MODELING THE EFFECTS OF ADVANCED DRIVER ASSISTANCE SYSTEMS ON DRIVER BEHAVIOR

by

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ABSTRACT

RAGHUVEER PRASAD GOURIBHATLA. Modeling the Effects of Advanced Driver Assistance Systems on Driver Behavior. (Under the direction of DR. SRINIVAS S. PULUGURTHA)

About 38,000 fatalities are reported every year in the United States and traffic crashes (referred to as crashes) are the leading cause of deaths among people up to 54 years. Additionally, economic loss due to crashes is estimated equal to $380 million, annually, in direct medical bills. Further, new vehicles are added to the roads every year increasing the traffic exposure and vehicle miles traveled. Driver errors are the leading cause of crashes and contribute to about 94% of crashes. Automobile manufacturers are striving to enhance the vehicles to eliminate driver errors, which can help avoid the major chunk of crashes. These enhancements include development of various types of advanced driver assistance systems (ADAS) that are designed to assist or in some cases also take over certain driving maneuvers. They include lane departure warning (LDW), blind spot warning (BSW), over speeding warning (OSW), lane keep assist (LKA), front collision warning (FCW), adaptive cruise control (ACC), and automatic emergency braking (AEB). Each of these features are focused at addressing a particular task of driving, thereby, reducing the driving load on the driver and also enhancing safety.

The ADAS are expected to reduce crashes and yet a 14% increase in crashes was observed from the year 2014 to the year 2016. On the other hand, the acceptance levels of ADAS among drivers are questionable. Many surveys determined that the drivers are unaware of the applications and limitations of ADAS. To catalyze the issue, drivers admitted to blindly trusting such features which makes the problem critical. Hence, there

is a need to understand how the driver behavior is influenced when driving a vehicle with ADAS compared to when driving a vehicle without ADAS.

The National Advanced Driver Simulator (NADS) miniSim^{TM} driver simulator was used to capture driver behavior in this research. Three different driving scenarios namely; urban, rural and freeway scenarios were developed to test on the drivers (participants) with varying weather and lighting conditions. Other variables like the demographic characteristics of the participants were also considered for analyzing and modeling the data. This enabled an extensive analysis of the effects of ADAS on driver behavior while also magnifying the applicability of this research.

The research can be categorized into four vital stages. The first stage is to develop appropriate driving scenarios to test the effects of ADAS in all driving conditions experienced in the real-world. The second stage involves the careful selection of participants such that the sample population is an accurate representation of the general population. The third stage involves the data processing and analysis of data to derive meaningful results. The fourth stage involves the identification of changes in driver behavior and applying them to propose any possible changes that could further enhance ADAS.

LDW was observed to reduce lane departure events in all the three scenarios (rural, urban, and freeway). OSW reduced the average and maximum speeds making driving less aggressive in rural and urban scenarios only, indicating they were not as effective in the freeway scenario. Similarly, BSW was also observed to affect the brake pedal force and influence aggressive driving. Providing two advanced features at a time also affected brake pedal force indicating they were effective in influencing aggressive driving. Further, none of the warning features were observed to influence the participant following behavior as the average headway difference between with and without ADAS was not found to be statistically significant.

Driving behavior improved further when vehicles with automated features like ACC and LKA were provided individually or in combination to the participants. Automated features improved braking, vehicle handling, and lane-following behaviors in all the three driving scenarios. However, more aggressive car-following behavior was observed with the automated features. The variation in driving behavior among participants when provided with automated features reduced drastically. The effects of automated features were influenced by the type of driving scenario. The intervention of ADAS with driving tasks led to safer driving conditions. The driving safety improved with the level of assistance provided to the drivers.

While the ADAS is effective in meeting their intended objectives, they seem to inadvertently affect other driving behaviors. The type of driving scenario (rural, urban, or freeway) also influenced the way an advanced feature affects the driver behavior. Braking behavior is predominantly affected by the presence of an advanced feature in most cases, which also influenced vehicle handling events like lane-following, turning, and car-following in some cases. Lighting and weather conditions had similar effects on driver behavior when not provided with any advanced features, when provided with warning features, and when provided with advanced features as well. Longer headways were observed in nighttime conditions and rainy conditions. However, less aggressive lane-following, braking, and vehicle handling behavior was observed. Also, more speeding was observed on freeways in clear weather. Male drivers displayed aggressive driving maneuvers when provided with both warning and automated features. On the other hand, female drivers maintained smaller headways in urban scenario and longer headways in rural and freeway scenario. Similarly, drivers aged under 25 years maintained smaller headways in urban scenario but maintained longer headways in rural and freeway scenarios. Further, drivers aged above 25 years showed more aggressive braking and speeding behavior with both warning and automated features in urban scenario.

The type of ADAS provided, the type of driving scenario, the lighting and weather conditions, as well as the age and gender of the participants affected the driver's behavior. The nature of the effects of ADAS, however, varied by the type of driving scenario. Further, the effects of all these factors varied when segregated by the type of ADAS (warning or automated feature) provided compared to when not provided with any advanced features. The effects of both warning and automated features varied when provided individually and in combination. However, warning features had limited behavioral changes when provided in combination, but automated features displayed evidently different driving behavioral changes in combination and individually.

Based on the observations made from this research, it is suggested to accommodate both operational and safety standpoints while developing ADAS. Further, developing adaptive ADAS, formulating educational policies, and developing methods to collect naturalistic driving data are also emphasized.

The findings can be used to define vehicle parameters within microscopic simulation software and mimic the effect of vehicles with and without advanced features on transportation system performance. Additional samples can be collected and other advanced features may also be tested and compared using the driver simulator.

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LIST OF ABBREVIATIONS

ACC	Adaptive Cruise Control
ADAS	Advanced Driver Assistance Systems
AEB	Automatic Emergency Braking
BSW	Blind Spot Warning
CACC	Cooperative Adaptive Cruise Control
FCW	Front Collision Warning
ISAT	Interactive Scenario Authoring tool
LDW	Lane Departure Warning
LKA	Lane Keep Assist
TET	Time Exposed Time to Collision
TIT	Time Integrated Time to Collision
TMT	Tile Mosaic Tool
OSW	Over Speed Warning
VSL	Variable Speed Limit

CHAPTER 1: INTRODUCTION

The background, motivation to conduct this research, problem statement, and research objectives are presented in this chapter.

1.1 Background and Motivation

Traffic deaths are a major issue in the United States today, and they are the leading cause of deaths among people up to 54 years in age (Association for Safe International Road Travel, 2020). More than 38,000 people are killed in road crashes annually in the United Sates, which equals to a rate of 12.4 deaths per 100,000 population (Association for Safe International Road Travel, 2020). An estimated $380 million/year is lost in direct medical bills while total economic impacts of the crashes, be they direct or indirect, account to roughly $871 million/year (Association for Safe International Road Travel, 2020). To magnify the problem, new vehicles are added to the roads with every passing year, with more than 17.6 million passenger cars and trucks sold in 2016 alone (Garcia, 2017) and a total recorded 3.21 trillion miles of vehicle miles traveled in 2018 (Alternative Fuels Data Center, 2020). The increase in the traffic exposure is expected to contribute to an increase in the number of crashes.

It is estimated that 94% of crashes occur due to driver error (Injury Facts, 2020). The nature of the driver errors varies widely and has been broadly classified into four types; recognition errors, decision errors, performance errors, and non-performance errors (Bellis & Page, 2008). Recognition errors account for about 41% of the crashes making them the most common reason of getting involved in a crash (Bellis & Page, 2008). These could be errors such as incorrectly estimating the distance or speed of the vehicle. Decision errors account for about 34% of the crashes (Bellis & Page, 2008) and include speeding, following too closely or making illegal actions. Performance errors account for about 10% of the crashes (Bellis & Page, 2008), and encompass issues such as losing control of the vehicle. Non-performance issues like health issues account for about 7% of the crashes (Bellis & Page, 2008).

Although it is not possible to address the non-performance issues owing to their random nature, the majority (85%) of errors can be handled effectively using advanced features. The advanced driver assistance systems (ADAS) enhance or automate the driving tasks and are aimed at achieving safety. Figure 1 shows a schematic of different types of ADAS.

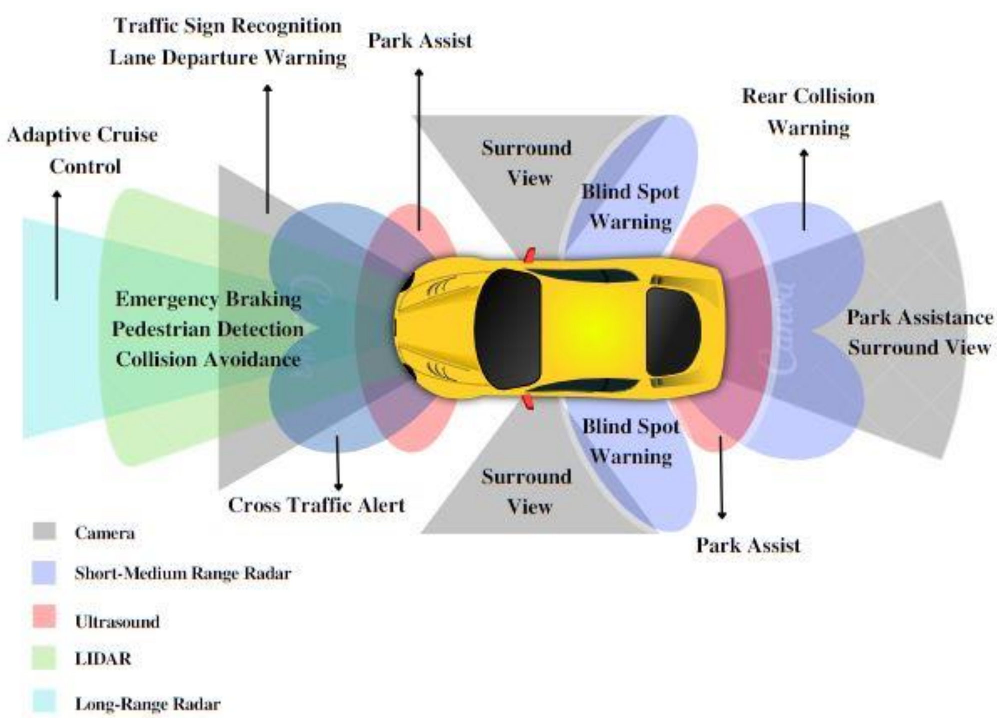


Figure 1 Schematic of advanced driver assistance systems

All the external advanced features are driven by sensors with varying detection ranges. The smallest range of detection is for parking assist system as they are mostly engaged in low speeds in parking lots that do not require long stopping distances. On the other hand, adaptive cruise control (ACC) has the lowest detection range as it is mostly engaged at higher speeds and on freeways. The cone of detection is narrow as the vehicle acts in response to its leading vehicle. Blind spot warning (BSW) also has a smaller detection range as it responds to the vehicle in the adjacent lane. ADAS like emergency braking and collision avoidance are powered by medium range sensors to best suit their purpose.

Overall, different types of sensors are used to suit the purpose of the advanced features. ACC uses long range radar systems while emergency braking and collision avoidance systems use light detection and ranging (LiDAR). The warning or alerting features use sensors that have smaller detection ranges while partially automated features use sensors with longer detection ranges. These features also deliver progressive levels of assistance based on the user needs. The levels are classified next (Safelite, 2020).

- Adaptive features – these are features that can trigger actions based on input from close vicinity of the vehicle (examples: ACC, adaptive head lights, and adaptive light control).
- Automated features – these are features that can perform certain actions without the intervention of the driver (examples: automated parking, automatic emergency braking - AEB, and collision avoidance system).
- Monitoring features – these features essentially monitor the conditions in the vicinity of a vehicle and evaluate if a corrective action needs to be carried out (examples: parking assist, speed monitoring, pedestrian monitoring, and proximity monitoring).

- Warning features – these features actively monitor the conditions in the vicinity of a vehicle and warn the drivers of any potential safety hazards (examples: BSW, forward collision warning - FCW, and lane departure warning - LDW).

The advanced features are targeted at addressing the first three types of driver-related errors, that contribute to majority of the crashes. Extensive efforts are being made every day to improve traffic safety, especially in the automotive market where new warning and automated features are evolving. Despite these efforts, a 14% increase in road related deaths were recorded from 2014 to 2016 (Naughton, 2017).

There have also been many debates over ADAS making drivers more reluctant and distracted, resulting in unwanted side effects (Naughton, 2017). Past studies revealed that 70% of drivers preferred ADAS for their vehicles (McDonald et al., 2018). However, the question of whether they understand the functionality and purpose of these features still remains.

A survey by the American Automobile Association (AAA) revealed that 21% of vehicle owners assisted with BSW did not understand the limitations of the feature while Fleet Manager expected the number to be about 80% (McDonald et al., 2018, Fleet Manager, 2019). On the other hand, 33% of the vehicle owners did not understand that the sensors engaging the Emergency Braking System (EBS) could be blocked (McDonald et al., 2018). Also, 40% of drivers misunderstood the application of FCW believing that FCW would automatically apply brakes (Fleet Manager, 2019). While the extent of driver understanding of ADAS is evident, what magnifies the issue of driver safety is their reliance on such features. It was reported that 29% of the respondents to a survey felt comfortable engaging in other activities when provided with ACC, 30% did not do shoulder checks when provided with BSW, and 25% did not look back over their shoulder when provided with rear cross traffic alert (McDonald et al., 2018).

ACC and active lane keeping/ lane keeping assist (LKA) were tested under multiple driving conditions by the Insurance Institute for Highway Safety (IIHS) in a series of track tests. ACC is an automated feature that maintains a designated speed and following distance from the leading vehicle. This feature can adjust its speed based on the leading vehicle and can also make a complete stop if required. LKA is another automated feature that maintains the vehicle in its respective lane by steering control. However, these features do have some limitations. The tests by IIHS revealed ACC reacted aggressively in some scenarios while failing to react to already stopped vehicles. Similarly, LKA was also observed to steer over the shoulder in some cases where the lanes were not detected.

In addition to this, a survey revealed that 74% of the respondents were very satisfied with LKA while 85% of the respondents were very satisfied with ACC (Consumer reports, 2017a). While 65% of the respondents trusted LKA to work every time, ACC was trusted by 72% of the respondents (Consumer reports, 2019). Most tests on ADAS like ACC and LKA are performed under safer conditions compared to real-world traffic conditions and with better trained drivers (Consumer reports, 2019). Also, it is possible that such features make drivers more reluctant and less prompt when driving. Further, a few consumers also complained of LKA not working properly at nighttime and during rain (Consumer reports, 2019).

The percentage of users relying on ADAS, the limitations that apply to various advanced features, and the lack of knowledge of the application of ADAS among drivers can lead to many unsafe driving conditions. While on the one hand, these ADAS make driving tasks easier, they may also make driving more difficult at the same time. The ADAS takes up certain driving tasks making a driver's job easier to some extent, but the driver needs to be cautious at all times to take over driving as soon as any of these features fail to react or disengage.

This brings forth the argument whether ADAS lead to other unforeseen effects on drivers. This can be assessed by evaluating the behavior of drivers using vehicles with advanced features and comparing with drivers using vehicles without ADAS to better understand the driving patterns and safety implications.

While it is difficult to precisely capture driver behavior in the real-world, there have been few research studies where drivers were provided with a test vehicle to capture and analyze driving behavior (Dunn et al., 2019) or by conducting surveys (Kim et al., 2019). Though these research studies captured some aspects of the driver understanding, they are not entirely accurate, limited to selected scenarios, and may involve a long and cumbersome process. Privacy may also be a trade-off. This brings the application of a driver simulator into the play.

Driver simulator is a platform that can address this issue as it can be used to capture driver behavior, and at the same time ensure safety and privacy of the drivers (participants). Driver simulators also enable researchers to capture a wide range of driving characteristics, which are customizable, in a shorter span of time. Hence, capturing driving behavior with the aid of a driving simulator may bridge the knowledge gaps which are relatively hard to capture in the field. Therefore, the focus of this research is to evaluate drivers' response to scenarios when driving vehicles with and without advanced features like LDW, BSW, OSW, ACC, and LKA.

The response or behavior could vary with the advanced feature, driving scenario, and driver characteristics. They also could depend on lighting and weather condition. Therefore, rural, urban and freeway driving scenarios were developed in a driver simulator and tested on drivers (participants) in the age groups of sixteen years to sixty-five years. Some drivers were provided a vehicle with advanced features, while other drivers were provided a vehicle without advanced features. This study aims at capturing general driving behavior in all types of settings as discussed later in detail.

1.2 Need for Research and Problem Statement

Human errors are the major contributor of road crashes. A constant effort is being made by automobile manufacturers and researchers every year to reduce human intervention in driving that will help improve safety with the ultimate goal of complete automation in the future. The National Highway Traffic Safety Administration (NHTSA) and Federal Highway Administration (FHWA) have also been investing efforts to constantly monitor the performance of various emerging advanced features (Learner et al., 2020) and also to evaluate their acceptance and ease of use via testing procedures (NHTSA, 2019; IIHS, 2020). Further, NHTSA constantly publishes articles and publicizes the advantages of ADAS while explaining their working mechanisms and limitations to help educate drivers (NHTSA, 2020).

Considerable research efforts have been expended to investigate the effectiveness of ADAS. The data collected for these evaluations mainly stems from the reported incidents. Despite the proven records of these features, a low level of acceptance seems to exist among drivers. Many drivers are confused with the application of ADAS, which could lead to drastic outcomes and is alarming.

The ADAS cannot be assessed for specific driving conditions in a real-world and their effects can only be anticipated or can be collected only post-event. Employing a driver simulator helps design specific driving condition scenarios that can test the limits of such features and help analyze their applicability at a deeper level. A wide range of testing conditions can be simulated which otherwise may be difficult to analyze.

Although there have been significant efforts to evaluate the effectiveness of ADAS, a model with a broad sense of applicability does not exist in the literature. Past studies on the effects of ADAS on drivers are limited to very specific conditions or to a defined set of parameters. However, the driving behavior, use of ADAS, and effectiveness could vary based on the road functional class (freeway compared non-freeway roads) and area type (urban compared to rural) when driving. There is a need to evaluate the effect of ADAS on driving behavior under various driving conditions. The findings from such a study would guide policymakers and automotive companies to formulate well-defined testing criteria. Therefore, this research focuses on developing driver behavior models for different driving condition scenarios such as urban, rural, and freeway.

Younger drivers may be more comfortable using advanced features while older drivers may not be equally comfortable or even familiar with advanced features. Thus, the socio-economic aspects and driving history also have a bearing on driving behavior and the use of ADAS. Therefore, considering variables such as demographic, socio-economic, driving history, and their prior understanding of ADAS during sampling and data collection could allow researchers to better understand their role, generate defined parameters, and design optimal ADAS for the drivers.

The purpose of this research is to evaluate the effects of ADAS on driver behavior. The advanced features are tested in different driving conditions that include urban, rural and freeway scenarios. Further, lighting conditions (daytime and nighttime) and weather conditions such as rain or snow are also included in the research. This enables the comparison of the effects of ADAS across multiple facets and also identify any gaps with a high degree of applicability that encapsulates multi-faceted situations that arise in real-world.

1.3 Research Objectives

The objectives of this research are:

1. to model and evaluate the effects of ADAS on driver behavior for different area types (urban, rural and freeway),
2. to model and evaluate the effects of ADAS on driver behavior for different weather and lighting conditions, and,
3. to model and evaluate the effects of ADAS on driver behavior for different age and gender.

1.4 Organization of the Report

The remainder of the report is organized as follows. Chapter 2 presents an extensive review of the various methods adopted to evaluate ADAS. The chapter discusses survey methods, field test methods, microsimulation methods, and driver simulator methods and identifies prevailing gaps. Chapter 3 synthesizes the driver simulator system. The various tools involved in developing the simulation conditions and participant selection criteria are discussed in detail. Chapter 4 discusses the methodology adopted along with data collection and processing efforts. Chapter 5 presents results from the research, while conclusions and scope for further work are discussed in Chapter 6.

CHAPTER 2: LITERATURE REVIEW

Investigating previous research efforts invested into addressing any issues related with ADAS is vital to understand the advancements in this area. Also, at the same time, this exercise will help in identifying any prevailing gaps as well as methodologies adopted by previous researchers which will serve as a guiding platform to establish a more specified modeling framework. An extensive synthesis of previous literature was, therefore, carried out. This chapter presents an overview of the past studies categorized based on the research areas.

2.1 Surveys and Mathematical Methods to Assess Driver Behavior

Abdul et al. (2007) investigated driver behavior based on the pressure applied on brake and gas pedals. They employed a cerebellum model articulation controller (CMAC) to model driver behavior. They observed the application of CMAC to be reasonable for predicting various driver behavior characteristics and understand the effects of a drivers' emotion and subconscious mind. Similarly, Wang et al. (2014) evaluated driver behavior based on the acceleration and brake force parameters and steering wheel angle using mathematical models. They used these parameters to incorporate into ADAS and observed that driver behavior varies for different driving actions and generalizing driver behavior based on only a few actions is not ideal.

Kuge et al. (2000) evaluated driver behavior using hidden Markov models (HMM). They demonstrated the efficiency of HMM in both application and in modeling driver behavior, particularly for lane change behaviors. Similarly, Sathyanarayana et al. (2008) developed framework using HMM to assess driver behaviors and distractions.

Kamarudding et al. (2010) tried predicting driver behavior based on speech configuration. They evaluated driver behavior based on the emotion conveyed in their speech patterns and observed that it can be used to profile driver behavior, especially when they are sleepy. Yannis et al. (2010) investigated the acceptance of ADAS among older drivers via surveys from 23 European countries. They developed ordered logit models, and the results showed relatively better acceptance of ADAS among older drivers and females. Tran et al. (2012) used vision-based foot gestures and HMM to analyze and predict braking behaviors of drivers. While they used visual methods to capture driver behavior data, they employed HMM to predict the pedal pressing gestures, and achieved a 94% accuracy by this method. Morignot et al. (2014) evaluated the effectiveness of and acceptance of ADAS via a surveying method. They presented results to enhance ADAS.

2.2 Field Test Methods to Assess Driver Behavior

Alkim et al. (2007) investigated the effects of ADAS on driver behavior using a field vehicle in Netherlands. They employed ACC and LDW in full traffic conditions with mixed traffic. They observed 8% improvement in traffic safety, while the fuel consumption reduced by 3%. Additionally, the estimated reduction in emissions was about 10%.

McCall et al. (2007) focused on developing human-centric ADAS like predictive braking and ACC, and its effects on driver behavior using a test vehicle in real-world driving conditions. Cognition-based adjustments were made to the vehicle to capture driver behavior and the framework showed promising results. Ziefle et al. (2008) evaluated the effects of visual and auditory ADAS on older drivers. They observed better driving performance in the absence of any ADAS while auditory systems contributed the highest to distraction. Their findings indicate that older drivers preferred auditory systems over visual systems.

Inata et al. (2008) modeled driver behavior using micro-electric sensors mounted on vehicles which were driven in real-world traffic environment. The sensing equipment recorded the pedal operation of the vehicle, which was used for analyses. They developed a theoretical model to estimate driver behavior and then compared it to the collected urban driving data to distinguish hurried driving from relaxed driving. Angkititrakul et al. (2009) used mathematical models (Gaussian mixture model) and algorithms (piecewise auto regressive exogenous) to understand driver behavior and incorporate them into car-following models. The data used was obtained from real-world driving conditions. They captured the braking and acceleration parameters in response to the distance from leading vehicle. The framework was then used to evaluate and model driver behavior.

Kondyli et al. (2009) investigated driver behavior using data obtained from driver responses to various questions that addressed their thinking while merging from a ramp onto a highway. They tried to correlate the driver's behavioral thinking to driver characteristics. Pauwelussen et al. (2010) investigated the effect of ADAS like ACC and LDW on driver behavior in real-world driving conditions. They observed that the ACC led to larger headways between vehicles while manual override of the feature resulted in shorter headways.

Farah and Koutsopoulos (2014) probed into the effect of infrastructure to vehicle (I2V) assistance systems on the drivers using test vehicles. They observed reduced ranges of acceleration and deceleration while the car-following was more synchronized. Monreal et al. (2014) probed into the effect of the location and angle of in-vehicle displays on driver safety. They observed the driver gaze when looking at driver information systems (DIS) in the vehicle that are currently existing in the market and inferred that they meet the NHTSA guidelines for the gazing away from road values. The driver preferences with the in-vehicle display and location converged with that in the market while mobile applications and social media were not found to be necessary in the vehicle.

Son et al. (2015) employed a road-testing method to evaluate the acceptance of FCW and LDW based on the age and gender of the driver. While females and younger drivers showed lowest acceptance for ADAS, males and late middle-aged drivers showed higher likelihood of acceptance. Miyajima et al. (2016) developed machine learning models to analyze data collected from real-world driving conditions over 15 years. They observed various driver behavior like lane changes, car-following and pedal operation. They developed statistical models to predict risky driving and frustrated driving behaviors. Sieber et al. (2016) investigated driver behavior in collision avoidance using a field test study. They observed driver behavior and perception with different times of collision and observed that the movement speed of the obstacle had the greatest effect on driver behavior.

Cades et al. (2017) investigated the effects of LDW on driver behavior while the participants performed a secondary task. They observed no significant effect of LDW on reducing workload on driver cognition while performing secondary tasks. Lyu et al. (2019) investigated the effect of ADAS on driver behavior using field operational tests in China on a test route. The effects of FCW and LDW were primarily assessed in their study. They observed increased braking time and decreased relative speed when provided with ADAS. Also, higher acceptance of FCW was observed over LDW. The acceptance was higher on freeways compared to urban roads.

2.3 Microsimulation Methods to Assess Driver Behavior

Kikuchi et al. (2003) probed into the effects of using ACC in platooning based on the different positions of the vehicle using microsimulation. They observed reduced reactions times to achieve stability in the platoon. Both, ACC equipped and non-ACC vehicles were observed to display enhanced safety. Derbel et al. (2012) investigated the effect of mixed traffic, comprising of vehicles equipped with ACC in a crash scenario. Enhanced safety and reduced crash risk were observed when vehicles equipped with ACC were involved in a crash.

Jeong et al. (2014) investigated the effect of an inter-vehicle safety warning information system (ISWS), which communicates hazardous maneuvers of vehicles that could lead to a crash. The driver behaviors captured using probe vehicles were fed into VISSIM simulation while the Surrogate Safety Assessment Model (SSAM) was used to measure safety. Rear-end conflicts were observed to reduce with penetration rates, while congestion increased. The standard deviation of speed was observed to decrease by 40%.

Researching the effectiveness of multiple integrated systems, Li et al. (2016) evaluated the effect of integrating I2V with ACC and variable speed limit (VSL) in different combinations on traffic safety. The time exposed time to collision (TET) which indicates the total time spent by a vehicle in safety-critical situation and time integrated time to collision (TIT) which is time remaining for a collision to occur if two vehicles continue to maintain the same speed were used as surrogate safety measures in their study. The effect of integrating technologies led to better results when compared to individual effects. Employing a similar methodology, Li et al. (2017) evaluated the effects of ACC on safety of freeways. Enhanced safety was observed with the increase in penetration rates, while the combination of ACC and VSL were observed to produce best results. Li et al. (2017) also investigated the effect of cooperative adaptive cruise control (CACC) on rear-end crash risk on freeways. A significant reduction in crash risk was observed with CACC while the TET and TIT reduced by over 90%.

Cicchino (2017) analyzed the effectiveness of FCW, AEB, and a combination of both in reducing rear-end crashes. FCW, AEB and combination of both reduced rear-end crashes by 27%, 43% and 50%, respectively. The vehicles themselves being struck in rear-end crashes reduced in case of vehicles with individual features but increased when the vehicles were equipped with both the features. In an attempt to investigate the effects of integrating connected vehicles technology with advanced features, Yue et al. (2018) probed into integrating connected vehicles with different ADAS. About a 70% reduction in crashes was achieved by the integration, while FCW could reduce rear-end crash risk by 35% in foggy conditions.

2.4 Driver Simulator Methods to Assess Driver Behavior

Kaptein et al. (1996) revealed that driver simulator-based study results are valid and the validity increases with the resolution of the simulation and the presence of a moving base. Strayer and Johnston (2001) investigated the effect of conversing on cellular phones while driving using a driver simulator. They observed longer reaction times to traffic lights while conversing irrespective of hand-held or hands-free devices. Similarly, in another driver simulator-based study, involving in conversations using hands-free devices was observed to increase reaction times when stopping at intersections, due to reduced visual attention (Strayer et al., 2003). The effect of cell phone conversations was higher on young drivers compared to older drivers (Strayer and Drew, 2004). It was also observed that the drivers were involved in comparatively higher number of crashes when talking on cell phones owing to elongated reaction times to braking while intoxicated driving led to smaller headways from leading vehicles (Strayer et al., 2006). Overall, the effect of conversing and intoxication were observed to have similar effects when the driving conditions and time to task were the same in their study. Text messaging also constrains the driver attention to braking lights significantly, leading to crashes (Drews et al., 2009).

Lundgren and Tapani (2006) investigated the safety effects of ADAS using a driver simulator. They observed that the functionalities of ADAS and changes in driver behavior for ADAS equipped vehicles could affect safety. Driver-vehicle behavior was observed to substantially affect safety. Driel et al. (2007) evaluated the effectiveness and acceptance of congestion assistant using a driver simulator. They observed improved driving safety behavior in drivers when approaching a traffic jam. Lee and Abdel-Aty (2008) captured driver responses to warning messages and VSL using a driver simulator. They observed that the variation in driving speeds reduced, leading to better traffic flow and reduced congestion.

Hoogendoorn and Minderhoud (2002) investigated the effect of intelligent cruise control and intelligent speed adaptation on driver behavior. They observed improved capacities and reduced reliability at bottlenecks when cruise control was deployed while no improvement in either capacity or reliability was observed in the case of intelligent speed adaptation. No improvement in safety was observed. Martin and Elefteriadou (2010) researched the effect of ADAS on driver behavior using a driving simulator. They observed changes in driver behavior when using vehicles equipped with ACC and lane change on arterials/ freeways. Calvi and Blasis (2011) evaluated the driver behavior on acceleration lanes. They observed that merging behavior was dictated by the traffic volume on main road and not the length of acceleration lane. Son et al. (2011) assessed the effect of voice recognition system on driver distraction, especially older drivers. The distraction effects were evaluated for both urban and highway sections, and it was observed that both age and environmental conditions effected the driving behavior when the driver had to perform two tasks.

Maag et al. (2012) investigated the effects of ADAS on drivers using single and multi-driver simulators. They evaluated the effects of merging systems and advanced features and supported the use of multi-driver simulators to understand and capture driver behavior. Saleh et al. (2013) probed into the compatibility of driver and ADAS with LKA using driver simulator. They observed improved lane keeping when the feature was engaged despite varied driver behavior. Aziz et al. (2013) investigated the understanding and effects of LDW on driver behavior using a driver simulator. They found that the dynamic nature of the driving environment could limit the driving cognitive model leading to cautious driving scenarios that could result in a tragedy, irrespective of any secondary tasks performed by the drivers.

Rommerkirchen et al. (2014) investigated the human-machine interaction to understand the effect of ADAS on drivers using a driver simulator. They observed that game-time (interaction) reduced in complex driving situations. In a similar study, Biondi et al. (2014) investigated the effect of a beeping ADAS on driver behavior using driver simulator. They observed that the beeping sounds disrupted the vehicle trajectory as the drivers deviated from the lane. They observed such sounds to be distracting for the driver in contrast to their original functionality.

Using a low fidelity simulator, Spivey and Pulugurtha (2016) evaluated the visibility of two-wheelers encountered by left-turning motorists at urban intersections in nighttime conditions, compared to other hazards. The observed response times to a two-wheeler were not different from the response times to a passenger car with two headlights. However, the response times were significantly shorter than the times to recognize no hazard or a two-wheeler with no headlight. Differences were observed when response times were compared for daytime and nighttime conditions.

Gasper et al. (2016) evaluated driver behavior when provided with FCW and LDW using a driver simulator. They compared the effect on both distracted and undistracted drivers and observed that the driver behaviors fell into categories based on distraction. Significant variation in driver lane-changing behavior was also observed in their research. Mas et al. (2016) investigated the effect of lateral control assistance systems on driver behavior in avoiding obstacles using driver simulator. They observed an equal effect from both assisted and non-assisted drivers in avoiding obstacles. However, the lateral control assistance feature contributed to faster reaction times. Choudhary and Velaga (2017) investigated the effects of talking and texting on phone on driving behavior in a suddenly arising situation (pedestrian crossing) using driver simulator. The mean speeds were observed to be lower when the drivers were on phone, while the probability of a crash increased by 3 to 4 times. Witt et al. (2018) investigated the effect of driver characteristic and personality on their driver behavior using virtual and driving simulations. They attempted to develop a driver cognitive model to help design ADAS. Phone use was found to significantly affect driving for both younger and older drivers with younger drivers having a higher crash risk compared to experienced drivers in a driver simulator study by Choudhary and Vengala (2019).

2.5 Effectiveness of ACC and LKA

ACC maintains a designated speed and distance for a vehicle with respect to its leading vehicle, while the LKA ensures that the vehicle stays in its respective lane. Consumer Reports (2017b) considers ACC to be more of a luxury feature than a safety feature due to its functionality (Consumer reports, 2017b). Combining ACC with other ADAS may mask the minimal effectiveness of the system. Further, ACC functionality seems to vary across automotive makers (Consumer reports, 2017c). ACC has been observed to be jerky with acceleration and braking maneuvers, and its response to already stopped vehicles was identified as a limitation. Additionally, it was observed that drivers with ACC were driving at higher speeds compared to drivers without ACC (IIHS, 2021).

Similarly, there are anticipated advantages and limitations of the LKA feature. The LKA and LDW were expected to mitigate over half a million crashes in 2016 alone (Benson et al., 2018). The LKA performs a lane keeping test every five to fifteen seconds and provides a stipulated steering torque to maintain the vehicle in its lane, allowing the driver to take over if required (VDA, 2020). It is expected to have significant effects on safety especially on run-off and head-on crashes (Tan et al., 2020, TAC, 2020). It is estimated that a 100% effective lane departure prevention system could reduce single vehicle run-off crashes by 65% (Penmetsa et al., 2019).

The ACC and LKA features in combination control both the longitudinal and lateral movements of a vehicle and provide a basis for a more advanced automated driving version. The reliability of drivers on these features also plays a vital role in their effectiveness, as it dictates the attention they are paying while driving. Many studies have highlighted the direct impacts of these features but a deeper understanding of their effects on driving behavior needs to be investigated. This will help establish parameters that can be used as inputs to evaluate the effects of vehicles with advanced features in a traffic stream using microsimulation software.

2.6 Limitations of Past Research

Extensive research has been done in the direction of addressing the issues related with the effects of various tasks that could be influencing driver behavior. Various methodologies have been adopted to investigate the effects of ADAS on driver behavior. Surveys and mathematical models aimed at researching the adaptability of the methods in modeling driver behavior, though some researchers focused at studying the acceptance levels of different ADAS. Some of these studies also focused at predicting driver behavior, which yielded reasonable results. However, these methods rely on self-reporting and the participants could be biased when answering questions, especially when they are being scrutinized by another person. Further, most of the past studies focused on participants response to the questions and their comfort-level with ADAS. This is more of a perspective driven approach while the effects of ADAS is not captured.

Field test methods were conducted to capture driver behavior in some cases, while some researchers focused at capturing acceptance rates of the ADAS. Some researchers looked at the acceptance rates of different ADAS based on the age and gender while some investigated the focused effects of ADAS on driving behavior. Some researches focused on capturing the effect of ADAS on traffic safety rather than on the driver behavior. A few researchers probed into understanding the acceptance of ADAS while some researchers looked into the design criteria. Further, some researchers focused on the performance of ADAS on traffic operational performance, but the effect of ADAS specifically on driver behavior was seldom captured in the reviewed field tests. Hence, there still persists a gap to identify the effect of ADAS on driver behavior.

Microsimulation-based studies were also conducted to research the effect of vehicles and driver behavior on safety or operational performance of traffic stream. CACC, BSW, FCW, or AEB were evaluated in the past studies. While these studies highlight the effectiveness of such ADAS, evaluating driver behavior may not be possible with the aid of microsimulation. On the other hand, microsimulation platforms do not provide the ability to investigate the effects of ADAS in specific scenarios and can only be observed from a one-dimensional perspective (improvement or degradation). In addition to this, currently available traffic simulation software cannot incorporate many variables like demographic or socio-economic characteristics, weather conditions, or lighting conditions. The ADAS evaluated are pre-designed to behave in a certain way in a conflict situation which may limit the nature of data captured in micro-simulation-based studies.

Driver simulator studies focused on evaluating the effect of ADAS in only certain conditions (weather or traffic). Most of the driver simulator studies did not take demographic characteristics into consideration, while some past studies just compared the driver behavior across two demographic groups of participants (young and old). Some past studies probed into the level of acceptance of the ADAS and the optimal designing of the ADAS for better user-friendly experience.

Some researchers investigated the effects of ADAS under a pre-defined set of conditions or evaluated their effect across some demographic characteristics like age or gender. A few researchers reviewed the applicability of ADAS when drivers were engaged in secondary tasks. Some researchers focused only on the effectiveness of ADAS only during certain traffic maneuvers (merging or turning) which only represents ADAS to certain extent. Overall, majority of the past research was under very controlled conditions that lead to tunneled application.

The results from the past driver simulator studies captured the effect of ADAS on driver behavior in a comparison style of representation. They addressed how one category of participants responded in comparison to another group. Some studies evaluated their effect on safety in specific weather conditions. Also, many of the researchers did not capture the driving history or the familiarity of participants to ADAS.

Overall, a persisting gap was observed in the previous studies as they seem to be more hypothesis driven, which leads to concentrated research and their applicability is limited. This research focuses at capturing driver behavior under various driving situations (urban/rural and freeway/arterial) and also includes different types of ADAS to arrive at conclusions with a broader perspective. This will help design ADAS or develop models that can be applied in a multitude of cases.

Driver simulator provides a perfect platform to simulate different driving conditions while ensuring precision. The results can be deliberated and extracted per need to develop an accurate model of driving behavior. This methodological approach was explored in this research.

This research also accounts for variables like previous driving history and demographic data, which have been seldom ventured in previous researches. The familiarity of an ADAS or similar technology are important and were also captured in this research. In short, evaluating the effectiveness of ADAS on driver behavior in all types of driving conditions (urban, rural, and freeway), weather conditions (rain or snow), and lighting conditions (day or night) reinforces the applicability of this research to a larger audience. The gathered results can help understand the effect of ADAS from a proper driver perspective.

CHAPTER 3: DRIVER SIMULATOR AND DRIVING CONDITION SCENARIOS

The National Advanced Driver Simulator (NADS) miniSim^{TM} was used for this study. The information provided in this section is based on the user guide manuals provided for each of the tools associated with the process. The driver simulator was used as it provides a perfect platform to replicate real-world conditions. It helps record driver behavior when they are subjected to driving conditions that are very close to the real-world. The other advantage of the driver simulator is the ability to simulate desired conditions that can help assess driver behavior in response to the pre-defined driving conditions. However, developing the desired driving conditions in the simulator involves multiple processes. Figure 2 summarizes the functional flowchart of the process involved in developing simulated driving condition scenarios.

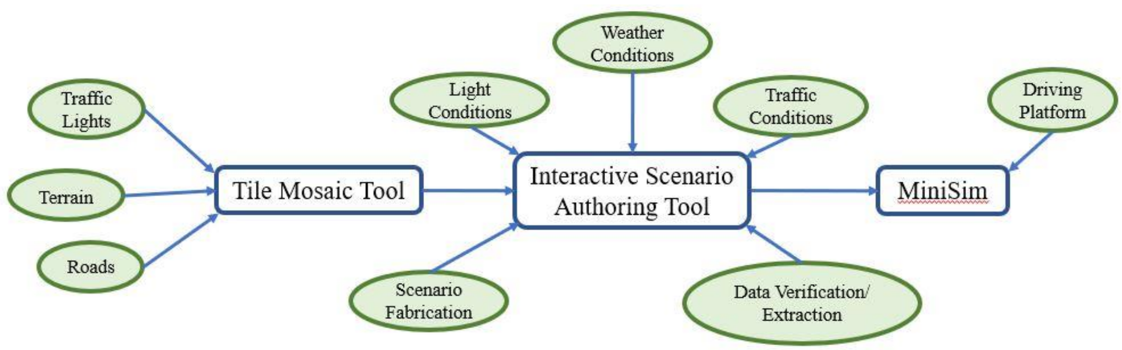


Figure 2 Functional flowchart of driving simulation development

As displayed in Figure 2, three tools are required to develop the final driving simulation scenarios. The initial step involved developing a road network, which is handled in the Tile Mosaic Tool (TMT). The initial road network along with terrain conditions was built in the TMT. After developing the road network, it was imported into the Interactive Scenario Authoring Tool (ISAT). This tool allows users to define various driving conditions including weather conditions (rain, snow, fog, or clear weather), lighting conditions (day or night), traffic lights, or for a specific type of vehicle with a desired level of traffic. The output file from ISAT is then imported into miniSim^{TM} which then simulates the scenario to test driving behavior. The development process to attain the final simulation product is discussed next in detail.

3.1 Tile Mosaic Tool (TMT)

The TMT allows users to generate world or database files. The world files are constructed using tile models, where each tile model contains information about the roads, terrains, and feature objects. Placing tile models adjacent to each other in a desired pattern forms a road network. There are multiple categories including city, commercial, fillers, freeway, industrial, mountain, railroad, residential, rural, urban, special, and suburb. The tiles are named for the type of road they depict. For example, freeway tiles contain roads that replicate freeway conditions, whereas residential tiles represent local roads that are typically found in residential areas. Commercial tiles have terrains with commercial blocks with trading and shopping locations. Filler tiles can be used to fill in gaps between other tiles, varying from small road sections to intersections. Special tiles are similar to filler tiles and create locations such as interchanges.

The TMT offers several types of roads that exist in the real-world, while also providing special tiles that create conditions such as snowy or wet roads. The tiles also display road markings, terrain conditions, and vegetation. The more complex tiles display both traffic signs and control devices such as signals and stop/yield signs. Figure 4 shows a screenshot of a road network created with a set of tiles.

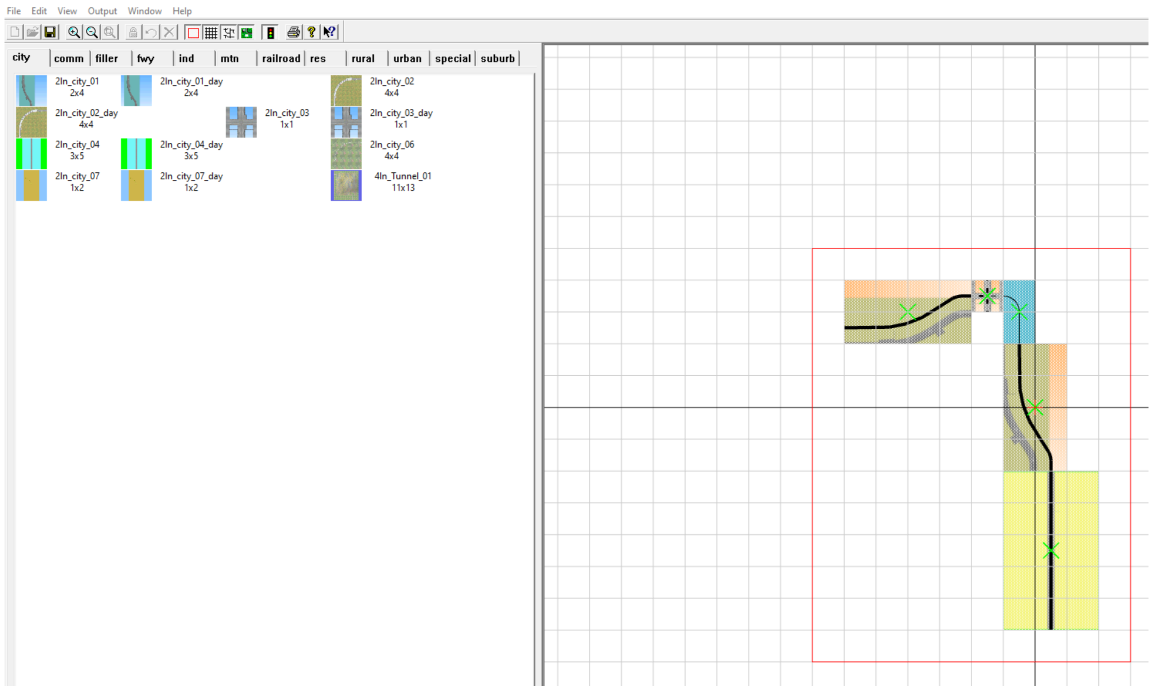


Figure 3 Screenshot of a sample road network in the TMT

The tiles need to be attached such that the roads align to ensure no gaps prevail when they are visualized in the simulator. The road in the blue colored tile looks thin compared to its adjacent tiles, which is an implication that it is a two-lane curved road connected to a four-lane road at the end. This may lead to small inconsistencies in visualization and proper care needs to be taken. The red colored line surrounding the tiles is the boundary of the tiles that can be displayed using the red colored square symbol in the menu bar as seen Figure 3.

The grid in the background helps place tiles easily when developing a network file and can be activated using the grid symbol. However, it is important that the tiles are created while developing the world files within the TMT so that they can be adjusted in ISAT before the simulation. The green cross seen in the tiles indicates that they have been created in TMT and can be activated using the traffic light symbol. Examples include changing a Stop sign to a Yield sign or assigning signal timings.

TMT is initially set up as a grid on which the tiles are placed. There are a few important points to be remembered while developing world files in the TMT. Firstly, not all tiles can be placed adjacent to each other. For example, one cannot place a two-lane rural road tile adjacent to a four-lane urban road tile. A dialog box with the list of compatible tiles with their categories, rotation, and size is displayed when the right mouse button is pressed after selecting the adjacent tile, which is then added from the list. A non-compatible tile may also be added forcefully by pressing the Shift key. Some issues such as a gap showing empty space or a failed visualization may occur in such cases.

There are certain tiles that have unique controls, such as tiles that contain traffic signs, traffic lights, or road signs that need to be changed in ISAT or while visualizing. For example, all the roads are given the same road name in the default condition that can be changed while visualizing. Similarly, speed limit signs can be altered to change speed limits. To edit the tiles, the unique controls need to be enabled in the TMT by clicking the right mouse button and selecting the appropriate option. After the completion of a desired world file, a set of commands need to be run in the "command prompt" window that generates a set of visual and logical files to capture information from the TMT. It is important to generate both visual and logical files in the same session to maintain consistency of information and avoid any mismatches. The TMT tool generates a file in the ".mos" format, or the mosaic file. This mosaic file is then imported into ISAT for further development.

3.2 Interactive Scenario Authoring Tool (ISAT)

The ISAT puts together all the information designed by users and generates a scenario file (.scn) that can be imported into miniSim™ for simulated driving. Additionally, the ISAT is also capable of extracting data from the final output files. Developing a scenario file involves multiple processes, which starts with defining the traffic conditions. Figure 4 shows a screenshot of the same road network imported into the ISAT. The task bar to the left shows a list of different elements that can be added into the scenario using icons available in the menu bar at the top of the screenshot.

The icons highlighted using the gray circle deal with the navigation through the map or network, including zooming in or out, viewing the entire network, finding any element, or using the undo or redo options. The icons highlighted by black circle show the different modes offered by the ISAT that allow users to play, record, and analyze driving conditions. The red circle highlights icons that are used to add dynamic and static objects such as vehicles, traffic signs, and virtual objects to the simulation. The blue circle shows icons that represent different types of weather conditions such as rain, snow, lightning, and fog. The green circle represents triggers that are used to simulate driving, while the orange circle shows the traffic and traffic light manager that controls traffic in the simulation, as desired by the user. The boxes by the side of the road network add certain actions into the scenario.

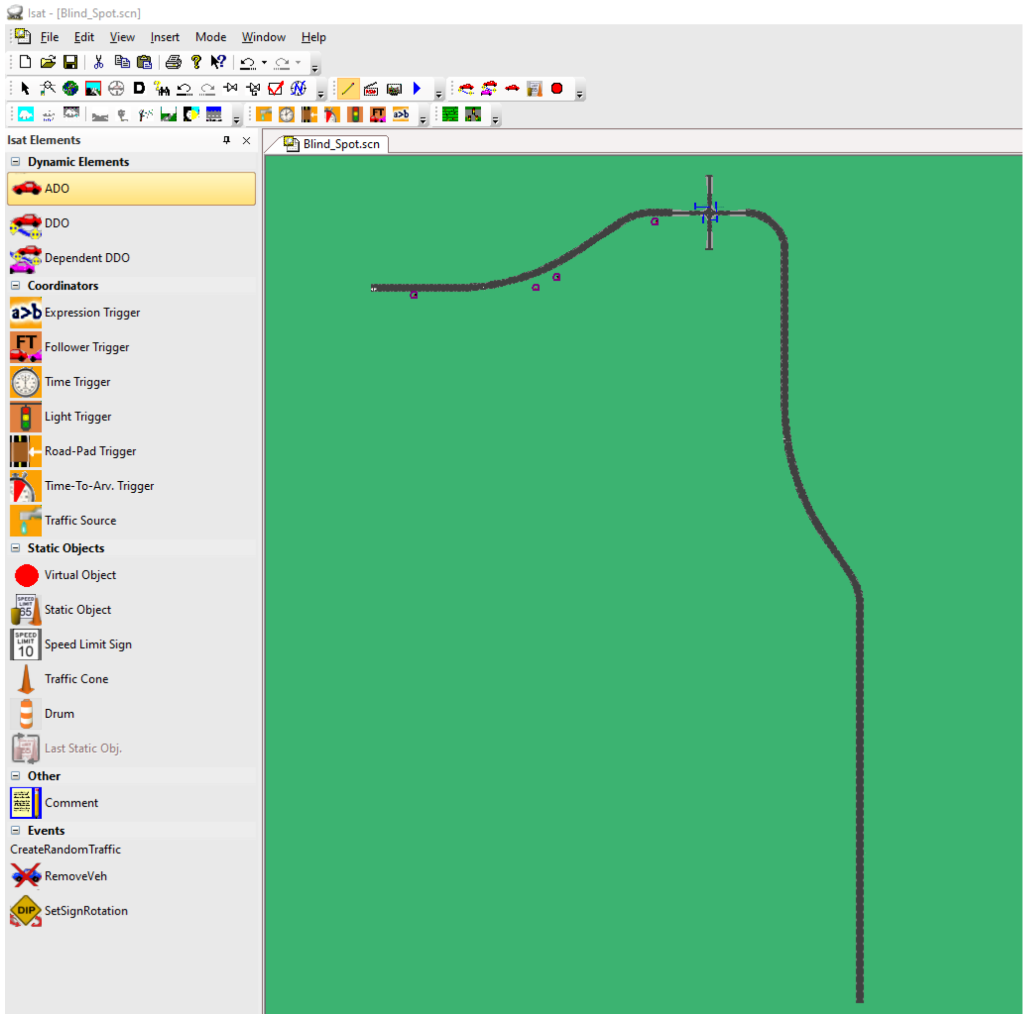


Figure 4 Screenshot of a road network in ISAT

3.2.1 Traffic Conditions

ISAT allows users to select pedestrians or any type of vehicle ranging from bicycles to trains. Additionally, multiple features such as color, speed, tire condition, brake condition, etc. can also be specified. ISAT also allows users to also select the type of drivers in the vehicles, which are in turn deemed to be dynamic objects in the ISAT. There are two types of dynamic objects that can be added into a scenario. The first type is the Deterministic Dynamic Object (DDO) whose actions are pre-determined by the user. These objects simply follow a path that is pre-defined and the speed of the DDO can be set at each node of the path. These objects do not follow traffic rules and cannot avoid collisions and, as such, can be called intuition-less objects. The second type of dynamic object is the Autonomous Dynamic Object (ADO). These objects resemble human drivers and follow traffic rules. However, they can be instructed to perform certain actions that defy the traffic rules.

Adding each vehicle individually in the scenario is a tedious and time-consuming process. The ISAT offers a “traffic source” option that allows users to add multiple vehicles at regular intervals throughout the simulation from a designated point in the network. Multiple vehicles can be added to each traffic source that are generated in a loop. For example, if five vehicles are added to a traffic source, it generates the same five vehicles once it has generated all of them.

Pedestrians can be added into the scenario as DDOs, defining their path to cross a road. There are multiple ways to generate an object in a simulation. By default, the simulation generates objects at the start, but this may not work under some conditions. For example, if the user wants to simulate a pedestrian crossing the road at a mid-block section when the driver is at the location, the default case may generate the pedestrian as soon as the simulation starts, and the pedestrian may have already crossed the road by the time the driver reaches the specific point. To overcome such challenges, the simulation can also delay the generation of the object in a simulation. There is an “activation delay” option available when adding objects to the scenario. This allows the object to be generated after a specified period of time. This is a good approach; however, the driving time may differ from one driver to another driver, thus each driver may be at a different point in the simulation at the given time and as such the previously mentioned simulation may work only in some of the cases. The third way of generating an object in a simulation is to define the “creation radius” of the object which works with reference to the location of external driver who is driving in the simulator simulation. This is a good way to ensure that a desired scenario is executed with reference to the location of the driver.

The lifetime option allows users to determine how long an object remains in the simulation. For example, a car may be temporarily inserted behind another vehicle to create a lane-changing scenario. Static objects can also be added into the scenario to convey additional information like the speed of the road, traffic cones, warning signs, etc. While the TMT already provides sign information (speed, curve, etc.), more can be added using static objects if the user feels they are not abundant enough. However, it is important to remember that these only provide visual information and do not play a role in defining the simulation’s behavior. For example, if an ADO is set to follow the speed limit, it follows the speed limit set on the default signs imported from the TMT.

The next step in defining traffic conditions is to allocate the traffic signal split times. Figure 5 shows a screenshot of the “traffic light manager” which shows a list of all the traffic signals available in the network. Upon selecting a signal, all the traffic lights associated with the signal are shown. The user can configure the desired number and duration of states using the “add state” option. It is important to remember that when a light is green, only its complementing light or all the other lights are red. Figure 5 depicts a traffic signal head which controls traffic movements on the right side. This helps users to determine the cycle of the traffic signal. The other signal heads turn red when one is green or yellow.

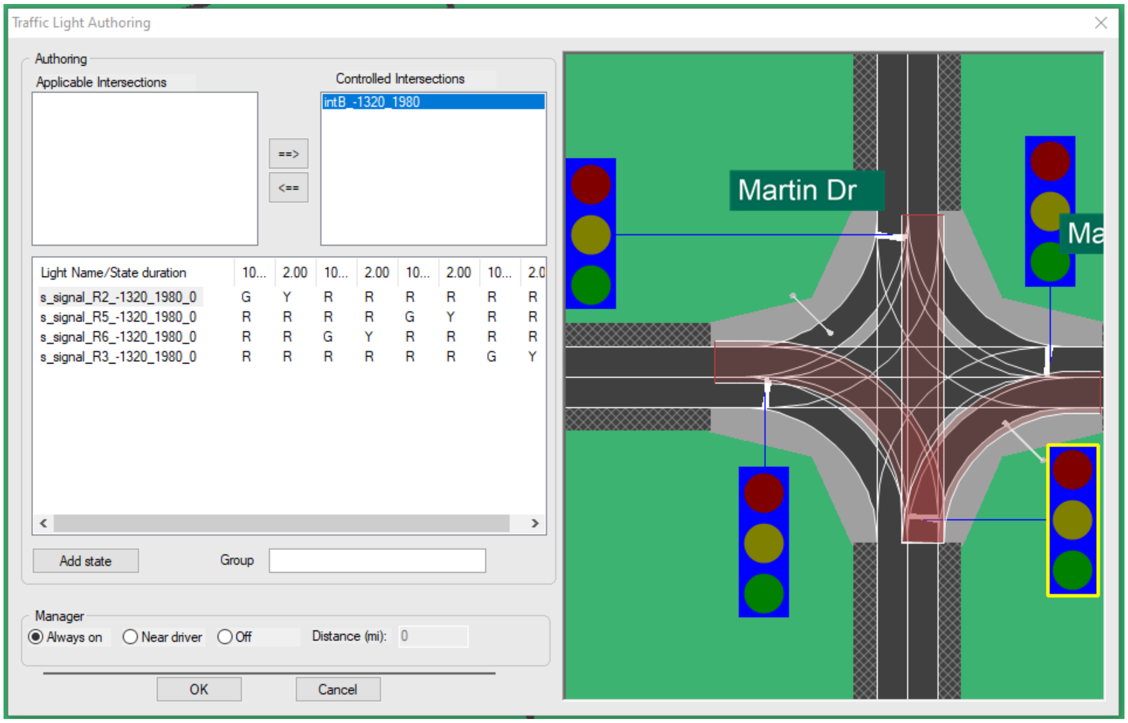


Figure 5 Traffic light manager for a four-legged intersection

While this scenario only contains one traffic signal, the window shows all the available signals which can be assigned cycles as necessary, turned off, or triggered when a driver is nearby, at a distance determined by the users.

3.2.2 Weather Conditions

The ISAT allows the user to select weather conditions from rain, snow, fog, and lightning. Further, the ISAT lets users simulate weather conditions at specific stretches or for the whole network route. Upon selecting the weather option, the user can draw a polygon to define the area. Varying levels of intensity (for example, light vs. severe rainfall) are also configurable options.

3.2.3 Light Conditions

The "initial conditions" tab allows users to configure light conditions according to time of day, and the appropriate lighting for that time of the day can be seen in the simulation. This is where other vehicle conditions of the external driver can be specified as well. Light conditions cannot change during a simulation and remains constant throughout. The properties tab allows the users to configure headlight options for all the vehicles in the scenario. Figure 6 shows the "initial conditions" tab that allows users to configure the light and vehicle conditions. The first option is to select the type of vehicle and users can choose between cab and trailer options for certain types of vehicles.

Users can also configure tire and brake conditions. The headlights of the vehicle can also be turned on in the "initial conditions" tab. They can be turned on while driving as well using a button available on the driver simulator. Various characteristics of the headlights can be defined as well. The vehicle can also be assigned a failure type that allows users to observe behavior of participants in failed conditions. The simulation can also be prompted to stop on the detection of a collision. Light conditions and the date of the simulation can also be changed.

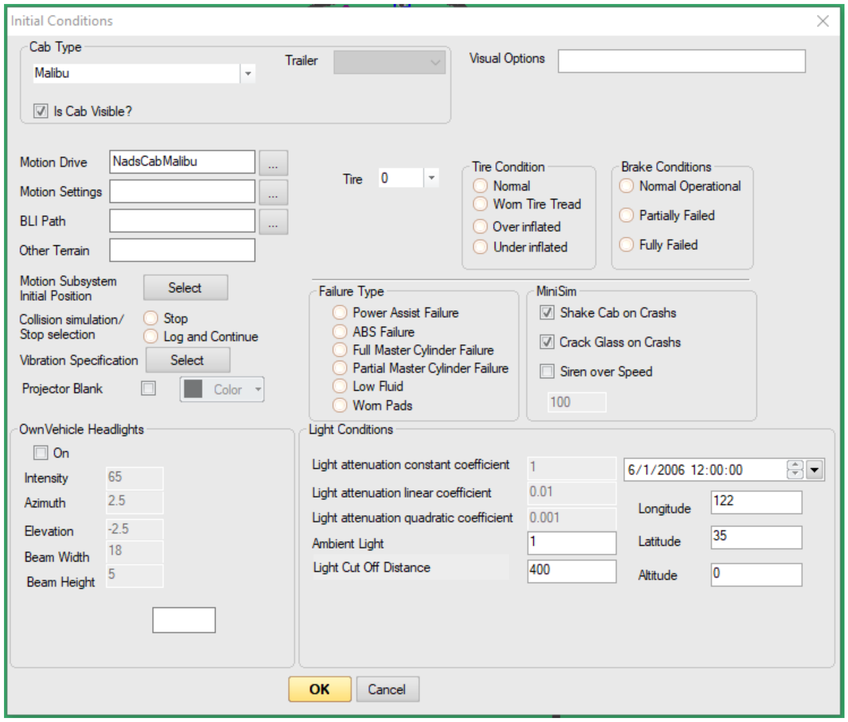


Figure 6 Defining initial conditions

3.2.4 Scenario Fabrication

After all the required elements have been added to the simulation, the simulation conditions can be fabricated as desired using triggers. While all the previous sections simply add elements to the simulation that would just normally follow the pre-defined rules, this is where they can be instructed to perform certain actions that would help create testable driving conditions for the participants. There are different types of triggers that perform various functions. A few terms that help define the actions associated with triggers are: firing which refers to performing any action defined by a trigger; target set is any set of elements that would be affected by the trigger's action; and instigator set is the set elements whose actions fire a trigger.

The ISAT offers six different types of triggers that can be used to define the actions for various elements in a simulation. They are the global time trigger, roadpad trigger, time to arrival trigger, follow trigger, traffic light trigger, and expression trigger. Figure 7 shows an image of a roadpad trigger.

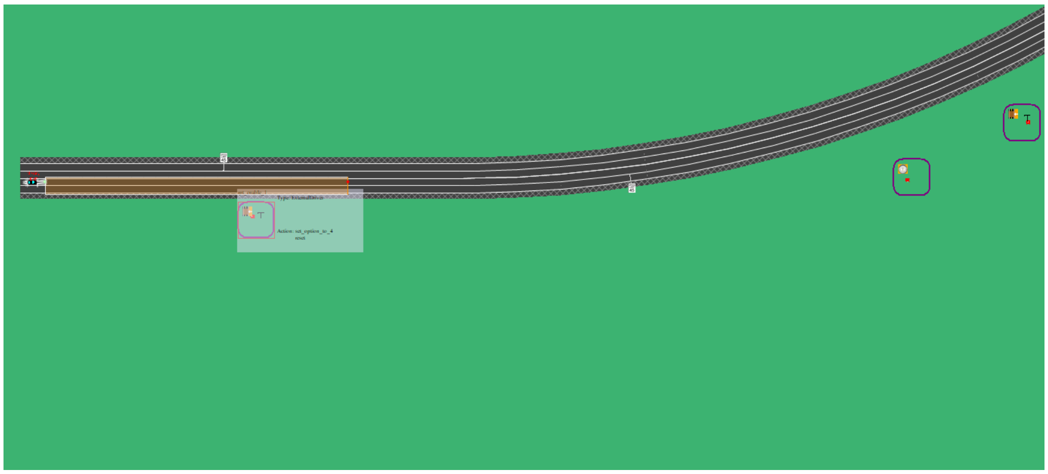


Figure 7 “Road Pad” trigger in ISAT

Figure 7 depicts the roadpad which fires when the vehicle is on the pad. The roadpad needs to be placed on the driver side to trigger the action while the external driver is placed on the road before the roadpad. Other triggers can also be observed to the right of the image. Additionally, there are a few more settings that can be explored related to each type of trigger.

Figure 8 shows the steps involved in setting up a trigger, which in this case is the roadpad trigger. There are four tabs in a trigger window. They are predicate, general, action, and comment. The instigator set can be assigned in the predicate tab which could be a designated ADO, the external driver, or any other desired element in the scenario.

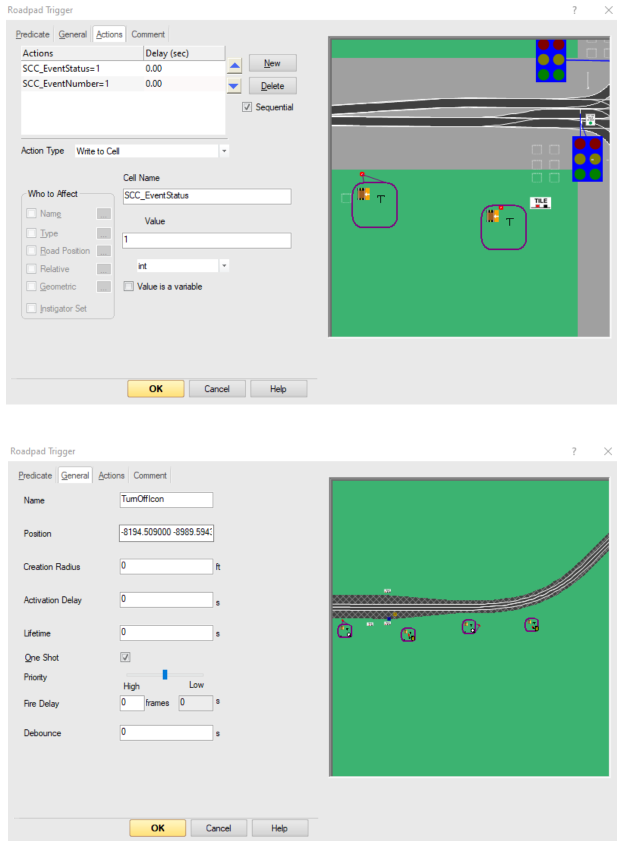


Figure 8 Setting up a trigger

Figure 8 depicts the general tab on the left-hand side. The one-shot option deletes a trigger from the simulation after an action has been fired once. The fire-delay option can be used to delay the actions that are fired by a trigger until after all the necessary conditions are met as set by the instigator. The default value used by the ISAT is ‘0’, which immediately fires the actions. A trigger can be prompted to perform an action multiple times during a simulation using the debounce option. The default value is usually set to ‘0’ and can be changed as required, which dictates the time gap between each action. The effects of activation delay and creation radius options were discussed previously and the action tab defines the action that need to be fired by the trigger, which prompts the system to capture the event information in post-simulation reports. The comment tab allows users to make notes for future simulations or other users. When there are multiple triggers in a scenario, they can be assigned priorities, allowing one trigger to fire after another.

The global time trigger follows the time of the simulation and fires when the simulation reaches a specific time. This trigger does not require any other settings by the instigator and solely follows the clock. The roadpad trigger designates actions to objects at certain points in the simulation. Actions can be specific to certain objects—for example, if the user requires a vehicle to drive in the opposite lane, they can name and add an ADO to the trigger so only that the vehicle performs the specified action. The time to arrival trigger is very similar to a roadpad trigger but in addition to a pad, the time taken by the instigator set to reach a designated point is less than or equal to a defined value. These triggers are typically used to create near collision scenarios. The follow trigger allows the user to define the firing conditions when a vehicle follows another vehicle for a specified period and distance. In this case, the instigator set could be either the leading or the following car. The trigger also allows users to define tolerance levels in the specified values, and also enables the vehicles to follow the same or different lanes.

For example, this function can be used to generate a BSW condition in the simulation. The traffic light trigger performs actions that can be fired based on signal changes. In this case, the traffic lights in the scenario make up the instigator set. Users can select the traffic light and define the color (green, red, or yellow) to trigger an action. In addition to all the aforementioned triggers, small expressions can also be written in the scenario using the expression trigger where the system can be prompted to read if a value is equal to, more, or less than a defined value for a variable. This trigger can be fired at the beginning of the simulation or by a creation radius. For example, an expression trigger may be used to alert a driver if they cross a speed limit.

3.2.5 Data Verification/ Extraction

The ISAT allows for the verification of created scenarios and the extraction of data from the simulation. The ISAT provides four different modes that target different levels of scenario development. The authoring mode enables users to add new elements to the scenario or edit the existing elements. The rehearsal mode generates a walkthrough of the conditions in a scenario. The rehearsal mode runs the scenario on the ISAT platform using an autonomous driver model and any element can be followed. Since the driver is an autonomous model (similar to an ADO), it is more precise than a human participant in the simulation.

The driving behaviors and dynamics are stored as frames that encompass a defined time-period of the run and a collection of such frames is called a buffer. The ISAT also allows users to record the rehearsal to be stored for reference in the future. The ISAT also plays the simulations that were driven by human drivers in miniSim^{TM} to observe and extract data from the files. The simulations are then stored as data acquisition (DAQ) files that can be imported into the ISAT using the playback mode. Additionally, the movie option records parts of the simulation that captures desired time frames.

The ISAT also displays certain variables of the external driver during the playback to observe how their behaviors were changing at any point of interest. As previously mentioned, the behaviors are stored as frames which can be searched for information or conditions. For example, the frames could be extracted if speed limits exceed a certain value. The ISAT offers multiple variables that can be extracted from the simulation DAQ file using the playback mode. It can also be exported in various formats.

3.3 MiniSim^{TM}

Along with participant simulations, miniSim^{TM} offers several options that can be handy for users. Every simulation automatically generates DAQ files with time and date stamps. In addition to this, a text file is generated that can capture eleven different variables. The authoring needs to be done in the ISAT to prompt the capture of the variables. However, only up to twenty events can be captured by this method. The driving report can be viewed immediately on the screen at the end of a simulation by selecting the option in miniSim^{TM}.

MiniSim^{TM} also enables users to specify multiple levels of selection paradigms by defining the priority levels. Additionally, users can select the type of vehicle at the start of the simulation, such as a passenger car, pickup truck, or a luxury car. The default vehicle type assigned to a simulation is a passenger car. Figure 9 shows a screenshot of the window in miniSim^{TM}.

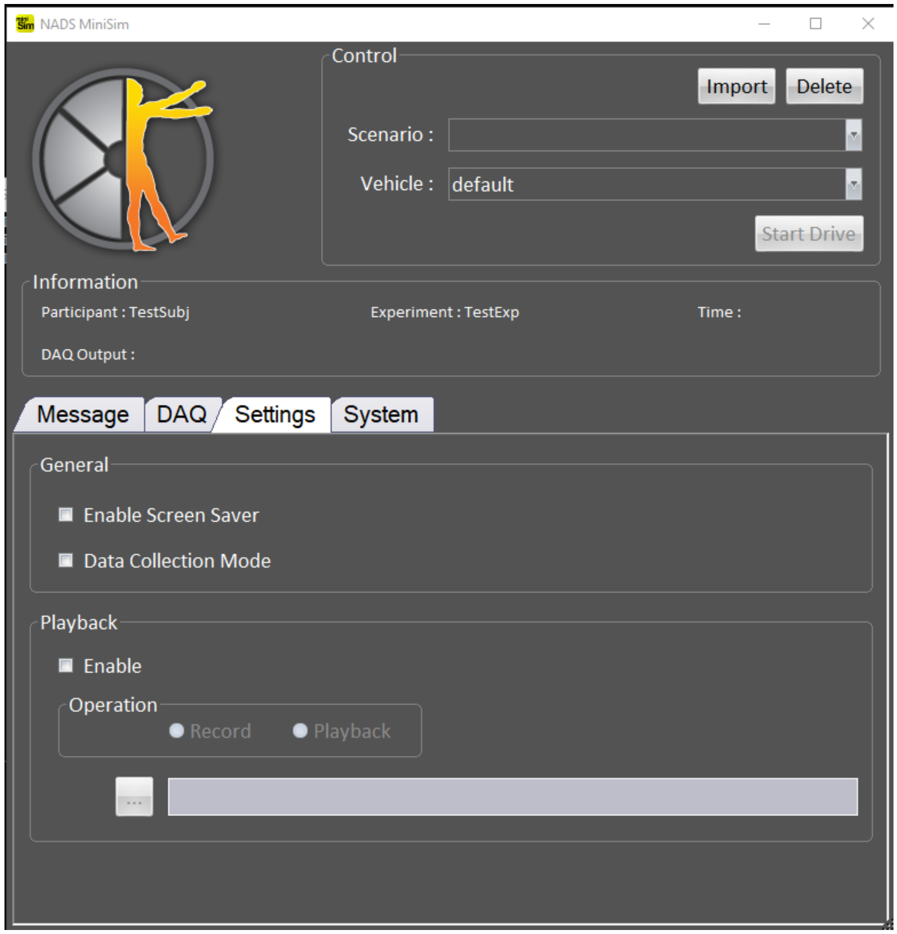


Figure 9 Initialization window in miniSim™

The scenario and the type of vehicle can be selected from the available drop-down menus. The DAQ tab allows users to specify the name of the participant and scenario type. A unique folder is created for each test subject or participant which is especially helpful when each participant tests multiple scenarios. The DAQ output is generated at the end of a simulation. The screensaver mode simply activates a screensaver when the simulator is not in use. The data collection mode lets users collect data while the playback option lets them record the simulation. The message tab displays the success or failure messages of a simulation. The DAQ tab names the files and segregates them appropriately. The settings tab enables users to select options related to the simulation while the system tab indicates that the associated systems are online and communicating.

3.4 Technical Paradigm

While the different stages handled by each tool were discussed in the previous section, a set of files carries the information forward, putting together information from these platforms towards a final focal point. This section discusses the technicalities and needs for the three tools to work together. Figure 10 shows a schematic of the transfer of files that handle the data.

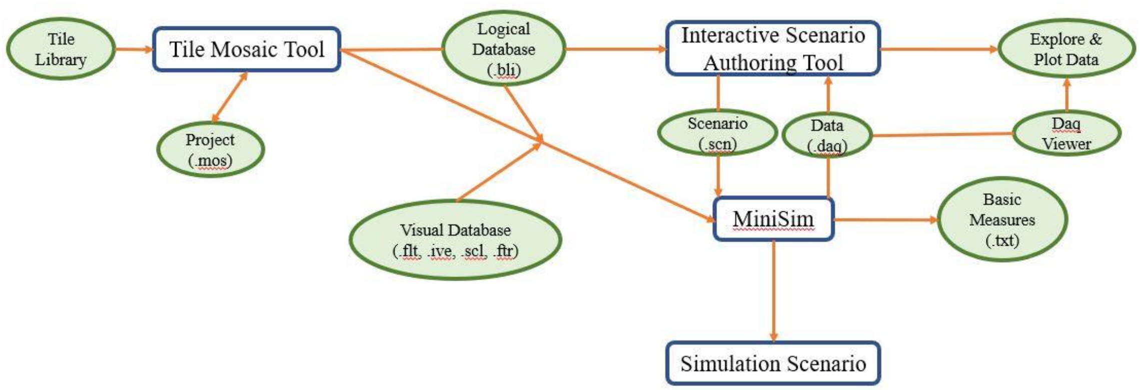


Figure 10 Technical interaction schematic of driver simulator

The tile library contains information of different types of tiles offered in the TMT to build a road network. After putting the tiles together in the TMT, the output generated from the TMT is a project file in the ".mos" format. This file holds the information of elements used in a project file and acts as an information holding file. The information is passed both ways from the TMT to the project files, as depicted in Figure 10. After developing a complete project file, several other files also need to be generated from the TMT to access the data in the ISAT and miniSim^{TM}. One such file created in this process is a logical road information (LRI) file that stores information about the types of roads and the type of authoring that can be allowed for the tiles to be edited in the ISAT. This file is further converted into a binary LRI file called the BLI that stores the same information in a binary format. It optimizes the memory used to store information to be later accessed by the ISAT or miniSim^{TM}.

Other files that are created in the process include a "scenario control list" (SCL) file that summarizes the elements used in the TMT. The open flight or FLT files are necessary to convert the 2D tiles into 3D for visualization in miniSim^{TM}. The other file required in this process is the "tile reference" (FTR) file that stores information on tile combinations required to configure a terrain along with the coordinate information, the rotation angle of a tile, and the category of the tile. Additionally, the system creates a three-dimensional model binary file (with "IVE" as the file extension) that optimizes the storage of the necessary information for miniSim^{TM} to access later. As per Figure 10, the ISAT uses the logical database to carry the operations further as it only handles 2D portions of the process, while miniSim^{TM} uses a combination of both logical and visual databases to configure simulation settings.

Additionally, there are many other files that are generated by default when TMT outputs are created. It is important to create both the logical and visual databases at the same time while building scenarios to maintain the consistency of information and avoid mismatches. Although the TMT allows users to copy built tiles from one file to another, copying large files may cause disruptions that needs to be carefully monitored to avoid losing work.

The ISAT uses the BLI file from the TMT to further add additional elements that have been discussed in the functional section. While the BLI files hold the logic of information from the TMT, additional layers are added to the same file to keep the comparative information constant. The ISAT then generates a scenario file that contains the additional information added while pointing to the base file adopted from the TMT. This allows for miniSim^{TM} to cross reference with the other visual files that are developed in the TMT. This scenario (SCN) file is delivered to miniSim^{TM} as shown in Figure 10. The miniSim^{TM} then generates DAQ files that are sent back to the ISAT for analysis. The features and purpose of these files were discussed in the previous section. A DAQ viewer can also be used to explore the data individually as shown in Figure 11.

3.5 Driving Simulator

The driver simulator simulates the driving scenarios which are used to capture driving behavior under different conditions. It resembles the interior of a vehicle to give an accurate driving feel to the participants. Figure 11 shows the driving simulator setup.

Figure 11 Driver simulator setup

The setup of the driver simulator consists of five screens, seating, and a panel with a driving wheel, brake, and accelerator, as well as buttons that handle certain functions in the simulation. While the tab in Figure 11 is handled on the screen placed on the table in the left picture, the four screens seen in the right picture simulate the scenarios. The three adjacent screens are placed such that they cover the vision cone of the participants to emulate the feel of driving in the real-world. The screen placed below the three screens displays the vehicle panel and contains the speedometer, fuel gauge, etc. The driving wheel and panel buttons are placed in front of the bottom screen. Figure 12 shows the panel buttons and steering wheel.

Figure 12 Driving wheel and panel buttons

There are multiple panel buttons that handle multiple actions in the simulation. The first picture from the left shows the orientation of the steering wheel within the simulator setup. The two buttons highlighted by red circles in the first picture have three buttons on each side of the wheel. The first button on the top on each side can be used for turning signals, the second button can be used for making half shoulder checks that pan until the first side window, and the third button can be used for a complete shoulder check/view rotation until the rear passenger window. These can be used in case of lane-changing for shoulder checks.

The second picture shows the left panel which contains the mirror adjustment panel. The white button in the center toggles the mirror selection to left and right, and rear mirrors can be adjusted using the four surrounding black buttons. The green button is used to turn on the headlights while the blue button turns on the high beam. The two black buttons handle the auxiliary input for two input points.

The third picture shows the right panel buttons of the simulator. The big red button turns on the vehicle in the simulation and a vibration is generated when the vehicle is turned on, like in the real-world. The two small red buttons beside the power buttons allow the participant to switch between parking, reverse, neutral, and driving gears. The yellow button is used for parking lights and the black button is used for wipers. The related symbols are also shown beside each button to provide general information for participants.

The fourth picture shows the brake and accelerator that are set up at the bottom of the screens highlighted by a red circle. They operate the movement of the vehicle in the simulation.

Figure 13 shows the setup of buttons to activate and control ACC and LKA during the simulation. The functions of the buttons as discussed from Figure 12 were revised in order to achieve the functions as shown in Figure 13. Activating one of these systems enables control of the vehicle at a level 1 automation stage, while activating the systems simultaneously simulates the vehicle at level 2 automation stage.

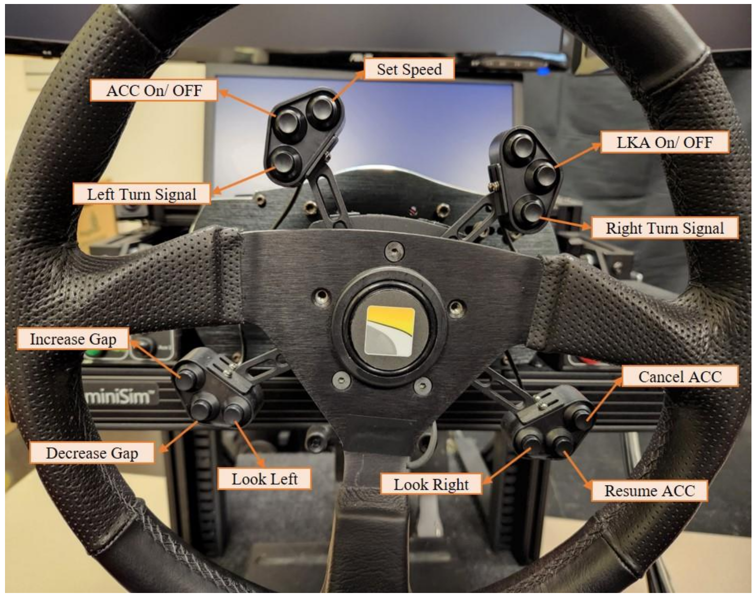


Figure 13 Buttons to control ACC and LKA during simulation

As can be observed from Figure 14, the simulation is set in daylight conditions where the vehicle is stopped at an intersection. The traffic lights are red while other vehicles are crossing the intersection from right side of the driver. The bottom screen can also be seen displaying the panel of the vehicle. The fifth screen in the left picture can be seen recording the time, featuring information on the type of scenario and vehicle as well.

Figure 14 Simulating a Scenario in Driver Simulator

CHAPTER 4: METHODOLOGY

This chapter provides an overview of the methodology adopted in this research. A flowchart outlining the methodology is presented in Figure 15. The first stage involved developing appropriate driving scenarios. In order to improve the applicability of the results, rural, urban, and freeway driving scenarios were simulated as these are the typical settings encountered by a driver. The second stage involved the careful selection of driver participants so that the sample population is an accurate representation of the general population. The participants in the age group of sixteen to sixty-five years were selected for the study. Each participant was provided with all the three driving scenarios while a vehicle with or without advanced features was allocated to them at random.

The third stage involved data processing and analysis to derive meaningful results. The analysis of variance (ANOVA) test was performed to evaluate the effectiveness of advanced features. Parameters of driver behavior like hard braking, hard cornering, lane departures, speeding events, average headway, and brake pedal force were assessed. The fourth stage involved the identification and application of changes in driver behavior to identify the behavioral differences among vehicles with and without advanced features.

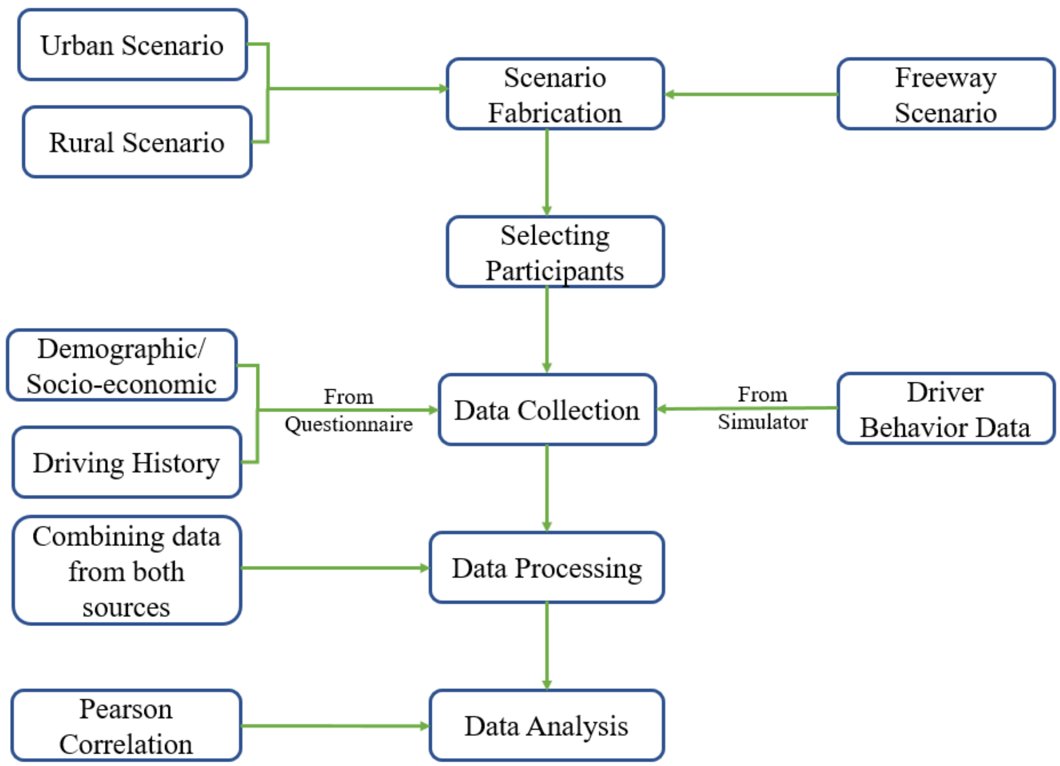


Figure 15 Methodological framework

4.1 Scenario Fabrication

As stated previously, three types of driving scenarios were developed—the rural scenario, the urban scenario, and the freeway scenario. These scenarios were developed with the intention of mimicking real-world conditions. The idea of developing them was to allow the results to be attributed to general driving behavior rather than one type of scenario. Since the focus of this study is to test the effect of different types of advanced features on driver behavior, various conditions were simulated as follows.

- The rural scenario was set up with two-lane undivided roads (one lane in each direction) later extending into four-lane undivided roads (two lanes in each direction). The scenario consists of only one traffic signal and one intersection with an all-way stop. The remaining route mostly represents county roads. The vehicles in this scenario consist of passenger cars, pickup trucks, and trucks. The speed limits were set at 55 mph. The simulation also consists of a gravel road for a small portion, which was intended to capture driver behavior (changes in speeding or braking). This scenario was developed to last for seven to eight minutes.

- The urban scenario was set up for drivers to interact with the elements that are typical of urban conditions, such as traffic signals, passenger cars, trucks, school buses, motorcycles, and pedestrians. The speed limits were set at 45 mph or 50 mph. The scenario is developed to last seven to eight minutes and consisted of four-lane undivided roads (two lanes in each direction).
- The freeway scenario was developed to last for six to seven minutes and consists of two interchanges that allow drivers to transition from one freeway to another freeway. The freeways were designed to be four-lane divided roads (two lanes in each direction). The speed limits were set at 65 mph for the first freeway and 70 mph for the second freeway. The vehicles in this scenario mostly comprise trucks and passenger cars. The simulation was set up to force interactions between the drivers and trucks while merging onto another highway.
- The scenarios used clear weather and daytime conditions—typically referred to as base conditions—until they were specifically set to display other weather or light conditions.
- The simulator provides the option to also simulate the same driving scenarios under varying weather and light conditions. Varying weather conditions like rain, snow, and fog can be simulated and compared to the clear weather condition. Further, varying lighting conditions (dawn, dusk, and night) can also be used during the

simulation.

- The primary focus of the study is to evaluate the effect of advanced features on the driver behavior. Therefore, the simulations are generated with LDW, BSW, and OSW as the warning features. They are used individually and in combination and are then compared to simulations without advanced features. The simulator allows users to assign advanced features to scenarios rather than vehicles which can be enabled via expressions that can be added prior to a simulation. The participants are provided with a vehicle with or without advanced features at random.
- The LDW displays a warning on the screen when the vehicle departs from its lane. BSW displays a warning light on the mirror when another vehicle is detected in a blind spot of the car, and the OSW displays a text alerting the driver of over-speeding. The overspeed limit can be set using “expression”.
- Additionally, LKA and ACC were provided as a part of the automated features to the participants which can be activated during a simulation using the appropriate buttons on the wheelbase. Once the LKA is activated, it maintains the vehicle in the travel lane during the simulation. Likewise, ACC maintains a designated headway from the leading vehicle during the simulation.
- The navigation instructions are provided to the participants as text on the driving screen, which represents a heads-up display (HUD).

4.2 Selecting Participants

Permission was obtained from the Institution Review Board (IRB) to conduct this study. Drivers between sixteen and sixty-five years of age with a valid driver’s license were determined as the target participant population. The selection of participants was scrutinized carefully such that the sample is an accurate representation of the general population. The selection criteria included many factors, including demographic and socioeconomic characteristics of the participants. While the selection cannot be pre-controlled, identifying gaps in the data (demographic and socioeconomic) at every stage of the data collection process and selecting participants to accommodate for the missing data points is necessary. This was done throughout the data collection.

Once a participant was finalized for the study, they were given a small survey that captured demographic information. No personal information was collected in the survey to maintain anonymity. Participants were also informed that their participation was completely voluntary and they could choose to drop out of the study at any point. Similarly, if desired, they could opt to skip questions in the survey if they were not comfortable answering it.

Three types of driving conditions were provided to the participants—rural, urban, and freeway. The vehicle type was assigned based on the type of vehicle the participant drives for their regular commutes. This was captured from the responses to the survey questions before the start of simulated driving. The consent forms were provided to the parent/guardian for participants below the age of eighteen.

The survey provided to the participants captured information including their education, income, gender, and driving experience. Along with such information, other information like their driving history (previous crash involvement/ citations), vehicle ownership, and if they have already driven a vehicle with any kind of advanced features was gathered. This type of information was used to account for the driving behaviors based on their previous experience to different conditions.

Other information like alcohol consumption or lack of sleep on the previous day, that could affect the driving behavior were also collected in the survey. The participants were also given consent forms for them to understand their rights before participating in the survey.

4.3 Data Collection

The data collected from two sources were combined to form a single database. The socioeconomic and demographic data was collected from the survey questionnaire that the participants answered during the simulator study, as depicted in Figure 15. The questionnaire also collected participants' driving history, as well as variables such as age, gender, type of vehicle owned, race, education, household income, any record of prior crashes or citations, alcohol consumption in the last twenty-four hours, hours of sleep, medication, marital status, and any advanced safety features in their personal vehicles. This data was used to determine the type of vehicle and advanced features to be assigned randomly to the participants. Data on participants' driving behavior was collected by the driver simulator and extracted using the ISAT via the DAQ file viewer.

4.4 Data Processing

Ensuring that the right data extracted from ISAT is assigned to the right participant is very vital for the research. Considering the diversity of various variables from the questionnaire, any mismatch of data will lead to faulty results. Each participant is awarded the same participant ID, both, on the questionnaire and the DAQ files that are generated from their driving profiles. Each DAQ file was changed and assigned the corresponding participant ID immediately after driving each scenario to avoid any confusion later. The

DAQ files allow users to extract a wide range of variables that capture driving behaviors like hard braking, hard cornering, maximum speed, minimum speed, average speed, average headway, lane departures, speeding events, and hard cornering. This data was combined with the data from the survey questionnaire for further analysis. This enables an in-depth analysis of driver behavior considering the extent of information collected.

Table 1 summarizes the distribution of samples collected for this research. The participant selection is made with an intent to fill any gaps to ensure a representation of the actual population. This is to warrant the applicability of the research results to typical rural, urban, and freeway areas.

As can be observed from Table 1, about 54% of the participants are within the age range of 16 – 25 years, about 26% are within the age range 25 – 45 years, 11.5% are within the age range 46 – 55 years, and about 9% are within the age range of 56 – 65 years. The average age of the participants involved in the research is 30 years. The gender distribution is 60% male and 40% female for the participant group. Similarly, about 57.2% of the participants are Caucasians, 22.8% are African-Americans, 5.7% are Hispanics, and 14.3% are Asians.

Table 1 Data distribution of collected data

Variable	Category	Frequency	Percentage
Age	16–25 years	28	47.7
	25–45 years	20	33.3
	46–55 years	8	13.3
	56–65 years	4	6.7
Gender	Male	36	60
	Female	24	40
Race	Caucasian	29	48.3
	African–American	12	20
	Hispanic	5	8.3
	Asian	14	23.3
Education	High School	15	25

	Associate	5	8.3
	Bachelor’s	23	38.3
	Master’s	16	26.7
	Doctorate	1	1.7
Income	Less than 25k	11	18.3
	25k–49k	8	13.3
	50k–75k	2	3.3
	75k–99k	6	1
	100k–150k	11	18.3
	150k or more	14	23.3

4.5 Data Analysis

Carefully studying the data once all the data is combined is important to understand and propose appropriate data analytical methods that yield meaningful results. The variables that can be used to evaluate the effectiveness of the advanced features were selected. For example, average speed and maximum speed were used to analyze OSW. Similarly, lane departures were used to analyze LDW.

The primary aim of the research is to capture differences in driving behavior when driving a vehicle with advanced features compared to driver behavior when driving a vehicle without advanced features. Given the number of groups to compare and relevant variables, an ANOVA test was applied. ANOVA compares the mean values of multiple groups and determines if they are statistically different (SPSS Tutorials, 2020). An example hypothesis for ANOVA test is as follows.

- Null hypothesis: The number of times participants exceed the speed limit with OSW is the same as the number of times participants exceed the speed limit without OSW.
- Alternate hypothesis: The number of times participants exceed the speed limit with

OSW is less than the number of times participants exceed the speed limit without OSW.

An ANOVA test determines if we reject or fail to reject this hypothesis. The expected outcome is a rejection of the hypothesis, due to the difference in driving behavior with advanced features. Once the results from ANOVA are established, evaluating the magnitude of the difference helps capture the nature of effects of advanced features.

CHAPTER 5: DESCRIPTIVE STATISTICS

Tables 2, 3, and 4 depict descriptive statistics for various driving behaviors in rural, urban, and freeway scenarios, summarizing the following variables: number of hard braking events; number of hard cornering events; number of lane departure events; average speed; average headway; maximum speed; and brake pedal force. Hard braking represents the total number of times a participant applied sudden brakes during a simulation. Similarly, hard cornering is the total number of times a participant made sudden turns in the simulation. The number of times the participant deviated from their lane is represented by lane departures. These variables indicate aggressive or unsafe driving behaviors.

The average speed is the speed maintained by a participant throughout a simulation and is measured in miles per hour. Similarly, the maximum speed is the maximum speed reached during a simulation by a participant in miles per hour. The average headway is measured in feet and is the distance maintained by a participant from the leading vehicle. The brake force is the average force applied on the brake by a participant during a simulation and is measured in pounds.

Table 2 Driver behavior parameters (rural)

Driver Behavior	Minimum	Mean	Maximum	Std. Dev.
Hard Braking	0.00	1.47	4.00	0.97
Hard Cornering	0.00	2.73	12.00	2.33
Lane Departures	0.00	6.08	30.00	6.18
Average Speed (mph)	14.60	40.96	62.10	7.29
Average Headway (ft)	49.50	319.56	853.70	223.89
Maximum Speed (mph)	42.80	61.41	107.50	12.77
Brake Force (lbs)	0.33	16.29	60.00	14.06

Note: Braking, cornering and lane departures are numbers without units. They are the number of times the corresponding action was performed per participant per simulation.

Table 3 Driver behavior parameters (urban)

Driver Behavior	Minimum	Mean	Maximum	Std. Dev.
Hard Braking	0.00	1.58	4.00	1.06
Hard Cornering	0.00	1.74	5.00	1.10
Lane Departures	0.00	4.57	21.00	4.76
Average Speed (mph)	30.50	42.35	55.30	5.13
Average Headway (ft)	94.00	550.33	1660.20	444.20
Maximum Speed (mph)	49.40	62.15	102.20	7.59
Brake Force (lbs)	1.09	15.92	61.20	15.96

Note: Braking, cornering and lane departures are numbers without units. They are the number of times the corresponding action was performed per participant per simulation.

Table 4 Driver behavior parameters (freeway)

Driver Behavior	Minimum	Mean	Maximum	Std. Dev.
Hard Braking	0.00	0.35	2.00	0.53
Hard Cornering	0.00	2.88	10.00	1.68
Lane Departures	0.00	12.12	39.00	9.79
Average Speed (mph)	40.40	56.59	67.80	5.21
Average Headway (ft)	77.30	304.89	823.70	182.98
Maximum Speed (mph)	61.50	76.29	95.50	7.38
Brake Force (lbs)	0.03	6.76	41.00	8.58

Note: Braking, cornering and lane departures are numbers without units. They are the number of times the corresponding action was performed per participant per simulation.

Table 5 Provision of vehicles with or without advanced features to participants

ADAS	Rural	Urban	Freeway
LDW	6	7	7
BSW	7	7	7
OSW	7	6	5
LDW & BSW	2	2	5
LDW & OSW	7	8	4
BSW & OSW	5	4	4
All	2	3	5
ACC	9	9	9
LKA	8	8	8
ACC & LKA	17	17	17
None	7	6	6

5.1 Rural Driving Scenario

The descriptive statistics are provided as a side-by-side comparison to show the values across the groups with the ADAS and the group without the ADAS. Table 6 shows the descriptive statistics comparing the participant group provided with one of the warning features (LDW, BSW, and OSW), the participant group provided with one of the automated features (ACC and LKA) and the participant group not provided with any ADAS. The mean values for hard braking, hard cornering, and lane departures for the participant group without LDW are higher, as indicated in Table 6. Additionally, the average headway for the participant group without LDW was lower than for the participant group with LDW. This indicates aggressive driving behaviors from participants without LDW while participants with LDW demonstrated safer driving behaviors. On the other hand, average speed, maximum speed, and brake force have similar values between the two participant groups.

The average headway and brake pedal force values are different between the participant groups while the other parameters are similar. The participants with BSW seem to maintain shorter headways, while the other behavior parameters such as hard braking, lane departures, and average speed have lower values compared to participants driving a vehicle without BSW. It can be observed that hard braking, average speed, average headway, and maximum speed have higher mean values for the participant group without OSW compared to the participant group driving a vehicle with OSW. On the other hand, hard cornering events, lane departure events, and brake pedal force have higher mean values for the participant group driving a vehicle with OSW.

The mean values of lane departures, average speed, average headway, and brake force are lower for the participant group with LKA compared to the participant group with LDW. The standard deviation for these driver behaviors is also low, which shows lower variation in participants' driving behavior. The mean values of average headway and brake force are lower for the participant group that drove a vehicle with ACC compared to the participant group that drove a vehicle with BSW or OSW.

Table 6 Driver behavior parameters - ADAS (rural)

Parameters	**Statistics**	**LDW**	**BSW**	**OSW**	**ACC**	**LKA**	**No ADAS**
Braking	Minimum	0.00	0.00	0.00	1.00	0.00	1.00
Cornering		0.00	0.00	0.00	2.00	2.00	1.00
Lane Departures		0.00	1.00	0.00	8.00	2.00	2.00
Avg_Speed (mph)		14.60	33.40	14.6	35.30	39.80	29.90
Avg_Headway (ft)		49.50	65.50	49.50	94.30	383.80	89.50
Max_Speed (mph)		42.80	48.30	42.80	55.40	61.60	50.00
Brake Force (lbs.)		3.20	0.33	0.33	1.19	14.60	10.30
Braking	Mean	0.88	1.06	1.00	2.25	1.50	2.14
Cornering		2.24	3.38	4.19	2.50	2.75	3.00
Lane Departures		5.65	7.75	10.38	10.25	3.50	8.57
Avg_Speed (mph)		41.14	40.59	37.02	36.53	41.43	45.20
Avg_Headway (ft)		478.71	370.56	412.25	97.15	440.30	421.71
Max_Speed (mph)		59.05	64.59	53.48	57.35	68.20	69.20
Brake Force (lbs.)		26.01	19.58	26.72	1.29	19.60	22.64
Braking	Maximum	3.00	3.00	4.00	3.00	3.00	3.00
Cornering		6.00	10.00	12.00	3.00	4.00	10.00
Lane Departures		16.00	27.00	30.00	13.00	5.00	23.00
Avg_Speed (mph)		60.30	55.6	47.60	38.20	43.40	62.10
Avg_Headway (ft)		853.70	664.80	853.70	102.80	506.50	631.30
Max_Speed (mph)		107.50	95.40	56.90	59.10	73.40	89.00
Brake Force (lbs.)		48.50	36.40	60.00	1.46	23.40	38.00
Braking	Standard Deviation	0.93	0.85	1.14	0.96	1.29	0.69
Cornering		1.60	3.26	3.49	0.58	0.96	3.11
Lane Departures		4.18	7.15	7.99	2.22	1.29	7.14
Avg_Speed (mph)		9.89	6.67	7.10	1.21	1.64	12.46
Avg_Headway (ft)		240.40	217.67	246.10	3.88	50.74	181.18
Max_Speed (mph)		18.10	16.56	4.08	1.70	5.08	15.33
Brake Force (lbs.)		9.37	11.94	14.26	0.12	3.75	8.80

Note: Braking, cornering and lane departures are numbers without units. They are the number of times the corresponding action was performed per participant per simulation.

Young people are classified as people aged ten to twenty-five years by the World Health Organization. The participant groups were segregated accordingly to evaluate their driving behavior. Table 7 shows descriptive statistics of driving behavior parameters comparing young (fifteen to twenty-five years) and adult participants (above twenty-five years), male and female participants, daytime and nighttime conditions, and clear weather and rainy weather conditions for the rural scenario. The mean of hard braking events is higher for adult participants compared to young participants. The mean values of average speed and maximum speed are also higher for adult participants whereas the mean values of other driving behavior parameters are similar in the rural driving scenario.

The mean values of the average headway and brake force are slightly higher for female participants compared to male participants. The other driver behavior parameters are similar in the rural driving scenario. The mean values of hard cornering, lane departures, and average headway are higher for the participants group who drove in nighttime conditions compared to the participant group who drove in daytime conditions. The mean values of average speed and maximum speed are higher for daytime conditions. More aggressive driving was observed during daytime conditions, while risky driver behaviors like hard cornering and lane departures are higher during nighttime. The mean values of average headway and brake force are higher for the participant group that drove in rainy conditions compared to the participant group that drove in clear weather. The mean values of other parameters such as hard braking, hard cornering, and lane departures are higher for participants who drove during in clear weather conditions. More aggressive driving behavior was observed during clear weather conditions while rain tended to make participants more careful.

Table 7 Driver behavior parameters - age, gender, lighting condition, and weather condition (rural)

Driver Behavior	**Minimum**		**Mean**		**Maximum**		**Std. Dev.**	
Age	**≤ 25 Years**	**> 25 Years**	**≤ 25 Years**	**> 25 Years**	**≤ 25 Years**	**> 25 Years**	**≤ 25 Years**	**> 25 Years**
Hard Braking	0	0	1.28	1.62	4	3	1.02	0.91
Hard Cornering	0	0	2.71	2.74	12	10	2.28	2.39
Lane Departures	0	1	5.69	6.4	30	27	6	6.38
Avg. Speed (mph)	14.6	29.9	39.6	42.09	55.6	62.1	6.31	7.92
Avg. Headway (ft)	49.5	72.3	319.98	319.2	853.7	664.8	244.79	207.89
Maximum Speed (mph)	42.8	47.7	58.95	63.46	92.5	107.5	11.11	13.79
Brake Force (lbs.)	1.26	0.33	15.73	16.76	48.5	60	13.91	14.33
Gender	Male	Female	Male	Female	Male	Female	Male	Female
Hard Braking	0	0	1.47	1.47	4	3	0.99	0.95
Hard Cornering	0	0	2.82	2.59	10	12	2.34	2.34
Lane Departures	1	0	6.53	5.44	27	30	6.13	6.29
Avg. Speed (mph)	29.9	14.6	41.44	40.28	62.1	55.6	7.06	7.68
Avg. Headway (ft)	49.5	49.5	324.7	312.32	853.7	757.6	224.05	227.04
Maximum Speed (mph)	46.1	42.8	60.69	62.42	95.4	107.5	11.55	14.44
Brake Force (lbs.)	1.11	0.33	15.39	17.56	37.1	60	12.57	16.04
Lighting Condition	Day	Night	Day	Night	Day	Night	Day	Night
Hard Braking	0	0	1.42	1.56	3	4	0.93	1.05
Hard Cornering	0	0	2.5	3.15	10	12	2.1	2.68
Lane Departures	0	1	4.34	9.29	16	30	3.66	8.35
Avg. Speed (mph)	14.6	29.9	41.42	40.09	62.1	51.6	7.93	6.01
Avg. Headway (ft)	49.5	81.5	273.67	404.53	625.9	853.7	193.01	254.5
Maximum Speed (mph)	42.8	46.1	63.25	57.99	107.5	101.1	13.39	10.93
Brake Force (lbs.)	0.33	1.11	15.36	18.03	60	42	14.26	13.77
Weather Condition	Clear	Rain	Clear	Rain	Clear	Rain	Clear	Rain
Hard Braking	0	0	1.53	1.33	4	3	1.01	0.87
Hard Cornering	0	0	2.28	3.71	6	12	1.23	3.6
Lane Departures	1	0	5.47	7.42	23	30	5.19	7.91
Avg. Speed (mph)	29.9	14.6	41	40.86	62.1	60.3	6.59	8.83
Avg. Headway (ft)	49.5	72.3	291.79	380.88	757.6	853.7	213.39	238.7
Maximum Speed (mph)	48.3	42.8	61.73	60.69	107.5	101.1	12.94	12.62
Brake Force (lbs.)	1.11	0.33	14.97	19.22	38	60	12.84	16.35

Note: Braking, cornering and lane departures are numbers without units. They are the number of times the corresponding action was performed per participant per simulation.

When a vehicle engages both LKA and ACC while driving, a level 2 vehicle is simulated. Table 8 compares descriptive statistics between participant groups who drove vehicles with automated features, warning features and without any ADAS for the rural scenario. The mean values of lane departures, average headway, maximum speed, and brake force are lower for the participant group who drove a vehicle with automated features compared to the participant group who drove a vehicle with warning features or without ADAS. Further, the standard deviation for all driver behavior parameters is low for the participant group who drive a vehicle with automated features compared to warning features or without ADAS i.e. lower variation in driving behavior.

Table 8 Driver behavior parameters - no ADAS, warning and automated features (rural)

Driver Behavior	**Statistic**	**No ADAS**	**Warning**	**Automated**
Hard Braking	Minimum	1.00	0.00	1.00
Hard Cornering		1.00	0.00	1.00
Lane Departures		2.00	0.00	1.00
Avg. Speed (mph)		29.90	14.60	36.90
Avg. Headway (ft)		89.50	49.50	94.00
Maximum Speed (mph)		50.00	42.80	52.80
Brake Force (lbs.)		10.30	0.33	1.11
Hard Braking	Mean	2.14	1.06	2.14
Hard Cornering		3.00	3.30	2.14
Lane Departures		8.57	8.31	1.43
Avg. Speed (mph)		45.20	40.33	39.46
Avg. Headway (ft)		421.71	433.12	112.00
Maximum Speed (mph)		69.20	61.33	57.56
Brake Force (lbs.)		22.64	24.85	1.67
Hard Braking	Maximum	3.00	4.00	3.00
Hard Cornering		10.00	12.00	4.00
Lane Departures		23.00	30.00	3.00
Avg. Speed (mph)		62.10	60.30	41.60
Avg. Headway (ft)		631.30	853.70	175.40
Maximum Speed (mph)		89.00	107.50	61.20
Brake Force (lbs.)		38.00	60.00	2.72
Hard Braking	Std. Dev.	0.69	1.01	0.69
Hard Cornering		3.11	2.94	1.07
Lane Departures		7.14	7.05	0.79
Avg. Speed (mph)		12.46	8.47	1.72
Avg. Headway (ft)		181.18	223.99	28.68
Maximum Speed (mph)		15.33	16.61	2.99
Brake Force (lbs.)		8.80	12.87	0.56

Note: Braking, cornering and lane departures are numbers without units. They are the number of times the corresponding action was performed per participant per simulation.

5.2 Urban Driving Scenario

Table 9 depicts descriptive statistics comparing the participant group with one of the warning features (LDW, BSW, and OSW), the participant group with one of the automated features (ACC and LKA) and without any ADAS in the urban scenario. Hard cornering and lane departures have lower mean values for the non-ADAS participant group while the average headway is higher when compared to the LDW participant group. On the other hand, hard braking, average speed, maximum speed, and brake force are similar in values for both participant groups. The difference in the mean values indicate non-aggressive driving behaviors among participants provided with LDW, but these participants also tended to speed more compared to the participants who did not have any ADAS.

The mean values for hard braking, hard cornering, lane departures, average speed, and maximum speed for participants without ADAS are lower compared to participants provided with BSW. Further lane departures, average headway, and brake pedal force for participants without ADAS are higher compared to participants provided with BSW. Overall, BSW seems to make participants' car-following and speeding behavior more aggressive as they also exhibited fewer safe driving maneuvers such as speeding, braking, and handling the vehicle. Similar to the rural scenario, the mean values of the number of lane departure events and brake force are higher for the participant group provided with OSW but the mean of average headway is lower for the participant group provided with OSW. Other driving behaviors like handling the vehicle, speeding, turning, and sudden braking seem to be more frequent among drivers for the participant group that drive a vehicle without ADAS.

Table 9 Driver behavior parameters - ADAS (urban)

Parameters	Statistics	LDW	BSW	OSW	ACC	LKA	No ADAS
Braking	Minimum	0.00	0.00	0.00	1.00	1.00	0.00
Cornering		0.00	0.00	0.00	1.00	1.00	0.00
Lane Departures		0.00	1.00	0.00	7.00	1.00	0.00
Avg. Speed (mph)		31.50	35.50	30.50	44.60	36.90	37.20
Avg. Headway (ft)		157.70	282.60	356.00	97.60	311.20	616.70
Max. Speed (mph)		49.40	49.40	49.40	59.30	64.20	51.90
Brake Force (lbs.)		6.10	3.90	3.90	1.11	15.60	18.30
Braking	Mean	1.45	1.75	1.24	2.00	2.00	1.50
Cornering		0.90	1.94	1.33	3.00	2.25	1.50
Lane Departures		3.50	4.50	6.86	10.50	1.75	6.83
Avg. Speed (mph)		40.35	44.33	39.35	45.77	40.53	41.72
Avg. Headway (ft)		904.86	750.15	979.27	102.55	363.75	937.93
Max. Speed (mph)		62.87	63.63	58.40	61.10	68.25	59.22
Brake Force (lbs.)		26.82	19.63	25.58	1.44	19.00	38.48
Braking	Maximum	4.00	4.00	4.00	3.00	3.00	3.00
Cornering		2.00	5.00	5.00	2.00	3.00	3.00
Lane Departures		11.00	10.00	21.00	14.00	3.00	20.00
Avg. Speed (mph)		53.90	53.90	50.30	47.10	44.70	55.30
Avg. Headway (ft)		1432.20	1460.80	1660.20	108.10	432.60	1170.30
Max. Speed (mph)		102.20	89.70	61.8	62.10	71.00	75.40
Brake Force (lbs.)		49.30	49.30	60.30	1.63	22.20	61.20
Braking	Standard Deviation	1.36	1.24	1.37	0.82	0.82	1.05
Cornering		0.79	1.53	1.28	0.82	0.96	1.22
Lane Departures		3.09	2.99	5.50	3.11	0.96	7.94
Avg. Speed (mph)		6.27	6.06	5.32	1.10	3.29	6.88
Avg. Headway (ft)		345.18	411.27	337.14	4.93	51.42	218.89
Max. Speed (mph)		12.40	9.61	3.66	1.26	3.13	8.21
Brake Force (lbs.)		12.73	15.37	17.75	0.23	3.03	17.10

Note: Braking, cornering and lane departures are numbers without units. They are the number of times the corresponding action was performed per participant per simulation.

The mean of the number of hard cornering events is higher for LKA which also yielded lower mean values for lane departures, average headway, and brake force. The mean values of hard braking and hard cornering are higher for the participant group that drove a vehicle with ACC compared to BSW and OSW, whereas the mean values of average headway and brake force are lower.

Table 10 depicts descriptive statistics of driver behavior parameters comparing participant groups containing young and adult participants, male and female participants, daytime and nighttime conditions, and clear weather and rainy weather conditions in the urban scenario. The mean values of hard braking are higher for the adult participant group compared to the young participant group. On the other hand, the mean values of lane departures, average headway, and brake force are higher for the young participant group compared to the adult participant group. Higher braking force was applied by younger participants along with a greater frequency of lane departures. The mean values of hard braking, average headway, maximum speed, and brake force are higher for the male participant group compared to the female participant group. The other driver behavior parameters are similar for both the participant groups. The male participants seem to apply hard brakes and more pressure while braking. They also drove at higher speeds compared to female participants. The higher speeds seem to lead to maintaining a higher average headway in urban conditions.

Table 10 Driver behavior parameters - age, gender, lighting condition, and weather condition (urban)

Driver Behavior	**Minimum**		**Mean**		**Maximum**		**Std. Dev.**	
Age	**≤ 25 Years**	**> 25 Years**	**≤ 25 Years**	**> 25 Years**	**≤ 25 Years**	**> 25 Years**	**≤ 25 Years**	**> 25 Years**
Hard Braking	0	0	1.34	1.78	4	4	1.06	1.02
Hard Cornering	0	0	1.77	1.71	4	5	1.03	1.17
Lane Departures	0	0	4.77	4.4	21	19	5.59	4.01
Avg. Speed (mph)	31.6	30.5	42.56	42.17	55.3	53.6	5.32	5.02
Avg. Headway (ft)	94	95.6	570.83	533.25	1460.8	1660.2	443.64	449.31
Maximum Speed (mph)	50.8	49.4	61.94	62.34	89.7	102.2	6.7	8.35
Brake Force (lbs.)	1.09	1.23	17.83	14.34	61.2	50.3	18.13	13.96
Gender	Male	Female	Male	Female	Male	Female	Male	Female
Hard Braking	0	0	1.89	1.15	4	4	0.98	1.02
Hard Cornering	0	0	1.62	1.91	5	4	1.09	1.12
Lane Departures	0	0	4.8	4.25	20	21	4.81	4.76
Avg. Speed (mph)	31.5	30.5	42.3	42.41	55.3	53.6	4.93	5.47
Avg. Headway (ft)	95	94	622.19	449.28	1460.8	1660.2	466.15	396.58
Maximum Speed (mph)	51.9	49.4	62.97	61	102.2	78.7	8.65	5.74
Brake Force (lbs.)	1.09	1.11	18.56	11.91	61.2	60.3	16.54	14.38
Lighting Condition	Day	Night	Day	Night	Day	Night	Day	Night
Hard Braking	0	0	1.45	1.87	4	4	0.95	1.23
Hard Cornering	0	1	1.72	1.79	5	4	1.21	0.83
Lane Departures	0	1	3.24	7.5	14	21	3.31	6.09
Avg. Speed (mph)	31.6	30.5	42.77	41.41	53.9	55.3	4.94	5.52
Avg. Headway (ft)	94	96.1	465.23	738.27	1432.2	1660.2	388.21	507.66
Maximum Speed (mph)	49.4	55.4	61.43	63.77	89.7	102.2	6.52	9.52
Brake Force (lbs.)	1.11	1.09	12.72	22.87	48.8	61.2	12.27	20.6
Weather Condition	Clear	Rain	Clear	Rain	Clear	Rain	Clear	Rain
Hard Braking	0	0	1.47	1.81	4	3	1.1	0.94
Hard Cornering	0	0	1.76	1.69	4	5	0.97	1.35
Lane Departures	0	0	4.57	4.58	21	20	4.83	4.73
Avg. Speed (mph)	30.5	31.6	42.62	41.82	53.9	55.3	4.92	5.57
Avg. Headway (ft)	94	94.8	472.88	702.26	1660.2	1432.2	408.32	479.74
Maximum Speed (mph)	49.4	51.9	62.49	61.49	102.2	78.7	8.11	6.57
Brake Force (lbs.)	1.11	1.09	12.94	21.64	60.3	61.2	13.9	18.26

Note: Braking, cornering and lane departures are numbers without units. They are the number of times the corresponding action was performed per participant per simulation.

Table 11 compares descriptive statistics between the participant group that drove a vehicle with automated features compared to the participant group that drove a vehicle with warning features or without any ADAS in the urban scenario. The mean values of lane departures, average headway, and brake force are lower for the participant group who drove a vehicle with automated features. Lower standard deviation values for lane departures, average speed, average headway, maximum speed, and brake force indicated less variance in participants' driving behavior.

Table 11 Driver behavior parameters - no ADAS, warning and automated features (urban)

Driver Behavior	Statistic	No ADAS	Warning	Automated
Hard Braking	Minimum	0.00	0.00	0.00
Hard Cornering		0.00	0.00	0.00
Lane Departures		0.00	0.00	0.00
Avg. Speed (mph)		37.20	30.50	34.77
Avg. Headway (ft)		616.70	157.70	94.00
Maximum Speed (mph)		51.90	49.40	57.90
Brake Force (lbs.)		18.30	3.90	1.09
Hard Braking	Mean	1.50	1.51	1.71
Hard Cornering		1.50	1.54	2.14
Lane Departures		6.83	5.16	1.43
Avg. Speed (mph)		41.72	42.00	43.66
Avg. Headway (ft)		937.93	838.35	126.44
Maximum Speed (mph)		59.22	62.29	61.23
Brake Force (lbs.)		38.48	23.03	1.65
Hard Braking	Maximum	3.00	4.00	3.00
Hard Cornering		3.00	5.00	4.00
Lane Departures		20.00	21.00	4.00
Avg. Speed (mph)		55.30	53.90	45.80
Avg. Headway (ft)		1170.30	1660.20	230.90
Maximum Speed (mph)		75.40	102.20	64.40
Brake Force (lbs.)		61.20	60.30	2.69
Hard Braking	Std. Dev.	1.05	1.28	0.95
Hard Cornering		1.22	1.28	1.21
Lane Departures		7.94	4.88	1.27
Avg. Speed (mph)		6.88	6.31	3.93
Avg. Headway (ft)		218.89	386.39	49.34
Maximum Speed (mph)		8.21	9.94	2.10
Brake Force (lbs.)		17.10	14.99	0.55

Note: Braking, cornering and lane departures are numbers without units. They are the number of times the corresponding action was performed per participant per simulation.

5.3 Freeway Driving Scenario

Table 12 depicts descriptive statistics comparing the participant group with one of the warning features (LDW, BSW, and OSW) compared to the participant group with one of the automated features (ACC and LKA) or without any ADAS in the freeway scenario. It can be observed that lane departures and hard cornering events have different mean values between the participant group with LDW and participant group not provided with any ADAS, while other driver behavior parameters have similar values. The mean values of these driver behaviors are higher for the participant group without warning features. Participants that drove a vehicle without warning features seem to be more aggressive in lane-following and turning. Participants that drove a vehicle with LDW seem to demonstrate safer driving behavior.

The mean values for hard braking events and brake pedal force are higher for the participant group who drove a vehicle without any ADAS compared to the participant group who drove a vehicle with BSW. The hard cornering events, lane departure events, maximum speed, and average headway were lower for the participant group who drove a vehicle without BSW. The participant group who drove a vehicle with BSW seemed to exhibit more aggressive lane-following and speeding but displayed safer car-following and braking behaviors. The mean brake force is higher for the participant group who drove a vehicle with OSW across all driving conditions. This could be because of the speed warning that may have triggered participants to brake immediately. Similarly, the speeding behavior of the participant group who drove a vehicle without any ADAS is also similar across driving conditions.

Table 12 Driver behavior parameters - ADAS (freeway)

Parameters	**Statistics**	**LDW**	**BSW**	**OSW**	**ACC**	**LKA**	**No ADAS**
Braking	Minimum	0.00	0.00	0.00	1.00	1.00	0.00
Cornering		0.00	1.00	0.00	2.00	1.00	3.00
Lane Departures		0.00	0.00	0.00	8.00	1.00	16.00
Avg. Speed (mph)		40.40	40.4	47.40	35.30	36.90	49.50
Avg. Headway (ft)		77.30	118.40	123.50	94.30	311.20	114.50
Max. Speed (mph)		64.50	71.90	69.80	55.40	64.20	73.60
Brake Force (lbs.)		1.60	0.70	1.60	1.19	15.60	2.20
Braking	Mean	0.43	0.38	0.50	2.25	2.00	0.50
Cornering		2.81	3.43	3.33	2.50	2.25	5.33
Lane Departures		11.67	17.57	16.17	10.25	1.75	25.83
Avg. Speed (mph)		57.31	57.49	56.51	36.53	40.53	58.73
Avg. Headway (ft)		374.80	428.80	393.35	97.15	363.75	356.62
Max. Speed (mph)		78.87	80.52	77.75	57.35	68.25	79.40
Brake Force (lbs.)		10.99	8.48	12.51	1.29	19.00	6.65
Braking	Maximum	2.00	2.00	2.00	3.00	3.00	1.00
Cornering		7.00	9.00	9.00	3.00	3.00	10.00
Lane Departures		26.00	36.00	27.00	13.00	3.00	39.00
Avg. Speed (mph)		66.60	65.10	62.90	38.20	44.70	67.80
Avg. Headway (ft)		823.70	823.70	823.70	102.80	432.60	588.90
Max. Speed (mph)		95.50	95.50	84.40	59.10	71.00	87.50
Brake Force (lbs.)		41.00	28.80	41.00	1.46	22.20	12.60
Braking	Standard Deviation	0.68	0.59	0.62	0.96	0.82	0.55
Cornering		1.44	1.89	1.81	0.58	0.96	2.66
Lane Departures		6.58	8.55	8.70	2.22	0.96	8.28
Avg. Speed (mph)		6.10	5.40	3.81	1.21	3.29	6.79
Avg. Headway (ft)		240.06	249.98	228.77	3.88	51.42	193.53
Max. Speed (mph)		7.24	7.19	4.11	1.70	3.13	5.66
Brake Force (lbs.)		9.98	8.01	11.49	0.12	3.03	4.22

Note: Braking, cornering and lane departures are numbers without units. They are the number of times the corresponding action was performed per participant per simulation.

Table 13 compares descriptive statistics between young and adult participants, male and female participants, daytime and nighttime conditions, and clear weather and rainy weather conditions for the freeway scenario. The mean values of average headway, maximum speed, and brake force are higher for adult participants compared to young participants. The adult participants were observed to maintain longer headways and also speed more than young participants in the freeway driving scenarios. The mean value of average headway is higher for female participants in the freeway driving scenarios. The mean values of lane departures and brake force are higher for male participants indicating more aggressive driving behavior.

Table 14 compares descriptive statistics between the participant group who drove a vehicle with automated features compared to the participant group who drove a vehicle with warning features or without any ADAS in the freeway scenario. The mean values of hard braking, lane departures, average speed, average headway, maximum speed, and brake force are lower for the participant group who drove a vehicle with automated features. Lower standard deviation was also observed for these driver behaviors, indicating less variance in participant driving behavior.

The mean values of some of the variables vary based on the advanced feature provided to the participant. The type of driving scenario also influenced the driving behavior. LDW and OSW affected the mean values of the majority of the driver behaviors in all the three driving scenarios, but BSW affected fewer driving behaviors. Additionally, age, gender, lighting and weather conditions also had an effect on participants' driving behaviors. They exhibited safer car-following maneuvers during rainy and nighttime driving conditions. The type of driving scenario also affected male and female participants' driving behavior. The differences in the mean values need to be further investigated to derive meaningful results. The sample sizes were not equal for different groups (for example, the number of participants provided with LDW, BSW or OSW are not the same). A one-way ANOVA test can accommodate comparison groups of unequal sample sizes. The next chapter presents and discusses the one-way ANOVA test results.

Table 13 Driver behavior parameters - age, gender, lighting condition, and weather condition (freeway)

Driver Behavior	**Minimum**		**Mean**		**Maximum**		**Std. Dev.**	
Age	**≤ 25 Years**	**> 25 Years**	**≤ 25 Years**	**> 25 Years**	**≤ 25 Years**	**> 25 Years**	**≤ 25 Years**	**> 25 Years**
Hard Braking	0	0	0.37	0.33	1	2	0.49	0.57
Hard Cornering	1	0	3.03	2.76	9	10	1.64	1.72
Lane Departures	0	0	12.06	12.17	36	39	9.89	9.82
Avg. Speed (mph)	49.7	40.4	56.37	56.77	65.4	67.8	4.02	6.08
Avg. Headway (ft)	117	77.3	275.89	329.06	814.9	823.7	148.32	206.17
Maximum Speed (mph)	64.5	61.5	75.58	76.88	92.7	95.5	7.3	7.49
Brake Force (lbs.)	0.07	0.03	5.75	7.52	41	31.3	8.55	8.62
Gender	Male	Female	Male	Female	Male	Female	Male	Female
Hard Braking	0	0	0.31	0.41	2	1	0.56	0.49
Hard Cornering	0	1	2.82	2.97	10	6	1.85	1.42
Lane Departures	0	1	13.51	10.16	39	27	10.44	8.58
Avg. Speed (mph)	47.4	40.4	56.71	56.41	65.3	67.8	4.78	5.84
Avg. Headway (ft)	77.3	109.7	308.04	300.46	775.9	823.7	182.19	186.92
Maximum Speed (mph)	61.5	64.2	76.21	76.41	95.5	92.7	7.59	7.19
Brake Force (lbs.)	0.03	0.07	7.84	5.34	41	24.7	9.94	6.21
Lighting Condition	Day	Night	Day	Night	Day	Night	Day	Night
Hard Braking	0	0	0.35	0.35	2	1	0.56	0.48
Hard Cornering	0	1	2.73	3.19	9	10	1.55	1.89
Lane Departures	0	1	9.84	16.58	27	39	8.06	11.41
Avg. Speed (mph)	40.4	49.5	56.73	56.31	67.8	65.3	5.66	4.29
Avg. Headway (ft)	77.3	109.7	253.3	406.08	823.7	814.9	147.41	205.56
Maximum Speed (mph)	63.6	61.5	76	76.85	92.7	95.5	6.74	8.62
Brake Force (lbs.)	0.03	0.09	7.35	5.42	41	28.8	9.28	6.69
Weather Condition	Clear	Rain	Clear	Rain	Clear	Rain	Clear	Rain
Hard Braking	0	0	0.36	0.33	2	2	0.52	0.56
Hard Cornering	1	0	2.6	3.5	5	10	0.93	2.6
Lane Departures	0	0	11.62	13.21	36	39	9.67	10.18
Avg. Speed (mph)	47.7	40.4	56.89	55.92	66.6	67.8	4.49	6.59
Avg. Headway (ft)	77.3	114.5	268.25	385.8	714.6	823.7	144.94	230.69
Maximum Speed (mph)	61.5	63.6	75.79	77.37	92.7	95.5	7.32	7.56
Brake Force (lbs.)	0.03	0.08	6.75	6.79	41	20.7	9.31	6.79

Note: Braking, cornering and lane departures are numbers without units. They are the number of times the corresponding action was performed per participant per simulation.

Table 14 Driver behavior parameters - No ADAS, warning and automated features (freeway)

Driver Behavior	Statistic	No ADAS	Warning	Automated
Hard Braking	Minimum	0.00	0.00	0.00
Hard Cornering		3.00	0.00	2.00
Lane Departures		16.00	0.00	1.00
Avg. Speed (mph)		49.50	40.40	48.20
Avg. Headway (ft)		114.50	77.30	117.00
Maximum Speed (mph)		73.60	64.50	63.60
Brake Force (lbs.)		2.20	0.70	0.03
Hard Braking	Mean	0.50	0.41	0.00
Hard Cornering		5.33	3.05	3.14
Lane Departures		25.83	15.70	3.29
Avg. Speed (mph)		58.73	57.29	50.69
Avg. Headway (ft)		356.62	366.21	206.57
Maximum Speed (mph)		79.40	79.17	66.36
Brake Force (lbs.)		6.65	11.58	0.12
Hard Braking	Maximum	1.00	2.00	0.00
Hard Cornering		10.00	9.00	6.00
Lane Departures		39.00	36.00	6.00
Avg. Speed (mph)		67.80	66.60	54.70
Avg. Headway (ft)		588.90	823.70	269.30
Maximum Speed (mph)		87.50	95.50	69.90
Brake Force (lbs.)		12.60	41.00	0.27
Hard Braking	Std. Dev.	0.55	0.60	0.00
Hard Cornering		2.66	1.63	1.46
Lane Departures		8.28	8.41	1.80
Avg. Speed (mph)		6.79	4.95	2.00
Avg. Headway (ft)		193.53	219.78	59.32
Maximum Speed (mph)		5.66	6.59	2.14
Brake Force (lbs.)		4.22	10.15	0.08

Note: Braking, cornering and lane departures are numbers without units. They are the number of times the corresponding action was performed per participant per simulation.

CHAPTER 6: RESULTS

This chapter presents the results from the ANOVA test on the significant differences in participant group mean values for hard braking, hard cornering, lane departures, average speed, average headway, maximum speed, and brake pedal force. While many variables can be extracted from miniSim^{TM}, the variables that convey the maximum blanket of information were chosen for the analysis. Since the focus of this research is to capture the effect of advanced features on driving behavior, the factors that can best explain these differences were selected. The hard braking and hard cornering events help differentiate safe and aggressive driving behavior. The lane departure event was selected to verify the effectiveness of LDW on driving behavior. Similarly, the maximum speed parameter was chosen to evaluate the effectiveness of OSW. OSW was set up to activate when the participant crosses the designated speed limit (5 mph higher than the posted speed limit) in the simulations. The maximum speed represents the event when a participant would have crossed the set speed limit for OSW. This helps to compare the two participant groups.

The LKA was tested using both the lane departure events and lane departure percentage parameter. The ACC was tested using the average headway and distance from the leading vehicle. Also, a level 2 automated vehicle was tested on some randomly selected participants with LKA and ACC engaged simultaneously. The behavior of these participants was compared to the participant group that was provided with warning features and groups using vehicles without any ADAS.

6.1 Rural Driving Scenario

In order to evaluate the effectiveness of LDW, the number of lane departure events from the simulations were extracted. The lane departure data was combined with the ADAS provision data. A one-way ANOVA test was performed on the dataset as the sample sets were unequal. The inequality in the data samples is due to the random assignment of the ADAS to the participants. The ANOVA test results are presented by the scenario type. The ANOVA results of only the driver behaviors that were significant at a p-value of 0.05 for rural scenario are presented in Table 15. The results from Table 15 include the effects of ADAS, lighting, and weather conditions.

Table 15 ANOVA results – ADAS, lighting, and weather conditions (rural)

Source of Variation	**Driving Behavior & ADAS**	**SS**	**df**	**MS**	**F**	**P-value**	**F-critical**
Between Groups	Lane Departures - LDW	205.23	1	205.23	4.57	0.04	4.08
Within Groups		1,840.54	41	44.89			
Total		2,045.77	42				
Between Groups	Brake Pedal Force - BSW	615.20	1	615.20	4.44	0.04	4.08
Within Groups		5,678.58	41	138.50			
Total		6,293.78	42				
Between Groups	Maximum Speed - OSW	692.88	1	692.88	9.83	<0.01	4.08
Within Groups		2888.48	41	70.45			
Total		3,581.37	42				
Between Groups	Average Speed - OSW	3,423.67	1	3,423.67	17.54	<0.01	4.08
Within Groups		8,003.22	41	195.20			
Total		11,426.89	42				
Between Groups	Brake Pedal Force - Two ADAS	7.07	1	7.07	7.27	0.01	4.09
Within Groups		37.96	39	0.97			
Total		45.02	40				
Between Groups	Average Headway – Day vs Night	375828.10	1	375828.10	9.76	<0.01	4.09
Within Groups		1578003.00	41	38487.90			
Total		1953831.00	42				
Between Groups	Lane Departures – Day vs Night	623.70	1	623.70	17.98	<0.01	4.09
Within Groups		1422.10	41	34.70			
Total		2045.80	42				
Between Groups	Average Headway – Clear vs Rain	180865.2	1	180865.20	5.31	0.03	4.09
Within Groups		1226487	36	340691			
Total		1407352	37				

BSW was set up to show a warning light on the mirror when the participants were driving only at certain periods of time. This feature was simulated by setting up a car-following session and activating BSW at the same time to capture the participants reaction. BSW was found to affect the brake pedal force variable in the rural scenario. OSW was set up using the "expression" trigger which was set to go off when the participant was exceeding speeds of more than 5 or 10 mph than the posted speed limit. Similar to LDW, OSW feature was also tested for effectiveness using the maximum speed variable. The maximum speed is a direct measure of the effects of OSW.

A significant difference in lane departure events between participants who drove a vehicle with LDW compared to participant group who were not provided with LDW was observed. Provision of BSW led to a significant difference in brake force between participant group with BSW and participant group without BSW. Provision of OSW had a significant effect on both the maximum and average speeds between participant group provided with OSW and participant group not provided with OSW. Additionally, provision of two types of warning features also influenced the brake pedal force compared to one warning or no warning features. Further, the average headway and lane departure events were found to be significantly different for day and night lighting conditions. Also, rainy condition significantly influenced the average headway compared to clear weather condition.

Table 16 presents the effects of lighting and gender segregated by the advanced feature and without ADAS. The average headway maintained in rural scenario was significantly different between the participant group who drove in daylight conditions and the participant group who drove in nighttime conditions for the participants who were not provided with any ADAS. The lane departure events and average headway were significantly different between daytime and nighttime driving conditions for the participant group who were provided with warning features. Additionally, the brake force for the participant group who were not provided with any ADAS varied significantly between the genders.

The ANOVA test results of the effects of automated features on driver behavior compared to warning features and vehicles without ADAS for rural scenario are presented in Table 17. The automated features were simulated where both LKA and ACC were engaged. The vehicle maintained a constant headway and the lane in this condition, simulating a level 2 automated vehicle. The warning features include the simulation of any one of LDW, BSW, or OSW or in combination.

Table 16 ANOVA results – lighting, gender, and weather conditions by ADAS (rural)

Source of Variation	**Driving Behavior & ADAS**	**SS**	**df**	**MS**	**F**	**P-value**	**F-critical**
Between Groups	Day vs Night (No ADAS) – Avg Headway	125728.6	1	125728.6	8.83	<0.05	6.61
Within Groups		71221.58	5	14244.32			
Total		196950.1	6				
Between Groups	Day vs Night (Warning) – Lane Departure	536.06	1	536.06	15.14	<0.01	4.13
Within Groups		1203.58	34	35.39			
Total		1739.64	35				
Between Groups	Day vs Night (Warning) – Avg Headway	264352.4	1	264352.4	6.03	<0.05	4.13
Within Groups		1491766	34	43875.46			
Total		1756118	35				
Between Groups	Male vs Female (No ADAS) – Brake Force	305.14	1	305.14	9.55	<0.05	6.61
Within Groups		159.69	5	31.94			
Total		464.84	6				

The average headway, maximum speed, and brake force were significantly different for the participant group who were not provided with any ADAS compared to the participant group provided with ACC. However, the provision of LKA to a participant group had a significant effect only on the lane departure events when compared to the participant group not provided with any ADAS. The participant group provided with automated features had significantly different lane departure events, average headway, maximum speed, and brake force compared to the participant group who were not provided with any ADAS. Similarly, the lane departure events, average headway, maximum speed, and brake force were significantly different between the participant group provided with ACC and the participant group provided with LKA. However, a significant difference in lane departure events was observed between the participant group provided with ACC compared to the participant group provided with automated driving features. When compared to the participant group provided with LKA, the participant group provided with automated driving features had significantly different cornering events, lane departure events, average speed, average headway, maximum speed, and brake force. The participant group provided with ACC had significantly different average headway and brake force, while the participant group provided with LKA had significantly different lane departures when compared to the participant group provided with warning features. Further, the braking events, cornering events, lane departure events, average headway, and brake force were significantly different for participant group provided with automated features compared to participant group provided with warning features.

Table 17 ANOVA results – automated, warning, and no ADAS (rural)

Source of Variation	**Driving Behavior & ADAS**	**SS**	**df**	**MS**	**F**	**P-value**	**F-critical**
Between Groups	No ADAS vs ACC – Average Headway	408912.1	1	408912.1	29.05	<0.01	4.6
Within Groups		197097.3	14	14078.38			
Total		606009.4	15				
Between Groups	No ADAS vs ACC – Maximum Speed	473.55	1	473.55	4.58	<0.05	4.6
Within Groups		1446.12	14	103.29			
Total		1919.67	15				
Between Groups	No ADAS vs ACC – Brake Force	1756.81	1	1756.81	52.79	<0.01	4.6
Within Groups		465.87	14	33.28			
Total		2222.69	15				
Between Groups	No ADAS vs LKA – Lane Departure	143.34	1	143.34	5.79	<0.05	4.67
Within Groups		321.59	13	24.74			
Total		464.93	14				
Between Groups	No ADAS vs Automated –	258.36	1	258.36	18.24	<0.01	4.3
Within Groups		311.59	22	14.16			

Source of Variation	Driving Behavior & ADAS	SS	df	MS	F	P-value	F-critical
Total	Lane Departure	569.96	23				
Between Groups	No ADAS vs Automated – Average Headway	493616.8	1	493616.8	53.67	<0.01	4.3
Within Groups		202333.7	22	9196.99			
Total		695950.6	23				
Between Groups	No ADAS vs Automated – Maximum Speed	686.96	1	686.96	10.07	<0.01	4.3
Within Groups		1500.66	22	68.21			
Total		2187.62	23				
Between Groups	No ADAS vs Automated – Brake Force	2167.78	1	2167.78	102.02	<0.01	4.3
Within Groups		467.48	22	21.25			
Total		2635.26	23				
Between Groups	ACC vs LKA – Lane Departure	108.84	1	108.84	13.15	<0.01	4.54
Within Groups		124.09	15	8.27			
Total		232.94	16				
Between Groups	ACC vs LKA – Avg Headway	435544.6	1	435544.6	284.71	<0.01	4.54
Within Groups		22946.44	15	1529.76			
Total		458491	16				
Between Groups	ACC vs LKA – Max Speed	321.79	1	321.79	23.68	<0.01	4.54
Within Groups		203.82	15	13.59			
Total		525.62	16				
Between Groups	ACC vs LKA – Brake Force	1415.26	1	1415.26	129.15	<0.01	4.54
Within Groups		164.38	15	10.96			
Total		1579.64	16				
Between Groups	ACC vs Automated – Lane Departure	218.36	1	218.36	45.93	<0.01	4.26
Within Groups		114.10	24	4.75			
Total		332.46	25				
Between Groups	LKA vs Automated – Cornering	3.43	1	3.43	5.08	<0.05	4.28
Within Groups		15.53	23	0.68			
Total		18.96	24				
Between Groups	LKA vs Automated – Lane Departure	5.68	1	5.68	6	<0.05	4.28
Within Groups		21.76	23	0.95			
Total		27.44	24				
Between Groups	LKA vs Automated – Avg Speed	56.79	1	56.79	4.7	<0.05	4.28
Within Groups		277.8	23	12.08			
Total		334.59	24				
Between Groups	LKA vs Automated – Avg Headway	536168.83	1	536168.8	437.57	<0.01	4.28
Within Groups		28182.87	23	1225.34			
Total		564351.7	24				
Between Groups	LKA vs Automated – Max Speed	493.09	1	493.09	43.89	<0.01	4.28
Within Groups		258.35	23	11.23			
Total		751.44	24				
Between Groups	LKA vs Automated – Brake Force	1775.6	1	1775.6	246.05	<0.01	4.28
Within Groups		165.98	23	7.22			
Total		1941.58	24				
Between Groups	Warning vs ACC – Avg Headway	801600.8	1	801600.8	19.63	<0.01	4.07
Within Groups		1756265	43	40843.37			
Total		2557866	44				
Between Groups	Warning vs ACC – Brake Force	3920.28	1	3920.28	29.06	<0.01	4.07
Within Groups		5801.33	43	134.91			
Total		9721.61	44				
Between Groups	Warning vs LKA	230.21	1	230.21	5.51	<0.05	4.07

Source of Variation	Driving Behavior & ADAS	SS	df	MS	F	P-value	F-critical
Within Groups	– Lane Departure	1755.51	42	41.79			
Total		1985.73	43				
Between Groups	Warning vs Automated – Braking	7.89	1	7.89	9.22	<0.01	4.03
Within Groups		43.65	51	0.86			
Total		51.55	52				
Between Groups	Warning vs Automated – Cornering	29.55	1	29.55	4.81	<0.05	4.03
Within Groups		313.17	51	6.14			
Total		342.72	52				
Between Groups	Warning vs Automated – Lane Departure	558.18	1	558.18	16.31	<0.01	4.03
Within Groups		1745.52	51	34.23			
Total		2303.69	52				
Between Groups	Warning vs Automated – Avg Headway	1234184	1	1234184	35.73	<0.01	4.03
Within Groups		1761502	51	34539.25			
Total		2995686	52				
Between Groups	Warning vs Automated – Brake Force	6172.7	1	6172.7	54.25	<0.01	4.03
Within Groups		5802.93	51	113.78			
Total		11975.63	52				

6.2 Urban Driving Scenario

The ANOVA test results of only the driver behaviors that were significant at a p-value of 0.05 for urban scenario are presented in Table 18. The results from Table 18 include the effects of ADAS, lighting, gender, and weather conditions for urban scenario.

Table 18 ANOVA results – ADAS, lighting, gender and weather conditions (urban)

Source of Variation	Driving Behavior & ADAS	SS	df	MS	F	P-value	F-critical
Between Groups	Lane Departures - LDW	134.32	1	134.32	5.23	0.03	4.08
Within Groups		1,053.96	41	25.71			
Total		1,188.28	42				
Between Groups	Hard Cornering - LDW	15.07	1	15.07	11.97	<0.01	4.08
Within Groups		51.63	41	1.26			
Total		66.70	42				
Between Groups	Maximum Speed - OSW	4,876,652	1	4,876,652	74.94	<0.01	4.07
Within Groups		2,733,042	42	65,072.42			
Total		7,609,694	43				
Between Groups	Average Headway – Light Condition	1166855.00	1	1166855.0	10.63	<0.01	4.09
Within Groups		4498522.00	41	109720.00			
Total		5665377.00	42				
Between Groups	Brake Pedal Force – Light Condition	1774.44	1	1774.44	8.36	<0.01	4.09
Within Groups		7852.38	37	212.22			
Total		9626.82	38				
Between Groups	Lane Departures	488.42	1	488.42	28.61	<0.01	4.09

Source of Variation	Driving Behavior & ADAS	SS	df	MS	F	P-value	F-critical
Within Groups	– Light Condition	699.85	41	17.06			
Total		1188.27	42				
Between Groups	Average Headway – Weather Condition	909143.10	1	909143.10	7.56	<0.01	4.09
Within Groups		4330524.00	36	120292.30			
Total		5239667.00	37				
Between Groups	Brake Pedal Force – Weather Condition	1016.15	1	1016.15	4.95	0.03	4.09
Within Groups		6569.83	32	205.31			
Total		7585.97	33				
Between Groups	Hard Braking - Gender	10.04	1	10.04	10.08	<0.01	3.97
Within Groups		74.66	75	0.99			
Total		84.7	76				

The participant group provided with LDW had significantly different lane departure events and hard cornering events when compared to the participant group not provided with LDW. The maximum speed was significantly different for the participant group provided with OSW compared to the participant group not provided with OSW. The light condition (day vs night) significantly influenced the average headway, brake force and lane departure events. Further, the weather condition (clear vs rainy) significantly influenced the average headway and brake force. The hard braking events were significantly different for male and female participants.

Table 19 presents the effects of lighting, weather, and age on driver behavior segregated by the advanced feature and without ADAS. Only the ANOVA test results of the driver behaviors that were significant at a p-value of 0.05 for urban scenario are presented.

For the participants who were not provided with any ADAS, the participant group who drove in daytime conditions had significantly different average headway and brake force compared to participant group who drove in nighttime conditions. Similarly, for the participants who were provided with warning features, the participant group who drove in daytime conditions had significantly different lane departure events, average headway, and brake force compared to the participant group who drove in nighttime conditions. Further, significantly different lane departure events, average headway, and average speed were observed between participant groups who drove in daytime and nighttime conditions than the participant groups who were provided with automated features. Male and female participants had significantly different average headway among the participants provided with warning features. Further, participant group below 25 years of age had significantly different hard cornering events, average speed, and maximum speed compared to participant group above 25 years of age among the participants provided with automated features.

Table 19 ANOVA results – lighting, gender, and weather conditions by ADAS (urban)

Source of Variation	Driving Behavior & ADAS	SS	df	MS	F	P-value	F-critical
Between Groups	Day vs Night (No ADAS) – Avg Headway	1048237	1	1048237	13.66	<0.05	6.61
Within Groups		383640	5	76728.01			
Total		1431878	6				
Between Groups	Day vs Night (No ADAS) – Brake Force	203	1	203	8.38	<0.05	7.71
Within Groups		96.93	4	24.23			
Total		299.93	5				
Between Groups	Day vs Night (Warning) – Lane Departure	557.35	1	557.35	33.52	<0.01	4.13
Within Groups		565.39	34	16.63			
Total		1122.75	35				
Between Groups	Day vs Night (Warning) – Avg Headway	506742.1	1	506742.1	4.64	<0.05	4.13
Within Groups		3715600	34	109282.4			
Total		4222342	35				
Between Groups	Day vs Night (Warning) – Brake Force	1923.48	1	1923.48	8.91	<0.01	4.16
Within Groups		6690.87	31	215.83			
Total		8614.35	32				
Between Groups	Day vs Night (Auto) – Lane Departure	2.97	1	2.97	4.99	<0.05	4.54
Within Groups		8.92	15	0.59			
Total		11.88	16				
Between Groups	Day vs Night (Auto) – Avg Speed	37.44	1	37.44	4.58	<0.05	4.54
Within Groups		122.63	15	8.18			
Total		160.06	16				
Between Groups	Day vs Night (Auto) – Avg Headway	4519.65	1	4519.65	5.05	<0.05	4.54
Within Groups		13433.69	15	895.58			
Total		17953.34	16				
Between Groups	Male vs Female (Warning) – Avg Headway	807718.1	1	807718.1	8.04	<0.01	4.13
Within Groups		3414624	34	1000430.1			
Total		4222342	35				
Between Groups	Below 25 vs Above 25 (Auto) – Cornering	4.72	1	4.72	8.61	<0.05	4.54
Within Groups		8.22	15	0.55			
Total		12.94	16				
Between Groups	Below 25 vs Above 25 (Auto) – Avg Speed	38.72	1	38.72	4.79	<0.05	4.54
Within Groups		121.34	15	8.09			
Total		160.06	16				
Between Groups	Below 25 vs Above 25 (Auto) – Max Speed	22.95	1	22.95	7.47	<0.05	4.54
Within Groups		46.09	15	3.07			
Total		69.04	16				

The ANOVA test results of the effects of automated features on driver behavior compared to warning features and vehicles without ADAS for urban scenario are presented in Table 20. The participant group not provided with any ADAS had significantly different lane departure events, average headway, maximum speed, and brake force compared to the participant group provided with ACC. The participant group not provided with any ADAS had significantly different lane departure events and average headway compared to the participant group provided with LKA. Further, significantly different lane departure events, average headway, maximum speed, and brake force were observed between the participant group not provided with any ADAS compared to the participant group provided with automated driving features. The provision of ACC to participants significantly influenced lane departure events, average headway, and brake force while the provision of LKA significantly influenced hard cornering events and average headway when compared to participants provided with warning features. The participant group provided with ACC had significantly different lane departure events, average speed, average headway, maximum speed, and brake force compared to the participant group provided with LKA. Similar to rural scenario, the participant group provided with ACC had significantly different lane departure events compared to automated driving features. Further, significantly different average speed, average headway, maximum speed, and brake force were observed between the participant group provided with LKA and the participant group provided with automated driving features. The participant group provided with warning features had significantly different hard cornering events compared to the participant group provided with automated features. Provision of automated features to participants significantly influenced lane departure events, average headway, and brake force compared to the participant group not provided with any ADAS.

Table 20. ANOVA results – automated, warning, and no ADAS (urban)

Source of Variation	**Driving Behavior & ADAS**	**SS**	**df**	**MS**	**F**	**P-value**	**F-critical**
Between Groups	No ADAS vs ACC – Lane Departure	37.34	1	37.34	4.49	0.052	4.6
Within Groups		116.41	14	8.32			
Total		153.75	15				
Between Groups	No ADAS vs ACC – Avg Headway	2445066	1	2445066	23.9	<0.01	4.6
Within Groups		1432005	14	102286.1			
Total		3877070	15				
Between Groups	No ADAS vs ACC – Max Speed	38.97	1	38.97	5.56	<0.05	4.6
Within Groups		98.21	14	7.01			
Total		137.18	15				
Between Groups	No ADAS vs ACC – Brake Force	665.31	1	665.31	28.81	<0.01	4.67
Within Groups		300.2	13	23.09			
Total		965.52	14				
Between Groups	No ADAS vs LKA – Lane Departure	72.04	1	72.04	14.11	<0.01	4.67
Within Groups		66.36	13	5.1			
Total		138.4	14				
Between Groups	No ADAS vs LKA – Avg Headway	1008364	1	1008364	9.06	<0.05	4.67
Within Groups		1446797	13	111292.1			
Total		2455160	14				
Between Groups	No ADAS vs Auto – Lane Departure	113.76	1	113.76	34.41	<0.01	4.3
Within Groups		72.74	22	3.31			
Total		186.5	23				
Between Groups	No ADAS vs Auto – Avg Headway	3007154	1	3007154	45.63	<0.01	4.3
Within Groups		1449831	22	65901.4			
Total		4456985	23				
Between Groups	No ADAS vs Auto – Max Speed	55.29	1	55.29	8.1	<0.01	4.3
Within Groups		150.12	22	6.82			
Total		205.42	23				
Between Groups	No ADAS vs Auto – Brake Force	797.83	1	797.83	55.36	<0.01	4.32
Within Groups		302.63	21	14.41			
Total		1100.46	22				
Between Groups	Warning vs ACC – Lane Departure	113.61	1	113.61	4.15	<0.05	4.07
Within Groups		1178.31	43	27.4			
Total		1291.91	44				
Between Groups	Warning vs ACC – Avg Headway	3989567	1	3989567	40.63	<0.01	4.07
Within Groups		4222469	43	98196.96			
Total		8212037	44				
Between Groups	Warning vs ACC – Brake Force	4577.09	1	4577.09	21.25	<0.01	4.08
Within Groups		8614.63	40	215.37			
Total		13191.72	41				
Between Groups	Warning vs LKA – Cornering	7.49	1	7.49	7.23	<0.05	4.07
Within Groups		43.51	42	1.04			
Total		51	43				
Between Groups	Warning vs LKA – Avg Headway	1483519	1	1483519	14.7	<0.01	4.07
Within Groups		4237261	42	100887.2			
Total		5720780	43				
Between Groups	ACC vs LKA – Lane Departure	236.47	1	236.47	58.09	<0.01	4.54
Within Groups		61.06	15	4.07			
Total		297.53	16				

Source of Variation	Driving Behavior & ADAS	SS	df	MS	F	P-value	F-critical
Between Groups	ACC vs LKA – Avg Speed	78.51	1	78.51	16.36	<0.01	4.54
Within Groups		72	15	4.8			
Total		150.51	16				
Between Groups	ACC vs LKA – Avg Headway	304892.96	1	304893	303.95	<0.01	4.54
Within Groups		15046.52	15	1003.1			
Total		319939.48	16				
Between Groups	ACC vs LKA – Max Speed	175.59	1	175.59	24.84	<0.01	4.54
Within Groups		106.01	15	7.07			
Total		281.6	16				
Between Groups	ACC vs LKA – Brake Force	1229.21	1	1229.21	516.02	<0.01	4.54
Within Groups		35.73	15	2.38			
Total		1264.94	16				
Between Groups	ACC vs Automated – Lane Departure	364.41	1	364.41	129.69	<0.01	4.26
Within Groups		67.44	24	2.81			
Total		431.85	25				
Between Groups	LKA vs Automated – Avg Speed	39.74	1	39.74	4.43	<0.05	4.28
Within Groups		206.48	23	8.98			
Total		246.23	24				
Between Groups	LKA vs Automated – Avg Headway	365096.8	1	365096.78	255.45	<0.01	4.28
Within Groups		32872.52	23	1429.24			
Total		397969.3	24				
Between Groups	LKA vs Automated – Max Speed	239.29	1	239.29	34.85	<0.01	4.28
Within Groups		157.92	23	6.87			
Total		397.21	24				
Between Groups	LKA vs Automated – Brake Force	1545.35	1	1545.35	931.51	<0.01	4.28
Within Groups		38.16	23	1.66			
Total		1583.51	24				
Between Groups	Warning vs Automated – Cornering	4.67	1	4.67	4.52	<0.05	4.03
Within Groups		52.58	51	1.03			
Total		57.24	52				
Between Groups	No ADAS vs Automated – Lane Departure	175.37	1	175.37	7.88	<0.01	4.03
Within Groups		1134.63	51	22.25			
Total		1310	52				
Between Groups	No ADAS vs Automated – Avg Headway	6240428	1	6240428	75.06	<0.01	4.03
Within Groups		4240295	51	83143.05			
Total		10480723	52				
Between Groups	No ADAS vs Automated – Brake Force	7158.96	1	7158.96	39.88	<0.01	4.04
Within Groups		8617.05	48	179.52			
Total		15776.01	49				

6.3 Freeway Driving Scenario

The ANOVA test results of only the driver behaviors that were significant at a p-value of 0.05 for freeway scenario are presented in Table 21. The results from Table 21 include the effects of ADAS, lighting, gender, and weather conditions for freeway scenario.

The participant group provided with LDW had significantly different lane departure events compared to the participant group not provided with LDW. The average headway and lane departure events were significantly different for participant groups who drove in daytime and nighttime conditions. Further, the weather conditions (clear vs rainy) significantly influenced the average speed and average headway.

Table 21 ANOVA results – ADAS, lighting, gender and weather conditions (freeway)

Source of Variation	**Driving Behavior & ADAS**	**SS**	**df**	**MS**	**F**	**P-value**	**F-critical**
Between Groups	Lane Departures - LDW	1,218.98	1	1,218.98	22.72	<0.01	4.08
Within Groups		2,199.44	41	53.65			
Total		3,418.42	42				
Between Groups	Average Headway – Light Condition	463506.20	1	463506.20	12.98	<0.01	4.09
Within Groups		1463141.00	41	35686.37			
Total		1926647.00	42				
Between Groups	Lane Departures – Light Condition	806.03	1	806.03	12.65	<0.01	4.09
Within Groups		2612.39	41	63.72			
Total		3418.42	42				
Between Groups	Average Speed – Weather Condition	121.54	1	121.54	5.39	0.02	4.09
Within Groups		835.09	37	22.57			
Total		956.63	38				
Between Groups	Average Headway – Weather Condition	515154.90	1	515154.90	15.54	<0.01	4.09
Within Groups		1226503.00	37	33148.72			
Total		1741658.00	38				

Table 22 presents the effects of lighting, weather and age on driver behavior segregated by the advanced feature and without ADAS. Only the ANOVA test results of the driver behaviors that were significant at a p-value of 0.05 for the freeway scenario are presented.

The participant group who drove during daytime conditions had significantly different lane departure events when compared to the participant group who drove during nighttime conditions among the participants provided with warning features and also among the participants not provided with any ADAS. The participant group who drove during daytime and nighttime conditions had significantly different average headway among the participants provided with warning features. Further, the provision of automated features during daytime and nighttime conditions led to significantly different maximum speeds. The participant group below the age of 25 years had significantly different brake force compared to the participant group above the age of 25 years among the participants who were not provided with any ADAS. The participant group below the age of 25 years had significantly different average speed compared to the participant group above the age of 25 years among the participants who were provided with warning features.

Table 22 ANOVA results – lighting, gender, and weather conditions by ADAS (freeway)

Source of Variation	**Driving Behavior & ADAS**	**SS**	**df**	**MS**	**F**	**P-value**	**F-critical**
Between Groups	Day vs Night (No ADAS) – Lane Departure	525	1	525	7.44	<0.05	6.61
Within Groups		353	5	70.6			
Total		878	6				
Between Groups	Day vs Night (Warning) – Lane Departure	427.82	1	427.82	6.98	<0.05	4.13
Within Groups		2082.93	34	61.26			
Total		2510.75	35				
Between Groups	Day vs Night (Warning) – Avg Headway	427508.3	1	427508.3	13.56	<0.01	4.13
Within Groups		1072195	34	31535.15			
Total		1499703	35				
Between Groups	Day vs Night (Auto) – Max Speed	28.6	1	28.6	7.12	<0.05	4.54
Within Groups		60.21	15	4.01			
Total		88.81	16				
Between Groups	Below 25 vs Above 25 (No ADAS) – Brake Force	346.07	1	346.07	8.77	<0.05	6.61
Within Groups		197.31	5	39.46			
Total		543.39	6				
Between Groups	Below 25 vs Above 25 (Warning) – Avg Speed	101.4	1	101.4	6.95	<0.05	4.13
Within Groups		496.26	34	14.59			
Total		597.66	35				

The ANOVA test results of the effects of automated features on driver behavior compared to warning features and vehicles without ADAS for the freeway scenario are presented in Table 23.

The average headway and brake force were significantly different between the participant group provided with ACC compared to the participant group not provided with any ADAS. The lane departure events and average speed were significantly different between the participant group provided with LKA and the participant group not provided with any ADAS. Lane departure events, average speed, average headway, maximum speed, and brake force were found to be significantly for the participant group provided with ACC compared to the participant group provided with LKA. Further, the participant group provided with ACC had significantly different lane departure events, average speed, and maximum speed compared to the participant group provided with automated features. The average speed, average headway, maximum speed, and brake force were found to be significantly different for the participant group provided with LKA compared to the participant group provided with automated features.

The participant group provided with automated features had significantly different lane departure events, average headway, maximum speed, and brake force compared to the participant group not provided with any ADAS. Hard cornering events, average headway, and brake force were found to be significantly different for the participant group provided with warning features compared to the participant group provided with ACC. Further, hard cornering events, lane departure events, and average speed were found to be significantly different for the participant group provided with warning features compared to the participant group provided with LKA. Automated features significantly influenced the lane departure events, average headway, average speed, maximum speed, and brake force when compared to the participant group provided with warning features.

Table 23 ANOVA results – automated, warning, and no ADAS (freeway)

Source of Variation	Driving Behavior & ADAS	SS	df	MS	F	P-value	F-critical
Between Groups	No ADAS vs ACC – Avg Headway	453285.7	1	453285.7	27.66	<0.01	4.6
Within Groups		229393.9	14	16385.28			
Total		682679.6	15				
Between Groups	No ADAS vs ACC – Brake Force	579.97	1	579.97	14.94	<0.01	4.6
Within Groups		543.42	14	38.82			
Total		1123.39	15				
Between Groups	No ADAS vs LKA – Lane Departure	1078.93	1	1078.93	15.9	<0.01	4.67
Within Groups		882	13	67.85			
Total		1960.93	14				
Between Groups	No ADAS vs LKA – Avg Speed	265.11	1	265.11	8.19	<0.05	4.67
Within Groups		420.56	13	32.35			
Total		685.66	14				
Between Groups	ACC vs LKA – Lane Departure	765.54	1	765.54	44.47	<0.01	4.54
Within Groups		258.22	15	17.21			
Total		1023.76	16				
Between Groups	ACC vs LKA – Avg Speed	54.59	1	54.59	11.89	<0.01	4.54
Within Groups		68.86	15	4.59			
Total		123.46	16				
Between Groups	ACC vs LKA – Avg Headway	153171.4	1	153171.4	185.47	<0.01	4.54
Within Groups		12388.04	15	825.87			
Total		165559.5	16				
Between Groups	ACC vs LKA – Max Speed	43.94	1	43.94	5.47	<0.05	4.54
Within Groups		120.41	15	8.03			
Total		164.34	16				
Between Groups	ACC vs LKA – Brake Force	331.51	1	331.51	340.47	<0.01	4.54
Within Groups		14.61	15	0.97			
Total		346.12	16				
Between Groups	ACC vs Auto – Lane Departure	990.5	1	990.5	82.99	<0.01	4.26
Within Groups		286.46	24	11.94			
Total		1276.96	25				
Between Groups	ACC vs Auto – Avg Speed	307.44	1	307.44	74.68	<0.01	4.26
Within Groups		98.8	24	4.12			
Total		406.25	25				
Between Groups	ACC vs Auto – Max Speed	716.87	1	716.87	88.04	<0.01	4.26
Within Groups		195.42	24	8.14			
Total		912.28	25				
Between Groups	LKA vs Auto – Avg Speed	636.68	1	636.68	149.49	<0.01	4.28
Within Groups		97.96	23	4.26			
Total		734.64	24				
Between Groups	LKA vs Auto – Avg Headway	179316.2	1	179316.2	72.12	<0.01	4.28
Within Groups		57183.5	23	2486.24			
Total		236499.7	24				
Between Groups	LKA vs Auto – Max Speed	1105.91	1	1105.91	247.86	<0.01	4.28
Within Groups		102.62	23	4.46			
Total		1208.54	24				
Between Groups	LKA vs Auto – Brake Force	429.79	1	429.79	675.62	<0.01	4.28
Within Groups		14.63	23	0.64			
Total		444.42	24				
Between Groups	No ADAS vs Auto	1354.72	1	1354.72	32.74	<0.01	4.3

Source of Variation	**Driving Behavior & ADAS**	**SS**	**df**	**MS**	**F**	**P-value**	**F-critical**
Within Groups	–	910.24	22	41.37			
Total	Lane Departure	2264.96	23				
Between Groups	No ADAS vs Auto	542181.3	1	542181.3	43.5	<0.01	4.3
Within Groups	–	274189.4	22	12463.15			
Total	Avg Headway	816370.7	23				
Between Groups	No ADAS vs Auto	533.26	1	533.26	44.99	<0.01	4.3
Within Groups	–	260.78	22	11.85			
Total	Max Speed	794.04	23				
Between Groups	No ADAS vs Auto	735.32	1	735.32	29.77	<0.01	4.3
Within Groups	–	543.44	22	24.7			
Total	Brake Force	1278.76	23				
Between Groups	Warning vs ACC	16.80	1	16.81	7.25	<0.05	4.07
Within Groups	–	99.64	43	2.32			
Total	Cornering	116.44	44				
Between Groups	Warning vs ACC	172682.5	1	172682.5	4.95	<0.05	4.07
Within Groups	–	1501487	43	34918.31			
Total	Avg Headway	1674170	44				
Between Groups	Warning vs ACC	738.07	1	738.07	9.96	<0.01	4.09
Within Groups	–	2845.5	38	74.88			
Total	Brake Force	3583.57	39				
Between Groups	Warning vs LKA	13.14	1	13.14	5.59	<0.05	4.07
Within Groups	–	98.75	42	2.35			
Total	Cornering	111.89	43				
Between Groups	Warning vs LKA	1424.04	1	1424.04	23.78	<0.01	4.07
Within Groups	–	2514.75	42	59.87			
Total	Lane Departure	3938.79	43				
Between Groups	Warning vs LKA	81.39	1	81.39	5.41	<0.05	4.07
Within Groups	–	631.67	42	15.04			
Total	Avg Speed	713.06	43				
Between Groups	Warning vs Auto – Land Departure	2354.49	1	2354.49	47.22	<0.01	4.03
Within Groups		2542.98	51	49.86			
Total		4897.47	52				
Between Groups	Warning vs Auto – Avg Speed	613.99	1	613.99	47.33	<0.01	4.03
Within Groups		661.61	51	12.97			
Total		1275.61	52				
Between Groups	Warning vs Auto – Avg Headway	246984.2	1	246984.2	8.15	<0.01	4.03
Within Groups		1546283	51	30319.27			
Total		1793267	52				
Between Groups	Warning vs Auto – Max Speed	2060.89	1	2060.89	66.12	<0.01	4.03
Within Groups		1589.55	51	31.17			
Total		3650.44	52				
Between Groups	Warning vs Auto – Brake Force	1171.13	1	1171.13	18.93	<0.01	4.05
Within Groups		2845.53	46	61.86			
Total		4016.66	47				

6.4 Discussion

The hard cornering, lane departures, and average headway had distinct mean values for the participant group with LDW compared to the participant group without LDW. The mean values of LDW and non-LDW group for different variables varied based on the driving scenario. For example, while the mean values of lane departure varied in the urban scenario, the mean values of brake pedal force varied in the freeway scenario. Similarly, the mean values of some of the driver behaviors were different for the OSW and non-OSW group, as well as the BSW and non-BSW group.

LDW was effective in all three driving scenarios. However, OSW was only able to influence the speeding behavior of participants in rural and urban settings. As participants tend to drive at higher speeds on freeways, there is a lower chance of drawing significantly different results when the two participant groups are compared. The brake pedal force was significantly affected by BSW in the rural driving scenario. The activation of BSW when a vehicle is in the adjoining lane could trigger a reaction from the participant to adopt safe maneuvering, possibly leading to the observed change in the brake pedal force. Similarly, providing two ADAS increased the interaction when both the features are engaged, invoking a natural response to drive cautiously or slowdown, which might have segregated the brake pedal force application.

Lighting and weather conditions also had a significant effect on some driving behaviors. Nighttime driving conditions were observed to affect car-following and lane-changing behavior of the participants in all three driving scenarios. Additionally, lighting conditions also affected the brake force applied by the participants in the urban scenarios. The participants maintained larger headway distance and had more lane departures at night compared to daytime.

The age of the participant also influenced the driving behavior. The braking behavior and average speed was higher for participants over twenty-five years in age. The young or teen participants below the age of twenty-five could be better accustomed to such driving simulators as they are more used to technology and video games, resulting in safer driving profiles. Smaller headways were observed for participants under the age of twenty-five in urban settings but had larger headways in rural and freeway scenarios.

The gender of the participant influenced the driving behavior. Male participants displayed more aggressive driving maneuvers, while female participants demonstrated higher brake force. Further, the type of driving scenario also affected the driving behaviors. Female participants had smaller headways in the urban scenario but had larger headways in rural and freeway scenarios.

The rainy driving conditions also affected the participants' car-following behavior. They were observed to maintain longer headways in rainy driving conditions in all three scenarios. However, the lane-changing, braking, and turning behaviors of the participants were observed to be less aggressive during rainy conditions. Also, participants applied higher brake force in rainy conditions, especially in urban driving settings which could be due to slippery roads. The change in average speed was also significantly different in freeway conditions, with higher speeds in clear weather conditions.

Automated features like LKA and ACC were also explored in this study. The results from the participant group that drove a vehicle with LKA and ACC were compared to the participant group provided with the warning features (LDW, BSW and OSW) as well as with the participant group without advanced features. Participants who used a vehicle with

LKA and ACC displayed less aggressive lane-following and braking behavior but maintained smaller headways. These results were observed in all the three driving scenarios. Better braking behavior was additionally observed in the freeway scenario. Further, LKA and ACC reduced the variation in lane-following, handling, speeding, and car-following behaviors among the participants compared to both warning features and no ADAS in all the three driving scenarios.

Participants provided with LKA displayed less aggressive lane-following and braking behavior compared to participants provided with LDW. The driving scenario was also observed to affect the type of effects LKA had on a participant compared to LDW. Participants who a drove a vehicle with only LKA demonstrated more aggressive car-following behavior in rural and urban scenarios. The effects of ACC on improved braking behavior compared to both BSW and OSW is very evident. Additionally, both LKA and ACC drastically reduced the variation in vehicle handling, lane-following, car-following, and braking behavior in all the three driving scenarios.

CHAPTER 7: CONCLUSIONS

The effects of three different warning features and two automated features on driver behavior were evaluated in different driving scenarios in this research. The warning features were shown to influence the participants' behaviors as per their intended purpose. For example, LDW was effective in influencing the lane departure behavior of the participants. Also, OSW was effective in influencing the maximum speed and average speed in some cases. BSW did not have a significant effect on any of the driver behavior variables.

The effect of different warning features on participants varied with the driving scenario. LDW had a significant effect on lane departure events, which indicates the number of times a participant went out of their lane. Overall, the effect of warning features on driving behaviors such as lane departures, speeding, and braking by driving scenario are evident.

The effects of automated features on braking, lane-following, and car-following behaviors in the rural scenario were found to be significant. Likewise, the effects of ACC on car-following and lane-following in the urban scenario were also found to be significant. In addition to braking, lane-following, and car-following behaviors, speed behavior was also significantly affected by automated features in the freeway scenario. Though the considered automated features led to aggressive car-following behavior, other driver behaviors were found to be less aggressive, leading to safer driving overall.

Further, car-following, lane-following, speeding and braking behaviors were also observed to vary when ACC and LKA are engaged individually compared to both warning and automated features. While safer speeding and braking behavior was observed with

ACC, warning features resulted in better lane following behavior. Similarly, ACC showed better car-following, braking, and speeding behavior whereas better lane following behavior was observed with LKA. Vehicles equipped with automated features either in combination or individually led to safer driving compared to warning features alone and vehicles without any ADAS. The change in driver behavior of the participants provided with automated features was more harmonized as well.

Overall, driver behavior was affected by ADAS, be it warning or automated features. However, the type of effects observed varied based on the type of feature. The type of driving scenario affected the nature of influence a feature had on driver behavior. LDW and OSW were able to achieve the targeted effect they were originally intended for and also triggered additional behavioral changes that varied by driving scenario. On the other hand, BSW did not have a significant effect on any of the driver's behaviors. Further, providing two warning features also had varied effects on driver behavior compared to single warning feature but the effects were limited.

Lighting and weather conditions had similar effects on driver behavior when not provided with any advanced features, when provided with warning features, and when provided with advanced features as well. Longer headways were observed in nighttime conditions and rainy conditions. However, less aggressive lane-following, braking, and vehicle handling behavior was observed. Also, more speeding was observed on freeways in clear weather. Male drivers displayed aggressive driving maneuvers when provided with both warning and automated features. On the other hand, female drivers maintained smaller headways in urban scenario and longer headways in rural and freeway scenario. Similarly, drivers aged under 25 years maintained smaller headways in urban scenario but maintained longer headways in rural and freeway scenarios. Further, drivers aged above 25 years showed more aggressive braking and speeding behavior with both warning and automated features in urban scenario.

The type of ADAS provided, the type of driving scenario, the lighting and weather conditions, as well as the age and gender of the participants affected the driver's behavior. The nature of their effects of ADAS, however, varied by the type of driving scenario. Further, the effects of all these factors varied when segregated by the type of ADAS (warning or automated feature) provided compared to when not provided with any advanced features.

In addition to this, the type of ADAS (warning or automated) affected the driving behavior differently when they were provided individually, in combination and not provided at all. Warning features when provided in combination had different effects on driver behavior in very few cases. However, automated features when provided individually and in combination had predominantly different effects on driver behavior. Further, these changes varied with the driving scenario. The type of effects automated features had on driver behavior varied from that of warning features and also when no features were provided. The efficiency of driver behavior improved from no feature condition to warning features to automated features. The different factors considered in this research, the type of features provided, the type of driving scenario, the lighting conditions, the weather conditions, the age of the driver, and the gender, all effected the driver behavior. Further, the type of effects each type of feature had on driver behavior varied for each factor. In other words, the effects of each type of feature varied by the type of driving scenario, the lighting conditions, the weather conditions and also by the age and gender of the driver. An intricate interaction of different factors effecting the driver behavior differently is evident. While the car-following behavior reflects the operational impacts, driver behaviors like speeding, lane-following, and braking behaviors shine light on the traffic safety. This goes to show that the effects of ADAS on driver behavior are not straight-forward and demand deeper understanding from safety and operational perspective as well.

These findings can be used to define vehicle parameters within microscopic simulation software and mimic the effect of vehicles with and without advanced features on transportation system performance.

7.1 Recommendations

The effects of warning and automated features have been discussed in detail in the previous section. The effects were observed to vary by the type of ADAS provided, the type of driving scenario, lighting and weather conditions, and also the age and gender. Both the operational aspects like the car-following behavior as well as the safety aspects like the lane-following and vehicle handling behaviors have been observed to be influenced by ADAS. Hence, there is a need to design ADAS from both operational and safety perspective. Further, the varying nature of effects different driving conditions and driver demographics encourage the need to design adaptive ADAS that can collect data from the vehicle's surroundings and respond appropriately. This will carve a path to the ultimate aim of fully autonomous vehicles in the future.

The limitations of ADAS are tested by automobile companies in a restricted or fabricated environment where the obstacles or test tracks are known to the drivers. Additionally, the drivers are trained and are young adults or middle aged. However, the customers using these features could be anywhere between teen drivers to elderly drivers. Further, the test tracks are built in places where all kinds of weather or driving conditions may not be encountered. This mandates the need to collect data for these ADAS taking the wide array of users and driving conditions into account, in other words, collect more naturalistic driving data.

The domain of advanced features is rapidly evolving which poses a challenge for drivers. Hence, there is a need to formulate policies that encourage both automobile manufacturers and dealerships to develop programs that encourage driver education on the applicability and limitations of advanced features.

7.2 Scope of Future Work

The effects of warning and automated features were explored in this research. Their effects were tested individually and in combination. The effects of driving scenario, lighting conditions, weather conditions, age, and gender were explored as well. However, limited availability of data especially due to limited participants restricted a more in-depth analysis of the effects of ADAS.

Evaluating the effects of other demographic characteristics like education and income can be pursued. The data was segregated into two groups for analysis. It was further segregated by lighting, weather, age, or gender. More samples would allow segregating the data even more and conduct a detailed investigation. Also, analysis based on the type of vehicle driven by the participant and previous familiarity with the features may also be explored in future studies. The availability of adequate data plays a key role in defining the level of analysis that can be performed on the data. Collecting additional samples and exploring the influence of other advanced features also merits further research.

REFERENCES

1. Abdul, W., Wen, T. G., & Kamaruddin, N. (2007, December). Understanding driver behavior using multi-dimensional CMAC. In *2007 6th International Conference on Information, Communications & Signal Processing*, 1-5.
2. Alkim, T. P., Bootsma, G., & Hoogendoorn, S. P. (2007, June). Field operational test "the assisted driver". In *2007 IEEE Intelligent Vehicles Symposium*, 1198-1203.
3. Alternative Fuels Data Center (AFDC), United States Department of Energy. (2019). Maps and data - annual vehicle miles traveled in the United States. https://afdc.energy.gov/data/10315, Accessed 02/03/2020.
4. Angkititrakul, P., Ryuta, T., Wakita, T., Takeda, K., Miyajima, C., & Suzuki, T. (2009). Evaluation of driver-behavior models in real-world car-following task. In *2009 IEEE International Conference on Vehicular Electronics and Safety (ICVES)*, 113-118.
5. Association for Safe International Road Travel (ASIRT). (2019). Road safety facts. https://www.asirt.org/safe-travel/road-safety-facts/, Accessed 02/03/2020.
6. Aziz, T., Horiguchi, Y., & Sawaragi, T. (2013). An empirical investigation of the development of driver's mental model of a lane departure warning system while driving. *IFAC Proceedings Volumes*, *46*(15), 461-468.
7. Bellis, E., & Page, J. (2008). National motor vehicle crash causation survey (NMVCCS) SAS analytical user’s manual. Report No. HS-811 053, Buffalo, New York.
8. Benson, A. J., Tefft, B. C., Svancara, A. M., & Horrey, W. J. (2018). Potential reductions in crashes, injuries, and deaths from large-scale deployment of advanced driver assistance systems. Research Brief, Washington, DC: AAA Foundation for

Traffic Safety.

9. Biondi, F., Rossi, R., Gastaldi, M., & Mulatti, C. (2014). Beeping ADAS: Reflexive effect on drivers' behavior. *Transportation Research Part F: Traffic Psychology and Behaviour*, *25*, 27-33.
10. Cades, D. M., Crump, C., Lester, B. D., & Young, D. (2017). Driver distraction and advanced vehicle assistive systems (ADAS): investigating effects on driver behavior. In *Advances in Human Aspects of Transportation,* Springer, Cham, 1015-1022.
11. Calvi, A., & De Blasiis, M. R. (2011). Driver behavior on acceleration lanes: driving simulator study. *Transportation Research Record*, *2248*(1), 96-103.
12. Choudhary, P., & Velaga, N. R. (2017). Mobile phone use during driving: Effects on speed and effectiveness of driver compensatory behaviour. *Accident Analysis & Prevention*, *106*, 370-378.
13. Choudhary, P., & Velaga, N. R. (2019). Effects of phone use on driving performance: A comparative analysis of young and professional drivers. *Safety Science*, *111*, 179-187.
14. Cicchino, J. B. (2017). Effectiveness of forward collision warning and autonomous emergency braking systems in reducing front-to-rear crash rates. *Accident Analysis & Prevention*, *99*, 142-152.
15. Consumer Reports (2017a). Consumer clarity and safety for today's advanced driver systems. https://data.consumerreports.org/wp-content/uploads/2020/05/auto-safety-report.pdf, Accessed 05/18/2021.

16. Consumer Reports (2019). Guide to lane departure warning and lane keeping assist. https://www.consumerreports.org/car-safety/lane-departure-warning-lane-keeping-assist-guide/, Accessed 05/11/2021.
17. Consumer Reports (2017b). Guide to lane departure warning and lane keeping assist. https://www.consumerreports.org/car-safety/lane-departure-warning-lane-keeping-assist-guide/, Accessed 05/11/2021.
18. Consumer Reports (2017c). Guide to adaptive cruise control. https://www.consumerreports.org/car-safety/adaptive-cruise-control-guide/, Accessed 05/11/2021.
19. Derbel, O., Mourllion, B., & Basset, M. (2012). Safety assessment of mixed traffic based on accident scenario. *IFAC Proceedings Volumes*, *45*(24), 126-131.
20. Drews, F. A., Yazdani, H., Godfrey, C. N., Cooper, J. M., & Strayer, D. L. (2009). Text messaging during simulated driving. *Human Factors*, *51*(5), 762-770.
21. Dunn, N., Dingus, T., & Soccolich, S. (2019). Understanding the impact of technology: do advanced driver assistance and semi-automated vehicle systems lead to improper driving behavior? Virginia Tech Transportation Institute, American Automobile Association, Washington, DC.
22. Farah, H., & Koutsopoulos, H. N. (2014). Do cooperative systems make drivers' car-following behavior safer? *Transportation Research Part C: Emerging Technologies*, *41*, 61-72.
23. Fleet Manager. (2019). The importance of educating drivers about the limits of ADAS. Wex Inc., Portland, OR, https://www.wexinc.com/insights/blog/fleet/the-importance-of-educating-drivers-about-the-limits-of-adas/, Accessed 03/07/2020.

24. Garcia A. (2017). CNN business, car sales set another US record. https://money.cnn.com/2017/01/04/news/companies/car-sales-2016/index.html, Accessed 02/03/2020.

25. Gaspar, J., Brown, T., Schwarz, C., Chrysler, S., & Gunaratne, P. (2016). Driver behavior in forward collision and lane departure scenarios. No. 2016-01-1455, SAE Technical Paper.

26. German Association of the Automotive Industry (VDA). (2020). Lane keeping assist systems. https://www.vda.de/en/topics/safety-and-standards/lkas/lane-keeping-assist-systems.html, Accessed 05/18/2021.

27. Green Car Congress (2021). IIHS study finds drivers significantly more likely to speed while using adaptive cruise control. https://www.greencarcongress.com/2021/03/20210314-iihs.html, Accessed 05/18/2021.

28. Highway Loss Data Institute, Insurance Institute for Highway Safety (IIHS). (2018). IIHS examines driver assistance features in road, track tests. https://www.iihs.org/news/detail/iihs-examines-driver-assistance-features-in-road-track-tests, Accessed 05/11/2021.

29. Highway Loss Data Institute, Insurance Institute for Highway Safety (IIHS). (2021). Advanced driver assistance. https://www.iihs.org/topics/advanced-driver-assistance, Accessed 06/18/2021.

30. Hoogendoorn, S. P., & Minderhoud, M. M. (2002). Motorway flow quality impacts of advanced driver assistance systems. Transportation Research Record, 1800(1), 69-77.

31. Inata, K., Raksincharoensak, P., & Nagai, M. (2008, October). Driver behavior

modeling based on database of personal mobility driving in urban area. In 2008 International Conference on Control, Automation and Systems, IEEE, 2902-2907.

32. Jeong, E., Oh, C., Lee, G., & Cho, H. (2014). Safety impacts of intervehicle warning information systems for moving hazards in connected vehicle environments. Transportation Research Record, 2424(1), 11-19.

33. Kamaruddin, N., & Wahab, A. (2010, June). Driver behavior analysis through speech emotion understanding. In 2010 IEEE Intelligent Vehicles Symposium, 238-243.

34. Kaptein, N. A., Theeuwes, J., & Van Der Horst, R. (1996). Driving simulator validity: Some considerations. Transportation Research Record, 1550(1), 30-36.

35. Kikuchi, S., Uno, N., & Tanaka, M. (2003). Impacts of shorter perception-reaction time of adapted cruise-controlled vehicles on traffic flow and safety. Journal of Transportation Engineering, 129(2), 146-154.

36. Kim, W., Kelley-Baker, T., Sener, I. N., Zmud, J., Graham, M., & Kolek, S. (2019). Users' understanding of automated vehicles and perception to improve traffic safety—results from a national survey. AAA Foundation for Traffic Safety, Washington DC.

37. Kondyli, A., & Elefteriadou, L. (2009). Driver behavior at freeway-ramp merging areas: focus group findings. Transportation Research Record, 2124(1), 157-166.

38. Kuge, N., Yamamura, T., Shimoyama, O., & Liu, A. (2000). A driver behavior recognition method based on a driver model framework. SAE Transactions, 469-476.

39. Lee, C., & Abdel-Aty, M. (2008). Testing effects of warning messages and variable speed limits on driver behavior using driving simulator. Transportation Research Record, 2069(1), 55-64.

40. Li, Y., Li, Z., Wang, H., Wang, W., & Xing, L. (2017a). Evaluating the safety impact

of adaptive cruise control in traffic oscillations on freeways. Accident Analysis & Prevention, 104, 137-145.

41. Li, Y., Wang, H., Wang, W., Liu, S., & Xiang, Y. (2016). Reducing the risk of rear-end collisions with infrastructure-to-vehicle (I2V) integration of variable speed limit control and adaptive cruise control system. Traffic Injury Prevention, 17(6), 597-603.
42. Li, Y., Wang, H., Wang, W., Xing, L., Liu, S., & Wei, X. (2017b). Evaluation of the impacts of cooperative adaptive cruise control on reducing rear-end collision risks on freeways. Accident Analysis & Prevention, 98, 87-95.
43. Lundgren, J., & Tapani, A. (2006). Evaluation of safety effects of driver assistance systems through traffic simulation. Transportation Research Record, 1953(1), 81-88.
44. Lyu, N., Deng, C., Xie, L., Wu, C., & Duan, Z. (2019). A field operational test in China: Exploring the effect of an advanced driver assistance system on driving performance and braking behavior. Transportation Research Part F: Traffic Psychology and Behavior, 65, 730-747.
45. Maag, C., Muhlbacher, D., Mark, C., & Kruger, H. P. (2012). Studying effects of advanced driver assistance systems (ADAS) on individual and group level using multi-driver simulation. IEEE Intelligent Transportation Systems Magazine, 4(3), 45-54.
46. Martin, B. B., & Elefteriadou, L. (2010). Driver behavior and advanced driver assistance systems: an exploratory driving simulator study. Advances in Transportation Studies, Dec 2010 Special, 79-88.
47. Mas, A., Merienne, F., & Kemeny, A. (2011, September). Lateral control assistance and driver behavior in emergency situations. 3rd International Conference on Road Safety and Simulation, Indianapolis, United States, 1-12.

48. McCall, J. C., & Trivedi, M. M. (2007). Driver behavior and situation aware brake assistance for intelligent vehicles. Proceedings of the IEEE, 95(2), 374-387.

49. McDonald A., Carney C., & McGehee D. V. (2018). American Automobile Association: Vehicle owner's experiences with and reactions to advanced driver assistance systems. Washington, DC, https://publicaffairsresources.aaa.biz/wp-content/uploads/dlm_uploads/2018/09/18-0621_AAAFTS-ADAS-Fact-Sheet_v1-BTjc.pdf, Accessed 03/07/2020.

50. Miksic M. Y. (2020). Institute for Education Policy - glossary. Baltimore, MD, https://edpolicy.education.jhu.edu/glossary/#:~:text=Comparison%20groups%20are%20often%20used,is%20called%20the%20control%20group, Accessed 12/7/2020.

51. Miyajima, C., & Takeda, K. (2016). Driver-behavior modeling using on-road driving data: A new application for behavior signal processing. IEEE Signal Processing Magazine, 33(6), 14-21.

52. Morignot, P., Rastelli, J. P., & Nashashibi, F. (2014, June). Arbitration for balancing control between the driver and ADAS systems in an automated vehicle: Survey and approach. In 2014 IEEE Intelligent Vehicles Symposium Proceedings, 575-580.

53. National Advanced Driver Simulator, The University of Iowa, Endor AG (2016). Fanatec Universal Hub Grant Wheel and Horn Installation Guide. Iowa City, IA, https://fanatec.com/media/pdf/0d/99/51/CSUH_Manual_webKzzoH6lofDdpy.pdf, Accessed 05/18/2021.

54. National Highway Traffic Safety Administration (NHTSA), United States Department of Transportation (2021). NHSTA launches influencer campaign to educate drivers on safety features. https://www.nhtsa.gov/press-releases/nhtsa-launches-influencer-

campaign-educate-drivers-safety-features, Accessed 06/18/2021.

55. National Safety Council (NSC), Advanced Driver Assistance Systems. (2020). Injury facts. https://injuryfacts.nsc.org/motor-vehicle/occupant-protection/advanced-driver-assistance-systems/, Accessed 03/07/2020.
56. Naughton K. (2017). The globe and mail: will driver-assist technology turn you into a bad driver? https://www.theglobeandmail.com/globe-drive/culture/commuting/will-driver-assist-technology-turn-you-into-a-bad-driver/article35967419/, Accessed 02/03/2020.
57. Olaverri-Monreal, C., Hasan, A. E., Bulut, J., Körber, M., & Bengler, K. (2014). Impact of in-vehicle displays location preferences on drivers' performance and gaze. IEEE Transactions on Intelligent Transportation Systems, 15(4), 1770-1780.
58. Pauwelussen, J., & Feenstra, P. J. (2010). Driver behavior analysis during ACC activation and deactivation in a real traffic environment. IEEE Transactions on Intelligent Transportation Systems, 11(2), 329-338.
59. Penmetsa, P., Hudnall, M., & Nambisan, S. (2019). Potential safety benefits of lane departure prevention technology. IATSS research, 43(1), 21-26.
60. Rommerskirchen, C. P., Helmbrecht, M., & Bengler, K. J. (2014). The impact of an anticipatory eco-driver assistant system in different complex driving situations on the driver behavior. IEEE Intelligent Transportation Systems Magazine, 6(2), 45-56.
61. Safelite Auto Glass. (2020). The features of ADAS: your driver assist system. https://www.safelite.com/windshield-auto-glass-technology/adas, Accessed 02/03/2020.
62. Saleh, L., Chevrel, P., Claveau, F., Lafay, J. F., & Mars, F. (2013). Shared steering

control between a driver and an automation: stability in the presence of driver behavior uncertainty. IEEE Transactions on Intelligent Transportation Systems, 14(2), 974-983.

63. Sathyanarayana, A., Boyraz, P., & Hansen, J. H. (2008, September). Driver behavior analysis and route recognition by hidden Markov models. In 2008 IEEE International Conference on Vehicular Electronics and Safety, 276-281.
64. Sieber, M., & Färber, B. (2016). Driver perception and reaction in collision avoidance: implications for ADAS development and testing. In 2016 IEEE Intelligent Vehicles Symposium (IV), 239-245.
65. Son, J., Lee, Y., & Kim, M. H. (2011). Impact of traffic environment and cognitive workload on older drivers' behavior in simulated driving. International Journal of Precision Engineering and Manufacturing, 12(1), 135-141.
66. Son, J., Park, M., & Park, B. B. (2015). The effect of age, gender and roadway environment on the acceptance and effectiveness of advanced driver assistance systems. Transportation Research Part F: Traffic Psychology and Behaviour, 31, 12-24.
67. Spivey, H., & Pulugurtha, S. S. (2016). Visibility of two-wheelers approaching left-turning vehicles compared with other hazards under nighttime conditions at urban signalized intersections. Transportation Research Record, 2587(1), 133-140.
68. Strayer, D. L., & Drew, F. A. (2004). Profiles in driver distraction: Effects of cell phone conversations on younger and older drivers. Human Factors, 46(4), 640-649.
69. Strayer, D. L., & Johnston, W. A. (2001). Driven to distraction: Dual-task studies of simulated driving and conversing on a cellular telephone. Psychological Science, 12(6), 462-466.

70. Strayer, D. L., Drews, F. A., & Crouch, D. J. (2006). A comparison of the cell phone driver and the drunk driver. Human Factors, 48(2), 381-391.

71. Strayer, D. L., Drews, F. A., & Johnston, W. A. (2003). Cell phone-induced failures of visual attention during simulated driving. Journal of Experimental Psychology: Applied, 9(1), 23.

72. Tan, H., Zhao, F., Hao, H., & Liu, Z. (2020). Estimate of safety impact of lane keeping assistant system on fatalities and injuries reduction for China: scenarios through 2030. Traffic Injury Prevention, 21(2), 156-162.

73. Tran, C., Doshi, A., & Trivedi, M. M. (2012). Modeling and prediction of driver behavior by foot gesture analysis. Computer Vision and Image Understanding, 116(3), 435-445.

74. Transport Accident Commission (TAC). (2020). How safe is your car?: lane keep assist. https://howsafeisyourcar.com.au/safety-features/lane-keep-assist, Accessed 05/18/2021.

75. Van den Berg R. G. (2020). SPSS Tutorials: one-way ANOVA tutorial. https://www.spss-tutorials.com/spss-one-way-anova/, Accessed 12/7/2020.

76. van Driel, C. J., Hoedemaeker, M., & van Arem, B. (2007). Impacts of a congestion assistant on driving behaviour and acceptance using a driving simulator. Transportation Research Part F: Traffic Psychology and Behaviour, 10(2), 139-152.

77. Wang, W., Xi, J., & Chen, H. (2014). Modeling and recognizing driver behavior based on driving data: A survey. Mathematical Problems in Engineering, https://www.hindawi.com/journals/mpe/2014/245641/, Accessed 05/18/2021.

78. Witt, M., Wang, L., Fahrenkrog, F., Kompaß, K., & Prokop, G. (2018, July). Cognitive driver behavior modeling: Influence of personality and driver characteristics on driver behavior. In International Conference on Applied Human Factors and Ergonomics, Springer, Cham, 751-763.

79. World Health Organization (WHO). (2021). Adolescent health in the South-East Asia region. https://www.who.int/southeastasia/health-topics/adolescent-health#:~:text=WHO%20defines%20'Adolescents'%20as%20individuals,age%20range%2010%2D24%20years., Accessed 06/18/2021.

80. Yannis, G., Antoniou, C., Vardaki, S., & Kanellaidis, G. (2010). Older drivers' perception and acceptance of in-vehicle devices for traffic safety and traffic efficiency. Journal of Transportation Engineering, 136(5), 472-479.

81. Yue, L., Abdel-Aty, M., Wu, Y., & Wang, L. (2018). Assessment of the safety benefits of vehicles' advanced driver assistance, connectivity and low-level automation systems. Accident Analysis & Prevention, 117, 55-64.

82. Ziefle, M., Pappachan, P., Jakobs, E. M., & Wallentowitz, H. (2008, July). Visual and auditory interfaces of advanced driver assistant systems for older drivers. In International Conference on Computers for Handicapped Persons, Springer, Berlin, Heidelberg, 62-69.

APPENDIX A: QUESTIONNAIRE FORM

This chapter includes the questionnaire and the consent form describing their participatory rights for the research study.

Date:_____________ Time:_____________

Age:________ Gender: ☐ Male ☐ Female

Possess Driver's License: ☐ Yes ☐ No Driving Experience (Years/ months):______

Own a Vehicle? ☐ Yes ☐ No, If Yes, Make:_______________ Model:________________

Color Blind? ☐ Yes ☐ No

Race: ☐ Native American ☐ Caucasian ☐ African-American ☐ Hispanic ☐ Asian

Education: ☐ No Schooling ☐ High School ☐ Vocational Training ☐ Associate Degree ☐ Bachelor's Degree ☐ Master's/ Professional Degree ☐ Doctorate Degree

Annual Household Income: ☐ Less than $25,000 ☐ $25,000 to $34,999 ☐ $35,000 to $49,999 ☐ $50,000 to $74,999 ☐ $75,000 to $99,999 ☐ $100,000 to $149,999 ☐ $150,000 or more

Number of Traffic Citations (Tickets):______________ Crashes involved in (Number):________

Answer the next question only if you are above 21 years of age:

Alcohol Consumption in last 24 hours: ☐ Yes ☐ No, If Yes, Quantity (in OZ):____

Medication/ Drugs: ☐ Yes ☐ No Hours of sleep in last 24 hours:___________

Marital Status: ☐ Single/ Never Married ☐ Married/ Domestic Partnership ☐ Widowed ☐ Divorced ☐ Separated

Advance Safety Features in Your Car: ☐ Yes ☐ No, If Yes, please select the feature below

☐ Adaptive Headlights ☐ Blind Spot Monitoring ☐ Front crash Prevention

☐ Lane Departure Prevention ☐ Park Assist

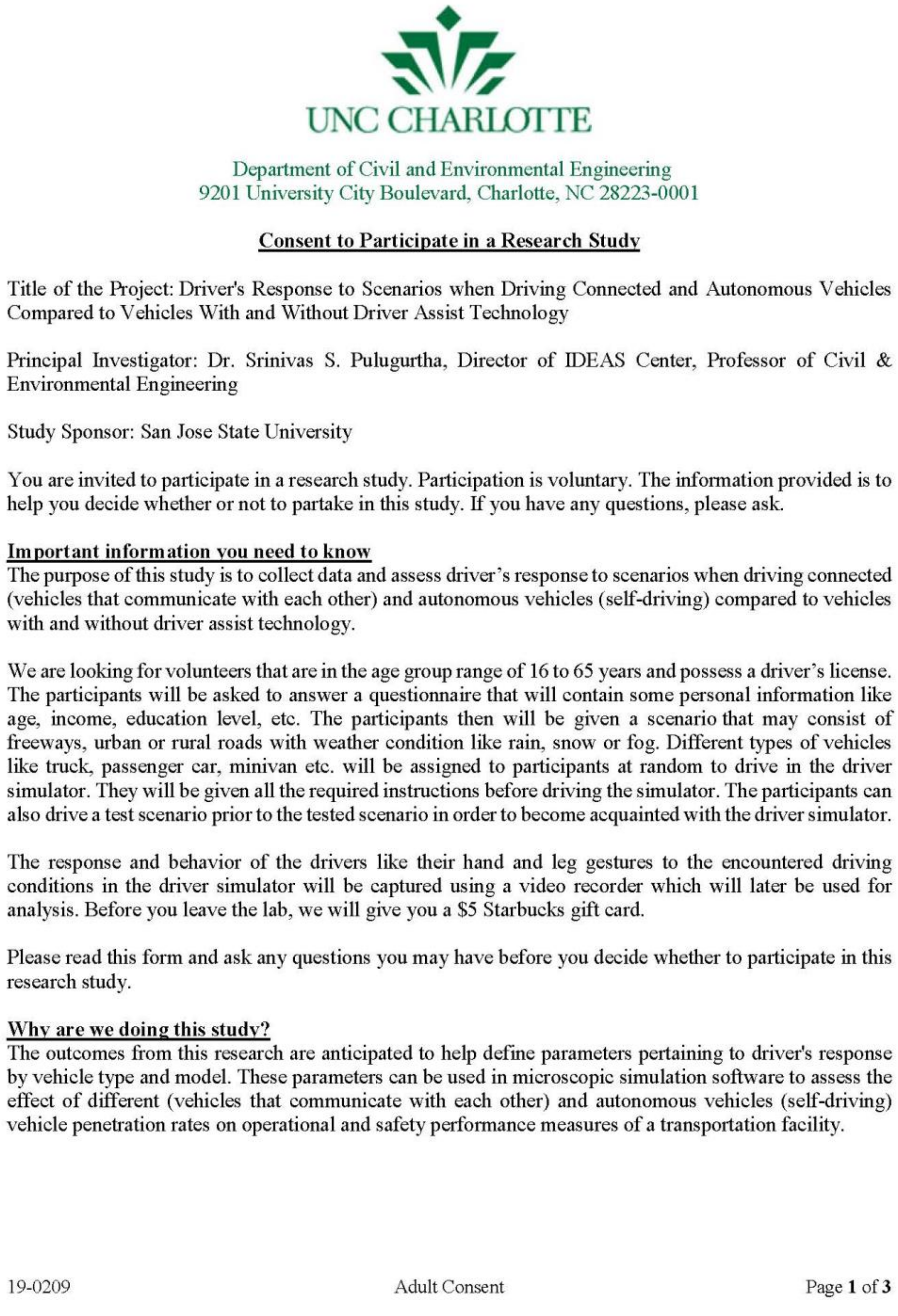
For Official Use:

Participant ID:_________________

Driving Scenario:_______________

Type of Vehicle: _________________

Figure A1 Survey questionnaire for participants



UNC CHARLOTTE

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Consent to Participate in a Research Study

Title of the Project: Driver's Response to Scenarios when Driving Connected and Autonomous Vehicles Compared to Vehicles With and Without Driver Assist Technology

Principal Investigator: Dr. Srinivas S. Pulugurtha, Director of IDEAS Center, Professor of Civil & Environmental Engineering

Study Sponsor: San Jose State University

You are invited to participate in a research study. Participation is voluntary. The information provided is to help you decide whether or not to partake in this study. If you have any questions, please ask.

Important information you need to know
The purpose of this study is to collect data and assess driver's response to scenarios when driving connected (vehicles that communicate with each other) and autonomous vehicles (self-driving) compared to vehicles with and without driver assist technology.

We are looking for volunteers that are in the age group range of 16 to 65 years and possess a driver's license. The participants will be asked to answer a questionnaire that will contain some personal information like age, income, education level, etc. The participants then will be given a scenario that may consist of freeways, urban or rural roads with weather condition like rain, snow or fog. Different types of vehicles like truck, passenger car, minivan etc. will be assigned to participants at random to drive in the driver simulator. They will be given all the required instructions before driving the simulator. The participants can also drive a test scenario prior to the tested scenario in order to become acquainted with the driver simulator.

The response and behavior of the drivers like their hand and leg gestures to the encountered driving conditions in the driver simulator will be captured using a video recorder which will later be used for analysis. Before you leave the lab, we will give you a $5 Starbucks gift card.

Please read this form and ask any questions you may have before you decide whether to participate in this research study.

Why are we doing this study?
The outcomes from this research are anticipated to help define parameters pertaining to driver's response by vehicle type and model. These parameters can be used in microscopic simulation software to assess the effect of different (vehicles that communicate with each other) and autonomous vehicles (self-driving) vehicle penetration rates on operational and safety performance measures of a transportation facility.

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Figure A2 Consent from (Page 1)

Why are you being asked to be in this research study?
You are being asked to be in this study because you are in the age group range of 16 to 65 years with a driver's license.

What will happen if I take part in this study?
If you choose to participate in this research, you will be asked to complete a questionnaire that will take approximately 4 to 5 minutes to complete. Afterwards, you will be asked to drive on the driver simulator where your responses and behavior will be captured using a video recorder. Your total time commitment if you choose to participate in this study, will be 30 to 40 minutes.

What benefits might I experience?
You will not benefit directly from your participation in this study. However, others will benefit, as the results from this study will help us replicate real world driver behavior to changing technologies. This will improve our understanding of the repercussions to coming technological advancements.

What risks might I experience?
There will NOT be any physical risk involved from your participation. The questionnaire we provide will contain some personal questions like name, age, gender, income etc. However, you can choose to skip answering any question if you don't feel comfortable.

How will my information be protected?
Each participant will be assigned a participant ID. Data will be entered and tracked by participant ID. All the physical copies of the questionnaires will be stored in locked cabinets with access only to the Principal Investigator. All soft copies of the data/ questionnaire and video recordings will be stored in a password protected folder. Access will be provided to the Research Team on approval from the Principal Investigator. Designated officials, with approval from the Principal Investigator, may need to see the information we collect about you, including people who work for UNC Charlotte and other agencies as required by law or allowed by federal regulations.

How will my information be used after the study is over?
The study data from this research survey will NOT be shared with anyone outside the Research Team. Once the research is completed, all the survey data will only be available with the Principal Investigator on a password protected hard disk to maintain total privacy of the data.

Will I be paid for taking part in this study?
You will receive a Starbucks gift card ($5 in value) for your participation.

What are my rights if I take part in this study?
Your participation in this study is completely voluntary. If you decide to participate now, you may change your decision at any point during the survey. You may choose not to answer any questions in the questionnaire that you are not comfortable with.

Who can answer my questions about this study and my rights as a participant?
For questions about this research, you may contact Dr. Srinivas S. Pulugurtha at sspulugurtha@uncc.edu or (704) 687-1233.

If you have questions about your rights as a research participant, or wish to obtain information, ask questions, or discuss any concerns about this study with someone other than the researcher(s), please contact the Office of Research Compliance at 704-687-1871 or uncc-irb@uncc.edu.

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Figure A3 Consent from (Page 2)

Consent to Participate
By signing this document, you are agreeing to be in this study. Make sure you understand what the study is about before you sign. You will receive a copy of this document for your records. If you have any questions about the study after you sign this document, you can contact the study team using the information provided above.

I understand what the study is about, and my questions so far have been answered. I agree to take part in this study.

____
Name (PRINT)

____
Signature Date

____
Name & Signature of person obtaining consent Date

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Figure A4 Consent from (Page 3)