate the crash potential of aggressive driving events on freeways. By incorporating a microscopic traffic simulation model, VISSIM, and modifying driving behavior parameters using the driving simulation results, the study found that aggressive driving negatively impacted both network safety performance and mobility. The driving simulation results were used to modify the driving behavior parameters of VISSIM. The study found that aggressive driving not only reduced network safety performance, as measured by the crash potential index (CPI), but also mobility, as indicated by travel speeds.

Despite the growing interest in CAVs, there is a lack of research that has utilized networked driving simulators to explore the impact of this technology on driving behavior and safety performance. The proposed research study aims to address the identified gap by designing and conducting multiple driving simulator experiments. The study will investigate eight different scenarios, specifically under highway and intersection settings such as signalized and non-signalized intersections. The focus will be on Level 2 and Level 3 Automated Driving Systems (ADS), with the aim of gaining a deeper understanding of the impacts of CAVs on psychological factors and driving behavior. According to SAE International, (2018), the dynamic driving task (DDT) is the complex task of driving a vehicle in a changing environment. The Society of Automotive Engineers (SAE) has classified Automated Driving Systems (ADS) into six levels of automation. Levels 3 to 5 indicate the automated driving features, but Level 3 requires the driver's intervention when assistance is needed or if there is a system failure. Conversely, Levels 4 and 5 can operate without any driver intervention, although Level 4 must meet certain restrictions to work adequately. On the contrary, Level 5 has no limitations and can function anywhere and under any circumstances. (SAE International, 2018). The levels of driving automation range from no automation (level 0) to full automation (level 5), depending on the roles of the driver, vehicle, and driving automation system. Crash avoidance features can be integrated into vehicles with driving automation at any level. For vehicles equipped with ADS such as levels three to five, crash avoidance is part of the ADS functionality. Despite advanced automation, safety systems such as emergency braking remain critical components of a vehicle's safety system, as safety is always a top priority.

2.3 Adverse Weather Conditions

Weather conditions are considered an essential safety factor and have grabbed researchers' attention. Li et al.(2015) designed a driving simulator experiment to assess the relationship between driving behavior on a continuous S-curve and foggy weather status and other variables. The results suggested that motorists were inclined to practice cautious driving during a severe fog. The foggy status could lead to decreased sight distance, which forced drivers to conduct a risky behavior to hinder a potential rear-end collision (Shangguan et al., 2020). Li et al. (2014) developed a VSL control strategy to mitigate the danger of secondary collisions during inclement weather by proposing two traffic conflict indicators. The authors found that VSL could significantly decrease the likelihood of secondary collisions risks. Huang et al. (2020) investigated the patterns of driving behaviors in a vehicle fleet using a multi-user driving simulator under three foggy conditions. They reported that the length of vehicle fleet was reduced when fog density was increased.

CV technology and its safety benefit have been studied by several researchers (Yang et al., 2017; Xie et al., 2018; Osman et al., 2015; Adomah et al., 2021; Zhao et al., 2021) from different perspectives and concerns. Yang et al. (2020) evaluated the effectiveness of CV alerts on drivers' speeds under various weather conditions. The results showed that mean speed values were lower in CVs than without CVs. Zhao et al. (2019) conducted a driving simulator experiment to assess the impact of variable speed limit in the CV technology (CV-VSL) by investigating drivers' reactions to CV alerts in multiple foggy weather conditions (i.e., no fog, slight fog, and heavy fog). The results found that the CV-VSL application was significant in decreasing drivers' travel speeds. In their driving simulator experiments, Abdel-Aty et al. (2018) and Gaweesh et al. (2021) also concluded that CV alerts could provide a significant safety benefit and reduce the operating speeds during unusual weather conditions. Gouribhatla & Pulugurtha (2022) performed a driving simulator experiment to assess the impact of advanced driver assistance system (ADAS) on drivers' behavior under various weather conditions. The result revealed that ADAS could effectively reduce the lane departures, speeding, and improving overall safety. Ali et al. (2020) investigated the impact of the CV environment on driving behavior and suggested that a favorable CV environment has the potential to positively affect drivers' behavior and safety. In addition, aggressiveness in driving and situational awareness are crucial factors that affect driving behavior and overall performance. It was illustrated that CVs could play a crucial role in mitigating the risks of such safety issues (Gugerty, 2011 ; Wang et al., 2019; Fitzpatrick et al., 2017; Li et al., 2018). Zhenlong Li et al. (2021) developed a driving simulator experiment to evaluate the effect of CV technology on driving behavior and safety in a tunnel entrance zone and a warning zone. The authors used the one-way ANOVA for comparisons between indicators. It was found that with the CV warning, the speed tended to be stable, and the likelihood of an accident risk was decreased 100 meters before the entrance of the tunnel as drivers could realize the tunnel in advanced. Therefore, this study aims to develop a driving simulator experiment under foggy weather conditions and in a freeway scenario to assess driving behavior and situation awareness levels after implementing proposed CV alerts.

2.4 Surrogate Safety Measures

Surrogate safety measures (SSM) play a crucial role in traffic safety assessment, primarily because reliable statistical safety models are often unavailable (Wang et al., 2021). One of the widely used applications of SSM is the assessment of vehicle interactions, with post-encroachment time (PET) being a key measure. PET is defined as the duration between when the first vehicle vacated a position and when the second vehicle subsequently occupied the same position (Gettman et al., 2008). PETs excel at accurately capturing angle/crossing conflicts when compared to other measures like TTC (Abdel-Aty et al., 2023; Wang et al., 2021). Karbasi & O'Hern, (2022) employed a traffic simulation tool to evaluate the impact of CAVs on road safety, employing SSM like TTC. They conducted two case studies, one involving a signalized grid network and the other an unsignalized intersection. The results suggest that CAVs have the potential to reduce conflicts, a finding consistent across both case studies. Notably, while this research offers valuable insights, it's worth noting PET demonstrate superior accuracy in capturing angle/crossing conflicts when compared to other measures, such as TTC (Abdel-Aty et al., 2023; Wang et al., 2021). Zheng et al. (2019) introduced a research method employing a bivariate extreme value model, specifically targeting rear-end conflicts occurring at signalized intersections. This method incorporates a range of traffic conflict indicators, including PET, to estimate road safety. Islam et al. (2023) computed PET between vehicles using video data to explore the correlation between PET and signal phasing at a major intersection. PET values ranging from 1 to 5 seconds were examined. The findings revealed that drivers tended to follow closely during the final moments of the yellow phase and throughout the duration of the all-red phase. Zheng et al. (2018) employed PET along with another SSM and proposed a modeling approach to estimate crashes associated with merging events at freeway entrance ramps. In a study conducted by Chen et al. (2017), drone-captured videos at an intersection were employed to compute PET, along with another measure, as a means to assess the risk of vehicle-pedestrian crashes at an urban intersection in China. In summary, although PET has demonstrated its value as an important SSM, there is a lack of research studies that have utilized PET to explore the influence of CAVs on safety-critical events, such as intersections and highway merging.

Multiple studies have investigated traffic conflict points as a crucial factor in enhancing traffic safety, employing SSM to achieve more robust safety performance evaluations. However, there is a shortage of studies that have employed traffic conflict as a factor to assess safety performance when developing latent variables related to psychological factors such as aggressiveness and unawareness. In a driving simulator experiment, It was found that among seven types of crash avoidance maneuvers, the brake response was the most repeated response to hinder the conflicts points (Li et al., 2019). In a study by Abdel-Aty et al. (2022), 36 participants were recruited for a driving simulator study to evaluate proposed variable pedestrian-to vehicle (P2V) warmings. The results revealed that utilizing warnings that can be gradually changed based on P2V distance might lead motorists to perform gradual driving adjustments to approaching conflicts and enhance driving performance. Reducing conflict between vehicles can be achieved in various scenarios. Reinolsmann et al. (2021) proposed active gap metering (AGM) warning signs to reduce conflict and enhance drivers' responses to merging on- ramp vehicles. The driving simulator study found that the AGM positively impacted driving behavior on the right lane where the distance to the lead vehicle was gradually incremented, leading to optimal headway merging on-ramp vehicles. Driver characteristics (i.e., gender and age) and the number of conflicts were found to be effective in exploring the safety performance effects on drivers' behavior (i.e., lane change) (Yuan et al., 2018). Yi et al. (2018) conducted a driver simulator study of construction conflict periods by using drivers' eye movements. The results suggested that the mean and maximum values of the pupil diameter might be considered as indices to identify conflicts.

2.5 Structural Equation Modeling (SEM)

The SEM is a multivariate statistical method that can be used to assess the degree to which a theory's relationships between observed and latent variables correspond to actual data , and it is able to test a series of dependent relationships simultaneously (Hair et al., 2009). The SEM consists of a couple of statistical methods including latent variable measurement and path analysis (Fan et al., 2016). Dion (2008) highlights several advantages of SEM. One notable benefit is the ability to estimate all coefficients in a model simultaneously, which allows for a comprehensive evaluation of individual relationships within the overall model. SEM also provides a solution for the problem of multicollinearity, which is commonly encountered in multiple regression analysis. In contrast to regression, SEM can handle situations where an independent variable becomes a dependent variable. Moreover, the use of latent variables in SEM eliminates measurement errors and results in obtaining more valid coefficients. In a driving simulator study, Wu et al. (2018) utilized partial least squares (PLS), one method of the SEM, to assess the impact of auditory alert features. The PLS found that direct and indirect impacts were observed to affect the crash's occurrence. Xie et al. (2017) adopted SEM to investigate the influence of secondary collisions on injury severity levels and risk factors responsible for secondary collisions. It demonstrated the advantage of using SEM in exploring the structural relationship in comparison to other statistical models. Dong et al. (2022) used the SEM to explore the changing in driving behaviors, after the outbreak of the COVID-19 pandemic, and its impact on the probability of crash severity. It was shown that the aggressiveness and inattentiveness of motorists spiked after the pandemic. An additional driving simulator study by Papantoniou (2018) adopted SEM in order to analyze the latent variables of weather conditions and multiple risk factors on the general driving performance. The SEM succeeded in evaluating the driving behavior not only on a one-dimensional scale, but also through overall performance. Asadamraji et al. (2019) applied SEM to determine the link between demographic and lifestyle and the driver response to road hazards. In a driving simulator test, Zhao et al. (2019) employed SEM to explore factors posing deteriorated driving behaviors and exposed sophisticated relationships among dependent and independent variables. Zolali et al. (2021) used SEMs to capture the interrelationships between variables. Eleven explanatory indicators and four latent variables were developed to explore the direct and indirect relations. The results revealed some positive and negative relationships (i.e., the mean speed was associated with “Novice Drivers”).

2.6 Summary

In summary, regarding Chapter 3, the literature showed that CV technology could positively influence traffic safety performance by altering driving behavior. However, a few studies have highlighted the role of CV in rectifying driving behavior under highway crash scenarios and the majority of them lack the development of rigorous statistical models to measure latent psychological factors (e.g., aggressiveness and situational awareness) and capture the interrelationship between CV alerts, driving behavior, psychological factors, and other factors. Thus, in this study, we design a driving simulator experiment under highway crash scenarios to gain further insights into the impacts of CVs on psychological factors and driving behavior. The SEM is a powerful tool as it can concurrently conduct the measurement and structural models and reveals the direct and indirect relationships between variables.

For Chapter 4, previous studies showed that driving simulators offer several advantages for testing CV applications in a costly-effective and informative manner, particularly in unclear whether conditions such as fog, where visibility is greatly reduced. This can lead to a better overall safety performance, particularly with regards to the risk of secondary crashes. However, using a simple and basic statistical model, as used in most previous studies, may not always reveal latent or indirect factors. Therefore, this chapter aims to develop a driving simulator experiment under foggy weather conditions and in a freeway scenario to assess driving behavior and situation awareness levels after implementing proposed CV alerts. The chapter also plans to utilize SEM models as they are rigorous statistical models that can capture the indirect relationships among related variables simultaneously.

For Chapter 5, the investigation aligns with existing literature, revealing a noticeable scarcity in research utilizing distributed driving simulators to understand the impact of CAV technologies on driving behavior and safety performance. This gap is particularly pronounced in safety-critical events like running red light intersections, running stop sign intersections, and highway merging scenarios. While some studies employed the logit model in driving simulator investigations, only a few delved into the logit model's participant-specific random effect to deeply understand the relationships between variables. This chapter bridges this gap by examining the factors influencing driver safety performance in CAVs during takeover events. Utilizing networked driving simulators, scenarios involving running red lights/stop signs and highway merging are simulated, employing logit models with individualized random effects to scrutinize the relationship between safety performance and influencing factors.

CHAPTER 3

INVESTIGATING THE IMPACTS OF CONNECTED VEHICLES ON DRIVING AGGRESSIVENESS AND SITUATIONAL AWARENESS IN HIGHWAY CRASH SCENARIOS

The way drivers behave on the road can be influenced by a number of psychological factors, including their level of aggressiveness and situational awareness. CVs have the potential to enhance driving performance by incorporating advanced sensors and communication features that enable them to send safety messages to drivers, potentially mitigating the impact of these psychological factors. This chapter explores the effects of CVs on driving behavior in highway crash scenarios, where a second crash may occur after a primary crash has already happened. To explore this topic, we developed a driving simulator experiment and distributed questionnaires to evaluate driving aggressiveness and the effectiveness of CVs. The study employs SEM to examine the interrelationships between the use of CV alerts, psychological factors, driving behavior, and other relevant factors, providing valuable insights into the potential impacts of CVs on road safety.

3.1 Experiment

3.1.1 Participants

A total of 26 participants with valid US driver's licenses and at least one year of driving experience were recruited for the experiment. The sample size is similar to some recent studies (Yang et al. 2020; Alyamani and Kavakli 2017; Son et al., 2020; Li et al., 2020). One participant encountered motion sickness and dropped out of the experiment, resulting in valid data from 25 participants. The participants consisted of various age groups from 46 to 22 years old (mean = 31.00 years, standard deviation = 6.03 years). The participants were all in good general health and had driving experience between 1 year and 34 years (mean = 12.04 years, standard deviation = 7.99 years). There were 21 male and 4 female participants.

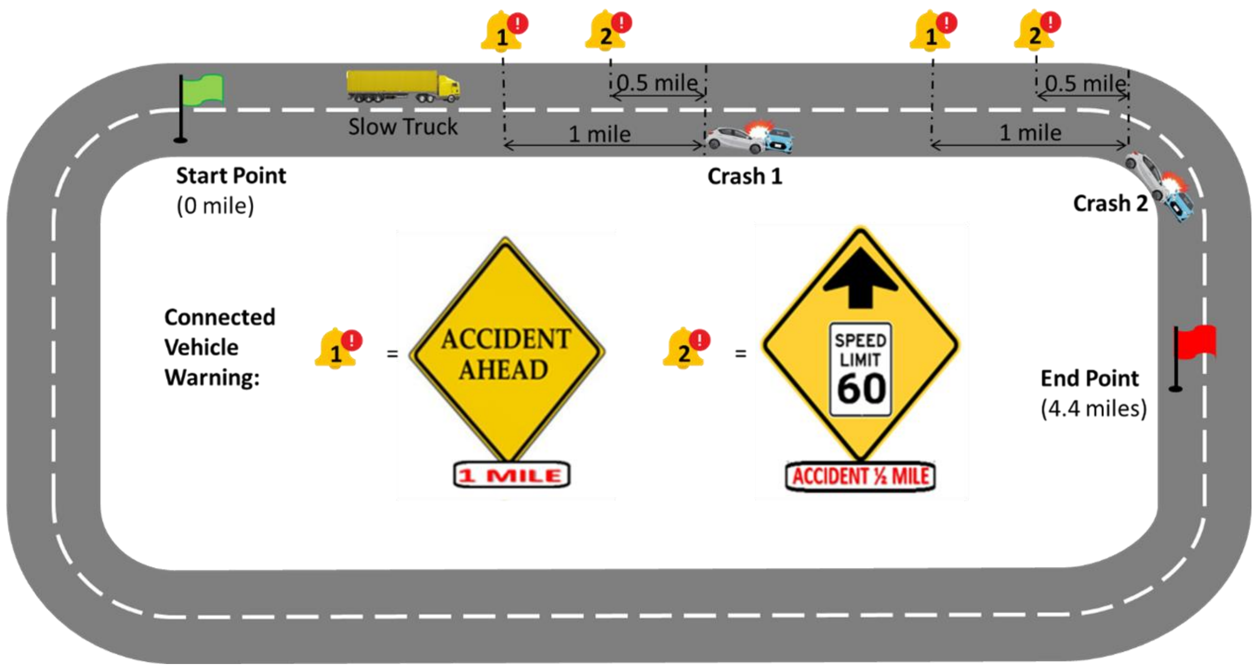
3.1.2 Procedure

Upon the arrival of the participants, each one read and signed a consent form that described the experiment and cautioned the possibility of motion sickness. It was highlighted that participants were free to quit at any time if motion sickness appeared or they were unwilling to persist for any other reasons. After signing the consent form, participants filled in pre-experiment questionnaires on demographics and driving aggressively. All participants carried out five to ten minutes of warm-up driving to familiarize themselves with the simulator and virtual driving environment before the experiment. After completing all the driving scenarios, participants were instructed to complete a post-experiment questionnaire form, report their opinion about the proposed CV scenarios, and answer the rest of the associated questions. A simulator sickness questionnaire was also filled out, where participants reported the severity of each symptom ordered by none, slight, moderate, and severe. Only one participant had moderate discomfort and quit consequently.

3.1.3 Scenario Development

The virtual driving environment was designed based on a two-way four-lane freeway. The posted speed limit was set to be 70 mile/hour, which is the maximum speed limit in the state of Virginia. To study the driving behaviors in response to crashes under different road geometric designs, we located two crashes, one on a straight section and the other on a horizontal curve, as illustrated in **Figure 4**. Both crashes occurred on the right lane. Reroute maneuvers were used to move ambient traffic gradually to the unblocked left lane when approaching each crash location, which would replicate the real-world driving behavior.

Each participant was tested in two driving scenarios: 1) the control scenario without a CV warning and 2) the experimental scenario with a CV warning. To account for the learning effect of participants, counterbalancing was implemented to have half of the participants drive in the control scenario first and the other half in the experimental scenario first. Additionally, some freeway landmarks, vegetation, and surroundings were changed to make the control and experimental scenarios appear different from each other.



(a)

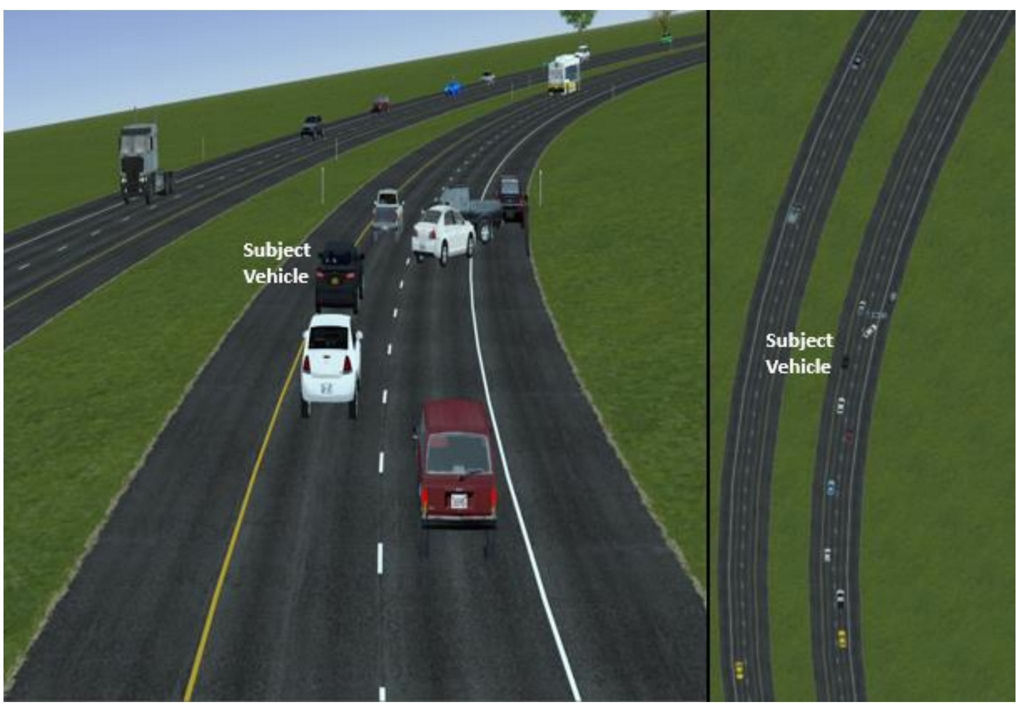
(b)

Figure 4. Driving simulator experiment scenario: (a) driving simulator scenario layout; (b) connected vehicle warning presented on the front screen.

Drivers were asked to drive in accordance with their normal practices and had the option to change lanes. As illustrated in **Figure 4 a**, the truck driving slowly on the left lane to encourage the drivers to change from the left to the right lane as the proposed crash is located; the drivers in the experimental scenario received two CV warnings one mile and a half mile prior to arriving at each crash location. The first warning was to prepare drivers for the upcoming traffic crash. The second one advised a reduction in speed limit by 10 mile (i.e., from 70 to 60 mile/hour), which was a common practice (Board, 2000; Li et al. 2018; Control, 2015; Abdel-Aty & Wang, 2017). The warning messages, as shown in **Figure 4 b**, were presented near the top left corner of the front screen and came along with a beeping sound to grab drivers' attention. We designed the warning signs based Federal Highway Administration (FHWA)'s Manual on Uniform Traffic Control Devices for Streets and Highways (MUTCD), which provides widely adopted guidelines for sign design. As presented in **Figure 4 a**, we slightly modified MUTCD signs by adding short texts at the bottom to convey more information on crash locations.

Data privacy and confidentiality were assured to all participants to maintain the Human Subjects Research (IRB) instructions. The driving data were collected at a rate of 60 observations per second within a single timeframe, encompassing 164 feet before the initial CV warning and extending 656 feet beyond the crash site. This uniform data collection approach was applied to both crash instances. The distance between the CV warning and the crash location is one mile for both the straight and curved segments, as depicted in **Figure 4 a**. The presentation of the first crash site can be seen in **Figure 5 a**, while the second crash site is illustrated in **Figure 5 b**. The descriptions and descriptive statistics of speed, longitudinal acceleration, brake, lane offset, steering, and yaw are listed in **Table 1**.

(a)



(b)

Figure 5. Traffic scenarios: (a) crash 1; (b) crash 2

Table 1. Descriptive analysis and descriptions key variables (N = 100 observations)

Variable	**Description**	**Statistics**	**Control**		**Experimental**	
			Crash 1	**Crash 2**	**Crash 1**	**Crash 2**
Speed	Longitudinal speed (mph)	SD	15.47	15.36	24.35	18.74
		Mean	56.05	54.15	54.70	55.18
		Max.	72.92	71.84	76.12	72.24
		Min.	28.00	24.68	8.12	15.16
Longitudinal Acceleration	Negative numbers are decelerations (ft/ s^2)	SD	3.94	3.51	5.25	4.26
		Mean	-0.39	-0.52	-0.98	-0.85
		Max.	4.53	5.58	8.40	6.50
		Min.	-17.06	-14.60	-21.13	-18.57
Brake	Brake force ranged between 0 and 38 (lb)	SD	3.50	2.75	4.94	3.76
		Mean	1.23	0.99	1.88	1.31
		Max.	16.77	13.48	21.65	18.44
		Min.	0.00	0.00	0.01	0.01
Lane Offset	vehicle's position from the center of the lane (ft).	SD	1.51	1.48	1.18	1.08
		Mean	-0.46	-0.49	-0.52	-0.72
		Max.	5.77	5.71	3.02	2.30
		Min.	-5.74	-5.84	-4.36	-4.10
Steering	The steering wheel angle (radians)	SD	0.16	0.09	0.12	0.15
		Mean	-0.01	0.00	0.04	0.02
		Max.	0.60	0.46	0.61	0.62
		Min.	-0.74	-0.41	-0.43	-0.60
Yaw	Rotation about a vertical axis (degree)	SD	1.37	1.22	13.66	12.71
		Mean	-0.04	0.03	10.01	8.24
		Max.	4.88	5.55	40.87	41.28
		Min.	-5.18	-3.86	-0.88	-0.69

3.1.4 Questionnaire Surveys

The driving aggressiveness of participants was measured in the pre-experiment questionnaire survey. The ADBS developed by Houston and Harris (2003) and validated by Houston et al. (2006) was deployed to examine driving aggressiveness, with Likert scale responses are reported in **Table 2**. It was designed to be a self-assessment instrument to measure aggressive driving behaviors by focusing on two factors (conflict and speeding). The first seven questions investigate the conflict behaviors and the last four measure the speeding conflict.

The result of the post-questionnaire experiment is presented in **Table 3**. In general, the participants agreed that the simulated experiment can well represent real-world driving scenarios. They reported a good level of perceived safety and a positive attitude towards the CV warning system. Most of them thought that warning messages were effective in enhancing their situational awareness and enabled them to take precautions.

Table 2. Results of the pre-experiment questionnaire on driving aggressive (1= "Never", 2= "Almost never", 3= "Sometimes", 4= "Fairly often", 5= "Very often", 6= "Always")

Variable	**Mean**	**SD**
Intentionally tap my brakes when another car follows too closely?	2.36	1.63
Make rude gestures at other drivers when they do something I don't like?	2.00	0.96
Honk when another driver does something inappropriate?	2.88	1.39
Merge into traffic even when another driver tries to close the gap between cars?	2.16	1.37
Speed up when another car tries to overtake me?	2.20	1.29
Follow another car in front of me closely to prevent another car from merging in front of me?	2.08	1.32
Flash my high beams at slower traffic so that it will get out of my way speeding?	2.28	1.51
Follow a slower car at less than a car length?	2.60	1.50
Drive 20 miles per hour faster than the posted speed limit?	2.44	1.26
Pass in front of a car at less than a car length?	1.84	0.99
Accelerate into an intersection when the traffic light is changing from yellow to red?	3.04	1.31

Table 3. Results of the post-experiment questionnaire (1 = "Strongly Agree", 2 = "Agree", 3 = "Uncertain", 4 = "Disagree", 5 = "Strongly Disagree")

Variable	Mean	SD
After completing the driving experiments, I can say that the driving simulator experience generally is realistic?	2.04	0.84
In general, I feel safer and more confident when driving with warning messages?	1.56	0.65
The alerts were reliable as they have appeared on time; hence I had an adequate time to react properly?	1.44	0.58
The warning /advisory visualizations were clear and easy to follow?	1.48	0.59
The warnings were not distracting me from my main driving tasks?	1.64	0.95
The warning messages were effective in enhancing my situational awareness and enabled me to take precautions?	1.44	0.65

3.2 Structural Equation Modeling

3.2.1 Model Specification

The SEM framework is utilized to transform multiple driving behavior indicators into aggressiveness and situation awareness latent variables and look at interrelationships between latent variables, CV, and other contributing variables. The conceptual framework of the proposed SEM is illustrated in **Figure 6**. The model hypothesized that drivers' behaviors would be affected by the proposed CV system, crash locations, drivers' characteristics, and the aggressiveness questionnaire. Hypothetically, motorists tended to drive less aggressively and with better situational awareness when the CV technology was adopted. A couple of latent variables were constructed, i.e., aggressiveness and awareness of drivers, which are represented by several driving indicators (e.g., longitudinal speed and acceleration) and affected by CV, crash locations, and other factors.

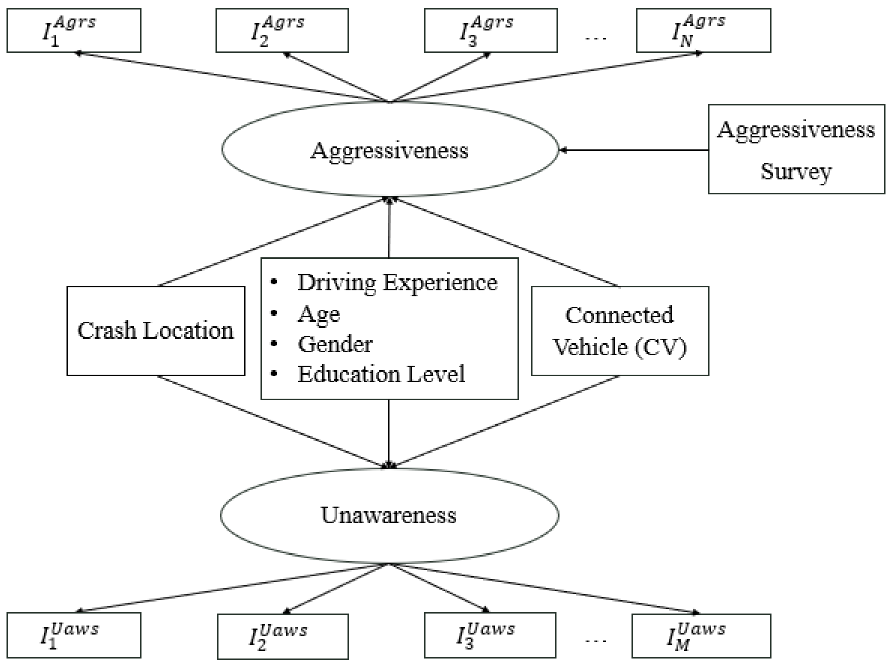


Figure 6. Conceptual path diagram of the proposed SEM

The prosed structural equation modeling is expressed through the following formula:

$$Agrs_i = \boldsymbol{X_i \alpha_{11}} + \alpha_{12}CV_i + \alpha_{13}CL_i \ + \alpha_{14}PAgrs_i + \varepsilon_i^{Agrs} \tag{1}$$

$$Uaws_i = \boldsymbol{X_i \alpha_{21}} + \alpha_{22}CV_i + \alpha_{23}CL_i \ + \varepsilon_i^{Uaws}$$

where i $(i = 1, 2, \dots, N)$ is the index for driving scenarios characterized by study subject, the presence of CV alert, and crash location; $Agrs_i$ is a latent variable measuring aggressive driving behaviors; $Uaws_i$ is a latent variable measuring situational awareness (the term unawareness is used for simplicity); $\boldsymbol{X_i}$ is a vector of drivers' characteristics such as experience, age, gender, and education level; CV_i indicates the presence of a CV alert (0 for no CV alert and 1 for CV alert);

CL_i indicates crash location (0 for the first crash on the tangent and 1 for the second crash on the curve); $PAgrs_i$ is the perceived aggressiveness, measured by the average score in the aggressiveness survey; $\boldsymbol{\alpha_{11}}$ and $\boldsymbol{\alpha_{21}}$ are vectors of coefficients corresponding to $\boldsymbol{X_i}$; α_{12} and α_{22} are coeffects corresponding to CV_i; α_{13} and α_{23} are coeffects corresponding to CL_i ; α_{14} is a coefficient corresponding to $PAgrs_i$; ε_i^{Agrs} and ε_i^{Uaws} are normally distributed errors. The measurement model is the SEM is given by:

$$\boldsymbol{I}^{Agr} = \boldsymbol{Agrs}\,\boldsymbol{\Lambda}^{Agrs} + \boldsymbol{\delta}^{Agr} \tag{2}$$

$$\boldsymbol{I}^{Uaws} = \boldsymbol{Uaws}\,\boldsymbol{\Lambda}^{Uaws} + \boldsymbol{\delta}^{Uaws}$$

where $\boldsymbol{I}^{Agrs}$ is a ($N \times p$) matrix of the observed driving behaviors associated with aggressiveness; $\boldsymbol{I}^{Uaws}$ is a ($N \times q$) matrix of the observed driving behaviors associated with situational awareness; $\boldsymbol{Agrs}$ is a ($N \times 1$) vector of the latent variable aggressiveness; $\boldsymbol{Uaws}$ is ($N \times 1$) vector of the latent variable situational awareness; $\boldsymbol{\Lambda}^{Agrs}$ is a ($1 \times p$) vector of factor loading for aggressiveness; $\boldsymbol{\Lambda}^{Uaws}$ is a ($1 \times q$) vector of factor loading for situational awareness; $\boldsymbol{\delta}^{Agrs}$ and $\boldsymbol{\delta}^{Uaws}$ are ($N \times p$) matrices of gaussian errors.

It was intended to use the maximum likelihood mean-variance adjusted (MLMV) to estimate the proposed SEM parameters as its significant and optimal performance in the closely resembled dataset (Maydeu-Olivares, 2017; Asparouhov and Muthen, 2021; Cham et al., 2014); it presumed the correlation based on the mean and variance. In general, normality is assumed within a large sample size and with a maximum likelihood (ML) estimator. This is not always the case as with a relatively small sample the data normal distribution is no longer presumed and an alternative estimator is suggested e.g., MLMV (Gao et al., 2020).

3.2.2 Model Assessment

To assess the validity of SEMs, a group of performance metrics can be employed. Chi-square (χ^2) is a vastly used statistical measure to assess the goodness-of-fit. It examines that there is no difference between the predicted covariances and population covariances (Kline, 2016). The null hypothesis of a chi-square test is that the proposed model can fit the data, so insignificant results are desired. The root mean square error of approximation (RMSEA) is another commonly used measure to assess goodness-of-fit, where 0 and 1 indicate the best and the worst fits, respectively. In general, an RMSEA of less than 0.05 suggests a very satisfactory fit (Browne & Cudeck, 1992). The RMSEA is determined in the SEM as:

$$RMSEA = \sqrt{\frac{(\chi_M^2 - df_M)}{df_M(N-1)}} \tag{3}$$

where df_M is the degree of freedom of model M , ${\chi_M}^2$ is the chi-square statistic for the proposed model M, N is the sample size.

Comparative fit index (CFI) and Trucker–Lewis's index (TLI) analyzes the model fit by examining the discrepancy between the data and the hypothesized model, while adjusting for the issues of sample size inherent in the chi-squared test of model fit (Hair et al., 2009). TLI and CFI formulas are given by:

$$TLI = \frac{\left[\left(\frac{\chi_B^2}{df_B}\right) - \left(\frac{\chi_M^2}{df_M}\right)\right]}{\left[\left(\frac{\chi_B^2}{df_B}\right) - 1\right]} \tag{4}$$

$$CFI = 1 - \frac{(\chi_M^2 - df_M)}{(X_B^2 - df_B)} \tag{5}$$

where χ_B^2 and df_B are the chi-square statistics and degrees of freedom for the baseline model, respectively.

The TLI/ CFI values are between 0 and 1; a value of 0.90 or greater is preferred, and a value of 0.95 or greater is considered to be a very good fit (Hair et al., 2009). Unlike ML which presumes data normality, a robust method (MLMV) where nonnormality is assumed results in the model best fit and accuracy of RMSEA and p-values (Gao et al., 2020). It is important to mention that SEM relies on specification between measured and non-measured variables (Washington et al., 2011).

3.2.3 Procedure of Model Development

SEM assesses the alignment between a theoretical framework and empirical observations within a dataset (Hair et al., 2009). It involves the integration of the measurement model and the structural model (Fan et al., 2016). In SEM analysis, researchers typically follow a sequence of six fundamental steps (Kline, 2016): initial model specification (informed by theory or hypotheses), model identification, measurement selection (data collection), evaluation of model fit, potential refinement of model specification, and the final reporting of results.

In development of the proposed SEM, procedures consistent with the aforementioned literature were followed. Drawing upon a theoretical foundation, the model specification was formulated. Subsequently, in the model assessment stage, the evaluation of model fit was conducted using various metrics such as chi-square, RMSEA, CFI, p-values, and others. Finally, the refinement stage was entered, testing different model specifications. Multiple iterations were employed until optimal model performance was achieved.

3.3 Model Results

Two latent variables were constructed for aggressiveness and awareness, where each included four observed variables. As for aggressiveness, speed, longitudinal acceleration, steering, and brake were selected to represent the most associated variables (Abou-Zeid et al., 2011; Lee &

Jang, 2019; Fitzpatrick et al., 2017). Likewise, significant indicators, brake, lane offset, steering, and yaw, were selected to reflect the impact of CVs on the performance of driving awareness (Gugerty and Falzetta, 2005; Khoda Bakhshi et al., 2021; Gaweesh et al., 2021). Performance metrics of the SEM are presented in **Table 4**. Furthermore, factors including CV warning, crash location, and aggressiveness survey were incorporated into the structural model. Drivers' characteristics, such as driving experience, age, gender, and education level, were meticulously examined. Among these factors, only age and education level exhibited significant or marginally significant results, contributing to satisfactory performance metrics.

The overall performance of the proposed SEM is satisfactory with performance metrics presented in **Table 4**. The score of the chi-square test is 45.446 with a p-value greater than 0.05, implying acceptable goodness-of-fit. Normed chi-square (Chi-square/Degrees of freedom) is 1.136, which is less than the 2.0 threshold used (Hair et al., 2009). The RMSEA of the SEM 0.037 is lower than 0.05, advising an acceptable fit to the data (Fan et al., 2016). The CFI and TLI of the SEM are 0.981 and 0.973, respectively. Both CFI and TLI are higher than the 0.95 threshold, suggesting excellent model fit while adjusting for the sample size (Hair et al., 2009).

Table 4. Performance metrics of the SEM

Performance Metric	**Value**
Chi-square statistics	
Chi-square	45.446
Degrees of freedom	40
P-value	0.256
RMSEA	0.037
CFI	0.981
TLI	0.973

The estimates of parameters in the SEM are presented in **Table 5**.The path diagram of the SEM is presented in **Figure 7.** Statistical indicator p-value was applied to examine the significance of explanatory variables. The explanatory variables were found to be statistically significant with p-values less than 0.05.

Table 5. Estimates of parameters in the SEM

	Estimate	Std. Err	P-value
Measurement Model			
Aggressiveness =~			
(SD) Speed	1.000		
(95^{th}) Longitudinal Acceleration	0.070	0.007	0.000**
(Max) Steering	0.033	0.008	0.000**
(Mean) Brake	0.416	0.043	0.000**
Unawareness =~			
(SD) Yaw	1.000		
(Mean) Steering	0.003	0.001	0.005**
(95th) Lane Offset	-0.016	0.005	0.001**
(Mean) Brake	0.066	0.035	0.062·
Structural Model			
Aggressiveness ~			
CV	-3.009	1.377	0.029*
Aggressiveness survey	-0.788	0.752	0.295
Crash location	5.550	1.401	0.000**
Age	0.203	0.090	0.024*
Unawareness ~			
CV	-0.501	0.201	0.014*
Crash location	11.922	0.252	0.000**
Education level	0.334	0.016	0.126

where the operator "=~" is used for latent variable whereas "~" is the causal paths (regressions).

Significance levels: · for 0.05 ≤ p-value < 0.1; * for 0.01 ≤ p-value < 0.05; ** for ≤ p-value < 0.01.

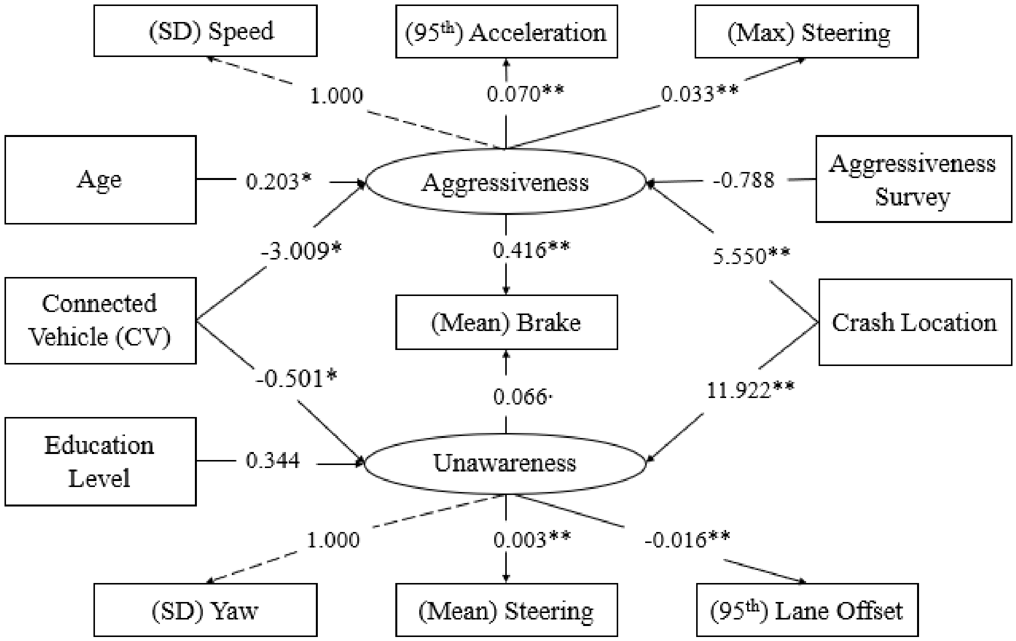


Figure 7. Path diagrams of the proposed SEM (Significance levels: for 0.05 ≤ p-value < 0.1; * for 0.01 ≤ p-value < 0.05; ** for ≤ p-value < 0.01).

3.4 Discussion

As we employed a data-driven approach, we carefully chose observed variables for our analysis. For instance, we incorporated variables such as the standard deviation of speed, 95th percentile of acceleration, and maximum acceleration to serve as indicators of the aggressiveness latent variable. These specific variables were selected based on their superior performance in the structural equation model (SEM). The measurement model in **Table 5** presents the indicators to aggressiveness and unawareness. The results illustrate that the standard deviation of speed, the 95^{th} percentile of longitudinal acceleration, the maximum steering angle, and the mean brake are positively associated with aggressiveness. Aggressive drivers would brake and accelerate frequently, resulting in a large variation in speed and a large mean brake. Aggressive drivers are also prone to adopt a high acceleration rate. Lee and Jang (2019) found that steep acceleration and deceleration events were associated with aggressive drivers. Li et al. (2020) reported that aggressive driving behavior would lead to increased speed variation, higher speed, and greater longitudinal acceleration. Similarly, aggressive drivers tend to steer more harshly, leading to a higher maximum steering angle. Consistent results were highlighted in the literature that oversteering maneuvers were associated with aggressive driving behavior (Kiefer et al., 2005; Lee & Jang, 2019). Harsh steering would increase the crash risk. Mazzae et al. (1999) reported that excessive steering angles were associated with scenarios that could be exposed to the risk of crashes. Furthermore, according to **Table 5**, the standard deviation of yaw, the mean of steering, and the mean of brake have positive relationships with the latent variable unawareness, while the 95^{th} percentile of lane offset is negatively associated with unawareness. Detecting yaw is typical in drivers' behavior and situational awareness studies such as Lee & Jang (2019) and Khoda Bakhshi et al. (2021). A steep change in yaw degree could depict drivers' behavior and awareness (Lee & Jang, 2019). Unawareness is positively associated with the mean steering angle. Unaware drivers would tend to steer frequently and harshly. Unawareness is negatively associated with the 95^{th} percentile of lane offset. The negative sign of the lane offset means that vehicles are in the left lane, while the positive sign signifies the right lane. Both crashes are located in the right lane so unaware drivers would be more likely to drive in the unblock left lane. Our conjecture is that drivers who received the CV warnings would switch to the right lane to driver more cautiously. Tan et al. (2022) reported that unaware drivers would brake their vehicles harshly to avoid crashes, which explains the positive association between unawareness and the mean brake. Wu et al. (2018) interestingly found that with an advanced warning system drivers' maximum lane deviation and maximum brake pedal force were larger in comparison to a without warning status.

According to the structural model in **Table 5**, drivers' aggressiveness and unawareness are affected by various exogenous variables including the use of self-reported aggressiveness in the survey, crash location (0 for the tangent and 1 for the curve), CV warnings, and drivers' characteristics. Aggressiveness and unawareness tend to lead drivers to be exposed to a higher risk of crashes. Li et al. (2020) found that drivers with aggressive and unaware patterns could be prone to more crash hazard. The self-reported aggressiveness survey relies solely on participants' answers in the distributed ADAB pre-questionnaire survey, while the aggressiveness latent variable is assessed through SEM performance. Interestingly, when comparing the results of self-reported aggressiveness with the aggressiveness measured in the SEM an inconsistency emerges. It was found that the aggressiveness survey outcome was negatively associated with drivers' aggressiveness, suggesting a contradiction between the self-reported aggressiveness and their real aggressive behavior during the experiment. Participants did not report high levels of aggressiveness in the questionnaire, but they exhibited tendencies toward aggressive driving behavior in our proposed highway crash scenario. The crash location variable (0 for the first crash on the tangent and 1 for the second crash on the curve) is positively associated with aggressiveness (presenting higher level of aggressive driving behavior) and unawareness (lower situational awareness). Drivers were found to be more aggressive and less aware when passing the second crash on the curve, possibly due to restricted sight distance. Alyamani & Kavakli (2017) also found that drivers showed low situational awareness in curved roads but high situational awareness in straight roads. Additionally, as highlighted in **Table 5**, the deploying of CV warnings would make drivers driving less aggressively, indicated by a reduction in observed variables including the standard deviation of speed, the 95th percentile of longitudinal acceleration, the maximum steering angle, and the mean brake. Theriot (2017) concluded that CV warnings significantly reduced drivers' aggressiveness and improved safety. Moreover, the use of CVs would lead to a decrease in unawareness by 0.501 unit (i.e., a better situational awareness), indicating a reduction in the three observed variables (the standard deviation of yaw, the mean steering, and the mean brake) and an increase in the 95^{th} percentile of lane offset. This finding is in line with previous situational awareness studies. Tan et al. (2022) reported that drivers would have enhanced situational awareness and a better response to hazards with the CV system. Li et al. (2018) also found that drivers with CV technology were able to recognize the road situation earlier than the baseline condition, which would have a positive impact on safety performance.

Regarding drivers' characteristics, a positive association between age and aggressiveness was found (coefficient: 0.203, p-value: 0.024), suggesting that aggressiveness tends to increase as individuals age, within the age spectrum of participants (22 to 45 years old). This pattern could potentially be attributed to the heightened self-assuredness and experience that often accompanies aging, leading to an unintended overconfidence in managing driving tasks and subsequently giving rise to aggressive behaviors. This observation aligns with the research by Zhang et al. (2017), who found older adults (49 to 60 years old) exhibited a greater inclination towards aggressive behavior compared to their younger counterparts (20 to 49 years old). Nonetheless, the landscape of findings isn't entirely homogeneous, as there are contrasting studies that indicate an opposing relationship between age and aggressiveness. For instance, Dahlen & White (2006) examined university students with a median age of 19 years old and discovered reduced levels of driving aggressiveness in older drivers. Gwyther & Holland (2012) revealed that older drivers (over 65 years) demonstrated the least aggressive driving behaviors, while middle-aged individuals (26 to 64 years old) displayed lower levels of driving aggressiveness compared to young drivers (18 to 25 years old). The education level shows marginal significance concerning unawareness. The findings suggest a modest link between higher education levels and increased unawareness. Specifically, individuals holding graduate degrees displayed a diminished level of situational awareness. Some potential explanations could be that individuals with higher education levels might become more engrossed in specialized knowledge or tasks, potentially diverting their attention from immediate surroundings. Shinar et al. (2001) also investigated the influence of education level in their study and reported that while the number of individuals who consistently adhered to the speed limit increased with age, it declined with higher levels of education.

3.5 Summary of Findings

The primary objective of this chapter is to evaluate the impact of CV technology on psychological factors, specifically situational awareness and aggressiveness. To achieve this, a within-subjects driving simulator experiment was conducted, collecting a range of driving data, including speed, acceleration, steering, lane offset, yaw, and other relevant variables, in addition to survey data. Notably, participants in the experiment expressed trust in the CV system and believed it had a positive influence on their driving behavior.

To analyze the complex relationships between the application of CV warnings, driving behavior, psychological factors, crash location, and driver characteristics, SEM was utilized. Within the SEM measurement model, latent psychological factors were constructed, encompassing aggressiveness and unawareness. Unawareness was assessed using metrics like yaw, brake, lane offset, and steering angle, while aggressiveness was measured through brake, speeding, steering angle, and longitudinal acceleration. SEM offered the advantage of simultaneously measuring latent psychological factors and modeling their interrelationships in a single statistical estimation procedure. The model's goodness of fit demonstrated high levels of satisfaction, with RMSEA = 0.037, CFI = 0.981, and TLI = 0.973. The findings of the study revealed that CV warnings resulted in a reduction in unawareness by 0.501 and aggressiveness by 3.009. Furthermore, it was observed that drivers exhibited higher levels of aggressiveness and lower situational awareness on curved road segments.

This chapter represents a significant contribution to the existing body of literature by introducing an innovative method for measuring psychological factors and investigating the influence of CVs on aggressiveness and situational awareness in the context of highway crash scenarios. The insights gained from this chapter advance our understanding of the role of CV technology in enhancing driving performance during unforeseeable abnormal events, such as the risk of secondary crashes. Additionally, the research provides valuable insights for the development of driving assistance systems that explicitly consider psychological factors.

CHAPTER 4

EXAMINING THE INFLUENCE OF CONNECTED VEHICLES ON DRIVING BEHAVIORS AND SAFETY OUTCOMES IN HIGHWAY CRASH SCENARIOS ACROSS VARIED WEATHER CONDITIONS

Abnormal weather conditions, such as foggy weather, can adversely affect driving behaviors by reducing visibility and creating turbulent traffic flow conditions (Zhibin Li et al., 2014). This chapter presents the results of a driving simulator study that investigates the impact of CV technologies on driving behaviors and safety outcomes in highway crash scenarios, including those that occur in both clear and foggy weather conditions. Our proposed approach for modeling the complex relationships among safety outcomes, driving behaviors, CVs, weather conditions, and other explanatory variables is a powerful multigroup SEM method. This method allows us to analyze the interplay among these factors and gain a comprehensive understanding of how they affect driving behavior and safety outcomes.

4.1 Experiment

4.1.1 Participants

A sum of 26 participants were recruited in the driving experiment. Each driver has valid US driver's license with one year of driving experience at minimum. The selected number of the sample size was used in closely similar experiments (Yang et al. 2020; Alyamani and Kavakli 2017; Son et al., 2020; Li et al., 2020).. Only one subject faced some symptoms of motion sickness and requested to discontinue the experiment, which ended up with valid collected data out of 25 participants. The gender of the participants was divided between 21 males and 4 females. The age groups of the participants ranged from 46 to 22 years old (mean = 31.11 years, standard deviation

= 6.03 years). All participants were in good health condition, with 1 year to 34 years of driving experience (mean = 12.04 years, standard deviation = 7.99 years).

4.1.2 Procedure

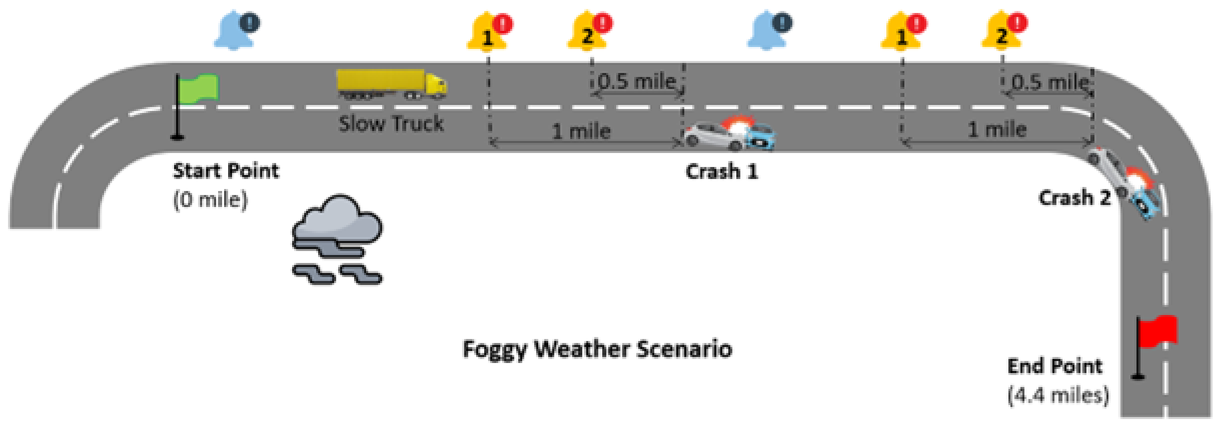
After the arrival of the participants, they were instructed to read and sign the consent form that depicted the goal and the detail of the experiment and warned about the likelihood of motion sickness. The participants were informed that they could quit at any time if they give up for any reason such motion sickness. Upon the signature of the consent form by the participants, pre-experiment questionnaires on demographics and driving aggressiveness were filled in. Each participant conducted five to ten minutes of warm-up to familiarize themselves with the driving simulator atmosphere prior taking the proposed driving scenarios. Following the driving experiment, a post-experiment questionnaire form was distributed and filled in by each participant. Participants were requested to report their perspective about the designed CV experiment and respond to the remainder of the related questions. Participants were also instructed to complete a simulator sickness questionnaire to report the how severe of each symptom was and arranged by none, slight, moderate, and severe. It was found that only one participant was exposed to moderate discomfort and stopped the experiment.

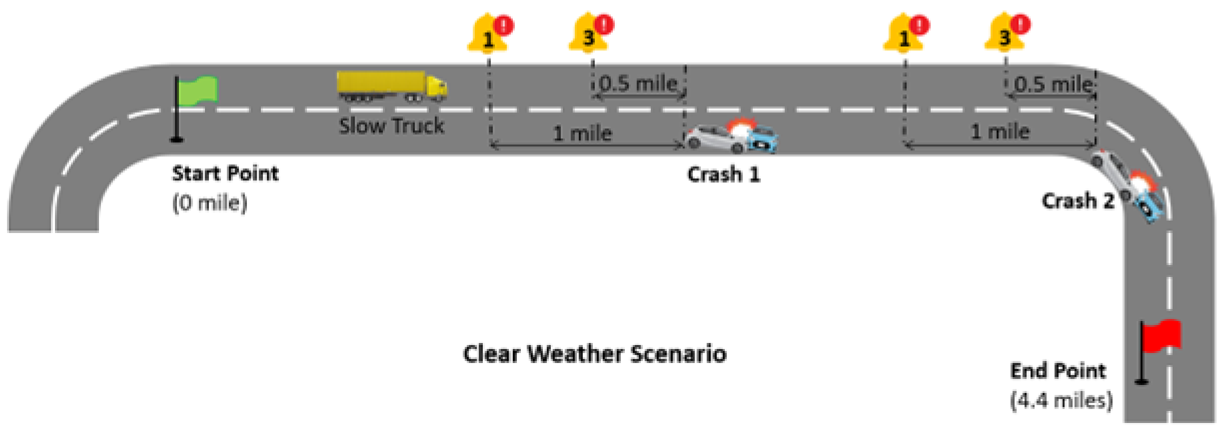
4.1.3 Scenario Development

To investigate how drivers react to accidents in different road environments, we created a virtual driving setting based on a four-lane highway with a 70 mile/hour speed limit, the maximum allowed in Virginia. Two crashes were introduced, one on a straight section and the other on a horizontal curve, as shown in **Figure 8**, both in the right lane. In order to replicate real-world conditions, we utilized reroute maneuvers to gradually shift surrounding traffic to the unblocked left lane when approaching each accident site.

Each participant was tested in two driving scenarios: 1) the control scenario without a CV warning and 2) the experimental scenario with a CV warning. To account for the learning effect of participants, counterbalancing was implemented to have half of the participants drive in the control scenario first and the other half in the experimental scenario first. Additionally, some freeway landmarks, vegetation, and surroundings were changed to make the control and experimental scenarios appear different from each other.

As depicted in **Figure 8 a**, the truck driving at a reduced speed in the left lane to prompt drivers to transition from the left lane to the right lane before reaching the intended crash location. Drivers in the CV scenario were alerted with two CV warnings: one a mile prior to arriving at the crash site, and another half a mile beforehand. The initial warning aimed to alert drivers about the imminent traffic crash ahead, while the second one instructed them to reduce their speed by 10 miles per hour (i.e., from 60 to 50 miles per hour), a widely practiced safety measure (Board, 2000; Li et al. 2018; Control, 2015; Abdel-Aty & Wang, 2017). The warning messages were displayed on the front screen accompanied by a beeping sound to ensure drivers were promptly notified. To create the warning signs, we followed the design guidelines recommended by FHWA *Manual on Uniform Traffic Control Devices for Streets and Highways* (MUTCD), which are widely accepted. As illustrated in **Figure 8 b**, we made slight alterations to MUTCD signs by incorporating concise texts at the bottom to provide additional details about the location of the crashes.


1
2
1
2
0.5 mile
0.5 mile
Slow Truck
1 mile
1 mile
Start Point
(0 mile)
Crash 1
Crash 2
Foggy Weather Scenario
End Point
(4.4 miles)


1
3
1
3
0.5 mile
0.5 mile
Slow Truck
1 mile
1 mile
Start Point
(0 mile)
Crash 1
Crash 2
Clear Weather Scenario
End Point
(4.4 miles)

(a)

(b)

Figure 8. The driving simulator experiment scenario involves the foggy and clear weather conditions: (a) driving simulator scenario layout and (b) connected vehicle messages.

To comply with the IRB guidelines, we ensured the privacy and confidentiality of all participant data. We collected driving data at a sampling rate of 60 observations per second, covering a distance of 164 feet before the first warning and 656 feet after the crash site for both crashes. **Figure 9** presents a comparison between crash one and crash two during clear and foggy weather conditions. **Table 6** displays descriptions and statistical measures for speed, longitudinal acceleration, brake, lane offset, steering, and yaw. This table provides detailed information and data-driven insights into each of these parameters.

(a) (b)

(c) (d)

Figure 9. Traffic scenarios (crash 1): (a) clear weather condition and (b) foggy weather condition; for (crash 2): (c) clear weather condition, and (d) foggy weather condition.

To provide further elaboration, **Figure 10** illustrates the trend in average speeds, indicating that the utilization of CV alerts led to a greater reduction in mean speeds among drivers during foggy weather in comparison to clear weather. Consistent results were obtained in previous studies such as Gaweesh et al. (2021) which reported that the provision of CV notifications during times of limited visibility and unclear weathers would lead to a decrease in both the mean operating speed and speed variation. Under foggy weather conditions, drivers tended to reduce their speed even without the CV scenario, compared to normal weather, due to the significant reduction in sight distance (Brooks et al., 2011; Klinjnhout, 1991). Additionally, **Figure 11** demonstrates that drivers exhibited a tendency to apply the brakes more intensely when exposed to the CV warning scenario while approaching the first crash location under clear weather conditions, and when approaching the second crash location under foggy conditions during the baseline scenario. These fluctuations in average speed and brake force in scenarios with low visibility contributed to traffic conflicts, as depicted by TTC values of less than or equal to two seconds, in both crash locations and under both weather conditions, as presented in **Figure 12**. Selecting the appropriate variables to assist in a comprehensive understating and assessment of the overall traffic safety and operation after a proposed countermeasure. Traffic conflict is a paramount variable that has the potential to efficiently evaluate driving behavior with and without CV technology (Pawar & Patil, 2017; Reinolsmann et al., 2021; Yuan et al., 2018).

Table 6. Descriptive analysis and descriptions key variables (N = 200 observations)

Variable (Def.)	Statistics	Clear Weather without CV		Clear Weather with CV		Foggy Weather without CV		Foggy Weather with CV	
		Crash 1	**Crash 2**	**Crash 1**	**Crash 2**	**Crash 1**	**Crash 2**	**Crash 1**	**Crash 2**
Speed	SD	15.47	15.36	24.35	18.74	13.62	13.89	13.18	12.69
A value in (mph)	Mean	56.05	54.15	54.70	55.18	52.42	49.94	43.86	43.28
	Max.	72.92	71.84	76.12	72.24	64.52	63.36	56.80	56.72
	Min.	28.00	24.68	8.12	15.16	15.32	15.60	12.08	8.32
Throttle Pedal position angle ranges from 0 to 90 (degree)	SD	8.45	7.79	7.90	7.39	6.32	7.24	6.17	7.49
	Mean	15.40	13.20	12.44	12.54	13.20	15.69	10.51	11.28
	Max.	31.25	25.48	28.80	25.49	27.87	30.37	26.01	29.84
	Min.	0.59	0.00	0.89	0.65	0.52	0.06	0.00	0.00
Brake Brake force Ranged between 0 and 38 (lb)	SD	3.50	2.75	4.94	3.76	4.22	5.03	3.49	3.99
	Mean	1.23	0.99	1.88	1.31	1.30	1.74	1.18	1.26
	Max.	16.77	13.48	21.65	18.44	22.46	25.50	20.63	22.97
	Min.	0.00	0.00	0.01	0.01	0.00	0.00	0.02	0.12
Lane Offset vehicle's position from the center of the lane (ft)	SD	1.51	1.48	1.18	1.08	1.25	1.31	1.21	1.08
	Mean	-0.46	-0.49	-0.52	-0.72	-0.46	-0.49	-0.43	-0.52
	Max.	5.77	5.71	3.02	2.30	3.64	5.18	3.28	4.13
	Min.	-5.74	-5.84	-4.36	-4.10	-4.99	-5.45	5.18	-4.59
Steering	SD	0.16	0.09	0.12	0.15	0.15	0.13	0.17	0.08
The steering wheel (rad)	Mean	-0.01	0.00	0.04	0.02	0.03	-0.003	0.01	0.002
	Max.	0.60	0.46	0.61	0.62	0.64	0.54	0.71	0.42

Variable (Def.)	Statistics	Clear Weather without CV	Clear Weather with CV	Foggy Weather without CV	Foggy Weather with CV	-0.47	-0.77	-0.79	-0.45
		Crash 1	**Crash 2**	**Crash 1**	**Crash 2**	**Crash 1**	**Crash 2**	**Crash 1**	**Crash 2**
Yaw Rotation about a vertical axis (degree)	SD	1.37	1.22	13.66	12.71	14.99	1.42	12.15	0.99
	Mean	-0.04	0.03	10.01	8.24	8.23	-0.13	7.15	-0.02
	Max.	4.88	5.55	40.87	41.28	47.43	5.10	41.41	3.75
	Min.	-5.18	-3.86	-0.88	-0.69	-8.27	-6.83	-1.29	-4.99

Note: Crash 1 is on a straight section while Crash 2 is on a horizontal curve.

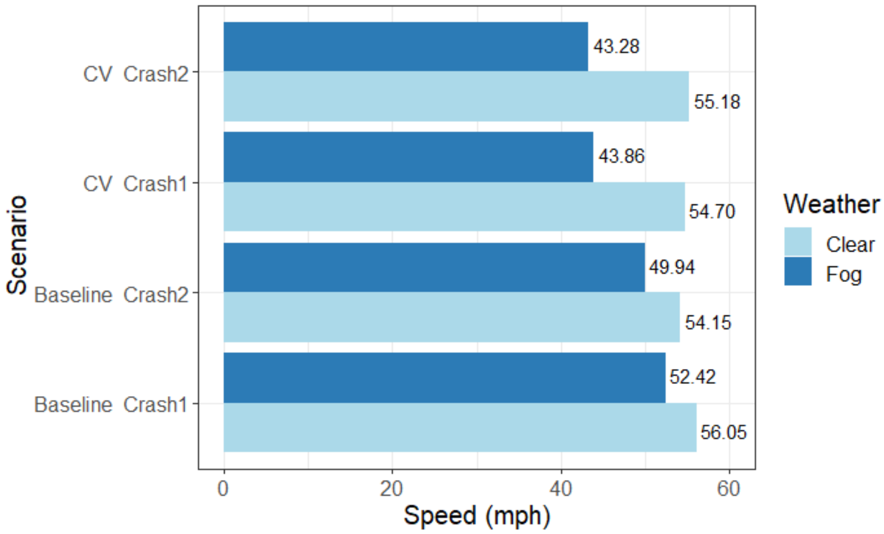


Figure 10. Mean speed comparison between the baseline and the CV scenarios under clear and foggy weather.

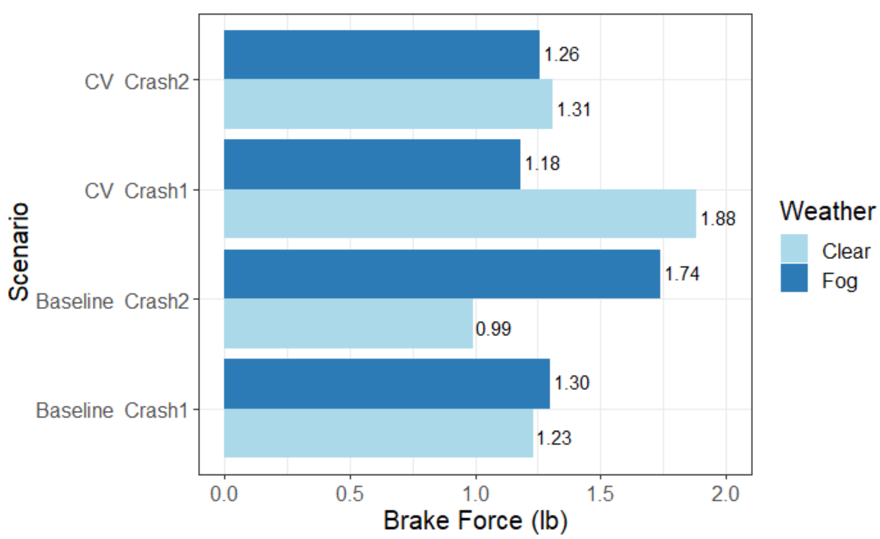


Figure 11. Mean brake comparison between the baseline and the CV scenarios under clear and foggy weather.

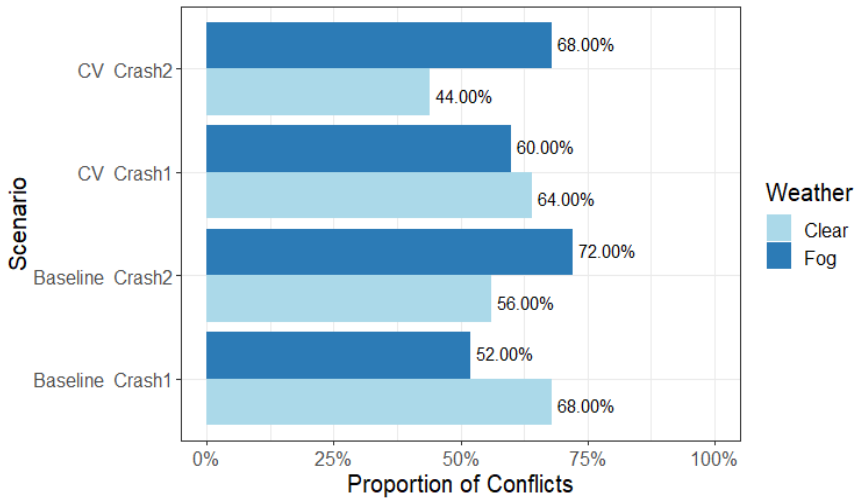


Figure 12. Traffic conflict comparison between the baseline and the CV scenarios under clear and foggy weather.

4.2 Multigroup Structural Equation Modeling

4.2.1 Model Specification

The multigroup SEM framework is employed to convert various indicators of driving behavior into latent variables of aggressiveness and situation awareness, and to examine the correlations among these latent variables, CV, and other related variables. **Figure 13** displays the conceptual framework of the proposed SEM. The model uses demographic data, and crash locations to hypothesize that driving behaviors are impacted by the proposed CV system. In theory, when the CV technology was implemented, drivers were believed to drive in a less aggressive manner and with improved situational awareness. Two latent variables were constructed, namely drivers' aggressiveness and situational awareness, which are indicated by several driving indicators such as longitudinal speed and acceleration, and are influenced by the CV system, crash locations, and other related factors.

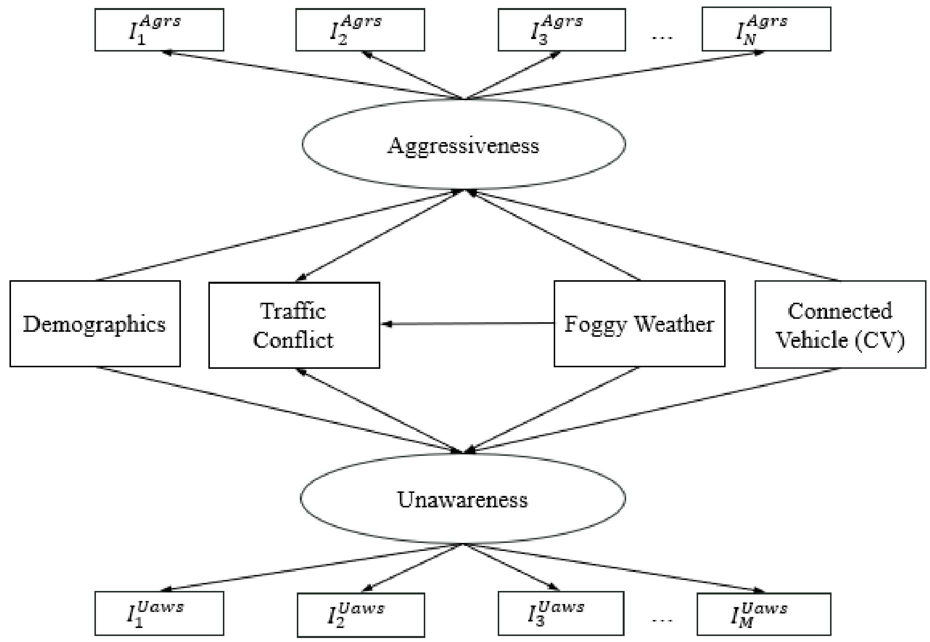


Figure 13. Conceptual path diagram of the multigroup SEM

The prosed structural equation modeling is expressed through the following formula:

$$Agrs_i = \boldsymbol{X_i}\boldsymbol{\alpha_{11}} + \alpha_{12}CV_i + \alpha_{13}Fog_i \ + \varepsilon_i^{Agrs} \tag{6}$$

$$Uaws_i = \boldsymbol{X_i}\boldsymbol{\alpha_{21}} + \alpha_{22}CV_i + \alpha_{23}Fog_i \ + \varepsilon_i^{Uaws}$$

$$\boldsymbol{y_i^*} = \alpha_{31}Fog_i \ + \ \alpha_{32}Agrs_i + \gamma_{33}Uaws_i + \varepsilon_i^{y}$$

$$y_i = 1, if \ y_i^* > \varphi, y_i = 0, otherwise$$

The index i $(i = 1, 2, \dots, N)$ is used to identify specific driving scenarios based on several factors. These factors include the study subject, whether the CV warning was present, and the location of the crash; $Agrs_i$ is a latent construct that assess the presence of aggressive driving behaviors, $Uaws_i$ is a latent construct that gauging an individual's level of situational awareness (for the sake of simplicity, the term unawareness is utilized); y_i^* is the propensity of traffic conflicts; y is the occurrence of the traffic conflict (0 for non- traffic conflict, 1 for traffic conflict); the vector $\boldsymbol{X_i}$ represents a collection of driver attributes such as experience, age, gender, and level of educational attainment; CV_i is a binary variable denotes the existence of CV alert, with 0 indicating no CV alert and 1 indicating the presence of CV alert; FW represents foggy weather status (0 for no fog and 1 for fog); the vectors $\boldsymbol{\alpha_{11}}$ and $\boldsymbol{\alpha_{21}}$ consist of coefficients that corresponding to $\boldsymbol{X_i}$; the coeffects corresponding to CV_i; the errors ε_i^{Agrs} and ε_i^{Uaws} are assumed to be normally distributed.

The measurement model in the SEM is characterized by:

$$\boldsymbol{I}^{Agr} = \boldsymbol{Agrs}\,\boldsymbol{\Lambda}^{Agrs} + \boldsymbol{\delta}^{Agr} \tag{7}$$

$$\boldsymbol{I}^{Uaws} = \boldsymbol{Uaws}\,\boldsymbol{\Lambda}^{Uaws} + \boldsymbol{\delta}^{Uaws}$$

where matrix $\boldsymbol{I}^{Agrs}$ is composed of N rows and p columns ($N \times p$), representing the observed driving behaviors associated with aggressiveness; the matrix $\boldsymbol{I}^{Uaws}$ ($N \times q$) represents the observed driving behaviors associated with situational awareness; the vector $\boldsymbol{Uaws}$ ($N \times 1$) represents the latent variable of situational awareness; the vector $\boldsymbol{\Lambda}^{Agrs}$ ($1 \times p$) represents the factor loading for the observed driving behaviors associated with aggressiveness; the vector $\boldsymbol{\Lambda}^{Uaws}$ ($1 \times q$) represents the factor loading for the observed driving behaviors associated with situational awareness; the $\boldsymbol{\delta}^{Agrs}$ and $\boldsymbol{\delta}^{Uaws}$ ($N \times p$) matrices represent the Gaussian errors with observed driving aggressiveness and awareness, respectively.

The weighted least squares mean-variance adjusted (WLSMV) was selected for estimating the proposed SEM parameters. While assuming normality is generally appropriate for large sample sizes and when using a maximum likelihood (ML) estimator, the WLSMV is a robust method that is particularly useful for analyzing categorical or ordinal data. Therefore, it is often the preferred choice in situations where the number of observed variables is small (Kline, 2016).

4.2.2 Model Assessment

To evaluate the validity of SEMs, a set of performance metrics can be utilized. The chi-square (χ^2) is a commonly used statistical measure for evaluating the goodness-of-fit in SEMs. It is used to evaluate whether the predicted covariances in the SEM significantly deviate from the population covariances (Kline, 2016). The chi-square goodness-of-fit test evaluates the hypothesis that the proposed SEM is an acceptable fit to the data, with non-significant results indicating that the model fits well. The root mean square error of approximation (RMSEA) is a widely used metric for evaluating goodness-of-fit in SEMs, with values ranging between 0 (indicating a perfect fit) and 1 (indicating a poor fit). According to Browne and Cudeck (1992), a commonly accepted criterion for evaluating the RMSEA metric is that values below 0.05 indicate a highly satisfactory model fit. A commonly used guideline for evaluating the RMSEA metric is that values below 0.05 suggest a very good fit (Browne & Cudeck, 1992). The RMSEA is computed in the SEM as:

$$RMSEA = \sqrt{\frac{(\chi_M^2 - df_M)}{df_M(N-1)}} \tag{8}$$

Where the degree of freedom for the model M is represented by df_M, The chi-square statistic for the proposed model M is denoted by ${\chi_M}^2$, N denotes the sample size. Comparative fit Index (CFI) and Tucker-Lewis index (TLI) are methods for assessing the fit of a model by evaluating the difference between the observed data and the hypothesized model, while also taking into account the limitations associated with the sample size used in the chi-squared test of model fit (Hair et al., 2009). TLI and CFI formulas are expressed by:

$$TLI = \frac{\left[\left(\frac{\chi_B^2}{df_B}\right) - \left(\frac{\chi_M^2}{df_M}\right)\right]}{\left[\left(\frac{\chi_B^2}{df_B}\right) - 1\right]} \tag{9}$$

$$CFI = 1 - \frac{(\chi_M^2 - df_M)}{(X_B^2 - df_B)} \tag{10}$$

where χ_B^2 and df_B represent the chi-square statistics and degrees of freedom for the non-CV model, respectively.

The values of the TLI and CFI range between 0 and 1, with a value of 0.90 or above is desirable, and a value of 0.95 or above indicating a very good model fit (Hair et al., 2009).

The TLI/ CFI values are between 0 and 1; a value of 0.90 or greater is preferred, and a value of 0.95 or greater is considered to be a very good fit (Hair et al., 2009). Assuming nonnormality in a robust method (WLSMV) result in a better model fit and accuracy for RMSEA and p-values compared to the ML that assumes data normality (Gao et al., 2020). It is noteworthy to mention that SEM depends on specification between observed and non-observed variables (Washington et al., 2011).

4.3 Model Results

The researchers employed a SEM framework to depict and analyze the complex interdependencies among various factors, including driving behavior, foggy weather, traffic conflict, and other relevant variables, as expounded in **Figure 13.** To measure the group differences between crash location one and crash location two, multigroup SEM was developed, which involves analyzing each group separately and comparing the results. The alternative model is a single group SEM, where the data from crash locations one and two were combined into one group and analyzed together. An identical set of measured and latent variables is utilized in constructing the two SEMs, enabling them to undertake a systematic and valid comparison of the two models.

In order to effectively measure aggressiveness and awareness, two latent variables were formulated, utilizing a set of four observable variables for each construct. For the aggressiveness construct, the indicators of brake, throttle, steering, and lane offset were chosen due to their high degree of association with the construct (Abou-Zeid et al., 2011; Lee & Jang, 2019; Fitzpatrick et al., 2017). Similarly, prominent indicators, namely yaw, lane offset, steering, and brake were chosen to represent the effects of CVs on driving awareness performance. (Khoda Bakhshi et al., 2021; Gugerty and Falzetta, 2005; Gaweesh et al., 2021).

Table 7 displays the performance metrics of the multigroup SEM and single group SEM. Although the chi-square test revealed no significant differences between the multigroup and single group SEM models (with p-values greater than the chosen significance value of 0.1 for both (Hair et al., 2009)), the multigroup SEM performed better overall. The RMSEA value for the multigroup SEM is 0.037, indicating an acceptable fit to the data, compared to 0.076 for the single group SEM, suggesting lower performance (Fan et al., 2016). The CFI and TLI of the multigroup SEM are higher than the recommended threshold of 0.95 for an excellent model fit (Hair et al., 2009), with values of 0.988 and 0.982, respectively. The single group SEM, on the other hand, scored 0.881 in CFI and 0.904 in TLI, reflecting a comparatively modest performance in comparison to the multigroup SEM.

Table 7. Performance metrics of the structural equation modeling (SEM)

Performance Metric	**Multigroup SEM**	**Single group SEM**
Chi-square statistics		
Chi-square	59.011	56.213
Degrees of freedom	58	26
P-value	0.235	0.235
RMSEA	0.037	0.076
CFI	0.973	0.881
TLI	0.978	0.904

Table 8 displays the parameter estimates for the multigroup structural equation model (SEM), while **Figure 14** depicts the path diagram of the SEM. To evaluate the significance of the explanatory variables, statistical indicator p-values was utilized. Results indicate that explanatory variables were statistically significant, as their p-values were less than 0.1.

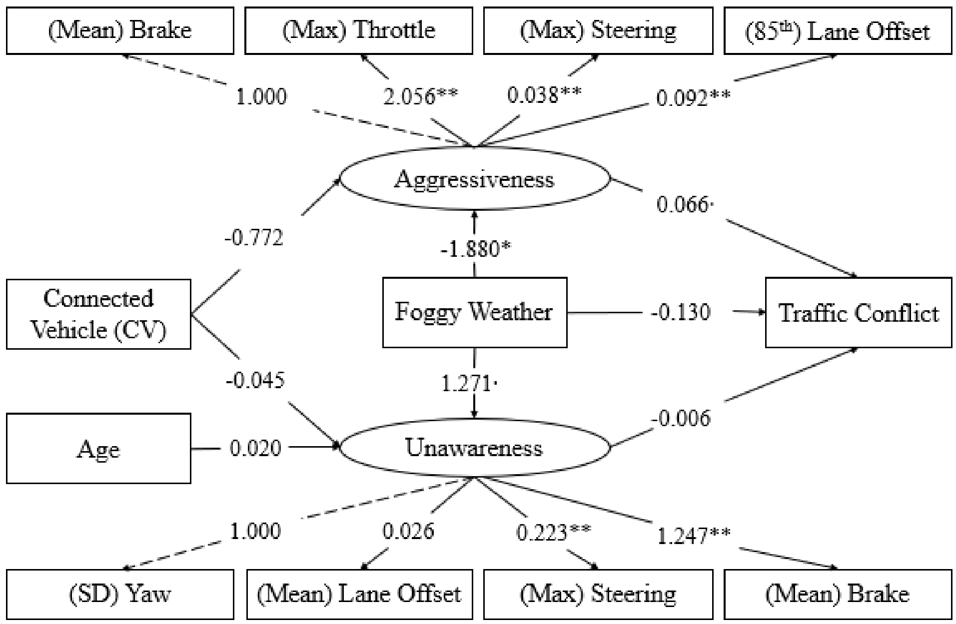
To compare the results, The estimated results for the single group SEM are presented in **Table 9.** However, this model's performance was deemed statistically insignificant in contrast to the multigroup SEM. The p-values of most variables were greater than 0.1, indicating a feeble relationship between the variables. All p-values of the structural model were greater than 0.1.

Table 8. Modeling results of the multigroup SEM

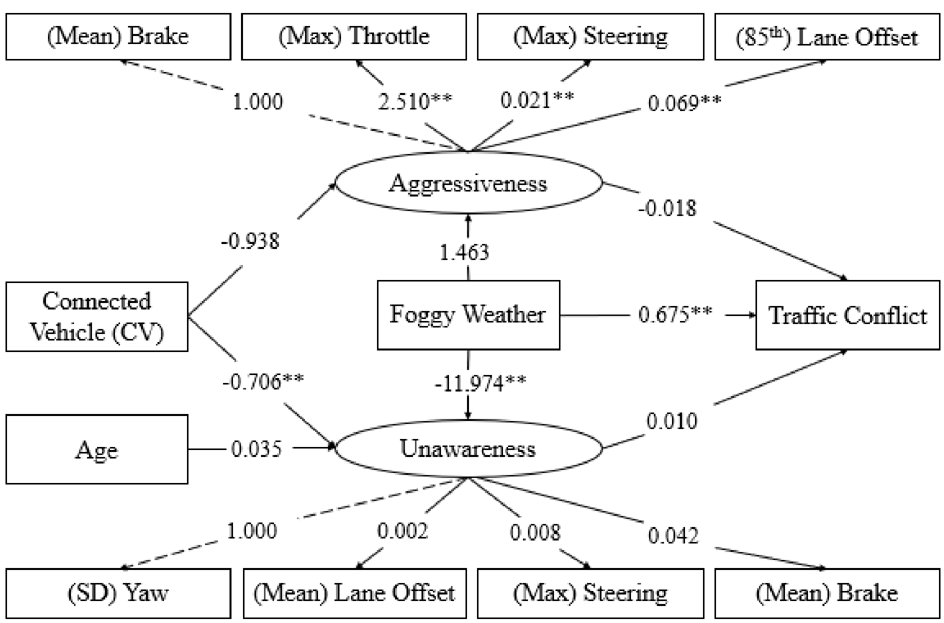
	Crash 1 on a straight section			Crash 2 on a horizontal curve		
	Estimate	**Std. Err**	**P-value**	**Estimate**	**Std. Err**	**P-value**
Measurement Model						
Aggressiveness =~						
(Mean) Brake	1.000			1.000		
(Max) Throttle	2.056	0.344	0.000**	2.510	0.339	0.000**
(Max) Steering	0.038	0.014	0.007**	0.021	0.009	0.016*
(85th) Lane Offset	0.092	0.015	0.000**	0.069	0.012	0.000**
Unawareness =~						
(SD) Yaw	1.000			1.000		
(Mean) Lane Offset	0.026	0.016	0.110	0.002	0.002	0.286
(Max) Steering	0.223	0.080	0.005**	0.008	0.007	0.275
(Mean) Brake	1.247	0.427	0.004**	0.042	0.044	0.343
Structural Model						
Aggressiveness ~						
CV	-0.772	0.833	0.354	-0.938	0.872	0.282
Foggy weather	-1.880	0.936	0.045*	1.463	0.975	0.133
Unawareness ~						
Age	0.020	0.074	0.786	0.035	0.024	0.155
CV	-0.045	0.556	0.936	-0.706	0.265	0.008**
Foggy weather	1.271	0.740	0.086*	-11.974	0.363	0.000**
Traffic Conflict ~						
Aggressiveness	0.066	0.034	0.054*	-0.018	0.026	0.497
Unawareness	-0.006	0.124	0.964	0.010	0.010	0.316
Fog Weather	-0.130	0.299	0.664	0.675	0.256	0.008**
Threshold (φ)	-0.346	0.721	0.631	-0.745	0.739	0.313

where the operator "=~" is used for latent variable whereas "~" is the Causal paths (regressions).

Significance levels: · for 0.05 ≤ p-value < 0.1; * for 0.01 ≤ p-value < 0.05; ** for p-value < 0.01.



(a) Crash 1 on a straight section



(b) Crash 2 on a horizontal curve

Figure 14. Path diagram of the proposed multigroup SEM (significance levels: · for 0.05 ≤ p-value < 0.1; * for 0.01 ≤ p-value < 0.05; ** for p-value < 0.01.)

Table 9. Modeling results of the single group SEM

	Estimate	Std. Err	P-value
Measurement Model			
Aggressiveness =~			
(Mean) Brake	1.000		
(Max) Throttle	2.328	0.344	0.000**
(Max) Steering	0.014	0.010	0.143
(85th) Lane Offset	0.083	0.012	0.000**
Unawareness =~			
(SD) Yaw	1.000		
(Mean) Lane Offset	0.010	0.007	0.164
(Max) Steering	0.181	0.089	0.042*
(Mean) Brake	0.681	0.175	0.000**
Structural Model			
Aggressiveness ~			
CV	-0.844	0.612	0.167
Foggy weather	-0.048	0.669	0.943
Unawareness ~			
Age	0.027	0.059	0.648
CV	-0.441	0.532	0.407
Foggy weather	0.027	0.522	0.814
Traffic Conflict ~			
Aggressiveness	0.035	0.026	0.170
Unawareness	-0.016	0.058	0.785
Foggy Weather	0.133	0.179	0.460
Threshold (φ)	-0.527	0.504	0.296

Significance levels: · for 0.05 ≤ p-value < 0.1; * for 0.01 ≤ p-value < 0.05; ** for p-value < 0.01.

4.4 Discussion

This section discusses the correlation between CV and foggy weather, their immediate impact on driving behavior and unawareness, as well as their indirect effects on traffic conflicts through the intermediaries of aggressiveness and unawareness. A data-driven approach was employed, with a focus on carefully selecting variables for observation during the data analysis. **Table 8** displays the measurement model displays the observed variables for both aggressiveness and unawareness. According to the results, the mean brake, the maximum throttle, the maximum steering angle, and the 85th percentile of lane offset are positively associated with aggressiveness in the first and second groups. Repeatedly applying brakes excessively and utilizing a high throttle angle can result in noticeable variations in speed and braking. These variations are often linked to aggressive driving behaviors. Li et al. (2020) observed that aggressive driving behavior is associated with a greater degree of variation in speed and a higher level of acceleration, which can be indicated by a greater degree of throttle angle. Lee and Jang (2019) demonstrated a close association between intense speed and acceleration and aggressive driving behavior. Likewise, Aggressive driving behavior is often characterized by severe steering movements, resulting in an increased maximum steering angle. This relationship has been confirmed in several studies, including Kiefer et al. (2005) and Lee & Jang, (2019), which reported that oversteering maneuvers were frequently observed in aggressive drivers; nonetheless, such behavior can increase the likelihood of crashes, as indicated by Mazzae et al. (1999) who showed that excessive steering angles were associated with risky scenarios. A positive relationship between driver's aggressiveness and the 85th percentile of lane offset, indicating that aggressive drivers tended to position vehicles on the right lane. Given that both crashes occurred in the right lane, the aggressive drivers were more likely to continue driving to the right despite having received the CV warnings.

Unawareness was also found to have a positive relationship with the mean lane offset, indicating that unaware drivers inclined to position vehicles to the right. Additionally, **Table 8** presents a positive relationship between unawareness and the standard deviation of yaw, the mean of lane offset, the maximum steering angle, and the mean brake. The measurement of yaw is considered critical in driving behavior studies, as demonstrated by the inclusion of this variable in research conducted by multiple authors including Khoda Bakhshi et al. (2021) and Lee & Jang (2019). According to Lee & Jang (2019), a sharp increase in the degree of yaw can indicate the behavior and the awareness of the drivers. The possible explanation that due to the decreased visibility derivers inclined to be more cautious and drive in the right lane despite the receiving the CV alert. The maximum steering angle and mean brake display a positive association with crash one and an insignificant relationship with crash two. In contrast, in the single group model, both indicators demonstrate a positive relationship with a significant p-value, as illustrated in the results **Table 9**.

The structural model depicted in **Table 8** demonstrates that the propensity of traffic conflicts (y_i^*) is influenced by two latent variables, namely aggressiveness and awareness, as well as two exogenous variables, namely foggy weather and CV warnings for of group one, which represents the first crash located at straight section. As illustrated in **Table 8**, an increase of one unit in aggressiveness corresponds to a 0.066 unit increase in the propensity of traffic conflicts. However, no significant direct influence was observed between unawareness and traffic conflict, with a p -value greater than 0.10. Interestingly, at the first crash location, the deployment of CV alerts did not have a statistically significant direct effect on driver aggressiveness and awareness, as indicated by p-values greater than 0.10. **Figure 14** shows the direct effect of CV on aggressiveness and unawareness latent variables and the indirect effect of CV on traffic conflict as both aggressiveness and unawareness first were impacted by CV and after that affected traffic conflict. The total indirect effect of CV on conflict propensity on a straight section was estimated to be -0.051 (-0.772×0.066 - 0.045×-0.006). Regarding the impact of foggy weather when passing the first crash location, **Table 8** shows that the existence of foggy weather (0 for clear weather and 1 for foggy weather) would lead to in a decrease of 1.880 units in aggressiveness. In contrast, the presence of the foggy weather would result in an increase of 1.271 units in unawareness, indicating decreased situational awareness. When visibility is restricted due to foggy weather, drivers may experience difficulty in obtaining information in a timely and accurate manner, which could increase the risk of crashes. According to Li et al. (2015), fog-induced restricted visibility hindered drivers' capability to acquire accurate and timely information. Unlike unawareness, no significant direct relationship was reported between foggy weather and the propensity of traffic conflicts. Based on the available evidence, it is plausible to suggest that low-visibility conditions naturally prompt drivers to become more cautious and reduce their level of aggressiveness, without the use of CV alerts. Li et al. (2015) found that drivers were more inclined to drive more cautious and employ safe driving practices during foggy conditions. Zhang et al. (2021) reported that drivers were more inclined to employ safe driving practices during foggy weather. The findings suggest a lack of a significant relationship between age and the latent variable of unawareness in a straight segment. Meaning that observed variables such as yaw, lane offset, steering , and brake were not affected by the age.

In terms of crash two on the curve segment, the relationships between aggressiveness and unawareness with traffic conflict were not statistically significant, as shown in **Table 8**. Similarly, CV had no significant impact on aggressiveness, but a significant relationship was found between CV warnings and unawareness. Utilizing CVs in the second curve crash resulted in a 0.706 unit reduction in unawareness, indicating improved situational awareness. The effectiveness of CVs in reducing unawareness can be attributed to the complexity of driving through curves, as highlighted by Tan et al. (2022), who reported that the integration of the CV system has the potential to improve drivers' situational awareness and enable them to respond better to potential hazards while driving. Consequently, this reduction in unawareness decreases the propensity of traffic conflicts. These findings align with earlier studies on situational awareness. For instance, Alyamani & Kavakli (2017) observed that drivers exhibited decreased situational awareness while navigating curved roads but had heightened situational awareness when driving on straight roads. Similarly, Charlton (2007) reported that driving through curved segments requires allocating greater attention and mental resources to gather information and make decisions. This highlights the genuine need for drivers to rely on CV warnings in such road segments to mitigate unawareness and improve safety. Unlike the straight section, the impact of foggy weather on aggressiveness on the horizontal curve segment was not significant, while the impact of the foggy weather on unawareness was statistically significant. Earlier studies demonstrated that fog increases the likelihood of road crashes and the risk of fatalities (Hautière et al., 2007 & Wu et al., 2018). According to **Table 8**, it can be observed that the presence of foggy weather led to a significant decrease of 11.974 units in unawareness, suggesting an improvement in situational awareness. This finding indicates that drivers were more aware of their surroundings and potential hazards in foggy conditions. However, despite the effectiveness of CV warnings in reducing unawareness, a positive association between foggy weather and the likelihood of traffic conflicts was detected. The overall effect of foggy weather on the propensity of conflicts was estimated to be 0.529 (0.675 + 1.463×-0.018 -11.974×0.010), indicating an increased probability of traffic conflicts occurring during foggy weather. Notably, the probability of traffic conflicts was found to be higher on curve segment than on the straight during foggy weather. This is possibly due to the reduced visibility on the curved segment compared to straight segment, leading drivers to exhibit a greater propensity for traffic conflicts while approaching curves. In contrast, Dong et al. (2022) found that during wet weather, drivers tended to maintain a safer distance from the vehicle in front of them. This cautious behavior is expected to result in fewer traffic conflicts propensity than in normal conditions. This may be attributed to the increased awareness in unclear weather conditions, such as decreased visibility and slippery road conditions, leading drivers to prioritize safety by adopting a more conservative driving style. Furthermore, it is worth mentioning that the type of roadway can influence drivers' compliance with warning signs in reduced visibility conditions. Hassan & Abdel-Aty (2011) found that drivers were more likely to follow variable speed limit (VSL) signs on two-lane roads than on freeways during heavy or medium fog. This could be due to the absence of a median on two-lane roads and increased driver confidence on wider freeways. The authors further suggested that the wider road on freeways may lead to increased driver confidence and decreased compliance with VSL signs. Despite the CV warning's role in reducing unawareness in crash two, the findings suggest a marginal direct relationship between age and unawareness One possible explanation is that drivers in this age group may have exhibited overconfidence, and as they were driving in reduced visibility and approached the curved section, which slightly and momentarily exacerbated the driving status, the level of unawareness marginally increased.

The results of the single-group SEM are presented in **Table 9** and were compared to the multigroup SEM estimates in **Table 8**. The combined data from crashes one and two revealed a relationship between the latent variables of aggressiveness and unawareness and their respective measured variables, except for the maximum steering of aggressiveness and the mean lane offset of unawareness. In contrast, the structural model of the single-group SEM produced insignificant findings for all exogenous variables, including aggressiveness, unawareness, and traffic conflict, and their explanatory variables, with p-values greater than 0.1. These findings suggest poor performance and indicate an unacceptable SEM result.

4.5 Summary of Findings

To investigate the impact of CV technology on driving behavior and safety outcomes across various weather conditions, this study designed and executed a within-subjects driving simulator experiment. Data, both conflict-related and driving-related, which encompassed variables like brake, throttle, steering, lane offset, and yaw, were collected throughout the experiment.

The study utilized a multigroup structural equation model (SEM) to explore the relationships between CV warnings, the likelihood of traffic conflicts, weather conditions, driving behaviors, psychological factors, and other relevant variables. Within the SEM measurement model, latent psychological factors were constructed, including aggressiveness and unawareness, assessed through variables like yaw, lane offset, steering angle, brake, and throttle angle. This approach allowed for the simultaneous measurement of latent psychological factors and their interrelationships in a single statistical estimation procedure. The multigroup SEM exhibited a highly satisfactory goodness of fit, with RMSEA = 0.037, CFI = 0.973, and TLI = 0.978.

The analysis using the multigroup SEM yielded significant findings. It showed that CV alerts effectively reduced unawareness on horizontal curves, with a noteworthy reduction of 0.706 units in unawareness on the horizontal curve, subsequently decreasing the likelihood of traffic conflicts. However, in the context of foggy weather, despite its potential to enhance situational awareness, there was an overall positive effect on the propensity of traffic conflicts on the horizontal curve, increasing it by 0.529 units. Notably, the multigroup SEM did not reveal any significant effect of CV warnings on driving aggressiveness.

Conversely, when data from both crash locations were combined and analyzed using a single-group SEM, no significant interrelationships were uncovered in the structural model. These results provide valuable insights into the development of CV technologies in enhancing traffic safety, taking into account weather conditions and location-specific factors.

CHAPTER 5

SAFETY PERFORMANCE OF DRIVERS IN CONNECTED AND AUTOMATED VEHICLES DURING SAFETY-CRITICAL EVENTS USING NETWORKED DRIVING SIMULATION

In this chapter we aim to explore factors influencing driver safety performance within CAVs during safety-critical events that request drivers to take over. Networked driving simulators are utilized to create safety-critical events involving running red lights/stop signs at intersections and highway merging. The investigation will cover eight different scenarios, focusing on Level 2 and Level 3 ADS. Networked driving simulator experiments can involve multiple drivers in one synchronized driving scenario, which reflects a real-world driving situation (Park et al., 2019b). The concept of networked driving simulation is illustrated in **Figure 15**.

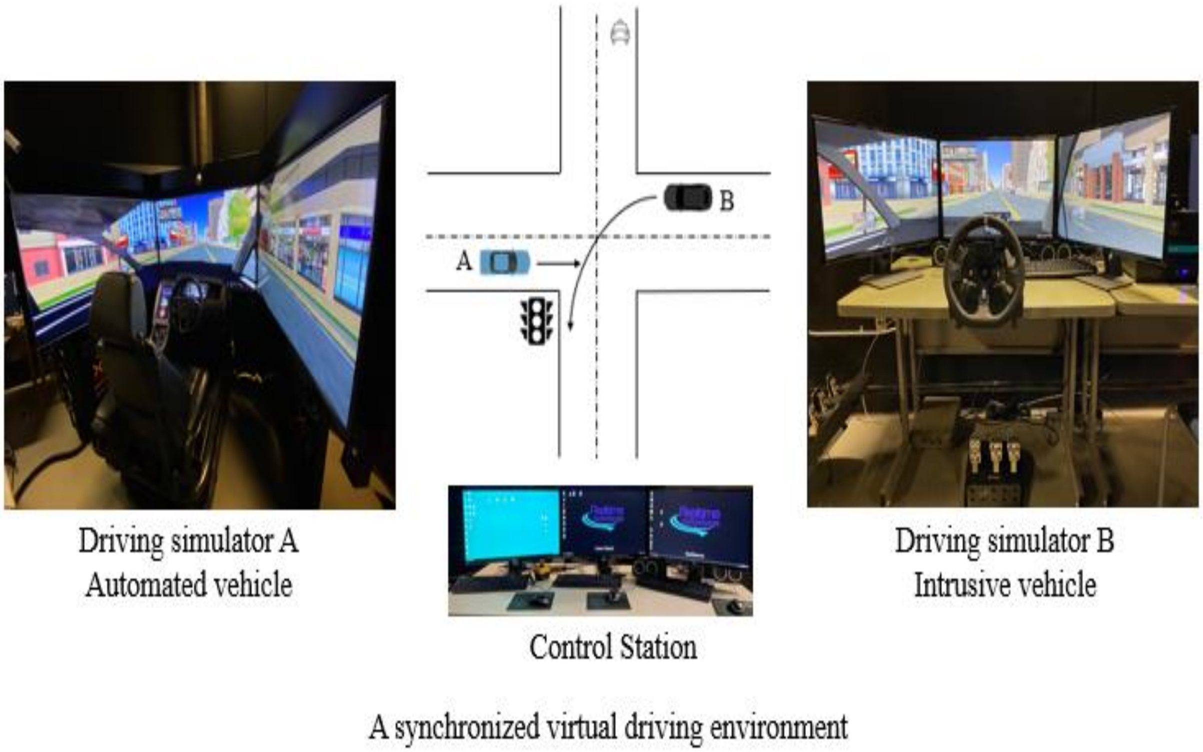


Figure 15. Concept of networked driving simulation

5.1 Experiment

5.1.1 Participants

A Previous study by Yang et al. (2020) noted that the typical sample size for driving simulator experiments is usually below 25 participants. The same sample size was also adopted in previous literature, such as in studies by Yang et al. (2020), Alyamani and Kavakli (2017), Son et al. (2020), and Li et al. (2020). A total of 39 participants were recruited from the Old Dominion University community for the driving experiment, and each participant possessed a valid US driver's license with a minimum of one year of driving experience. Out of the initial 39 participants, three experienced symptoms of motion sickness and requested to discontinue their participation. As a result, valid data were collected from 36 participants. Gender distribution among the participants was equal, comprising 18 males and 18 females. The participants' ages ranged from 18 to 41 years (mean = 31.00 years, standard deviation = 6.52 years). All participants were in good health, and their driving experience ranged from 1 year to 23 years (mean = 7.60 years, standard deviation = 6.07 years).

5.1.2 Procedure

When participants arrived, they read and verbally consented to a form that outlined the experiment details and included a caution about the potential for motion sickness. Participants were informed that they could withdraw from the experiment at any time, whether due to motion sickness or any other reason. Using the RDS-1000 simulator, all participants underwent a 5–10-minute warm-up drive to become familiar with the virtual driving environment and the autopilot mode before the main experiment. Each participant was assigned to either ADS Level 2 or ADS Level 3. The researchers provided clear driving instructions for each level, following the guidance provided by (Samuel et al., 2020), which explained how to operate the vehicle and handle ADS takeover steps in the event of a CV warning or the need for driver intervention. In level 2, participants were instructed to keep their hands on the steering wheel and their foot ready over the brakes, even though the simulator managed all aspects of maneuvering, such as steering, braking, and acceleration, throughout the simulation. They were also required to remain vigilant and monitor the forward roadway, even though the vehicle handled autonomous navigation. In contrast, in level 3, participants were informed that the simulation would handle all aspects of the drive, but they should be prepared to take control if necessary. Each simulated drive lasted about 60 minutes, with a skilled experimenter operating the RDS-100 simulator, which was connected to an identical simulated environment as the RDS-1000 simulator in a distributed driving setup.

5.1.3 Scenario Development

In a prior study by Mayhew et al. (2011), researchers identified differences between real-world traffic scenarios and driving simulator-based scenarios. To minimize these differences and create more realistic traffic events, as recommended by Zhao et al. (2019), We developed eight scenarios for our driving simulation experiment, with three participant groups assigned to different sets: 1) Level 2 with CV warning; 2) Level 3 with CV warning; and 3) Level 2 without CV warning. All groups underwent testing both with and without visual obstructions. The scenario design drew from four hazardous driving scenarios in the *NHTSA Pre-Crash Scenario Pre-Crash Scenario Typology for Crash Avoidance Research* (Najm et al., 2007). Specifically, two intersection scenarios and two highway merging scenarios were modeled with and without obstructions obscuring the view of the conflicting vehicle (i.e., also referred to as the intrusive vehicle).

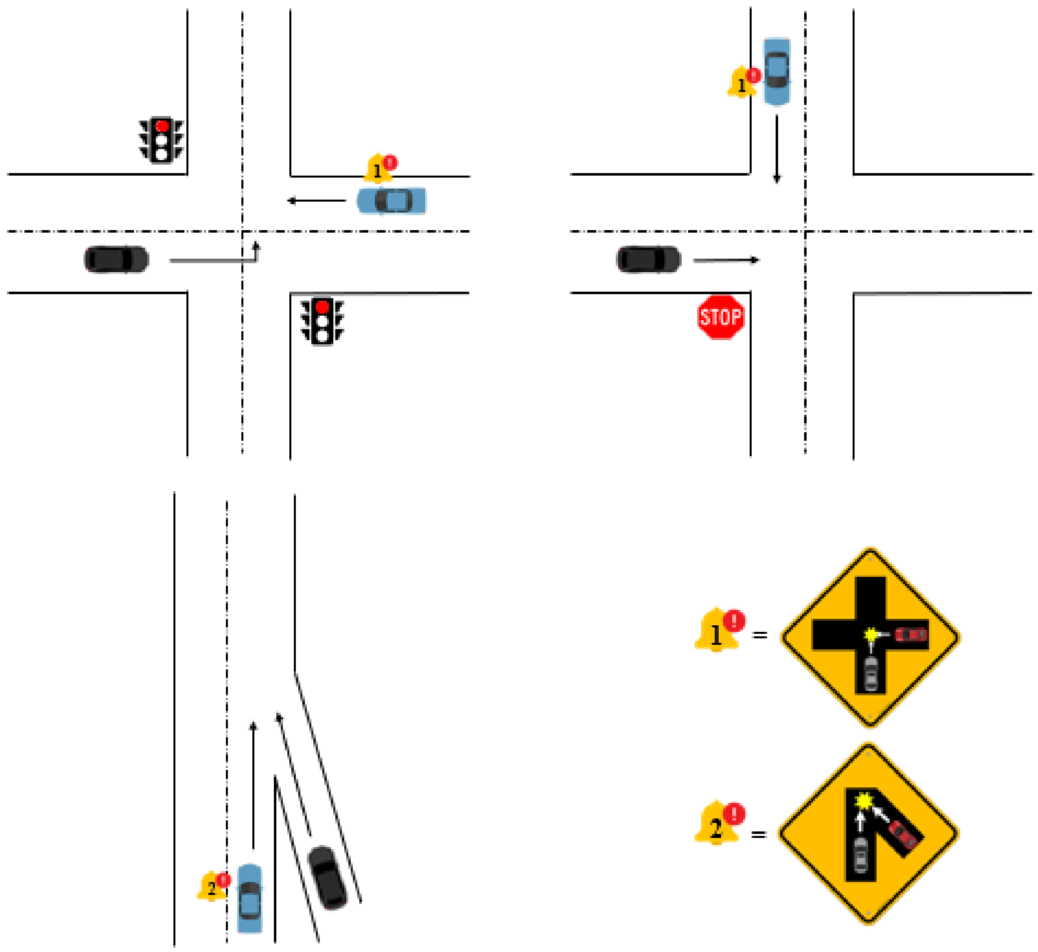
Eight driving scenarios were designed for each participant group, including four intersection scenarios (1-4) and four highway scenarios (5-8) as follows:

- Scenario 1. Running red light without obstruction.
- Scenario 2. Running red light with obstruction.
- Scenario 3. Running stop sign without obstruction.
- Scenario 4. Running stop sign with obstruction.
- Scenario 5. Daytime without obstruction.
- Scenario 6. Daytime with obstruction.
- Scenario 7. Nighttime without obstruction.
- Scenario 8. Nighttime with obstruction.

For a more in-depth explanation of intersection and highway merging scenarios, refer to the following:

(a) Runing red light scenarios (Scenarios 1-2): During daylight hours in an urban area with clear weather conditions, a vehicle is traveling at the designated speed limit of 35 mph through a rural area. Meanwhile, another vehicle (colored black) fails to adhere to the stop sign and conflicts with the first vehicle approaching from the left, as presented in the top of **Figure 16 a.** To evaluate the impact of obstructions, two scenarios were implemented: Scenario 1, conducted without obstructions, and Scenario 2, conducted with obstructions. In the case of obstructions, the participant in the blue vehicle is able to see the vehicle making the left turn before the intersection. In the CAV scenario, the warning is designed to detect and warn the driver of potential collisions at intersections. Prior to entering the intersection, the CAV triggers both visual and auditory warnings, including a "beeping sound," to alert the driver to the approaching collision.

(b) Runing stop sign scenarios (Scenarios 3-4): In this scenario, a vehicle is observed driving through a rural area in optimal weather conditions, with daylight prevailing and adherence to the stipulated speed limit of 35 mph. The top of **Figure 16 b** provides a visual representation of the critical moment as the vehicle approaches an intersection. At this juncture, another vehicle, identified as the black vehicle, disregards the stop sign and conflicts with the first vehicle approaching from the left. To assess the impact of obstructions, the scenario was conducted under two distinct conditions: one with obstructions, designated as Scenario 3, and another without, referred to as Scenario 4. In the presence of obstructions, the autonomous CAV demonstrates its safety measures by proactively triggering a combination of visual and auditory warnings. These warnings, including a distinctive "beeping sound," are initiated prior to entering the intersection, to alert the driver to the impending collision.



(a) (b)

Figure 16. Networked driving simulator experiment: (a) running red light and highway merging scenarios; (b) running stop sing scenario and CV warnings.

(c) Highway merging scenarios in two lighting conditions (Scenarios 5-8): In evaluating the influence of different lighting conditions, the scenario was executed during both daytime and nighttime. Scenario 5 and Scenario 6 represent daytime conditions, while Scenario 7 and Scenario 8 represent nighttime conditions. To assess the impact of obstructions, Scenarios 5 and 6 are identified with and without obstructions during the daytime, respectively. Conversely, Scenarios 7 and 8 represent nighttime conditions without and with obstructions, respectively. In this context, in clear weather conditions with moderate ambient traffic, the driver travels in the right lane of a straight highway section, adhering to the posted speed limit of 75 mph. Simultaneously, another vehicle enters the highway from the entrance ramp. The CAV system triggers alerts to notify the driver of the impending conflict just before entering the merging area. in the bottom of **Figure 16 a.**

(d) Across all eight scenarios, data privacy and confidentiality were assured to all participants to maintain the IRB instructions. Data on driving behavior and performance were consistently collected at a rate of 60 observations per second, encompassing the time span from the initiation of the CV warning to the projected crash point. This standardized data collection approach was applied uniformly to scenarios with and without obstructions, as well as those with and without a CV warning, with the latter serving as a reference point in scenarios where it was absent. The CV warnings were also presented in the bottom of **Figure 16 b** , where CV warning 1 functions in the intersection scenarios, while CV Warning 2 functions in the highway merging scenarios. Notably, the distance between the CV warning and the projected crash point varied across scenarios: 112.20 feet in the running led light scenario, 137.14 feet in the running stop sign scenario, and approximately 247.80 feet in both daytime and nighttime highway merging scenarios. For a more detailed visualization of the scenarios employed, please refer to **Figure 17** for intersection scenarios and **Figure 18** for highway merging scenarios.

(a) (b)

Figure 17. Runing red light scenario: (a) with obstruction ; (b) without obstruction

(a) (b)

Figure 18. Highway merging scenario: (a) with obstruction; (b) without obstruction

5.1.4 Data Assembly

The descriptions and corresponding descriptive statistics for various variables, including traffic conflict, obstruction, CV warning, stop sign , automation level, and daytime, are provided in **Table 10**. The concept of PET was initially introduced by Allen et al. (1978). PET is defined as the time interval commencing when the first vehicle departs from a conflict point and concluding when the second vehicle approaches the same point.

The formula for calculating PET is expressed as follows:

$$PET = t_2 - t_1 \tag{11}$$

Where:

t_1: denotes the departure time of the first vehicle from the conflict point; and

t_2: represents the arrival time of the second vehicle at the same conflict point.

Table 10. Key variables descriptions

Variable	**Description**
Traffic Conflict	1 when PET is lower than the threshold, 0 otherwise
Obstruction	1 for obstruction, 0 for no obstruction
CV Warning	1 for CV Warning, 0 for no CV Warning
Stop Sign	1 for stop sign running scenarios, 0 for red light running scenarios
Automation	1 for level 2 automation, 0 for level 3 automation
Daytime	1 for daytime scenarios for highway merging, 0 for nighttime scenarios

In the context of intersection scenarios, the typical PET thresholds often employ a time frame of 5 seconds or less, especially when dealing with relatively low speed limits, which is in line with established practices. When assessing traffic conflicts at intersections, interactions are categorized by their severity. Interactions falling within the range of 5 to 3 seconds are considered mild interactions, a classification initially established by Zangenehpour et al. (2016) and subsequently corroborated by Navarro et al. (2022). Consequently, for scenarios involving traffic light and stop sign intersections, the designated PET threshold is set at 5 seconds or less. Similarly, a common practice is to consider a range spanning from 3 seconds to 1 second for the evaluation of traffic conflicts measured by PET. This practice aligns with similar studies in the domain of highway traffic conflict analysis, exemplified by the research conducted by Qi et al. (2020) and Zhu & Tasic (2021) wherein the presence of traffic conflicts is associated with PET values below 3 seconds, frequently approximating 2.25 seconds. Hence, within the scope of the study, the PET threshold remains consistently defined as equal to or less than 3 seconds.

5.2 Logit Model with Random Effects

5.2.1 Model Specification

To explore the relationships between the presence of traffic conflicts (indicated by PET values) and multiple factors, this study adopts a binary logit model that incorporates participant-specific random effects. The considered factors include vehicle CV warning, the presence of obstructions, automation level (Level 2 vs Level 3), traffic control, and time of day (daytime vs nighttime).

The proposed binary logit model with rando effects is expressed as:

$$y_i \sim Bernoulli\ (\pi_i)$$

$$ln\left(\frac{\pi_i}{1-\pi_i}\right) = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ik} + u_j$$

Where y_i is the observation of a traffic conflict during the ith experiment, following a Bernoulli distribution with the probability π_i. π_i represent the probability of the binary outcome variable y_i equals 1. $X_{i1}, X_{i2}, \dots, X_{ik}$ are factors to investigate such as obstruction, CV warning, automation level, etc. β_0 is the fixed intercept. $\beta_1, \beta_2, \ldots, \beta_k$ are the fixed coefficients of the explanatory variables. u_j denotes the random effect associated with the jth participant, which can capture induvial-specific characteristics that would affect safety performance.

5.2.2 Model Assessment

Models are evaluated using likelihood estimation-based criteria like Akaike Information Criterion (AIC) (Akaike, 1974) and Bayesian Information Criterion (BIC) (Schwarz, 1978). AIC accounts for model complexity by penalizing the number of parameters, while BIC additionally considers sample size in its penalty term. These criteria can be represented as:

$$AIC = -2LL + 2K \tag{12}$$

$$BIC = -2LL + \mathrm{Kln}(N) \tag{13}$$

LL represents the model's log-likelihood, K stands for the count of parameters within the model, and N denotes the sample size.

5.3 Results

The study employed logit models to estimate the binary response variable, traffic conflict identified by PET, while considering various explanatory variables for both intersection and highway merging scenarios. These explanatory variables included obstruction, CV warning, stop sign, and automation levels (2 and 3) for intersection scenarios, encompassing running red light and running stop sign situations. For highway merging scenarios, the explanatory variables comprised obstruction, CV warning, daytime/nighttime, and automation levels (2 and 3). The model assessment, with and without random effects for both intersection and highway merging scenarios, is presented and summarized in **Table 11**.

Table 11 provides a comprehensive assessment of models, comparing those with and without participant-specific random effects. The logit model with random effects exhibits superior performance, especially in intersection scenarios, with higher log-likelihood values (-55.6 and -61.56 for models with and without random effects, respectively). While the AIC value of 125.2 is slightly higher than the AIC of 124.69 without random effects, the BIC value of the model with random effects (146) significantly surpasses that without random effects (157.91), indicating an overall improvement in model performance with the inclusion of random effects. Similarly, for highway merging scenarios, the log-likelihood, AIC, and BIC values for the model with random effects suggest a generally good fit. The log-likelihood of the random effects model (-79.9) surpasses that without participant-specific random effects (-90.95). Additionally, the AIC value of 173.8 is lower than the AIC of 186.64 without random effects, and the BIC value of the model with random effects (194.6) is notably lower than without random effects (216.69), pointing towards an overall superior model performance with random effects.

Table 12 and **Table 13** present the outputs of fixed and random effects for intersection and highway merging scenarios, respectively. These results address the crucial question of whether CV warnings are beneficial in driving automated modes in both intersection and highway merging scenarios.

Table 11. Model assessment with and without random effects

	Intersections		Highway Merging	
Statistical Measure	With Random Effects	Without Random Effects	With Random Effects	Without Random Effects
Log likelihood	-55.6	-61.56	-79.9	-90.95
AIC	125.2	124.69	173.8	186.64
BIC	146	157.91	194.6	216.69

Table 12. Parameters of the logit model for intersection scenarios

	Estimate	Std. Err	P-value
Fixed Effects			
Intercept	3.764	1.267	0.003**
Obstruction	-0.492	1.003	0.624
CV Warning	-1.858	1.004	0.064·
Stop Sign	-0.785	0.530	0.138
Automation	-0.565	0.736	0.442
Obstruction: CV	2.097	1.214	0.084·
Random Effects			
Intercept	Variance: 0.898	Std. Err: 0.947	

Significance levels: · for 0.05 ≤ p-value < 0.1; * for 0.01 ≤ p-value < 0.05; ** for p-value < 0.01.

Table 13. Parameters of the logit model for highway merging scenarios

	Estimate	Std. Err	P-value
Fixed Effects			
Intercept	3.162	1.258	0.012*
Obstruction	-0.634	0.805	0.431
CV Warning	-1.863	1.039	0.073·
Daytime	-0.486	0.446	0.276
Automation	-0.769	0.886	0.385
Obstruction: CV	0.775	0.965	0.422
Random Effects			
Intercept	Variance: 2.617	Std. Err: 1.618	

Significance levels: · for 0.05 ≤ p-value < 0.1; * for 0.01 ≤ p-value < 0.05; ** for p-value < 0.01.

5.4 Discussion

Interestingly, the presence of obstructions in both intersection and highway merging scenarios led to a reduction in the likelihood of traffic conflicts by 0.492 and 0.634 units, respectively, with corresponding p-values of 0.624 and 0.431. This surprising outcome can be attributed to the concept of risk compensation, as discussed by Streff & Geller (1988). Risk compensation suggests that individuals may perceive certain benefits in taking greater risks, especially when changes in the risk environment reduce the expected negative outcomes. In the context of this study, it can be inferred that drivers equipped with advanced CAV systems might exhibit an increased inclination toward risk-taking behavior. Drivers tend to adjust their driving behavior based on their perception of safety. When obstructions potentially diminish drivers' visibility, individuals tend to adopt a more cautious approach to vehicle control, resulting in a decreased likelihood of traffic conflicts. Furthermore, the interaction between obstruction and CV warning in the automated mode revealed an intriguing pattern. It was found to increase the probability of traffic conflicts, with a significance level of 0.084 for intersections and a non-significant level of 0.422 for highway merging scenarios. Essentially, the CV warning system appeared to be less effective in reducing the probability of traffic conflicts compared to scenarios without obstructions in both intersection and highway merging contexts. This observation aligns with the findings reported by Zavantis et al., 2022 , which suggest that while AVs were expected to decrease crash rates, they also had the potential to encourage increased risk-taking behavior among drivers who feel safer due to the presence of advanced technology. **Figure 19** displays a box plot showing the conflict numbers as indicated by mean PET values in scenarios with and without obstructions at intersections. Clearly, when a CV warning is present, the mean PET value is higher than when there is no CV warning. Similarly, in scenarios with obstructions, the mean

PET value is generally higher compared to scenarios without obstructions, signifying improved safety performance. Furthermore, **Figure 20**, depicts the conflict numbers indicated by PET, revealing higher mean values in CV warning scenarios, indicating enhanced safety performance in comparison to scenarios without CV warnings. Overall, there was no significant difference in safety performance between scenarios with obstructions and scenarios without obstructions, as the mean PET values were nearly identical.

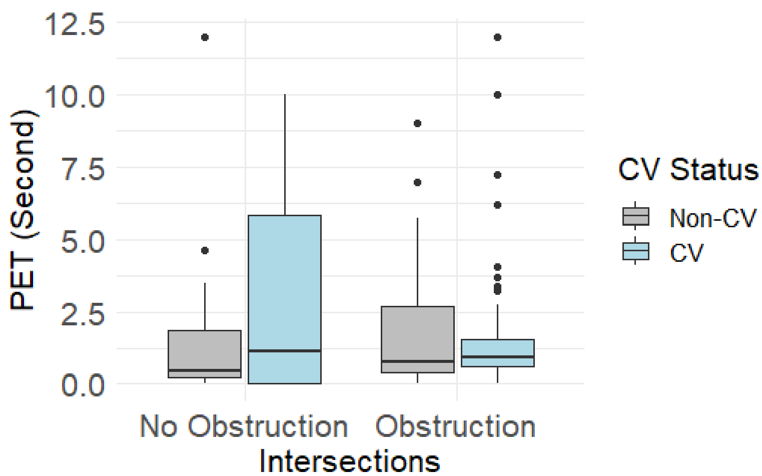


Figure 19. Boxplot of intersection scenarios

Figure 20. Boxplot of highway merging scenarios

The workload model could provide a plausible explanation for these findings. Workload, in this context, refers to the allocation of information processing resources required for task performance, as defined by De Waard & Brookhuis (1996) and Wickens et al. (2000). Distraction, in particular, places an excessive workload on drivers' limited attention, as noted by Lee (2014). In scenarios involving obstructions, the presence of a CV warning can act as a distraction for drivers approaching intersections or merging points, ultimately increasing the likelihood of traffic conflicts. This aligns with the findings of Patten et al. (2004), who observed that as drivers experience a rise in workload, their brain's capacity to process and respond to new information diminishes compared to situations with lower workloads.

Comparing the scenarios of running a stop sign and running a red light, it's interesting to note that the stop sign scenario displayed a negative relationship with the traffic conflict response variable, with a coefficient of 0.785 and a p-value of 0.138, as indicated in **Table 12**. This negative association suggests that a decrease in conflict frequency at stop sign intersections might contribute to lowering the probability of accidents and injuries. Research by Haleem and Abdel-Aty, (2010) suggested that setting speed limits below 45 mph at unsignalized intersections results in a notable reduction in the likelihood of severe injuries compared to cases where speed limits exceed 45 mph. However, in a non- CAV context, Strauss et al. (2014) provided empirical evidence indicating that signalized intersections exhibit a higher incidence of injuries and an increased risk of motor vehicle accidents when compared to non-signalized intersections.

When distinguishing between Level 2 and Level 3 automation, it was observed that Level 2 automation reduced the potential for traffic conflicts by probabilities of 0.565 and 0.769 in intersection and highway merging scenarios, respectively, with corresponding p-values of 0.442 and 0.385. That is likely because drivers at Level 2 were instructed to observe and monitor the traffic and intervene when necessary, unlike Level 3 were drivers were not required to monitor the environment when automated mode is active. **Table 13** further illustrates a negative relationship between the daytime variable and the likelihood of traffic conflicts, with a statistical p-value of 0.276. In a typical driving situation, the risk of a road accident is generally greater at night compared to daytime. A study by Massie and Campbell (1993) reported that the rate of fatal accidents at night is 4.6 times higher than during the daytime. This implies that drivers merging onto highways during nighttime hours were at a relatively higher risk of encountering traffic conflicts. To account for unobserved variables and capture individual-specific characteristics, random effects were integrated into the binary logit model. In the case of the intersection, it exhibited a variance of 0.898 and a standard error of 0.947. This variance indicates that there is variation in the intercepts across different units, with the standard error serving as a measure of uncertainty regarding this variance estimate. Similarly, for the highway merging scenario, a variance of 2.617 and a standard error of 1.618 were observed, implying significant variability among units.

5.5 Summary of Findings

The objective of this chapter was to shed light on the factors influencing driver safety performance in the context of CAV warnings, particularly during safety-critical events such as running red lights/stop signs at intersections and highway merging. This was achieved through the development and execution of a networked driving simulator experiment. For the safety evaluation, traffic conflict events were gathered using a commonly used surrogate safety measure, PET.

The binary logit model with random effects was employed to illustrate the relationship between the observation of a traffic conflict, and various factors, including CV warnings, obstructions, running stop sign scenarios, automation levels (Level 2 and Level 3), daytime conditions, obturation, and the interaction between CV warnings and obturation. The analysis of model performance, based on measures like AIC and BIC, has demonstrated the superiority of the random effects logit models over the standard logit model. This underscores the importance of accounting for individual driver characteristics and behaviors in assessing safety within CAVs. It was observed that the warning system in automated driving modes would reduce the likelihood of traffic conflicts, with statistical significance levels of 0.064 for intersections and 0.073 for highway merging scenarios. These results highlight the potential of CV technology to enhance safety during safety-critical events and improve the overall driving experience within CAV systems. In scenarios involving intersections, the presence of obstructions would lower the likelihood of traffic conflicts (p-value = 0.624). Additionally, the stop sign demonstrated a negative association with the traffic conflict response variable (p-value = 0.138), and the interaction of obstruction and CV warning in automated mode would heighten traffic conflicts (p-value = 0.084). For highway merging scenarios, the presence of obstructions was associated with a decreased likelihood of traffic conflicts (p-value = 0.431). The daytime variable displayed a negative relationship with the likelihood of traffic conflicts, as evidenced by a statistical p-value of 0.276. Furthermore, the interaction of obstruction and CV warning in automated mode indicated a non-significant increase in traffic conflicts (p-value = 0.422).

This chapter contributes to the existing literature by introducing an innovative approach that utilize networked driving simulators to investigate drivers' responses to safety-critical events. As CAV technology advances, real-world traffic scenarios become more complex and interactive, with the ongoing influence of human drivers. Networked driving simulators, a valuable tool for replicating real-world interactions between drivers, address a challenge often beyond the capabilities of conventional driving simulations. They offer significant advantages for studying driver interactions, faithfully recreating real-world scenarios using a controlled approach. The insights gained from this research have the potential to inform the development of human-machine interactions within CAV systems, with a specific emphasis on safety performance during critical events.

As a future direction, leveraging advanced statistical methods, such as functional data analysis, to extract deeper insights from driving experiment data could make valuable contributions to the existing literature.

CHAPTER 6

CONCLUSIONS AND FUTURE RECOMMENDATIONS

This dissertation explores the impact of CAV technology on driving behaviors and safety performance. Chapter 3 examines the effects of CV technology on drivers' aggressiveness and awareness during highway crash scenarios. Chapter 4 investigates how the CV system influences driving behaviors and safety outcomes in highway crash scenarios under varied weather conditions. Chapter 5 explores factors influencing drivers' safety performance within CAV technology during safety-critical events. These findings contribute valuable insights to the field of CAV technology and its potential to enhance driving safety, with implications for future research and practical applications. The findings of each chapter are summarized below.

In Chapter 3 of this dissertation, the objective is to examine the impact of CV technology on psychological factors such as situational awareness and aggressiveness. To accomplish this, an experimental setup was designed, involving a within-subjects driving simulator experiment. Driving data (i.e., speed, acceleration, steering, lane offset, yaw, etc.) and survey data were collected. Participants tended to trust the CV system provided in the experiment and believed it was beneficial in enhancing their driving behavior. The SEM was adopted to depict the interrelationships between the application of CV warnings, driving behavior, psychological factors, crash location, and the characteristics of drivers. The latent psychological factors including aggressiveness and unawareness were constructed in the SEM measurement model. Unawareness was measured by yaw, brake, lane offset, and steering angle, while aggressiveness by brake, speeding, steering angle, and longitudinal acceleration. The SEM has the advantage of achieving the measurement of latent psychological factors and interrelationship modeling simultaneously in one statistical estimation procedure. The goodness of fit of the SEM was highly satisfactory with

RMSEA = 0.037, CFI = 0.981, and TLI = 0.973. Results suggested that CV warnings would reduce the unawareness and aggressiveness by 0.501 and 3.009, respectively. It was also found that drivers drove more aggressively and less aware on the curve segment. The findings presented study have the potential to advance our understanding of how CVs contribute to driving performance in unpredictable abnormal events, such as the risk of secondary crashes.

Chapter 4 aims to investigate how CV technology affects driving behavior and safety outcomes under varied weather conditions, this study designed and conducted a within-subjects driving simulator experiment. Conflict data and driving data including brake, throttle, steering, lane offset, and yaw, was collected during the experiment. The multigroup SEM was employed to investigate the interrelationships between the CV warnings, propensity of traffic conflicts, weather conditions, driving behaviors, psychological factors, and other relevant factors. Latent psychological factors were constructed within the SEM measurement model to include aggressiveness and unawareness, which were measured by variables such as yaw, lane offset, steering angle, brake, and throttle angle. The multigroup SEM enabled the concurrent measurement of latent psychological factors and interrelationships in a single statistical estimation procedure. The goodness of fit of the multigroup SEM was highly satisfactory, with RMSEA = 0.037, CFI = 0.973, and TLI = 0.978. The analysis using multigroup SEM demonstrated significant results, indicating that CV alerts effectively decreased unawareness on horizontal curves. Specially, the use of CV decreased unawareness by 0.706 unit on the horizontal curve, which in turn decreased the propensity of traffic conflicts. However, despite its potential to improve situational awareness, foggy weather was found to have an overall positive effect on the propensity of traffic conflicts on the horizontal curve. The presence of foggy weather would increase the propensity of traffic conflicts by 0.529 unit on the horizontal curve. Additionally, the multigroup

SEM did not reveal any significant effect of the presence of CV warnings on driving aggressiveness. On the other hand, when data from both crash locations were combined and analyzed using a single-group SEM, no significant interrelationships were uncovered in the structural model.

Chapter 5 aims to explore the factors influencing driver safety performance in the context of CAV technologies, particularly during critical events such as running red lights/stop signs at intersections and highway merging. This exploration is conducted through a meticulously designed and executed networked driving simulator experiment. Safety performance is evaluated by assessing traffic conflicts using a surrogate safety measure, PET. The study utilized a binary logit model with random effects to explore the relationship between observing a traffic conflict and various factors, including CV warnings, obstructions, running stop sign scenarios, automation levels (Level 2 and Level 3), daytime conditions, obturation, and the interaction between CV warnings and obturation. Assessing model performance with measures like AIC and BIC revealed the superiority of random effects logit models over the standard logit model, emphasizing the need to consider individual driver characteristics and behaviors when evaluating safety within CAVs. The findings indicated that the warning system in automated driving modes significantly reduces the likelihood of traffic conflicts, with statistical significance levels of 0.064 for intersections and 0.073 for highway merging scenarios. In scenarios involving intersections, the presence of obstructions lowered the likelihood of traffic conflicts without statistical significance (p-value = 0.624). Additionally, the stop sign showed a negative association with the traffic conflict response variable (p-value = 0.138), and the interaction of obstruction and CV warning in automated mode significantly heightened traffic conflicts (p-value = 0.084). For highway merging scenarios, the presence of obstructions was associated with a decreased likelihood of traffic conflicts without statistical significance (p-value = 0.431). The daytime variable displayed a negative relationship with the likelihood of traffic conflicts, as indicated by a statistical p-value of 0.276. Furthermore, the interaction of obstruction and CV warning in the automated mode indicated a non-significant increase in traffic conflicts (p-value = 0.422). This study adds to the current body of literature by introducing an innovative approach that utilizes networked driving simulators to explore drivers' responses to safety-critical events.

This dissertation contributes to the existing literature by advancing the understanding of how emerging CAV technologies influence driving behaviors, psychological factors, and safety outcomes in various safety-critical situations. It introduces the innovative use of SEM to measure psychological factors including aggressiveness and situational awareness and to analyze the interrelationships among the use of CV warnings, psychological factors, driving behavior and safety outcomes. Another noteworthy contribution of this dissertation is its provision of insights into the effectiveness of CVs in highway crash scenarios under diverse weather conditions and different locations (curve vs tangent). Lastly, the dissertation enriches our comprehension of drivers' safety performance during emergence take overs in a connected and automated driving environment. This has been achieved through the innovative use of networked driving simulators, a technology available in only a few universities.

The dissertation provides crucial insights into the progression of driving assistance systems, placing a robust emphasis on explicitly considering psychological factors. The findings offer valuable perspectives on the development of CV technologies, particularly in enhancing traffic safety by considering weather conditions and location-specific factors, potentially leading to a substantial improvement in driving safety. Additionally, the study advocates for the development of customized warning systems that align with drivers' preferences, effectively reducing their driving behavior, increasing situational awareness, and promote proactive deriving behavior. The insights derived from this research have the potential to shape the evolution of human-machine interactions within CAV systems, with a specific emphasis on safety performance during critical events. This knowledge is pivotal for propelling the advancement of emerging CAV technology and realizing its profound potential to significantly enhance driving safety.

A limitation in the studies of both Chapter 3 and Chapter 4 is the uneven representation of participant gender, as most participants were sourced from the ODU engineering community. Additionally, the sample size in this study is constrained by limited available resources. The study would certainly derive significant benefits from a larger sample size, contributing to enhanced statistical power, reliability, and the generalizability of the findings.

To build upon the findings presented in this dissertation, future studies could expand the study's sample size to enhance the reliability and generalizability of the findings. Another possible future direction is to explore various operational design domains, which may include complex highway interchanges and challenging weather conditions, such as substantial snowfall and icy road conditions. These adverse weather conditions can significantly impact visibility, road surface conditions, and driver decision-making, potentially leading to unique effects on traffic conflicts and situational awareness. Investigating various roadway geometries, which may include complex highway interchanges such as a diverging diamond interchange (DDI) and displaced left turn (DLT), can significantly enhance our comprehension of the elements that contribute to safety. Further, the use of advanced statistical methods, such as functional data analysis can provide deeper insights from driving experiment data. Finally, considering that modern passenger cars are increasingly equipped with a multitude of safety features, including lane departure warnings, blind spot alerts, rear cross-traffic warnings, and more, it becomes crucial to examine the effects of these advancements on driving behaviors and overall safety performance.

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APPENDIX A

List of Publications Derived from this Dissertation

Alruwaili, Abdalziz, Xie, Kun, 2024 Investigating the Impacts of Connected Vehicles on Driving Aggressiveness and Situational Awareness in Highway Crash Scenarios: A Driving Simulator Study. Transportation Research Board 103rd Annual Meeting, Washington, D.C. (The study has also been submitted to the Journal of Accident Analysis and Prevention).

Alruwaili, Abdalziz, Xie, Kun, 2024 Exploring the Impact of Connected Vehicles on Driving Behaviors and Safety Outcomes in Diverse Weather Conditions. Transportation Research Board 103rd Annual Meeting, Washington, D.C. (The study has also been submitted to the Journal of Transportation Research Part F: Psychology and Behavior).

This study is currently undergoing the submission process to the Journal of Accident Analysis and Prevention under the title "Safety Performance of Drivers in Connected and Automated Vehicles During Safety-Critical Events: A Networked Driving Simulation Study."

APPENDIX B

List of Acronyms

ADAS	advanced driver Assistance System
ADS	Automated Driving System
AGM	Active Gap Metering
AIC	Akaike Information Criterion
ANOVA	Analysis of Variance
AV	Automated Vehicle
BIC,	Bayesian Information Criterion
CAV	Connected and Automated Vehicle
CFI	Comparative Fit Index
CPI	Crash Potential Index
CV	Connected Vehicle
DDI	Diverging Diamond Interchange
DDT	Dynamic Driving Task
DLT	Displaced Left Turn
FHWA	Federal Highway Administration
IRB	Human Subjects Research
ITS	Intelligent Transportation Systems
MANOVA	Multivariate analysis of variance
ML	Maximum Likelihood
MLMV	Maximum Likelihood Mean-Variance
MUTCD	Manual on Uniform Traffic Control Devices
NHTSA	National Highway Traffic Safety Administration
ODD	Operational Design Domain
P2V	Pedestrian-to Vehicle
PET	Post-Encroachment Time
PLS	Partial Least Squares
RDS	Real Time Technologies

RMSEA	Root Mean Square Error of Approximation
SAE	Society of Automotive Engineers
SSM	Surrogate Safety Measure
TLI	Trucker–Lewis's Index
TTC	Time to Collision
V2V	Vehicle-to-Vehicle
VISSIM	VISSIM Software
VSL	Variable Speed Limit
WLSMV	Weighted Least Squares Mean-Variance

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Selected Publications and Presentations

Alruwaili, Abdalziz, Xie, Kun, 2024 Investigating the Impacts of Connected Vehicles on Driving Aggressiveness and Situational Awareness in Highway Crash Scenarios: A Driving Simulator Study. Transportation Research Board 103rd Annual Meeting, Washington, D.C.

Alruwaili, Abdalziz, Xie, Kun, 2024 Exploring the Impact of Connected Vehicles on Driving Behaviors and Safety Outcomes in Diverse Weather Conditions. Transportation Research Board 103rd Annual Meeting, Washington, D.C.

Yamani Y, Glassman J, **Alruwaili A**, et al. Post Take-Over Performance Varies in Drivers of Automated and Connected Vehicle Technology, in Near-Miss Scenarios. Hum Factors. Published online 2023:00187208231219184.