ABSTRACT

Title of Dissertation:	EVALUATION AND VALIDATION OF THE EFFECT OF CONNECTED AND AUTOMATED VEHICLE SAFETY APPLICATIONS ON DRIVER BEHAVIOR—A DRIVING SIMULATOR APPROACH
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Background–Considering the rapid boom in information technology and people's increasing dependence on mobile data, automotive manufacturers have started equipping vehicles with wireless communication capabilities, manufacturing what are commonly known as connected vehicles, and automated systems to assist drivers with certain driving tasks. These technological advances have led to fast tracking the deployment of connected and automated vehicles, and an increased momentum in implementing these applications,

as the number of driving assistance systems pre-equipped in cars by automotive companies has witnessed a sharp increase during this decade. However, most of the new cars come pre-equipped with these applications, which means that the drivers' reactions to such applications are not fully examined since most of the experiments involving these applications are done using microscopic simulations with the behavior of the drivers' being assumed. Therefore, this rapid deployment and implementation has led to a lack of research in understanding the drivers' reactions to such applications before they actually use them, which is an essential element in ensuring the effectiveness and successful implementations of such applications.

Objectives–To investigate driver behavior in terms of braking, steering and throttle control, change in speed and eye gaze movements in the presence of connected and automated vehicle applications using a driving simulator. Some of these driving simulator findings are validated using real world data.

Method–Four distinct analysis are conducted to evaluate five different connected and automated vehicle applications. A hazard-based duration model is used to evaluate driver braking behavior while a random forest model is used to rank the most important variables impacting change in speed and steering wheel and throttle take over reaction times. A heat map of eye gaze movements is created to identify objects of interest with the most fixations.

Data–The study consisted of 93 participants from diverse socio-economic backgrounds who drove in 186 experiments. These participants answered a pre-simulation socio-demographic questionnaire as well as a post simulation, driving simulation

experience questionnaire. Two of the connected and automated vehicle applications in the driving simulator were validated using real world data obtained from University of Michigan Transportation Research Institute.

Results–The use of Pedestrian Collision Warning and Red-Light Violation Warning had a significant impact on participant braking behavior, where participants resorted to initial aggressive braking in the presence of these applications. The eye gaze heat map showed that majority of the participants glanced at the visual notification from these applications thus reinforcing the findings from the significant braking behavior. Forward Collision Warning had a positive influence on change in speed while Curve Speed Warning had no impact on speed. These findings were validated with the findings from the real-world data provided by University of Michigan Transportation Research Institute. Lastly, the steering wheel and throttle Take Over Reaction times in the post autonomous mode being 2.47 seconds and 2.98 seconds respectively, is greatly influenced by the annual miles driven, age, and familiarity with this technology. The gaze analysis shows that participants viewed the rearview mirror and speedometer more while also being involved in offscreen distractions, while in the autonomous mode.

Conclusions–This study shows that the CAV applications with the exception of the Curve Speed Warning (CSW) application, are effective in improving the safety and comfort of the drivers, confirming the hypothesis that these CAV applications impact the drivers' performance positively. The contributions and implications of the study are discussed.

EVALUATION AND VALIDATION OF THE EFFECT OF CONNECTED AND

AUTOMATED VEHICLE SAFETY APPLICATIONS ON DRIVER BEHAVIOR—A

DRIVING SIMULATOR APPROACH

by

Snehanshu Banerjee

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DEDICATION

To my mother, *Aparna Bandyopadhyay*

And my father, *Swapan Kumar Bandyopadhyay*

To my sister, *Sneha Banerjee*

and my brother-in-law *Arnab Chakrabarti*

To my niece, *Shreya Chakrabarti*

ACKNOWLEDGMENTS

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List of Abbreviations

ACC	Adaptive Cruise Control
AEB	Automatic Emergency Braking
AFT	Accelerated Failure Time
AFV	Alternative Fuel Vehicle
APGS	Advanced Parking Guidance Systems
ARC	Automated Assistance in Roadwork and Congestion
ATIS	Advanced Traveler Information System
AV	Automated Vehicle
BSW/LCW	Blind Spot/Lane Change Warning
CACC	Cooperative Adaptive Cruise Control
CAV	Connected and Automated Vehicles
CSW	Curve Speed Warning
CV	Connected Vehicle
CVRIA	Connected Vehicle Reference Implementation Architecture
DCM	Data Capture and Management
DMA	Dynamic Mobility Applications
DMS	Driver Monitoring Systems
DNPW	Do Not Pass Warning
D-RIDE	Dynamic Ridesharing
DS	Driving Simulator
EEBL	Emergency Electronic Brake Lights
FCC	Federal Communications Commission
FCW	Forward Collision Warning
FHWA	Federal Highway Administration
FRATIS	Freight Advanced Traveler Information Systems
FSP	Freight Signal Priority
HAVEit	Highly Automated Vehicles for Intelligent Transport

ICM	Integrated Corridor Management
IDTO	Integrated Dynamic Transit Operation
IMA	Intersection Movement Assist
INFLO	Intelligent Network Flow Optimization
IPAS	Intelligent Parking Assist Systems
ISA	Intelligent Speed Adaptation
ITS	Intelligent Transportation Systems
IVC	Inter-Vehicle Communications
LDW	Lane Departure Warning
LIDAR	Light Detection and Ranging
LTA	Left Turn Assist
MAW	Motorist Advisories and Warnings
MDG	Mean Decrease in GINI
MMITSS	Multi-Modal Intelligent Traffic Signal Systems
NHTSA	National Highway Traffic Safety Administration
NTC	National Transportation Center
PCW	Pedestrian Collision Warning
Q-WARN	Queue Warning
R.E.S.C.U.M.E.	Response, Emergency Staging and Communications, Uniform Management, and Evacuation
RLVW	Red Light Violation Warning
RWA	Road Weather Applications
SABA	Safety and Behavioral Analysis Center
SAE	Society of Automotive Engineers
SPD-HARM	Dynamic Speed Harmonization
TSP	Transit Signal Priority
TSR	Traffic Sign Recognition
TTI	Texas Transportation Institute
USDOT	United States Department of Transportation
V2C	Vehicle to Cloud
V2D	Vehicle to Device
V2I	Vehicle to Infrastructure
V2P	Vehicle to Pedestrian
V2R	Vehicle to Road Infrastructure
V2S	Vehicle to Sensor
V2V	Vehicle to Vehicle
V2X	Vehicle to Everything
VDT	Vehicle Data Translator

VII   Vehicle Infrastructure Integration
WRTINFO   Weather Response Traffic Information

Chapter 1. Introduction

With the rapid development of information technology and people's increasing dependence on mobile data, automotive manufacturers have started equipping vehicles with wireless communication capabilities, manufacturing what are commonly known as connected vehicles (Lu et al. 2014), and automated systems to assist drivers with certain driving tasks. Connected vehicles are "wireless connectivity-enabled vehicles that can communicate with their internal and external environments" (Lu et al. 2014). These vehicles are proactive and coordinated in a way that enables them to achieve the mobility and safety goals for road transportation through supporting a number of applications for road safety, smart and green transportation, location-dependent services, and in-vehicle internet access (Lu et al. 2014, Lioris et al. 2017). Furthermore, connected vehicles provide a two-way wireless communication environment that has led to the development of a number of applications by enabling the communication among vehicles and sensors (V2S), vehicle to vehicle (V2V), and vehicles and the road infrastructure (Lu et al. 2014) i.e. (V2R), or, more generally, vehicle-to-everything (V2X), such as: pedestrians' mobile devices (Lee and Park 2012, Amadeo, Campolo, and Molinaro 2016). In addition, connected vehicles can collect traffic data, such as vehicles' maneuvers and trajectories, and sharing this data with different transportation stakeholders will enhance the safety of road traffic (Lee and Park 2012).

A related yet separate technological development in the automobile industry is the emergence of automated vehicles. Automated vehicles are those equipped with electronic systems that can perform one or more of the tasks of the human drivers (Petit and Shladover

2014). These vehicles can range from ones with constrained or limited automation, such as automatic emergency braking or cruise control, to the fully automated vehicle, i.e., the self-driving vehicle (González et al. 2015). A fully automated vehicle will have the capability of navigating road networks and avoiding obstacles which will eliminate crashes resulting from human errors (Piao et al. 2016). Consequently, drivers' roles in these highly automated cars significantly changes from being an operator to being a supervisor who monitors the driving environment and assumes control of the vehicle in case of emergency (Merat and Jamson 2009).

A number of applications have been developed based on the new technologies of the connected and automated vehicles. These applications can significantly aid the drivers by helping them recognize hazardous situations in their driving environment and reducing the mental and physical efforts associated with some of the tedious driving tasks (Lu et al. 2014, González et al. 2015). Regarding connected vehicles, the development of such applications has gained a huge momentum, starting in 1999 when the Federal Communications Commission (FCC) allocated several short-range communication channels exclusively for vehicles' communications (Zeng, Balke, and Songchitruksa 2012). This led to the development of many applications for this technology that proved their effectiveness in reducing traffic congestion and CO_2 emissions, and improving the safety of road traffic (Olia et al. 2016). As a result, these applications can be broadly categorized under three main categories: mobility, environment, and safety (Zeng, Balke, and Songchitruksa 2012). Examples of these applications include: real-time data capture and management (DCM) and dynamic mobility applications (DMA); real-time information

synthesis system (AERIS) and road weather applications (RWA); and V2V and V2I communications, respectively (Zeng, Balke, and Songchitruksa 2012).

In terms of safety applications, these are designed to improve the situational awareness of the drivers and reduce traffic collisions that mainly result from distracted driving. Generally, there are three different kinds of this application (Zeng, Balke, and Songchitruksa 2012): 1) user advisories, which present the drivers with suggestive messages that help them take suitable preventive actions; 2) user warnings, which display urgent messages to increase the drivers' awareness with the surrounding environment in order to take immediate actions to avoid dangerous situations; and 3) vehicle and/or infrastructure controls, which are secondary actions taken by the vehicle's control system when the driver does not respond to the warnings. Concerning the mobility applications, these applications aim at capturing real-time data from onboard units inside the vehicle, as well as roadside equipment. This data will then be transmitted wirelessly to the relevant users of the transportations system to take better informed actions that can improve the mobility performance of the entire system. Lastly, when it comes to the environmental applications, similar to the mobility applications, these applications aim to transmit traffic and weather data to the drivers and road users to enhance their environmentally aware decision making (Merat and Jamson 2009). Consequently, vehicles equipped with these applications will be able to plan and make informed decisions about the routes to take, which will help transportation agencies better manage the traffic, while transportation companies will be able to better manage their fleets (Olia et al. 2016). These applications also satisfy the drivers' needs of being connected while operating a motor vehicle (Lu et al. 2014).

As for the automated vehicle applications, there are four different levels of automation involved, which are: driver assistance, partial automation, high automation, and full automation (Hoogendoorn, van Arerm, and Hoogendoom 2014). Taking over the need to perform certain tasks from the driver will increase safety as it will enable these drivers to focus more on the vehicle's maneuvering and the surrounding environment, while reducing their fatigue factor. A number of these applications have already proved their effectiveness in increasing the drivers' safety. For instance, steering assistance applications have been proven to reduce the driver's workload significantly and, in return, road accidents (Nguyen, Sentouh, and Popieul 2016); while lane keeping applications assist the drivers in keeping their positions and avoiding sudden lane changes (Llaneras, Salinger, and Green 2013). Similarly, automated vehicle applications have the potential of reducing traffic congestion levels by reducing the probability of traffic breakdown and optimizing the distribution of the traffic over the road lanes (Hoogendoorn, van Arerm, and Hoogendoom 2014). Furthermore, reducing the driver's workload will improve their driving comfort and enhance their overall experience (Gold et al. 2013). These applications offer a wide range of operational benefits for all road users and provide a foundation for the successful transition into autonomous driving (Llaneras, Salinger, and Green 2013).

All these benefits have led to fast tracking the deployment of connected and automated vehicles (Lu et al. 2014), and an increased momentum in implementing these applications as the number of driving assistance systems pre-equipped in cars by automotive companies has witnessed a sharp increase during this decade (Radlmayr et al. 2014). Moreover, legislation was put into place to encourage the wider adoption of these applications. For instance, in 2015, the European Parliament required that all new cars be

equipped with eCall technology, by which cars can automatically establish a telephone link for emergency services in case of a collision, starting in April 2018 (European 2018). Similarly, the USDOT put into place a strategic plan to accelerate the deployment of connected and automated vehicles through its Professional Capacity Building (PCB) Program that is used to educate the public sector's transportation workforce about these systems (USDOT). In addition, the internet-integrated vehicle services market is expected to exceed $43 million by 2023 (Newswire 2017); while the booming market of connected vehicles is expected to reach $131.9 billion in 2019 (Lu et al. 2014). However, most of the new cars come pre-equipped with these applications, which means that the drivers' reactions to such applications are not fully examined since most of the experiments involving these applications are done using microscopic simulations with the behavior of the drivers' being assumed (Hoogendoorn, van Arerm, and Hoogendoom 2014). Therefore, this rapid deployment and implementation has led to a lack of research in understanding the drivers' reactions to such applications before they actually use them, which is an essential element in ensuring the effectiveness and successful implementations of such applications.

1.1 Research Questions

Numerous ongoing research projects focus on CAV application development and cost benefit analysis of these applications. However, the author found no studies conducted to assess the impact of these applications on driver behavior as CAVs start becoming more prevalent on the road. This study, the first of its kind, will use a driving simulator to observe the impact of some of the CAV safety applications on driver behavior as they drive among

a mix of CAVs and non-automated vehicles and validate some of the driving simulator findings using real world data. The main research questions are as follows:

- Are the CAV application warnings effective in reducing speed or carrying out their intended purpose?

- Are these warnings distracting?

- Which type of warning is more effective?

- What is the average reaction time once the participant is warned?

1.2 Hypothesis and Research Objectives

To address the research questions, the research hypotheses are as follows:

1) The CAV applications have a positive influence on driver performance i.e. applications which warn the driver of an impending incident/obstacle, lead drivers to brake/slow down considerably.

2) The drivers remain focused and attentive when Level 3 autonomous mode is engaged, where being available to take over any time is a requirement.

3) The drivers' glance at the CAV application visual prompts, which influences their driving behavior in terms of braking, i.e. there is a reduction in speed.

The main objectives of this research are:

1) To investigate driver behavior in the presence of connected and automated vehicle applications using a driving simulator, in terms of:

   a) braking

   b) steering and throttle control

   c) change in speed

d) eye gaze movements

2) Validate some of these driving simulator findings using real-world data.

1.3 Dissertation Organization

The dissertation is organized into seven chapters and three appendices. The introduction chapter is followed by a thorough literature review on connected and automated vehicles and their applications in Chapter 2. The study methodology—consisting of the study network, scenario design, and types of analysis to be conducted—is described in detail in Chapter 3. Chapter 4 includes the data collection procedure, some descriptive statistics of the data, and simulator sickness symptoms involving the driving simulator. Chapter 5 describes the analysis of all five applications tested in this study. Chapter 6 discusses the findings of this study while Chapter 7 concludes the study with contributions made to the field. Appendices include survey questionnaires, flyer for recruiting participants, and the consent form for the study participants.

Chapter 2. Literature Review

2.1 Definitions

It is important to distinguish between autonomous and connected vehicles. We make the distinction clear in this section.

2.1.1 Autonomous Vehicles

The term "autonomous vehicle" is given to vehicles that have complete vehicle control capabilities without human interaction. This makes it possible for humans to pass driving tasks or the entire driving process to the vehicle. Transfer of control can either happen voluntarily, or involuntarily in circumstances where the vehicle takes over after detecting that the human cannot cope with the situation (Nåbo et al. 2013).

The UK Department for transport in its 2015 report "The Pathways to Driverless Cars" defined autonomous vehicles (AVs) as a vehicle which is developed to have the capability to complete journeys with safety without the requirement of a driver while on a road in external conditions like weather and traffic (Transport 2015). Some of the terms used for autonomous vehicles are driverless, autonomous, robotic, and self-driving vehicles. Autonomous vehicles are defined by (Zmud et al. 2015) as vehicles in which, at the minimum, certain aspects of the control functions critical to safety like throttling, steering, or braking do not require input from the driver.

2.1.2 Connected Vehicles

Connected vehicles are those equipped with devices of communication. These communication devices make information available to either the vehicle or the driver,

allowing them to corroborate with parts of the road infrastructure as well as other users on the road (Johnson 2017). A number of technologies help achieve connectivity such as the internet, global positioning systems (GPS), local area networks (LAN), wireless, etc., which may make information available on several dimensions of the external environment on the road, thereby assisting drivers and navigation on the road (Johnson 2017). In his report, "Readiness of the road network for connected and autonomous vehicles," (Johnson 2017) identified three types of connected vehicles:

(a) V2V - Vehicle-to-Vehicle,

(b) V2I - Vehicle-to-Infrastructure or vice versa, I2V and

(c) V2D - Vehicle-to-Device or vice versa, D2V.

In the case of V2D, V2P (Vehicles-to-Pedestrian mobile devices) and V2C (Vehicle-to-Cloud) are definite possibilities. Some developers of autonomous vehicles, such as Google, have the goal of developing safe and reliable vehicles by exploiting both connected as well as autonomous technologies, which are also known as connected and autonomous vehicles (CAVs), (Johnson 2017). This literature review refers to CAVs, and they will be treated separately in this research since they have different implications for design and development.

2.2 Connected Vehicles

Several research studies have been carried out in the past which are related to connected vehicles for the identification of available applications and for investigation of the feasibility of such applications (NHTSA 2011). The U.S. Department of Transportation (USDOT) has been studying evaluating the viability of creating efficient crash avoidance

systems by utilizing V2V communications. Manufacturers in the automotive sector established a consortium for vehicle safety communication projects by collaborating with the USDOT (USDoT and NHTSA). This consortium identified more than 75 applications for connected vehicle scenarios, out of which eight safety application scenarios which were perceived to have great prospective benefits for further research were selected. These scenarios were:

(a) curve speed warning,

(b) pre-crash warning,

(c) traffic signal violations warning,

(d) cooperative forward collision warning,

(e) lane change warning,

(f) left-turn assistance,

(g) stop sign movement assistance and

(h) emergency brake light application.

According to the USDOT webpage, connected vehicle applications are divided into three categories according to their functions:

(d) Safety applications: These applications may enhance situational awareness and play a role in preventing crashes with the assistance of wireless communication technology.

(e) Mobility applications: Such applications may provide real-time as well as multi-modal data on traffic for travelers, agencies as well as operators.

(f) Environment applications: Such applications can aid the driver by providing information on traffic in real time from other connected vehicles which may be utilized

to enhance the road environment holistically by informing drivers to keep away from routes which have congestion.

The Connected Vehicle Reference Implementation Architecture (CVRIA) provides four categories of Connected Vehicle applications, namely:

(a) Safety,

(b) Mobility,

(c) Environment and

(d) Support applications (CVRIA: Connected Vehicle Applications).

(USDOT and NHTSA) and (Chen, Jin, and Regan 2010) state that the classification of connected vehicle applications can also be done into periodic and event-driven applications by utilizing the transmission mode. In applications that are event-driven, like road condition warning and forward collision warning applications for safety, some events send situation related transmissions. In order to prevent secondary crashes, applications which are event-driven require a shorter interval for updates when compared to periodic applications in which automatic transmissions are provided at regular intervals.

2.2.1 Safety applications for Connected Vehicles

Crashes related to traffic were placed fourth in the causes which lead to total fatalities in the U.S. In the year 2010, motor vehicle crashes caused an economic loss of $242 billion (NHTSA 2015). Through wireless communication technologies, connected vehicles have the potential to prevent vehicle crashes and loss of human lives by making the driver aware of the situations and hazards. Such applications can be categorized as per

type of connected vehicle system namely V2V and V2I. (Kim 2015) highlighted these applications as per the described categories.

V2V Safety:

(a) EEBL: Emergency Electronic Brake Lights,

(b) FCW: Forward Collision Warning,

(c) IMA: Intersection Movement Assist,

(d) LTA: Left Turn Assist,

(e) BSW/LCW: Blind Spot/Lane Change Warning,

(f) DNPW: Do Not Pass Warning and

(g) Transit: Vehicle Turning Right in Front of Bus Warning (Transit).

Secondly, V2I safety applications were described as:

(g) Spot Weather Impact Warning,

(h) Reduced Speed/Work Zone Warning,

(i) Pedestrian in Signalized Crosswalk Warning (Transit),

(j) RLVW - Red Light Violation Warning,

(k) CSW - Curve Speed Warning and

(l) Stop Sign Gap Assist (Kim 2015).

2.2.2 Mobility applications for Connected Vehicles

According to Texas Transportation Institute, in 2011, highway users on urban roads in the US lost 5.5 billion hours of their time resulting from traffic congestion (TTI 2012). Various traffic management and operation programs consider travel delays due to traffic congestion to be one of the top areas that needs to be addressed. Mobility applications in

connected vehicles have the potential to solve this issue by providing multi-modal and real-time traffic data for agencies, travelers, and operators for mitigation of traffic congestion. The USDOT has defined two applications in connected vehicles to enhance mobility:

(a) Dynamic mobility and

(b) Real-time data capture and management.

The collection of real-time data can be done from diverse sources like mobile devices, infrastructure, and connected vehicles. The data can be utilized for the management of transportation systems through dynamic mobility applications. (Kim 2015) highlighted these applications as per the described categories:

(a) Multi-Modal Intelligent Traffic Signal Systems or MMITSS which includes I-SIG: Intelligent Traffic Signal System, TSP- Transit Signal Priority and FSP- Freight Signal Priority, PED-SIG- Mobile Accessible Pedestrian Signal System and PREEMPT- Emergency Vehicle Preemption.

(b) INFLO: Intelligent Network Flow Optimization includes SPD-HARM- Dynamic Speed Harmonization, Q-WARN Queue Warning, CACC- Cooperative Adaptive Cruise Control.

(c) R.E.S.C.U.M.E: Response, Emergency Staging and Communications, Uniform Management, and Evacuation includes applications such as RESP-STG- Incident Scene Pre-Arrival Staging Guidance for Emergency Responders, INC-ZONE- Incident Scene Work Zone Alerts for Drivers and Workers and EVAC- Emergency Communications and Evacuation.

(d) IDTO: Integrated Dynamic Transit Operation includes applications such as T-CONNECT- Connection Protection, T-DISP- Dynamic Transit Operations and D-RIDE- Dynamic Ridesharing.

(e) FRATIS: Freight Advanced Traveler Information Systems includes applications such as the DR-OPT- Freight-Specific Dynamic Travel Planning and Performance, Drayage Optimization and EnableATIS- Enable Advanced Traveler Information System.

2.2.3 Environmental applications for Connected Vehicles

According to the Texas Transportation Institute's Urban Mobility Report (TTI 2012), in the year 2011, congestion caused wastage of 209 billion gallons of fuel in urban areas in the U.S. During this urban congestion, 56 billion pounds of extra greenhouse gases—carbon dioxide were emitted. Connected vehicles have the capability to provide real-time information which can improve the environment by bypassing congested routes, leading to fewer emissions and opting for green transportation options from connected vehicle environment applications. Such applications can be categorized into two, namely:

(a) applications for environment, i.e., Real-Time Information Synthesis or AERIS and

(b) applications for road weather.

Development of AERIS is done to generate information in real-time to improve the environment by reducing emissions and fuel use. Road weather applications can make data available for assessment, forecasting, and addressing the effects of weather on travelers, roads, and vehicles (Kim 2015). The description of environment applications was given by (Kim 2015):

(a) AERIS includes Alternative Fuel Vehicle (AFV) Charging / Fueling Information, Connected Eco-Driving, Dynamic Eco-Routing (light vehicle, transit, freight) and Eco-Integrated Corridor Management (ICM) Decision Support System, Eco-Approach and Departure at Signalized Intersections, Eco-Cooperative Adaptive Cruise Control, Eco-

Speed Harmonization, Eco-Traveler Information, Eco-Lanes Management, Eco-Ramp Metering, Eco-Traffic Signal Priority, Eco-Traffic Signal Timing, Low Emissions Zone Management Eco-Smart Parking, Wireless Inductive/Resonance Charging.

(b) Road Weather applications include, Vehicle Data Translator (VDT), Weather Response Traffic Information (WRTINFO) and Motorist Advisories and Warnings (MAW).

2.2.4 Performance Measurement of Connected Vehicle and Applications

The requirement to measure the feasibility of connected vehicle systems and applications is fulfilled by the utilization of various types of measurements available. There are certain studies which have utilized information propagation through wireless technologies in order to assess the V2V performance. A widespread and quick propagation of information related to traffic incidents is crucial for managing traffic incidents as such incidents lead to secondary incidents, which account for 20 percent of all the incidents (FHWA). If a vehicle is disabled due to an incident or mechanical failure, such information must be sent quickly to the approaching traffic. (Shladover et al. 2007) utilized the average propagation distance of wireless messages to assess the performance of CAVs or cooperative vehicle systems which relied on traffic density and vehicle market penetration rates. With an increase in traffic density and market penetration rate, the distance of message propagation was increased. This message propagation distance also increased quickly as the ratio between mean separation among the vehicles and communication range increased. The performance of inter-vehicle communications (IVC) was studied by (Jung et al. 2010) by the utilization of an NS-2 communication network simulator. The results of the study found that the average maximum distance of information propagation increases

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when there is an increase in the transmission range as low traffic density and a shorter transmission range impact the message propagation in IVC over several vehicles negatively. But it needs to be noted that (Jung et al. 2010) considered equipped vehicle market penetration of only one level, i.e., 10 percent. (Yang and Recker 2005) tested the probability of communication success and traffic information propagation in arterial networks and freeways in the framework of a simulation. This study utilized a hypothetical area of study using a simple grid network. The measurement of the maximum distance of information propagation was evaluated relying on several combinations using:

(a) IVC capable vehicle's market penetration rate,

(b) traffic conditions,

(c) range of communication radius and level of service under conditions of incidents.

2.2.5 Connected Vehicles and Estimation of Real-time traffic information

According to (Kim 2015), connected vehicles can be utilized to investigate vehicles for monitoring and controlling real time information like speed, travel time, and traffic delay for several traveler information and traffic management applications. Some of the earlier studies in connected vehicle research have used connected vehicle's real-time traffic information estimation rate for connected vehicle performance measurement (Kim 2015). (Rim et al. 2011) used V2V and V2I communications for estimation of travel time at the lane level for traffic management. There was 6%–9% error rate in travel time estimation when the penetration of equipped vehicles was above 20%. (Rim et al. 2011) gathered individual vehicle's trajectory data within 7.42 kilometer of the VISSIM simulation network with reasonable highway traffic and geometric settings. (Li et al. 2008) utilized

probe data from V2I integration for measurement of arterial performance in real time. VISSIM was used to collect traffic information through V2I communication in an arterial simulation model with six intersections. In this study, the measurement of the effectiveness of traffic conditions was done using average travel time, and the error percentage of average absolute estimation was 13.9% for a traditional point-based detection model. The Vehicle Infrastructure Integration (VII) probe data-based model of (Li et al. 2008) performed better when compared with his previous models, although the penetration rate of probe vehicles was 5%.

The evaluation of performance of travel time estimation models was done by (Oh et al. 2010), through utilization of GPS and V2V communications during an incident and under normal traffic conditions. This study investigated functional requirements such as V2V communication range, equipped vehicle market penetration rate, and aggregation interval of travel time. The effectiveness of connected vehicle applications or real time traffic information systems is assessed by the utilization of speed estimation error of connected vehicles by deploying probe vehicles. (Argote et al. 2011) used connected vehicle data to generate estimation methods as a measurement of effectiveness and the determination of penetration rates required for each of the measurement of effectiveness such as delay, the number of stops, average speed, and acceleration noise. The average vehicle speed was determined through the total travel distance and total spent time on connected vehicles. When the penetration rate is greater than 50% within an error of 10%, average speed can be determined accurately. (Li et al. 2007) generated a probe sample size model for the estimation of the average link speed by the utilization of diverse probe vehicle penetration levels, intervals of speed estimation, and intervals of probe reports.

This study found that the average link speed had higher accuracy when there was an increase in the probe vehicle penetration rate and a decrease in the interval of probe reports.

The application of connected vehicle technology can be used for the reduction of delay at intersections by using applications for signal control. (Hu, Park, and Parkany 2014) developed a new method of TSP (transit signal priority) by utilizing connected vehicle technology that relied on two-way communication among traffic signal controllers and transit buses. The results of the VISSIM simulation study showed that wherever the congestion level was low, the TSP model was successful in reducing bus delays by up to 90% when compared to the non-TSP conditions. It is noteworthy that the benefits derived from the TSP model were reduced when there was an increase in the levels of congestion. In another study by (Wang et al. 2014), a cooperative bus priority system was assessed within the connected vehicle environment. It was found that due to the utilization of real-time traffic information derived from connected vehicles, there was a decrease in the number of stops and travel time though the optimization of bus speed, bus priority signal timings, and bus stoppage time at bus stops.

Connected vehicle technology was utilized by (Li et al. 2013), for the real-time estimation of queue length from signal timing data and probe trajectory with loop detector data. The queue length's estimation accuracy was evaluated under diverse market penetration rates. When the penetration was 50%, the MAPE (mean absolute percentage error) was below 18% for queue length. It is noteworthy that when the penetration rate was low (10%), MAPE increased to approximately 60%. (Christofa, Argote, and Skabardonis 2013) presented a study on methods of signal control strategy and queue spillback detection for queue spillback mitigation. Connected vehicle derived data was used to stop spillback

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occurrence within the queue spillback detection's next cycle. For accurate queue detection, a minimum of 20% of penetration rate was required. (Goodall, Park, and Smith 2014) utilized connected vehicle technology for the estimation of position on unequipped vehicles on an arterial road that is signalized. The study results proved that the connected vehicle mobility performance can be enhanced in a connected vehicle environment with low penetration due to the availability of the location algorithm for location estimation of unequipped vehicles.

2.2.6 Connected Vehicles and the Impact on the Environment

One of the objectives of research and development in connected vehicles is the improvement of the environment, and connected vehicle's environmental impacts are used to evaluate the performance of connected vehicle systems and applications (Kim 2015). Three optimization strategies for the minimization of energy-based consumption were tested by (Bhavsar et al. 2014), based on diverse information available with the utilization of connected vehicle technology. In the case study network, a linear relation was found between the penetration rate of connected vehicle technology supported plug-in hybrid electric vehicles and energy savings. Fuel consumption dropped by 30% to 35% when headway information and signal timing in peak hour volume were provided with a 30% penetration of connected vehicle technology. An eco-cooperative adaptive cruise control application was developed by (Kamalanathsharma and Rakha 2016), which minimizes consumption of fuel in the signalized intersection's vicinity. V2I communications were utilized to receive timing and signal phasing data for the prediction of vehicle trajectory. Using this application resulted in a 5% to 30% decrease in consumption of fuel in the

signalized intersection's vicinity. A study to investigate the feasibility of eco-lane applications was conducted by (Ahn and Rakha 2014) to improve environmental impacts by the application of strategies for lane management. Several algorithms of eco-lane and speed harmonization application were evaluated in this study. (Ahn and Rakha 2014) found that eco-lane systems have the potential to reduce fuel consumption and improve air quality, due to a reduction in total delay and average vehicle travel time.

2.3   Autonomous Vehicles

The levels, applications, and potential advantages and disadvantages of autonomous vehicles are described in detail in this section.

2.3.1   Levels of Autonomous Vehicles

NHTSA in its 2013 report "Preliminary Statement of Policy Concerning Automated Vehicles" underlined the following levels of autonomous vehicles (NHTSA 2013):

Level 0 – No Automation: Certain driver support/ convenience systems are present in the vehicle, but the driver has no control over braking, throttle or steering. The complete and exclusive responsibility of the vehicle lies with the driver at all the times and he/she is also accountable for monitoring the situation on the road.

Level 1 – Function-specific Automation: Particular control functions are automated such as automated parallel parking, lane guidance, and cruise control. For overall vehicle control, the driver is completely responsible and engaged in driving with his or her hands are on the steering wheel and foot on the pedal throughout the driving.

Level 2 - Combined Function Automation: At level 2, several integrated control functions like adaptive cruise and control lane centering are automated. The driver has the liability to monitor the roadway and they are required to be available at all times to take control. But under some situations they may not be completely engaged in the operation of the vehicle, with both hands off the steering wheel and foot off the pedal at the same time.

Level 3 - Limited Self-Driving Automation: In level 3, under certain conditions, the driver may let the vehicle take control of all functions critical for safety. Moreover, when the driver is in control of driving, safety is monitored by the vehicle.

Level 4 - Full Self-Driving Automation: In level 4, the system of the vehicle performs all the functions of driving under all normal types of roads, environmental conditions, and ranges of speed (NHTSA 2013).

As per these definitions provided by (NHTSA 2013), there is a decrease in driver engagement and traffic monitoring on the roadway with an increase in the levels of automation. From level 0 to level 4, the distribution of control functions of the vehicle among the driver and the vehicle ranges from:

(a) complete driver control,

(b) driver control is system augmented/ assisted,

(c) sharing of authority with a transition time which is short,

(d) shared authority with transition time which is sufficient and

(e) full automated control.

Table 1 presents a detailed comparison with examples provided by (Kockelman et al. 2017) which will be elaborated upon in the forthcoming section.

Table 1. Comparison of different Automation Levels

	Vehicle Controls*	Traffic and Environment (Roadway) Monitoring	Examples
L0	Drivers are *solely responsible* for all vehicle controls.	Drivers are solely responsible; System may provide driver support/convenience features through *warning*.	Forward collision warning (FCW); lane departure warning; blind spot monitoring; automated wipers, headlights, turn signals, and hazard lights, etc.
L1	Drivers have overall control. Systems can *assist or augment* the driver in operating one of the primary vehicle controls.	Drivers are solely responsible for monitoring the roadway and safe operation.	Adaptive cruise control; automatic braking (dynamic brake support and crash imminent braking); lane keeping; electric stability control (ESC).
L2	Drivers have *shared authority* with system. Drivers can cede active primary control in certain situations and are physically disengaged from operating the vehicles.	Drivers are responsible for monitoring the roadway and safe operations and are expected to be *available* for control *at all times* and *on short notice*.	Adaptive cruise control combined with lane centering.
L3	Drivers are able to *cede full control* of all safety-critical functions *under certain conditions*. Drivers are expected to be available for occasional control, but with *sufficient transition time.*	When ceding control, drivers can *rely heavily on the system* to monitor traffic and environment conditions requiring transition back to driver control.	Automated or self-driving car approaching a construction zone and alert the driver in advance.
L4	Vehicles perform *all safety-critical driving functions* and monitor roadway conditions for an entire trip. *Drivers* will provide destination or navigation input, but are *not expected to be available for control* at any time during the trip.	System will perform all the monitoring.	Driverless car.
L0 to L4= Level 0 to Level 4 automation; Vehicle controls refer to braking, steering, throttle control, and motive power.			

Source: (Kockelman et al. 2017), adapted from (NHTSA 2013))

2.3.1.1 Level 0 Technologies

The autonomous system has no control over the vehicle and just issues warnings.

Forward Collision Warning

Forward collision warning has been described by the National Highway Traffic Safety Administration as "one intended to passively assist the driver in avoiding or mitigating a rear-end collision via presentation of audible, visual, and/or haptic alerts, or any combination thereof" (NHTSA 2013). A forward collision warning system has the capability of detecting a vehicle in front using sensing technologies like LIDAR, radar, and cameras. After processing and analyzing sensor data, an alert is provided if there is a possibility of collision with another vehicle (Kockelman et al. 2017).

Blind Spot Monitoring

Blind spot monitors can be categorized into active and passive. The blind spot monitor that is active utilizes a camera or radar to detect when a different vehicle is in the blind spot of the discussed vehicle, and the driver of the vehicle is notified if a vehicle is detected (Kockelman et al. 2017). (Reports 2019) noted that the effectiveness of the blind spot technologies is reduced under specific conditions like inclement weather.

Lane Departure Warning (LDW)

The main goal of Lane Departure Warning is to prevent a vehicle from exiting its lane in an unsafe manner, and it is similar to blind spot monitoring. It utilizes a camera to detect lane markings and alerts the driver if the vehicle starts to move away from its lane, provided the turn signal is not on. The system releases a visual alert and an audible sound alert, and sophisticated applications of LDW have the capability to take the steering wheel's active control to rectify the direction of the vehicle automatically, which falls under level 1 automation (Kockelman et al. 2017).

Traffic Sign Recognition (TSR)

TSR recognizes and shows forthcoming traffic signs that might be missed by the driver. TSR operates with the aid of a camera to find forthcoming traffic signals and has a system for traffic sign recognition that matches the signs recorded by the camera, which are then shown to the driver. These systems have been created with high precision for the detection of traffic signs and can be further complemented by information from navigation systems and road maps (MobilEye 2015).

Driver Monitoring Systems (DMS)

Driver monitoring systems are safety applications used while driving to keep track of the inattention of the driver, which may be in the form of distraction or fatigue. The application of DMS can significantly reduce crashes caused by distraction and inattention. The characteristics of the vehicle such as speed, acceleration, position, seat belt use, seat occupancy, etc. are monitored by DMS. The data being monitored can be utilized in various ways such as:

(a) Communicate and alert the driver and drivers in the surrounding vehicles regarding abnormal driving characteristics, roadway safety concerns, and potential collisions.

(b) The recorded data can be used for investigation in case of a crash.

(c) DMS can be utilized to determine the cost or liability if a crash happens. A normal DMS, for recording the aptitude of drivers, uses cameras and infrared sensors to track any detection of inattention or drowsiness during the driving period (Kockelman et al. 2017).

2.3.1.2 Level 1 Technologies

The driver shares vehicle control with the autonomous system.

Adaptive Cruise Control (ACC)

A majority of the Adaptive Cruise Control systems utilize laser or radar headway sensors and processors for digital signals for determination of speed and distance of the vehicle in front (Honda-Motor 2015). Some auto manufacturers such as Subaru favor an optical system using stereoscopic cameras. These systems depend on two sensors which employ infrared detection namely:

(a) cut in sensor and

(b) the sweep long range sensor. These sensors emit infrared light beams that are reflected back by the vehicles in the front and are captured by the receiver (Kockelman et al. 2017).

Automatic Emergency Braking (AEB)

Automatic Emergency Braking (AEB), also referred to as forward collision avoidance technology, has the capability to reduce the severity and volume of collisions by automatically applying the brakes when there is a prediction of imminent collision. AEB systems are comprised of

(a) sensors which monitor and classify objects inside the range,

(b) control systems which portray the data that is sent by the sensors, and

(c) an actuation system for automatic braking which slows or stops the vehicle physically (Kockelman et al. 2017).

Lane Keeping

To stop a vehicle from wandering out of a lane while travelling on high-speed roads, both lane centering and lane keeping technologies are utilized. At first, lane keeping was invented to rectify the vehicles' position by slight braking with the aim of cautioning the driver. Later, lane centering technology was developed to retain a center position in the

lane by utilizing electronically controlled steering (Kockelman et al. 2017). This technology employs a camera, located on the vehicle's windshield and having the capacity to distinguish both yellow and white lines, to watch the road's lane markers. In a situation where the camera finds that the driver is starting to leave the lane without using the turn signal, a warning sound will be used to alert the driver, and later electronic power steering will be activated to steer the vehicle back to the center of the lane (Toyota-Motors).

2.3.1.3 Level 2 Technologies

The autonomous system takes control of the steering wheel, accelerator, and brakes but the driver must still be ready to take control in certain situations.

High-Speed Automation

General Motors developed a system of "super cruise" that has the capability to provide full-speed range Adaptive Cruise Control in addition to lane keeping. Radars and cameras are employed for sensing, and this system has the capability to automatically accelerate, steer, and apply brakes in highway driving. The driver may remove his or her hands from the steering wheel until the driver wants to switch lanes. However, the system cannot manage poor road conditions, or when some added problem occurs (Kockelman et al. 2017). A system developed by Nissan cuts the inconsistencies among the actual and intended path automatically, and Nissan has claimed that this system reduces driver fatigue by reducing small steering adjustments. The system developed by BMW provides longitudinal and lateral control along with response to merging traffic from the right as well as the ability to change lanes when the conditions are safe (Kockelman et al. 2017).

Automated Assistance in Roadwork and Congestion (ARC)

The ARC system was presented by the Highly Automated Vehicles for Intelligent Transport (HAVEit) project (AIDE-EU 2008) of Europe. According to (Chitor et al. 2010), the ARC system has the goal to facilitate automated driving within a work zone to assist the vehicle's driver in tough traffic conditions like driving through narrow lanes or work zone areas. This system considers that lanes might not be precise, and it utilizes several additional objects like beacons, trucks, and guide walls (Kockelman et al. 2017).

2.3.1.4 Level 3 Technologies

In this level, the driver is not required to supervise the vehicle directly and the driver is merely required for control, with some level of notice with ample time for transition.

On-Highway Platooning

Vehicles in a platoon have a shorter headway among them. On-highway platooning technology permits the investigation of potentially allowing a human driver to drive the lead vehicle which is pursued by a platoon of vehicles that are fully automated. SATRE from Europe developed a prototype of this technology by utilizing Volvo trucks and cars (Kockelman et al. 2017).

2.3.1.5 Level 4 Technologies

The driver cedes full car control to the autonomous system and doesn't need to pay attention at all.

Emergency Stopping Assistant

An emergency stopping switch is a safety feature that is deployed in the vehicle to stop the vehicle's operation if there is an emergency that renders the driver unable to drive..

This feature is mainly present in railway or train engineering in the form of a pedal or lever which should be engaged for the vehicle to stay in an active mode and which alarms the driver if it is disengaged and causes the vehicle to slow to a stop or shut down. This feature has been deployed in the Google self-driving car; when applied the car will automatically remove all capabilities of self-driving and come to the human mode of driving (Kockelman et al. 2017).

Automated Valet Parking

The automated valet parking feature allows certain vehicles to park themselves automatically, once the parking spot has been found by the vehicle's driver. These vehicles have a technology referred to as Advanced Parking Guidance Systems (APGS) or Intelligent Parking Assist Systems (IPAS). Fully autonomous self-parking valet systems make it possible for the vehicle to be left at the parking garage's entrance, pinpoint a parking spot, park itself, and come back to pick up the driver when called, all of which is done without human interaction. As per (Lavrinc 2013), auto makers like Volvo, BMW, and Audi have invented these systems and are in the testing phase under controlled settings.

The operational underpinnings of an autonomous vehicle are highlighted in Figure 1. (Thierer and Hagemann 2015) pointed out that researchers have been working toward identifying an optimal approach as there are concerns related to the interoperability of diverse autonomous vehicle technologies.

CAMERAS

The most cost-effective type of sensor. Camera data is very good for detecting the texture and color of lane markings, signs and traffic lights.

LIDAR

A laser-based sensor that can accurately detect the shapes of cars, pedestrians, curbs, undrivable areas and other structures.

RADAR

Detects obstacles' positions and speeds. Radar outputs are usually not informative enough to estimate obstacle shape.

CPU

Four computer cores installed in the car's trunk analyze the data from sensors. The computer takes control of the car when the driver activates a switch.

Data collected by sensors

| Shape | Color | Speed | Distance | Shape | Color | Speed | Distance | Shape | Color | Speed | Distance |

Location of sensors

GPS antenna

Computer

How the car performs on the road

Planning

The vehicle automatically generates a route from the user's current location to the desired destination, factoring in speed limits, traffic lights, stop signs, lane changes, and other information.

Pedestrians and bicyclists

The vehicle can detect pedestrians crossing the road and stop for them. It will detect bicyclists as well and keep a safe distance while looking for an opportunity to change lanes or go around.

Driving

The vehicle is able to keep itself in the right lane and at a safe distance between cars in city traffic. It can change lanes if it needs to merge to exit or if a neighboring lane is faster. The vehicle is also able to avoid on-road obstacles.

Intersections

The vehicle can navigate intersections with stop signs and traffic lights. At a four-way stop, it can decide when it should proceed. At traffic lights, the vehicle will stop on red and go on green.

Figure 1. Autonomous Car by Carnegie Mellon (source: Gibson, 2017)

2.3.2   Core Competencies of Autonomous Vehicles

Researchers have shown great interest in congested urban environments as a result of vehicle density, where location-specific traffic rules are required to be followed. The catalysis of the research work in autonomous vehicle driving on urban roads for several

organizations was done by The DARPA Urban challenge (Buehler, Iagnemma, and Singh 2009) and the V-Charge project (Furgale et al. 2013). According to (Pendleton et al. 2017), autonomous vehicle's core competencies can be largely described by three classifications, namely:

(a) Perception competency defines the capability of the autonomous vehicle to gather information and pull relevant environmental knowledge. Environmental perceptions refer to the development of the environment's contextual understanding like the location of obstacles, road signs, or marking detection, and the categorization of data based on their semantic meaning. The capability of the vehicle to establish its location in the environment is called localization.

(b) Planning competency implies the process of working out purposeful decisions with the objective of realizing the vehicle's higher order objectives, which entail bringing the vehicle from the starting point to the end point while carrying out obstacle avoidance and optimization over designed heuristics.

(c) Control competency implies the capability of the vehicle to carry forward actions in a planned manner produced by processes of higher order. The interaction among these competencies and the interaction of the vehicle with the environment have been portrayed in Figure 2 (Pendleton et al. 2017). Moreover, to accomplish additional improvements in the domain of perception and/or planning by the application of vehicle cooperation, V2V communications can be leveraged (Pendleton et al. 2017).
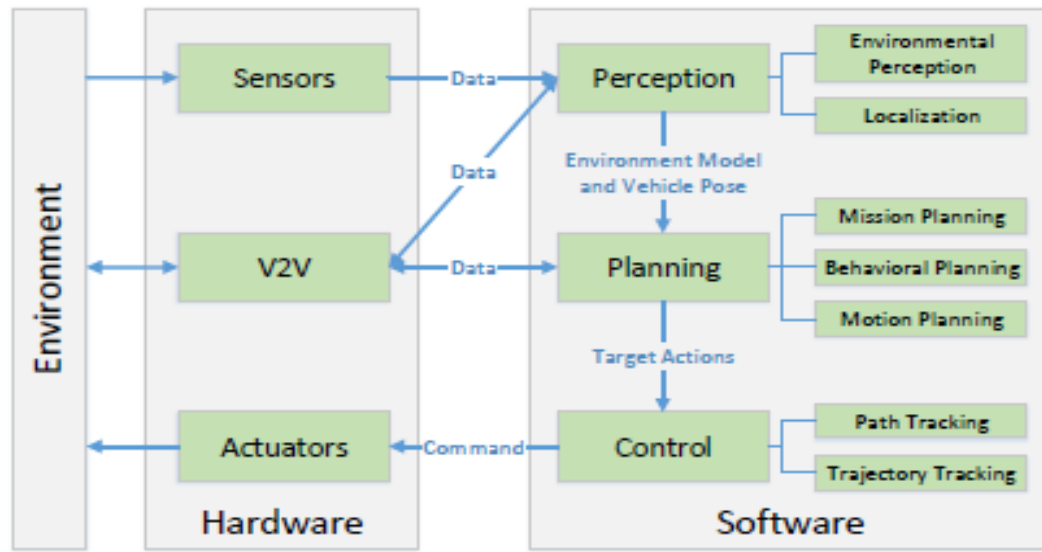
Figure 2. A typical autonomous vehicle overview, showcasing core competencies

Source: (Pendleton et al. 2017)

2.3.2.1 Perception

(Pendleton et al. 2017) stressed that environmental perception is the primary function that enables an autonomous vehicle and provides it with critical information about the external environment which includes free areas that are drivable, locations of the contiguous obstacles, their velocities, and even the future states of such obstacles. Depending on the implementation of the sensors, the perception of the environment can be comprehended by utilizing cameras, LIDARs, or a fusion of both devices. The conventional sources for environmental perception may also entail the application of radars of both short and long range as well as ultrasonic sensors. Irrespective of the sensors used, two central components of perception task are:

(a) on-road object detection and

(b) surface extraction (Pendleton et al. 2017).

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LIDAR

LIDAR signifies a light detection and ranging device. It emits light pulses in millions per second in a pattern which is well designed. LIDAR has the capability to generate an environment's dynamic map in a three-dimensional format. LIDAR is the central component of detection of objects for a majority of the autonomous vehicles that are currently available (Pendleton et al. 2017). A representation is shown in Figure 3.
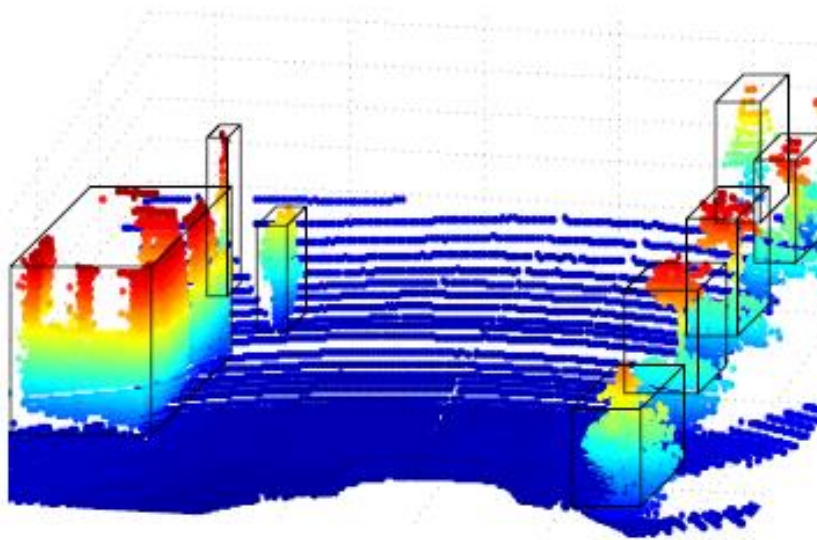
Figure 3. An ideal detection result from a 3D LIDAR

Source: (Pendleton et al. 2017)

Vision

According to (Pendleton et al. 2017), in an autonomous vehicle environment, the vision system generally involves on-road object detection as well as road detection. Road detection incorporates two components, namely:

(a) road surface detection and

(b) lane line marking detection.

Road Detection

(a) Road Surface Detection is a prerequisite for any type of control operation and path planning, and it provides information to the autonomous vehicle about the free space location where the vehicle can drive without colliding. Road surface detection methods can be classified into:

(1) Feature or cue-based detection—they first recognize feature points or patches in the original image, relying on the features which are predefined such as the Histogram of Oriented Gradients (HOG). The feature may relate to the disparity in the context of stereo images. Depending on the features found, algorithms of segmentation or model fitting type are applied in order to identify road surfaces.

(2) The feature or cue learning based methods also extract a collection of features that are related to image patches or pixels and they train a classifier relying on the features to allocate a road or non-road label to the patches of pixel.

(3) Deep Learning: The top five road detection performances belong to the class of deep learning as shown in a popular database KITTI, developed by (Fritsch, Kuehnl, and Geiger 2013). As stated by (Ranft and Stiller 2016), the framework of deep learning has become popular in contemporary times, specifically in the development of appropriate processors and their implementation (Jia et al. 2014).

(b) Lane Line Marking Detection involves the identification of the road lane line markings and estimates the position of the vehicle with respect to the lines detected. Such information can provide vehicle position feedback to the control system of the vehicle. In the past few decades, a lot of research has been done in this domain (Thorpe et al. 1987) but it has not been completely solved until now and it remains a challenge to the researchers. This is due

to the vast amount of uncertainties in road singularities and real conditions of road traffic (Labayrade, Douret, and Aubert 2006) that incorporate tree and car shadows, light condition variations, lane markings which are worn out and other markings on the road like warning text, zebra crossing, and directional arrows (XINXIN 2016).

On-Road Object Detection

Vehicle and pedestrian object classes are the main concerns of on-road object detection. The KITTI database for car, cyclist, and pedestrian detection has listed the top entries and state of the art methods, all of which are found to be based on deep learning schemes. A superior performance has been displayed by deep learning when compared with feature based or conventional learning approaches in the field of object detection (Pendleton et al. 2017)

Localization

Localization is a fundamental capability which enables autonomous driving and is concerned with the problem of the determination of the vehicle's position and an estimation of its own motion. Yet on most occasions it is very challenging and not practical to estimate the vehicle's precise orientation and position; hence the problem of localization is often stated as a problem of position estimation (Kelly 2013). The utilization of Global Positioning Systems in localization demands dependable service signals from external satellites. The described method is only dependable when the dead reckoning odometry and GPS of the vehicle is dependable, which may need accurate and expensive sensors. Some instances of trouble spots are underground tunnels, urban canyons, and indoor environments in which precise signals are blocked by tall buildings (Pendleton et al. 2017).

2.3.2.2 Planning

In a leap from the early autonomous or self-driving vehicles, the DARPA Urban Challenge of 2007 showcased broader capabilities (Buehler, Iagnemma, and Singh 2009) with which it was proven that a better and intricate planning framework can facilitate a self-driving vehicle to efficiently manage a diverse variety of scenarios in an urban context. The winning entries of Carnegie Mellon, Stanford, and Virginia Tech with their models named the BOSS, JUNIOR, and ODIN and many other entries deployed a comparable hierarchical planning framework which included:

(a) Mission planner: Mission planning is normally performed by the employment of a graph search through a directed graph network that shows the path/road network connectivity.

(b) Behavioral planner: It aids in decision making by ensuring that the vehicle follows all the road rules that are stipulated and interacts with diverse agents in a safe and conventional way while progressing incrementally through the predefined route of the mission planner, which may be realized by combining the placement of virtual obstacles, local goal setting, regional heuristic cost adjustment, and drivable region bounds adjustment.

(c) Motion planner: It refers to a process of deciding action sequences to reach an expected goal while avoiding obstacles and collisions. Motion planners are normally evaluated and compared relying on their completeness and computational efficiency (Pendleton et al. 2017).

2.3.2.3 Control

Motion control is the method of conversion of intentions into actions and it is crucial for the execution competency of an autonomous vehicle. The main purpose of

control is to perform planned intentions by giving inputs to the level of hardware which will lead to preferred motions. The mapping of the real word is done by controllers in terms of energy and forces. In an autonomous vehicle, the planning algorithms and cognitive navigation are generally related to the position and velocity of the vehicle in the context of its environment. Control system measurements can be utilized in the estimation of the behavior of the system, and the controller can react to alter the dynamics and reject disturbances to the system with the desired state (Pendleton et al. 2017).

2.3.3   Autonomous Vehicles - Potential Advantages and Disadvantages

Several other studies have identified the potential positive impacts of autonomous vehicles, as described below.

Table 2. Autonomous Vehicles – Positive Impacts

Positive Impact	Source
Improved public health and safety	(Dizikes 2010, Furda et al. 2010, Silberg et al. 2012, Anderson et al. 2014, Bierstedt et al. 2014, Fagnant and Kockelman 2014, Fraedrich and Lenz 2014, Flämig 2015, Somers and Weeratunga 2015)
Better quality of life and productivity	(USDoT , Billings 1996, Shaheen, Cohen, and Roberts 2006, Dizikes 2010, Silberg et al. 2012, Lutin, ITE, and Kornhauser 2013, Anderson et al. 2014, Hendrickson, Biehler, and Mashayekh 2014, Cyganski, Fraedrich, and Lenz 2015, Flämig 2015, Somers and Weeratunga 2015)

Reduced energy and environmental impact	(USDoT , Folsom 2011, Silberg et al. 2012, Anderson et al. 2014, Fagnant and Kockelman 2014, Howard and Dai 2014, Guerra 2016)
Reduction in congestion	(Furda et al. 2010, Folsom 2011, Silberg et al. 2012, Howard and Dai 2014, Guerra 2016)
Cost saving related to roadway expansion and improvements	(Folsom 2011, Silberg et al. 2012, Lutin, ITE, and Kornhauser 2013, Anderson et al. 2014, Fagnant and Kockelman 2014, Howard and Dai 2014, Le Vine and Polak 2014, Somers and Weeratunga 2015, Guerra 2016)
Reduction of the total cost of transportation or the proportion of income spent on transportation	(USDoT , Silberg et al. 2012, Anderson et al. 2014, Bierstedt et al. 2014, Fagnant and Kockelman 2014, Fraedrich and Lenz 2014, Howard and Dai 2014, Cyganski, Fraedrich, and Lenz 2015, Flämig 2015, Somers and Weeratunga 2015, Guerra 2016)
Accommodated car-sharing services	(Shaheen, Cohen, and Roberts 2006, Silberg et al. 2012, Dutzik and Baxandall 2013, Lutin, ITE, and Kornhauser 2013, Anderson et al. 2014, Le Vine and Polak 2014, Flämig 2015, Somers and Weeratunga 2015)
Enhanced accessibility,	(USDoT , Cheon 2003, Silberg et al. 2012, Lutin, ITE, and Kornhauser 2013, Anderson et al. 2014, Bierstedt et al. 2014,

mobility, and travel options	Fagnant and Kockelman 2014, Flämig 2015, Somers and Weeratunga 2015, Guerra 2016)

In addition, a number of impacts associated with the deployment of autonomous vehicles were identified by (Isaac 2016). The potential positive impacts identified include:

(a) decline in costs and enhancement of public safety,

(b) gains in mobility for certain population such as the disabled and elderly,

(c) reduction in congestion,

(d) lowering of demand for parking,

(e) increased options for personal mobility and enhanced safety and

(f) increase in the capacity of roads.

(Isaac 2016) identified potential negative impacts of autonomous vehicles as:

(a) higher vehicle miles travelled,

(b) job loss for taxi drivers, commercial vehicle operators and

(c) spread of urban sprawl. Even though autonomous vehicles are expected to make driving cheaper and easier, they may increase the dominance of vehicles, vehicle miles travelled (VMT), and vehicle trips and can have a negative impact on other modes of transportation such as biking and walking (Cheon 2003, Dutzik and Baxandall 2013, Anderson et al. 2014, Bierstedt et al. 2014, Fagnant and Kockelman 2014, Hendrickson, Biehler, and Mashayekh 2014, Guerra 2016).

2.4 CAVs - Connected and Autonomous Vehicles

According to (Ma et al. 2017), Connected and Automated vehicles (CAVs) are an outcome of the integration of both connected vehicle (CV) and autonomous vehicle (AV)

technologies which enable them to reach the next level of efficiency and sophistication by allowing autonomous control of the vehicle as per real-time information provided. If properly deployed, CAVs have the potential to achieve speed harmonization effectively. Moreover, (Talebpour, Mahmassani, and Hamdar 2013) added that CAVs also aim to increase safety, mobility, and comfort and decrease consumption of fuel while contributing to emissions reduction. CAVs are an achievement of technology in developing synergy among robotics, artificial intelligence (AI), information technologies, and automotive design. This achievement has the potential to empower a car to take control and make driving accurate, make decisions that are properly calculated, and interact with traffic flows and urban environments (Nikitas et al. 2017). A collaborative platform is provided by CAV technology that can use the information received to an optimal level for improving traffic operations.

Yet even after an enormous amount of interest and investment in the development of CAVs, according to (Nikitas et al. 2017), several obstacles still remain that must be overcome to make this technology a successful reality. The technology for CAVs is still not completely developed and it is necessary to make more breakthroughs for supporting paradigm shifts in mobility. Moreover, they need to be developed to deal with unexpected and complicated circumstances related to detection and identification of objects, and until then CAVs may not function properly in the contemporary road network. There is a need for friendlier road transport infrastructure that will provide an environment which is fit for their utilization, which requires an intensive investment in infrastructure. Traffic conditions with a mix of situations in which the road is shared by CAVs, partially autonomous vehicles, and human-driven vehicles can create issues. Hence, there is a requirement to

plan how to address a transition from human-driven to machine-driven vehicles (Nikitas et al. 2017).

2.5 Driving Simulators

In contemporary times, CAVs have become a hot topic of research in both the domain of transportation and control. Some of the areas which have been extensively researched are related to the impact of CAVs on:

(a) traffic flow (Lioris et al. 2017, Wang, Li, and Work 2017),

(b) traffic externalities like road accidents (Kalra and Paddock 2016) and fuel consumption (Zhao et al. 2016) and

(c) travel behavior (Agatz et al. 2016).

Driving Simulators (DS) are generally used to observe a driver's response to non-existent functionalities or situations which cannot be tested safely in real vehicles (Louw et al. 2017, Louw and Merat 2017). As per (Hou et al. 2015), generally a DS is employed to study the driving behavior of humans for a diversity of transportation scenarios. In a low-cost and safe environment, DS provides human-in-loop capability for the evaluation of technologies which are yet to be proven. Within the diverse area of study on driving support systems, the vehicle's longitudinal control is among the aspects which have been addressed the most. This is applicable to various tasks related to driving such as Intelligent Speed Adaptation (ISA), which generally works on free-flow scenarios while Automated Emergency Breaking (AEB) and Adaptive Cruise Control (ACC) work in car-following scenarios. Automation and assisting solutions, which are related to scenarios of car-following, are among the most effective with regard to safety as they are related to spacing

and speed (Jeong and Oh 2017). To test CAV effectively in car-following by means of a DS, verifying the variables related to safety in a virtual environment represents a fundamental activity, since it is crucial to achieve quantification of hazards and specifically address whether the driver's behavior is consistent with reality. It is noteworthy that this activity can be related to the general field of the behavioral validity of driving simulators (Godley, Triggs, and Fildes 2002). In related literature, there are several examples which are aimed at evaluating the simulator validity with respect to some specific tasks like cognitive load (Klüver et al. 2016) and speed (Godley, Triggs, and Fildes 2002).

This study uses a driving simulator to understand and analyze the effects that connected and autonomous vehicles have on driver behavior in diverse road conditions including complete streets. The parameters selected for connected vehicles will include Spot Weather Impact Warning, Reduced Speed/Work Zone Warning, Curve Speed Warning, and Queue Warning. For autonomous vehicles, the parameters to be used will be Restricted Lane Warnings, Audible Forward Collision Warning, Traffic Sign Recognition, and Blind Spot Assist. These parameters have been selected since the focus of the research is on the safety features of CAVs, which are currently a concern. This study will use the DS tool UC-win/Road (FORUM8) which is a Virtual Reality (VR) environment that allows the driver to navigate in a space which is three dimensional (3D). The environment, along with visualization tools and traffic simulation, uses ground texture maps and has the capability to include building images in 3D. The methodology and evaluation process will be presented in the forthcoming sections.

Chapter 3. Methodology

This chapter presents the tools and research methods used to conduct driver behavior analysis in this study. This research data was collected as part of a study funded by Morgan State University's Urban Mobility and Equity Center (UMEC), to evaluate driver behavior while using CAV technology. While the funded study provided the basis for this research, it delves only into the evaluation aspect of the CAV applications. This research takes the funded study further, by developing each of the CAV applications in a driving simulator environment, while also developing a tool for data extraction and analysis, using the driving simulator and the eye tracking device.

3.1 Driving Simulator

This study utilizes a medium-fidelity full-scale driving simulator, located at the Safety and Behavioral Analysis (SABA) Center at Morgan State University, to analyze driver behavior in response to CAV applications. The simulator is an advanced computer-based driving simulator, a product of Forum8 Company (FORUM8), based in Japan. The simulator has the capability of creating and designing network elements such as traffic signals, different terrains, road alignments, signage, traffic generation, and weather conditions as well as static objects such as three-dimensional buildings and trees. This driving simulator differs from many of the existing driving simulators because a realistic network of actual cities can be created, and drivers are free to choose their own route to reach their respective destinations. The simulator has the capability to capture data such as steering wheel control, braking, acceleration, travel times, lane changing information,

traffic mix, and speed, among others. A representation of the driving simulator is shown in Figure 4.

Figure 4. Driving Simulator at the SABA Center, Morgan State University

3.2 Survey Questionnaires

Two survey questionnaires (Refer to Appendix A); a pre-simulation sociodemographic survey and a post-simulation, driving simulation related experience surveys were developed by the author for this study. Before starting the driving simulation session, all participants filled out a socio-demographic survey. The survey was engineered to extract information regarding age, gender, education level, type of car driven, current employment status, driving license type, annual household income, and the size of household. Additional questions determined knowledge about CAVs, past driving experience with CAV applications, their trust in such applications and willingness to pay for such applications. A post simulation survey was administered in which participants were asked about their experience with the study, and questions related to CAV applications were reiterated, post driving. This information was used during analysis to

investigate the possibility of a correlation between driving behavior using different CAV applications and the socio-demographic characteristics.

3.3 Study Network

The VR-Design studio software developed by (FORUM8) was used to develop a virtual network of downtown Baltimore in Maryland. The idea behind choosing this location was that since the majority of the participants are familiar with the downtown Baltimore area, the virtual network creates a more realistic driving experience for them. Two scenarios were designed by the author in this virtual network, as shown in the study area map in Figure 5.

Figure 5. Study Area

3.4 Scenario Design

The following sections describe the events designed within two scenarios involving CAV applications and two scenarios without the applications, i.e., baseline scenarios.

3.4.1 Pedestrian Collision Warning (PCW)

This application can utilize either V2P technology or AV technology with the aid of wireless signals as shown in Figure 6.
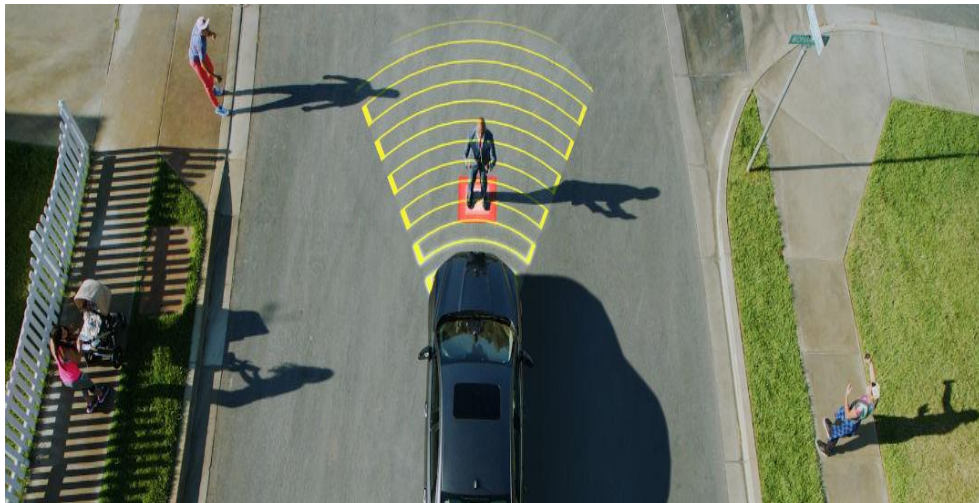
Figure 6. Pedestrian Alert

For this event, a major one-way four-lane road, Pratt Street in downtown Baltimore with a speed limit of 30 mph, was designed using the VR-Studio software. Pratt Street has a lot of foot traffic and as such would be an ideal location to evaluate a PCW system, when encountering a jaywalking pedestrian. A level of service B, light traffic, was used in these scenarios so that the participants are not slowed by high traffic, which may have been the case otherwise, creating issues evaluating the PCW system. Pratt Street is a complete street, with a 14-foot-wide shared bus and bike lane, three 12-foot lanes and wider sidewalks. For both the baseline and PCW system scenarios, as soon as the participating driver crosses a

waypoint, a jaywalking pedestrian appears at an approximate distance of 40 meters from

the waypoint. The distance of 40 meters was chosen based on visibility, traffic conditions,

road geometry, and, most importantly, NHTSA guidelines on stopping distance to avoid a

collision. According to the guidelines, to avoid a collision the initial gap between the

vehicle and the pedestrian should be greater than the stopping sight distance of the vehicle.

It is expressed as (NHTSA 2016):

Equation 1: Stopping Sight Distance

$$D_0 > \frac{-V_{vi}^2}{2a_v}$$

where, D_0 is the initial gap between the vehicle and the pedestrian, V_{vi} is the initial speed

and a_v is the acceleration/deceleration of the vehicle. A snapshot for this event is shown in

Figure 7.

Figure 7. A snapshot of the driving simulator environment

In this study, to evaluate the PCW system, the pedestrian always appeared at a

distance of 40 meters from the simulation vehicle. As prior studies have evaluated the

drivers' perception or visibility of an object at different distances, the intent of this study

is to evaluate driver behavior in the presence of the PCW system, which is capable of detecting the pedestrian, only at a certain distance from the vehicle, 40 meters in this case.

3.4.2 Red Light Violation Warning (RLVW)

This application utilizes V2I technology and warns the driver of an impending red-light infraction if the vehicle is above a certain speed near a signalized intersection and the light is about to turn red. For this event, the two-lane highway, Interstate 395, which has a speed limit of 30 mph as it approaches the Conway Street signalized intersection near downtown Baltimore, was recreated. The lanes are 12 feet wide with a 12-foot raised median separating the opposing lanes with a light traffic flow with a level of service B. In this event, when the participant reaches an arbitrary distance of 50 meters from the traffic signal stop line, the traffic light changes from green to yellow. The distance of 50 meters was chosen based on topography, road geometry, and, as mentioned previously, based on NHTSA guidelines on stopping distance to avoid colliding with vehicles entering the intersection. The equation is stated in Equation 1. A snapshot of this event is shown in Figure 8.

Figure 8. A snapshot of the driving simulator environment

To evaluate the RLVW system, the participant always received the RLVW as soon as they enter the dilemma zone, at a distance of 50 meters from the traffic signal stop line, when the light changes from green to yellow.

3.4.3   Forward Collision Warning (FCW)

This application can utilize both V2V or AV technology to warn the driver of an impending collision with a vehicle or object directly in its path. The three stages are illustrated in Figure 9.
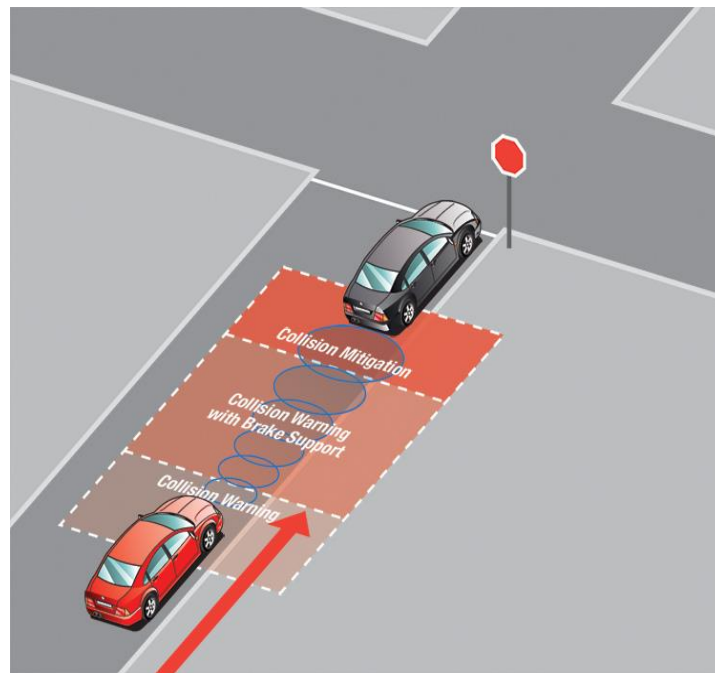
Figure 9. Forward Collision Warning

As shown in Figure 9, there are three stages in FCW: collision warning, collision warning with brake support, and collision mitigation. Due to the limitations of this driving simulator, only the first stage of an FCW system could be recreated for evaluation. This means that an FCW system, in this case, will not take any automatic action to avoid a collision or control the vehicle; therefore, post FCW, drivers will remain responsible for

the safe operation of their vehicles to avoid a crash. The advantage of using a one-stage warning system is twofold: one, to warn a distracted driver and two, to maintain the driver trust in the system, which could be in jeopardy with the false alarm rates in the multi-stage system.

This event was programmed to occur in both the scenarios, as the probability of such an event occurring is totally dependent on the individual participants' driving behavior. Since the goal of evaluating this application was to analyze the influence of FCW on change in speed, a perception reaction distance as defined by the National Association of City Transportation Officials (NACTO) was used to identify the appropriate timepoints to send an FCW to the driver based on the speed of the vehicle. The perception reaction distances, as replicated in the driving simulator, were based on the respective speeds as shown in Table 3.

Table 3. Perception Reaction Distances

MPH	Perception Reaction Distance (ft)
10	22
15	33
20	44
25	55
30	66
35	77
40	88
45	99
50	110
55	121
60	132
65	143
70	154

Source: (NACTO)

A snapshot of an FCW event is shown in Figure 10.

Figure 10. FCW snapshot in the driving simulation

Thus, the FCW in the driving simulator was activated, based on the perception reaction distances and the respective speeds, shown in Table 3.

3.4.4 Curve Speed Warning (CSW)

This application utilizes V2I technology and warns the driver if the speed of their vehicle exceeds the safe speed limits to navigate the approaching curve or ramp. For this event, the segment of the four-lane highway Interstate 95 was chosen to be replicated in the driving simulator. It has a speed limit of 55 mph as it approaches the exit ramp, exit 53 to downtown Baltimore. A distance of 75 meters (240 ft) was chosen for the taper, while the deceleration lane distance was relegated to 135 meters (440 ft) approximately. These distances were based of the diamond interchange ramp dimensions as shown in Figure 11.

The lanes are 12 feet wide with a 12-foot raised median separating the opposing lanes with a light traffic flow with a level of service B. As soon as the drivers approach the deceleration lane, a CSW is issued both visually and in the form of an audible beep, informing them about the reduced upcoming ramp speed of 25 mph, in this case.
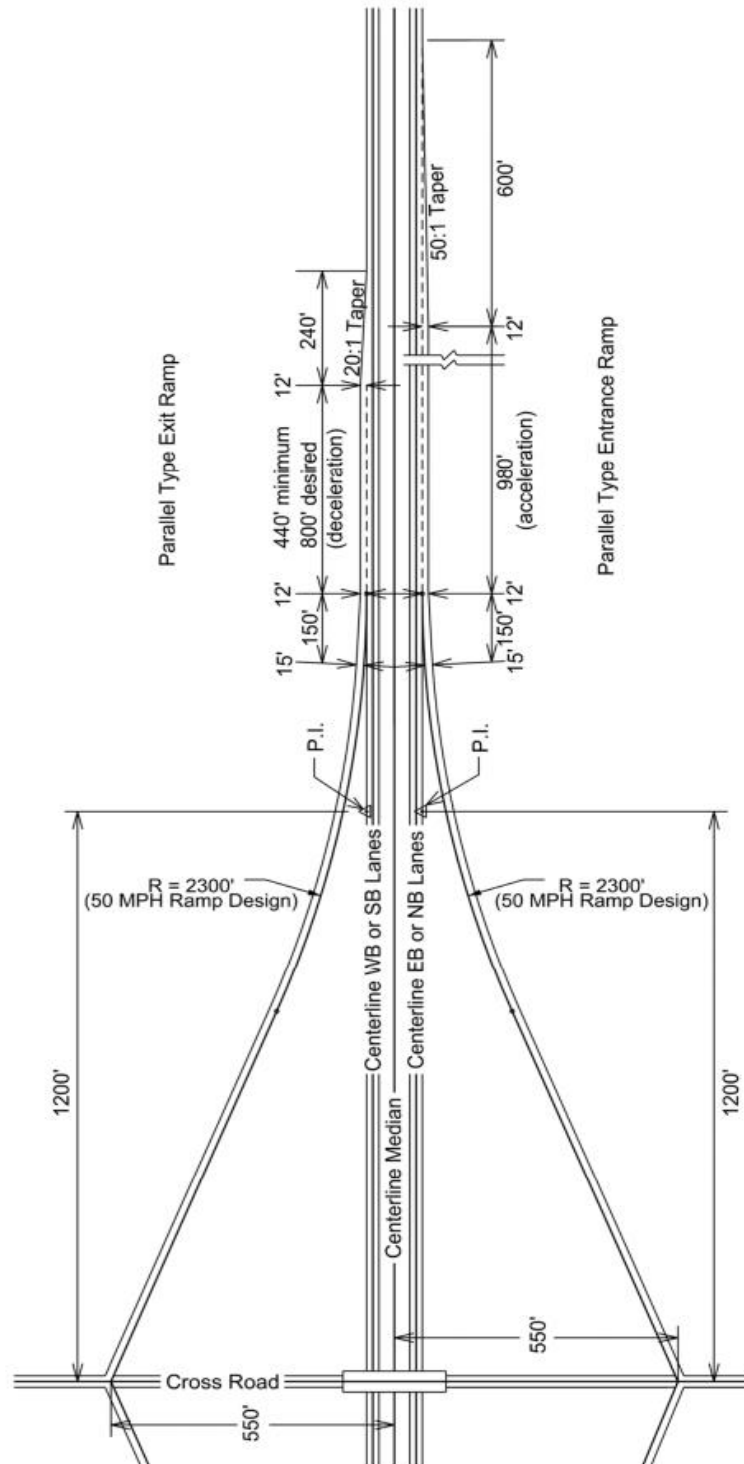
Figure 11. Diamond Interchange Dimensions

Source: (SDDOT, 2013)

A snapshot of a CSW event is shown in Figure 12.
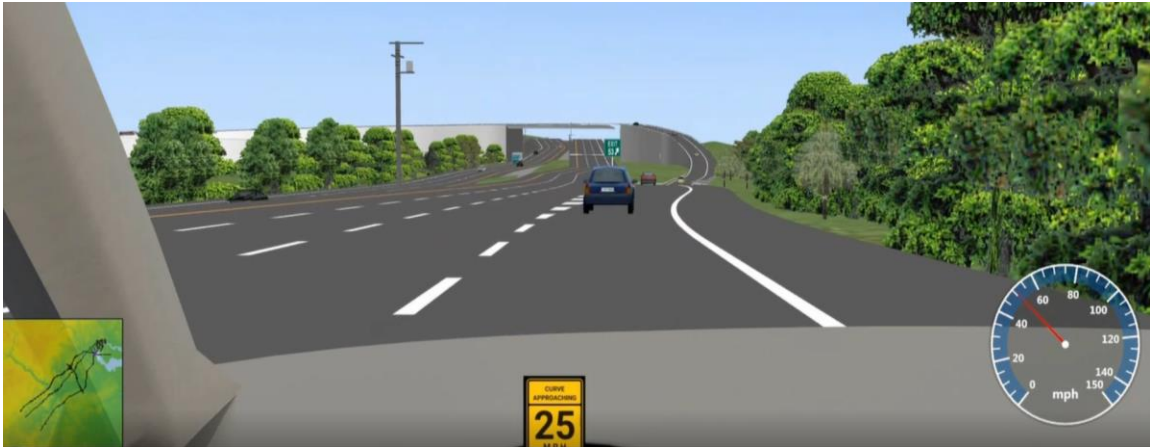
Figure 12. CSW snapshot in the driving simulator

Another application, informing drivers about their current speeds was attempted to be evaluated in tandem with the CSW application. Although the warning was used in the scenario, the evaluation was scrapped as the exit 53 ramp being a steep curve, drivers would have to slow down irrespective of a warning or any other information.

3.4.5 Level 3 – Autonomous Mode

This application is part of the SAE Level 3 AV technology. The application was programmed in such a way that the driver is prompted to relinquish control of the vehicle and the autonomous mode will be implemented. But, since this is Level 3 technology, the driver still must pay attention, even though the vehicle is in autonomous mode. In this scenario, following an incident, the driver was prompted to regain control of the vehicle. Before driving in this scenario, participants were briefly explained about SAE Level 3 technology and how it works. A snapshot of the event is shown in Figure 13.

Figure 13. Autonomous mode snapshot in the driving simulator

3.4.6   Control Scenarios

In addition to the two scenarios that have been described in the previous sections, two other scenarios were designed, but without any of the applications. These control scenarios were presented to the participants first in a random order before the scenarios involving CAV applications, to avoid bias or the learning effect of driving simulators.

3.5 *Behavioral Analysis*

3.5.1   Hazard-based duration model

Hazard-based duration models are probabilistic methods that are used to evaluate cases that have a definite origin point until the occurrence of an event (Collett 2015). The transportation field uses these models to study a number of time-related events such as assessing critical factors impacting crash durations and developing crash duration prediction models (Chung 2010, Chung, Walubita, and Choi 2010, Hojati et al. 2014), evaluating the impacts of cellphone usage on driver reaction time in response to a pedestrian crossing the road (Haque and Washington 2014, 2015), modeling the duration of highway traffic incidents (Nam and Mannering 2000, Hojati et al. 2013, Junhua, Haozhe,

and Shi 2013), etc. This study's duration variable is the speed reduction time, which is calculated from the moment the jaywalking pedestrian becomes visible to the participant driving the simulator until a minimum speed is reached, i.e., the participant lets the pedestrian cross or comes to a complete stop as well as when the participant enters the dilemma zone, coming to a stop at or before the stop line. Proportional hazard and accelerated failure time (AFT) models are two of the approaches that could have been used for this analysis. These models are used to evaluate the influence of covariates on the hazard function. As compared to the hazard model in which the hazard ratios are assumed to be constant over time, the AFT model enables the covariates to accelerate time in a survivor function, when all covariates are zero, resulting in easier interpretation (Washington, Karlaftis, and Mannering 2010). Based on this, an AFT modeling approach was selected for this study.

3.5.2 Longitudinal Jerk Analysis

Jerk is termed as the rate of change in acceleration or deceleration. Jerk can be either positive or negative. Positive longitudinal jerk values are associated with the abrupt release of the brakes, immediately followed by pressing the gas or throttle while negative longitudinal jerk values are associated with the abrupt release of the gas or throttle, immediately followed by pressing the brakes. The magnitudes of both the positive and negative jerks depend on the abruptness and extent to which the brakes and the throttle are pressed or released.

The boundaries for comfortable jerk were found to be $\pm 1 \text{m}/s^3$ while the acceptable limits of longitudinal jerk were defined as $\pm 2 \text{m}/s^3$ (Wei and Rizzoni 2004). Based on these limits, jerks can be classified as:

-1 m/s^3 $\leq$ Jerk $\leq$ 1 m/s^3 $\rightarrow$ Comfortable positive or negative jerk

-2 m/s^3 $\leq$ Jerk $\leq$ -1 m/s^3 $\rightarrow$ Acceptable negative jerk

 1 m/s^3 $\leq$ Jerk $\leq$ 2 m/s^3 $\rightarrow$ Acceptable positive jerk

Jerk $<$ -2 m/s^3 Or Jerk $>$ 2 m/s^3 $\rightarrow$ Unsafe jerk values

3.5.3 Random Forest model

Random forest is a supervised learning algorithm which can be used for both classification and regression modeling (Breiman 2001). This algorithm consists of an ensemble of decision trees, i.e., CART (classification and regression trees). It is commonly trained with the bagging technique in which the idea is to combine multiple models to improve classification accuracy, thereby reducing the risk of overfitting (Breiman 1996). The decision trees in a random forest are trained on bootstrap sample sets produced from bagged samples. Once the set of decision trees has grown, the unsampled observations are dropped down each tree from the test dataset and these 'out of bag' (OOB) observations are used for internal cross validation and to calculate prediction error rates. The error calculated is the mean decrease in node impurity (mean decrease Gini or MDG) which can be used for variable selection by ranking variables in the order of importance. The random forest package in "R" (Liaw and Wiener 2002) was used to compute MDG which is the sum of all decreases in Gini impurity due to a given variable and then normalized toward the end of the forest growing stage. MDG is the predictive accuracy lost by permuting a

given predictor variable from the tree used to generate predictions about the class of observation i, where $i \in [0,1]$, the Gini score range. Thus, predictor variables with a higher MDG score more accurately predict the true class of observation i which is also termed as the variable importance measure (VIM) in random forests.

3.5.4 Take over time analysis

Past studies have shown that automating a driving task has a possible detrimental effect on driver reaction time, which typically means regaining control of the steering wheel (Young and Stanton 2007). In a fully automated car, i.e., an SAE Level 5 car, a driver can shift their focus from driving to non-driving tasks, according to the planned amendment of Article 8 of the Vienna Convention of Road Traffic (Committee 2014). This is a valid regulation only because the driver can countermand the automated system at any time by reacting. The reaction time, also called take over reaction time (TORt), is calculated from the time the system issues a takeover request (TOR) to the time when the driver either regains control of the steering wheel, presses the throttle or brakes. Almost all of the past studies that dealt with TORt, as shown in Table 4 (Eriksson and Stanton 2017), either involve a limited number of driving simulator participants or only consider steering wheel control when measuring TORt.

Table 4. Perception Reaction Distances

Studies	TORt (seconds)
(Gold et al. 2016)	2.47 – 3.61
(Louw, Merat, and Jamson 2015)	2.18 – 2.47
(Kerschbaum, Lorenz, and Bengler 2015)	2.22 – 3.09
(Belderbos 2015)	5.86 – 5.87
(Walch et al. 2015)	1.90 – 2.75

(Lorenz, Kerschbaum, and Schumann 2014)	2.86 – 3.03
(Merat et al. 2014)	10 - 15
(Naujoks, Mai, and Neukum 2014)	2.29 – 6.9
(Zeeb, Buchner, and Schrauf 2015)	1.14
(Gold, Lorenz, and Bengler 2014)	1.67 – 2.22
(Radlmayr et al. 2014)	1.55 – 2.92
(Gold et al. 2013)	2.06 – 3.65
(Melcher et al. 2015)	3.42 – 3.77
(Feldhütter et al. 2017)	1.88 – 2.24
(Payre, Cestac, and Delhomme 2016)	4.30 – 8.70
(Körber et al. 2016)	2.41 – 3.66

As can be seen in Table 4, most TORts lie between 2 and 3.5 seconds with a few outliers. The TOR is usually given in both visual and audible forms. In this study, not only will a TOR be issued in both visual and audible forms, but the TORt will be calculated for both the steering control and throttle push.

3.5.5 Gaze Analysis

This research used an eye tracking system as shown in Figure 14, developed by Tobii Pro Labs (Tobii 2019), to analyze the eye and head movement of the participants driving the simulator.
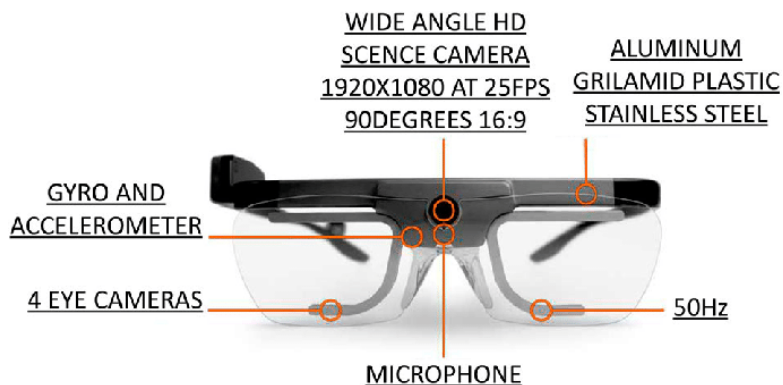

Figure 14. Tobii Pro eye tracking system

The wearable, head-mounted eye tracking tool tracks a participant's gaze in real time. Eye tracking data is composed of both fixations and noise data points. This study will use fixation data points to build heat maps where the eye tracker will group the raw entry records into fixations. The eye tracker generates eye gaze data which is mapped to a coordinate system that is relative to the eye tracking device. Real world mapping is achieved through the Tobii Pro Lab software, which maps the gaze points to static objects within the simulator environment. A heat map can be generated using the number of fixations the participants made in certain areas, with red indicating the highest number of fixations and green indicating the least number of fixations. The generated heat map just shows a count of the number of fixations on the object or area of interest.

3.6 Driving Simulator Data Validation

The U.S. Department of Transportation, in collaboration with the University of Michigan Transportation Research Institute (UMTRI) and partner organizations, undertook a pilot called the Safety Pilot Model Deployment (SPMD) from August 2011 to February 2014 (Bezzina and Sayer 2014). The objective of this pilot was to support the evaluation of DSRC technology for V2V safety applications in the real world. The test area included three major east-west corridors in Ann Arbor, Michigan, where nearly 3000 equipped vehicles were deployed, on more than 70 miles of instrumented roadway, which makes it the largest connected vehicle technology field test in the world to date (Bezzina and Sayer 2014). Data was collected on emergency electronic brake lights, forward collision warning, curve speed warning, intersection movement assist and basic safety

58

warning messages. To evaluate the findings of this driving simulator study, all instances of FCW and CSW were obtained from UMTRI.

3.6.1 Forward Collision Warning

The data obtained from UMTRI consisted of 106 unique device recorders or participants, including 8,235 trips involving 12,210 instances of FCW. A radar unit installed in the vehicles, manufactured by Mobil Eye, could look ahead as far as 650 feet with a 60-degree field of view. The data parsed and shared for this study included average speeds 5 seconds before and after the FCW was issued. Other variables provided were binary braking events, before and after the warning. The binary values signified whether braking had occurred before the FCW event and/or after the event. The data included information about turns or lane change indications, i.e., if the participants had their turn signal on before or after the FCW event, and whether they were left or right turn signals. The final variable used was daylight, i.e., if the trip took place during the daytime or at night.

3.6.2 Curve Speed Warning

The initial CSW data obtained from UMTRI consisted of 91 unique device recorders or participants, including 4,193 trips involving 12,305 instances of CSW. For SPMD, 6 of the 29-roadside equipment (RSE) were located at the start and end points of three road curves, i.e., 2 RSE per curve. The curves, located in Ann Arbor, Michigan are located on Plymouth Road, Bonisteel Boulevard and Fuller Road respectively, as shown in Figure 15.
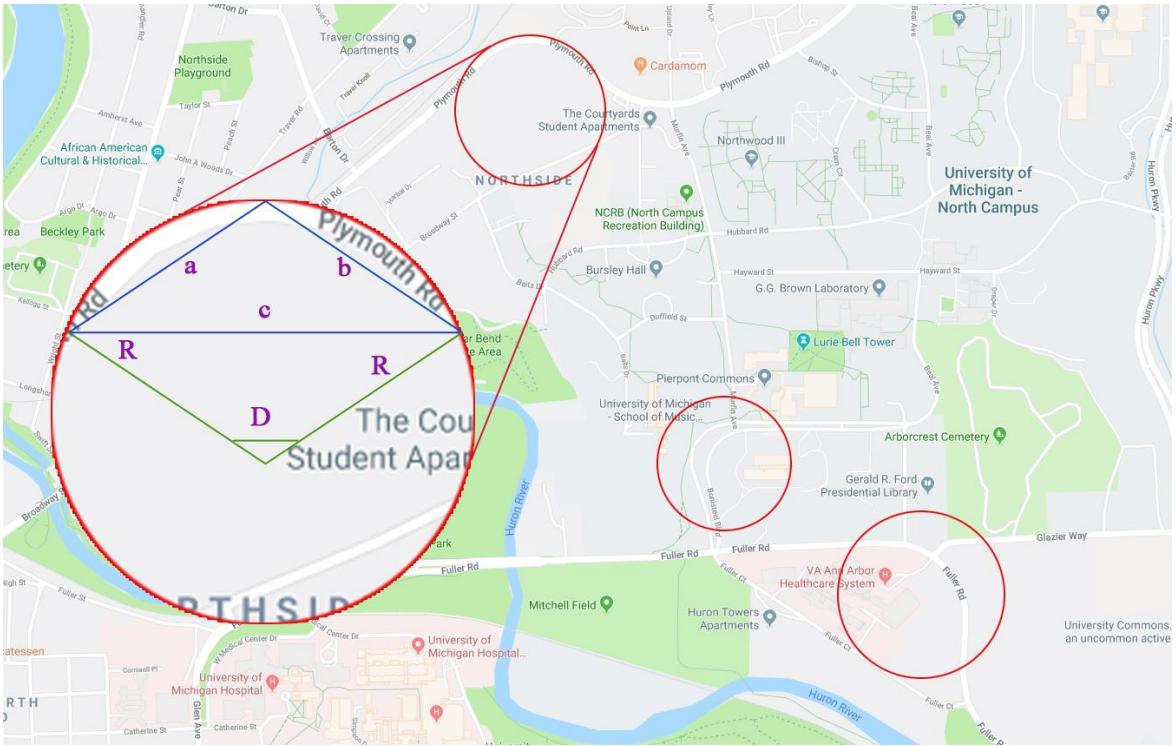
Figure 15. Curves where CSW was issued

To compute the radius of curvature of the three curves, three coordinates were identified, and the lengths of the segments were calculated. The radius of curvature or the circumradius was calculated using the following equation:

Equation 2: Circumradius calculation

$$R = \frac{abc}{\sqrt{(a + b + c)(b + c - a)(a + b - c)(a + c - b)}}$$

where,

a, b and c are the segment lengths, similar to the ones shown in Figure 15, Plymouth Rd curve, and R is the circumradius or radius of curvature. The degree of curvature of the curve is calculated from the following equation:

Equation 3: Degree of curvature

$$D = 2(Sin^{-1}\frac{c/2}{R})$$

where,

c - the length of the chord (Plymouth Rd curve in Figure 15),

R - the circumradius or radius of curvature of the curve,

D - the degree of curvature of the curve.

Equations 2 and 3 were also used to compute the radius and degree of the curve, used in the driving simulator study. The length of the segments a, b and c and their respective radius and degree of curvature are shown in Table 5.

Table 5. Radius and Degree of curvature statistics

Curve Location	a (meters)	b (meters)	c (meters)	R (meters)	D (degrees)
Plymouth Rd	190	242	371	210	123
Fuller Rd	248	271	439	243	129
Bonisteel Blvd	195	213	306	154	168
Baltimore (I-95 Exit 53)	404	397	678	376	129

The radius of curvature (R) in Table 5 shows that, Bonisteel Blvd with an R of 154 meters and Baltimore (I-95 Exit 53) curve with an R of 376 meters, were the curves with the smallest and highest radii, where a smaller radius depicts high curvature while a larger radius depicts a low curvature, as is evident from the respective degree of curvature (D) calculations.

As the coordinates of the Michigan trips were also provided, the trips were plotted, and a lot of noise was found in the data. Post cleaning, 2,507 trips involving 86 participants in 7,280 instances of CSW remained. The methodology used to evaluate CSW responses

to validate simulator findings was same as the ones in FCW, average speeds 5 seconds before and after the CSW was issued. The additional variables provided were similar to the ones provided for FCW.

3.7 Data Extraction and Analysis Tool

For the UMEC funded study, an application was developed by the author, for combining the outputs of the driving simulator and eye tracking device. This application was further enhanced to include data extraction for evaluating individual CAV applications, and conduct analysis while generating relevant plots at the same time.

Chapter 4. Study Data

This chapter gives an outline of the data collection process, the challenges faced, survey questionnaires, and some descriptive statistics about the sociodemographic information of the participants.

4.1 Recruitment Process

Institutional Review Board (IRB) approval was received before human participants were recruited. Participants signed a consent form (Refer to Appendix B) before participating in the study and were paid at the rate of $15 per hour of driving. Some ninety-three participants from diverse socio-economic backgrounds took part in this study. Participants were recruited through a combination of emails to participants from prior studies (Banerjee, Jeihani, and Khadem 2019, Banerjee et al. 2019, Banerjee, Jeihani, and Moghaddam 2018, Jeihani et al. 2018, Moghaddam et al. 2019) and distribution of flyers across the university and throughout Baltimore County (Refer to Appendix C). The study was briefly explained to the participants and they were given an opportunity to get familiar with the driving simulator.

4.2 *Descriptive Statistics*

This study involving some 93 participants consisted of a balanced group of male and female individuals. Table 6 presents some of the sociodemographic statistics of the participants.

Table 6. Participant socio-demographics

Variables	Characteristics	Percentage

Gender	Female	44
	Male	56
Age	18-25	37
	26-35	29
	36-45	14
	46-55	12
	>55	8
Education Level	High School or less	12
	College degree	61
	Post-graduate	27
Household income level	<$20,000	27
	$20,000 - $49,999	34
	$50,000 - $99,999	22
	>$100,000	17

Figures 16 through 22 highlight the stated preferences of the participants, which they offered through the pre and post simulation survey questionnaires.
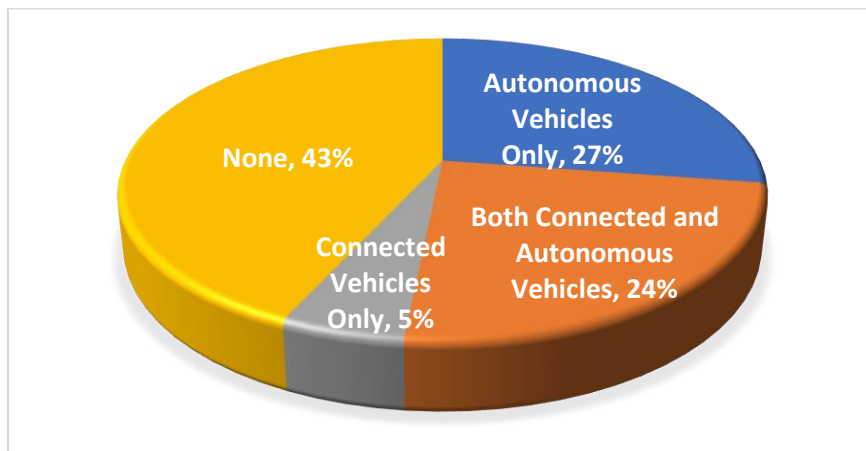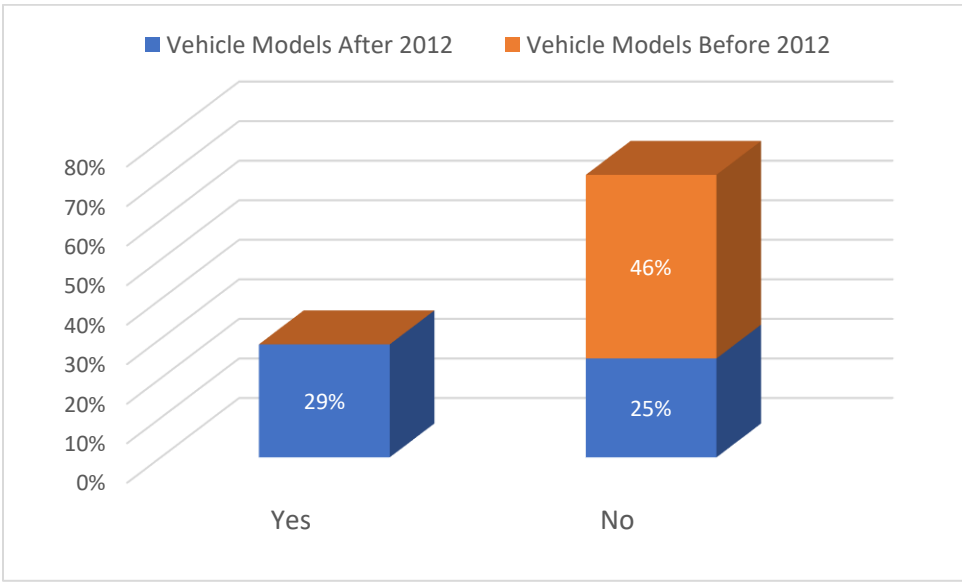

Figure 16. Familiarity with CAV
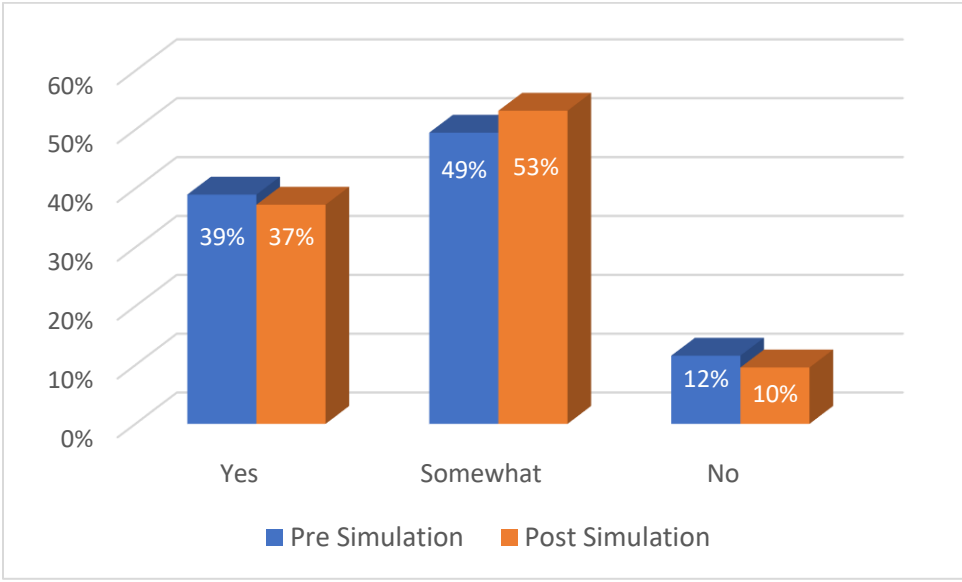
Figure 17. Experience using CAV Applications

Figure 18. Trust in CAV Applications
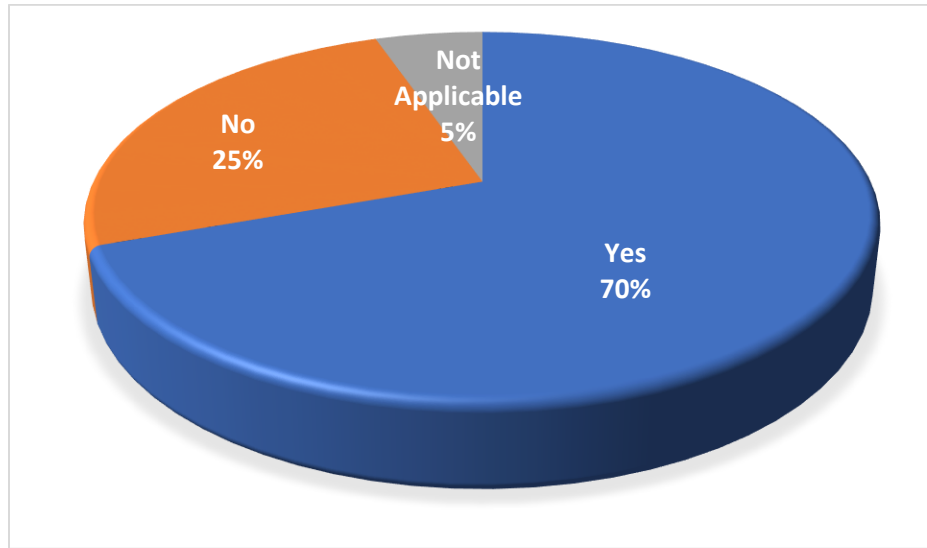
Figure 19. Participants who use 'Waze' while driving

Waze is a mobile application, similar to Google Maps, that guides users from point A to point B. It also warns users, through audio and visual warnings, about incidents on the way. Some 70% of the participants stated that they either currently use Waze or have used it before, which signifies that they have prior experience with technology-based applications that warn them about incidents.

Figure 20. Participant disposition during Autonomous Driving
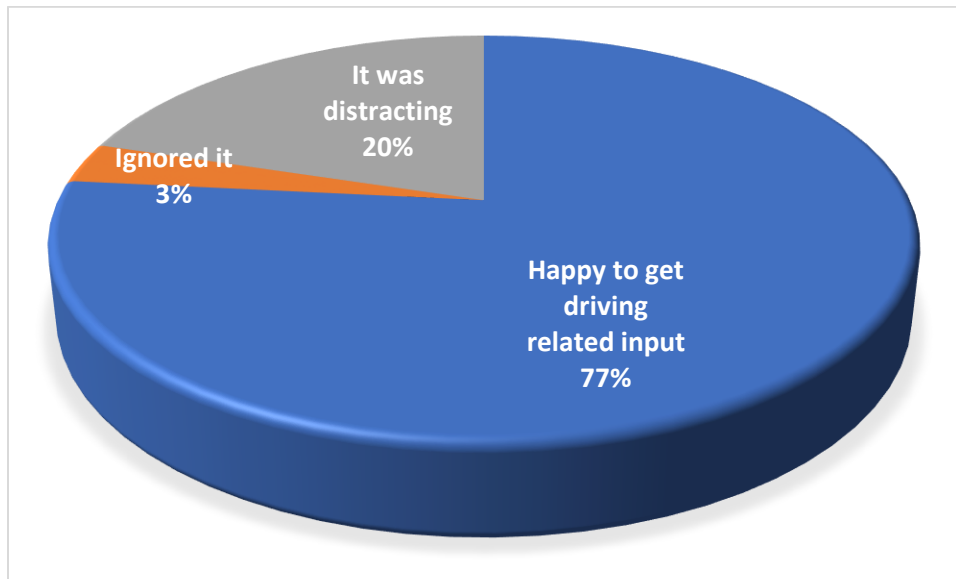
Figure 21. Participant reaction on using CAV technology

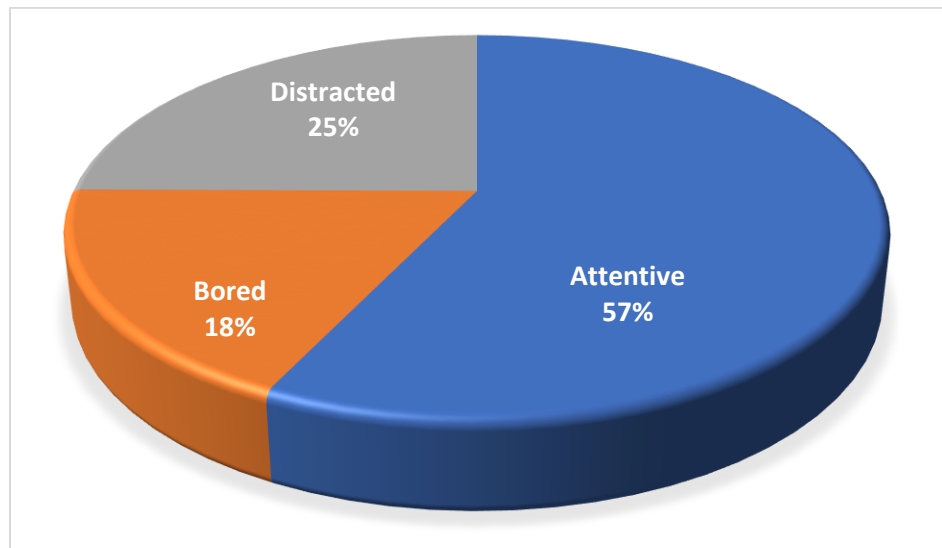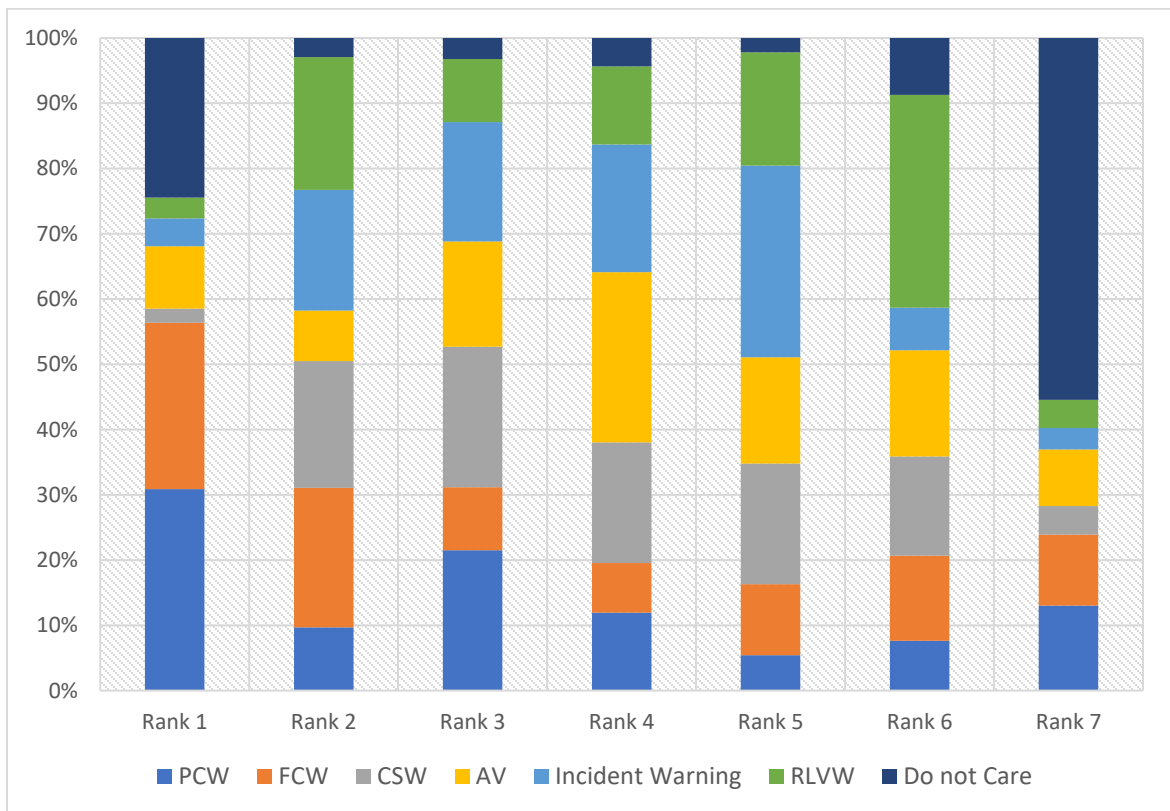**Figure 22. Ranked preferences of potential application importance**

4.3 *Driving Simulator Sickness*

Although a driving simulator is a valuable tool to study human behavior while driving, it causes a simulator sickness syndrome, which is similar to motion sickness. Past studies have found a positive correlation between simulator sickness and age as well as gender (Brooks et al. 2010, Garcia, Baldwin, and Dworsky 2010, Nickkar, Jeihani, and Sahebi 2019, Park et al. 2006). Nine common symptoms—general discomfort, fatigue, headache, eyestrain, blurred vision, salivation, sweating, dizziness, and nausea—were evaluated on a scale of severe, moderate, slight and none. In this study, the mean response for each symptom is shown in Figure 23.

Figure 23. Simulation Sickness Symptoms

Chapter 5. Analysis

This chapter summarizes the behavioral analysis conducted on each of the CAV applications and illustrates the preliminary findings of the study.

5.1 Pedestrian Collision Warning

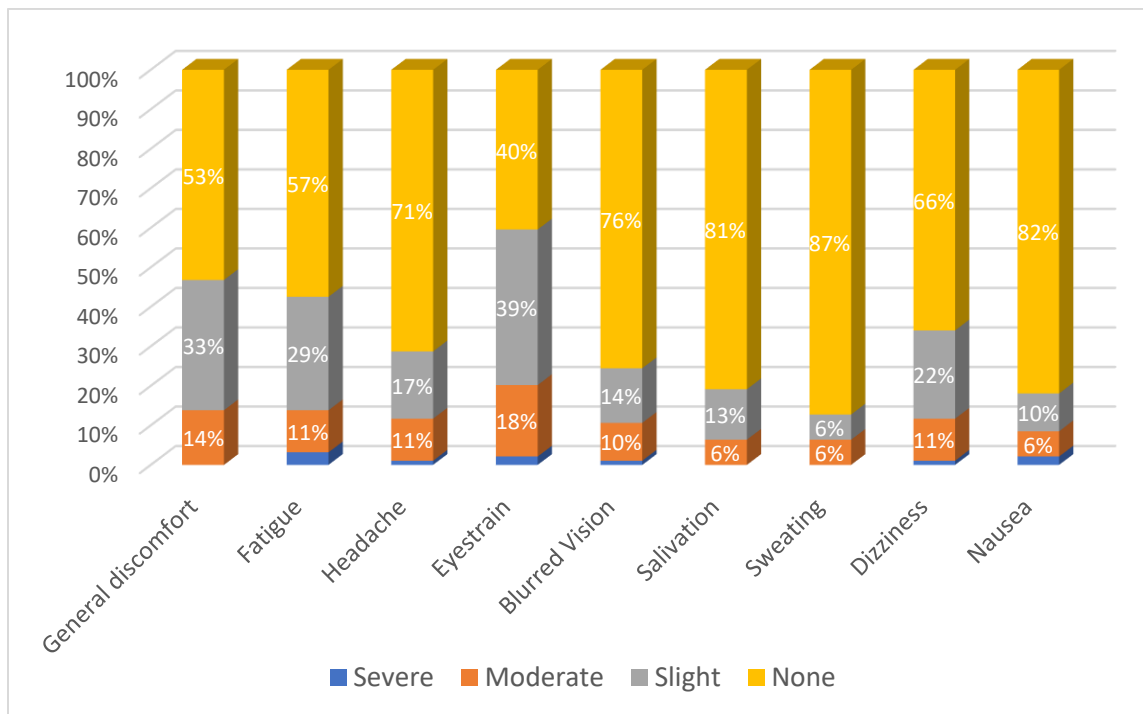Pratt Street, a major one-way four lane road in downtown Baltimore was replicated in the driving simulator for this analysis, where a jaywalking pedestrian appears at an approximate distance of 40 meters from the simulation vehicle.

5.1.1 Experiments

Some 186 experiments were conducted; however, in 83 of those the participants either failed to yield to the pedestrian or missed them completely due to over speeding; thus, the final dataset used in the analysis consisted of 103 observations of the participants' braking maneuvers. The braking maneuvers of the participants, the moment they encounter the jaywalking pedestrian, were analyzed, in both the baseline scenario as well as the scenario involving a PCW system.

The average deceleration rate (d_m) at the moment the jaywalking pedestrian became visible until the participants slowed down to let the pedestrian pass or came to a complete stop is given by (Bella and Silvestri 2016):

Equation 4: Average Deceleration Rate

$$d_m = \frac{V_i^2 - V_{min}^2}{2(L_{V_{min}} - L_{V_i})}$$

where,

V_i = Participant's initial speed as they approach the waypoint where the

jaywalking pedestrian first becomes visible

V_{min} = Participant's minimum speed reached during the deceleration phase

L_{V_i} = Distance between the vehicle's location when the initial speed was recorded
at the waypoint and the point at which the jaywalking pedestrian starts
crossing the street

$L_{V_{min}}$ = Distance between the vehicle's location when the minimum speed was
recorded at the waypoint and the point at which the pedestrian starts
crossing the street

The speed reduction time (S) is calculated as the elapsed time between the participant's initial speed (V_i) and the minimum speed (V_{min}) reached to allow the pedestrian to pass, before accelerating.

A plot of the participants' speed profile before and after the waypoint, 40 meters from where they first possibly spotted the pedestrian, was generated. Through this plot as shown in Figure 24, several parameters related to the participants' braking maneuvers were calculated. It can be seen that participants braked harder, when they receive a PCW, compared to when not receiving a warning.
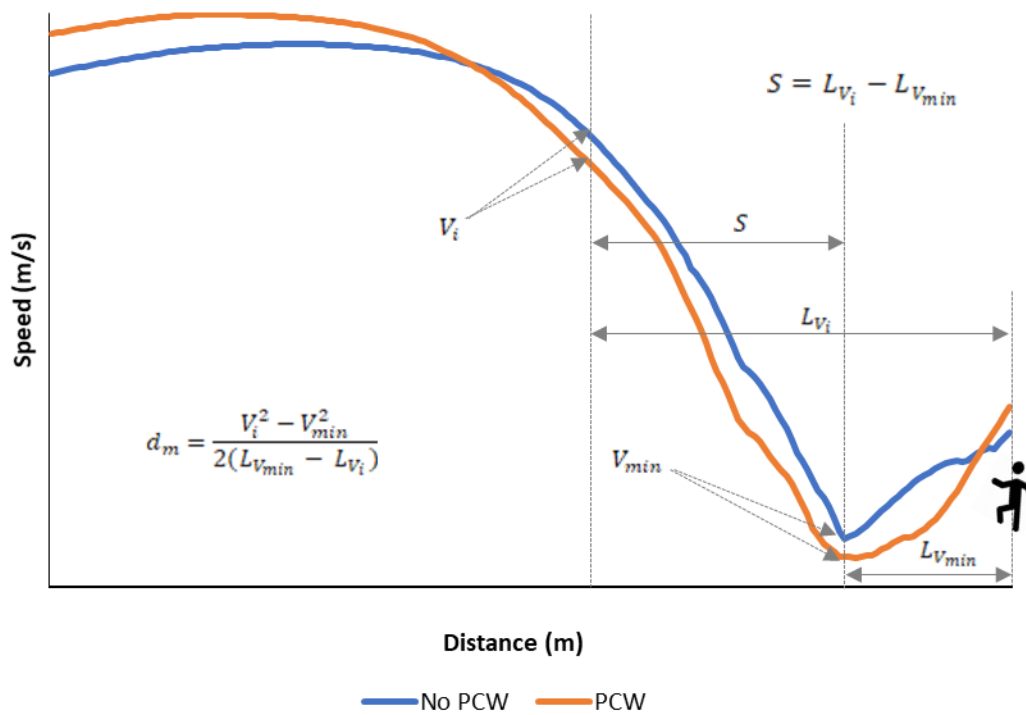
Figure 24. Participant speed profile comparison

To determine the braking behavior with and without the PCW, a plot of the

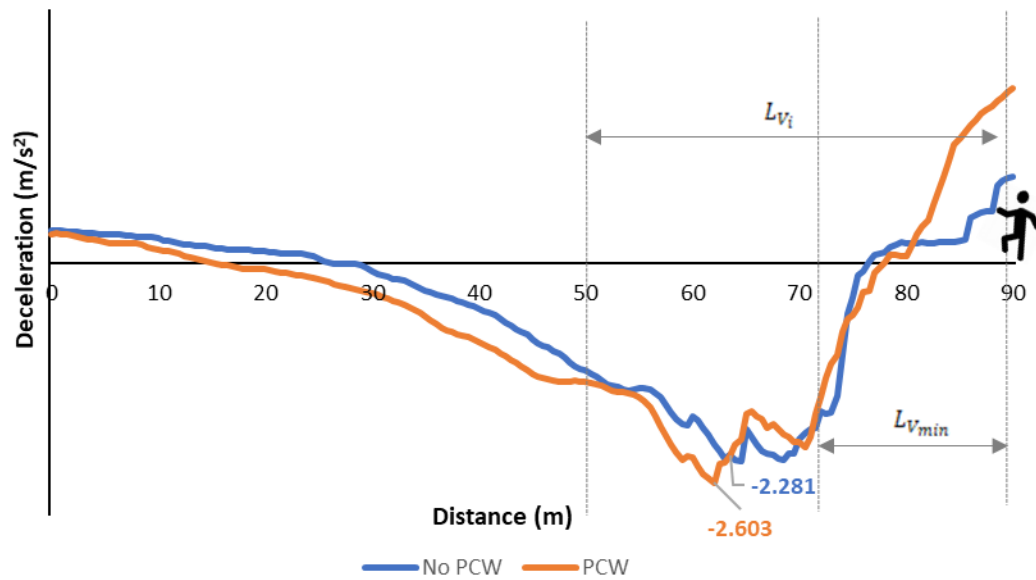average deceleration rates of all participants are plotted in Figure 25.

Figure 25. Participant average deceleration

The deceleration rate in Figure 25 shows that, the participants braked earlier, at the onset of the PCW. Average maximum deceleration (-2.603 m/s^2) for the PCW scenario is attained at 12 meters from the warning point, while maximum deceleration (-2.281 m/s^2) for the Non-PCW scenario is attained at 13.5 meters from the potential warning point. To confirm this braking behavior, the perception reaction time taken to release the throttle and the brake execution time from the moment the throttle is released until the initial brake application, is calculated for each participant. The braking intensity is calculated, one second after the brakes are pressed to determine the intensity, where on a scale of 0 to 1, 0 is no brake force and 1 is maximum brake force. The average reaction and braking execution time statistics are shown in Table 7.

Table 7. Reaction and braking execution time statistics

	Average Perception Reaction Time (s)	Average Brake Execution Time (s)	Average Time to Reach Max Deceleration (s)	Average Max Braking Intensity	Average Max Speed Change (m/s)
PCW	0.29	0.2	1.75	0.56	5.53
No PCW	0.36	0.2	2	0.47	6.03

From Table 7, it can be seen that, participants react quicker in the presence of a PCW system. The average perception reaction time is quicker in the PCW scenario, as the participants get the warning before they can anticipate the pedestrian, and thus start braking early, gradually slowing down to let the pedestrian pass. The average time to reach maximum deceleration is 1.75 seconds and 2 seconds respectively, for the PCW and Non-PCW scenario which confirms the hard-braking behavior. The average maximum braking intensities at these points were 0.56 and 0.47 respectively. The average maximum speed change is the difference in speed from the warning point until the average maximum

deceleration is reached. The slightly higher speed change (6.03 m/s compared to 5.53 m/s) can be attributed to the distance traversed in the additional 0.25 seconds. A representation of the numbers shown in Table 7 is presented in Figure 26.
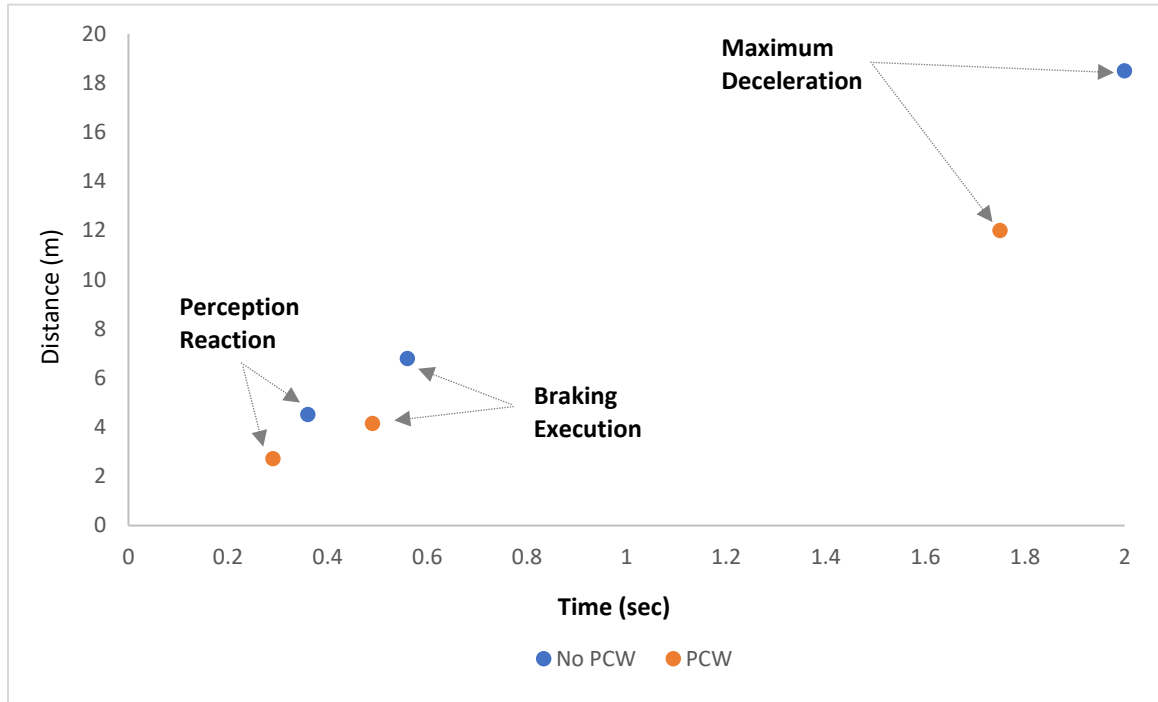
Figure 26. Sequence of events by time

From Table 7 and Figure 26, it can be said that, participants took slightly longer to react in the absence of a PCW system. The braking intensity and the total duration of the perception reaction time, and brake execution time with a PCW system (total duration of 0.49 sec), show that hard braking is involved in the initial stages of a PCW system. From Figure 25, the hard braking in the PCW scenario can be confirmed as maximum declaration is reached at 1.75 seconds compared to the 2 seconds, in the Non-PCW scenario, supported by the average maximum braking intensity (0.56 compared to 0.47) from Table 7, at the maximum deceleration points.

5.1.2 Jerk Analysis

Jerk is calculated for each participant and averaged over every second, from the waypoint where the PCW is issued. The participants average jerk, every tenth of a second, is shown in Figure 27.
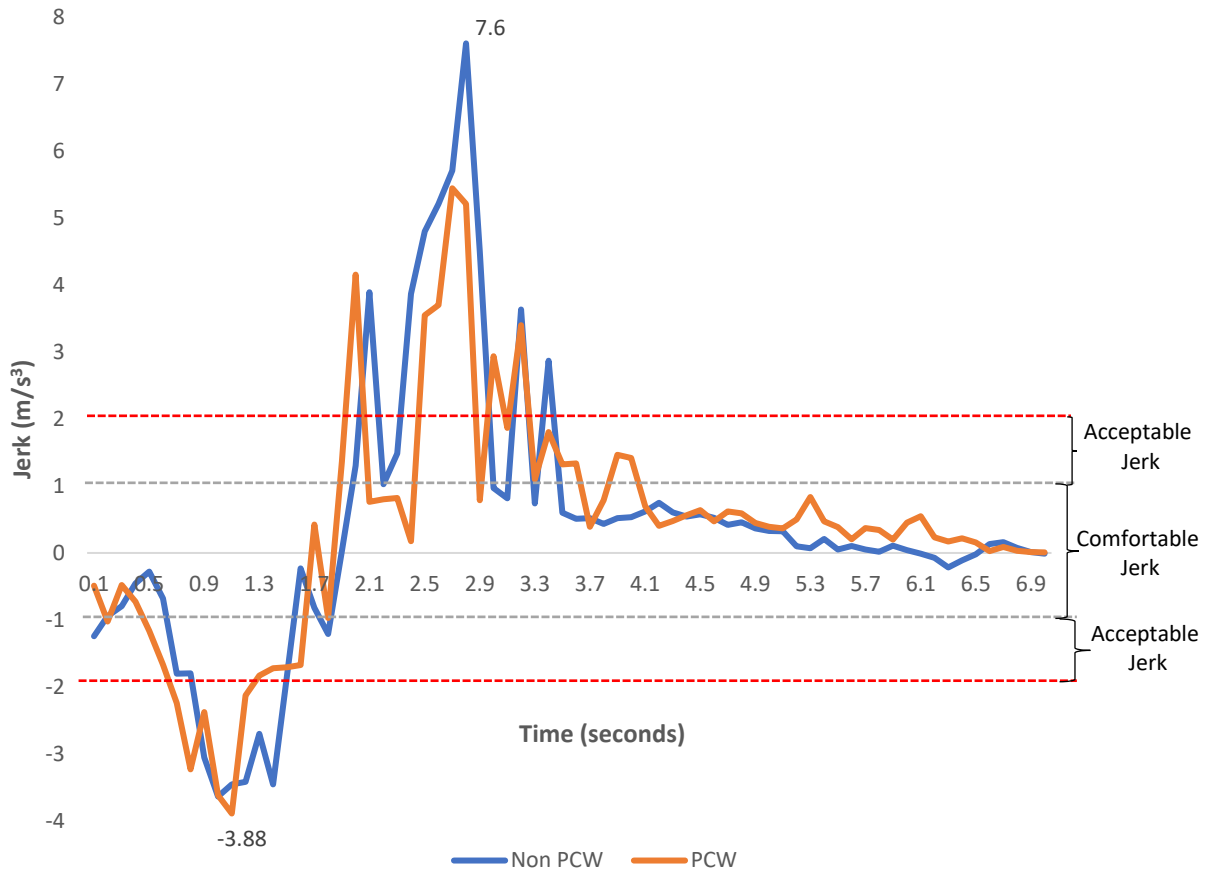
Figure 27. Participants Average Jerk by Time

It can be seen that, in the scenario with the PCW, the average initial jerk around 1.1 second after the warning is issued, is way below the acceptable jerk limit (Wei and Rizzoni 2004) and is thus unsafe. On the other hand, in the scenario without the PCW, around 2.8 seconds after the waypoint, the jerk is the maximum at 7.6 m/s^3. This being a positive jerk, it is from the sudden release of the brakes and can be termed as a highly uncomfortable

jerk. The jerk drops sharply at 2.8 seconds and is still positive, which means that, the participants in the Non-PCW scenario, press the throttle suddenly. This signifies that the participants slowed down enough, to let the jaywalking pedestrian pass, before accelerating.

5.1.3 Log logistic AFT model

An ANOVA analysis revealed that there was a statistically significant difference in speed reduction times between the baseline scenario and the scenario with a PCW system. The speed reduction times were longer in the scenario involving the PCW system (mean difference in time = 0.61 seconds, $\rho \leq 0.05$) at 3.14 seconds compared to 2.53 seconds in the baseline scenario. This implies that the overall deceleration rate when the PCW was used, is less compared to when the system was not used (2.99 m/s^2 vs. 3.19 m/s^2). Although, this infers a smoother braking maneuver, it is not the case as seen in Figure 24. Since deceleration rate or braking behavior is affected by CAV technology, in this case a PCW system, a hazard-based duration model was developed to comprehend the participant's braking behavior in terms of speed reduction times. As demonstrated by Bella and Silvestri (Bella and Silvestri 2016), this dependent variable is a positive duration dependence event as its probability increases as a result of an increase in the available time. A distribution assumption of the speed reduction time variable is required to estimate the hazard and the survival functions in a parametric setting. The hazard function gives the conditional failure rate while the survival function is the probability of a longer speed reduction time than a specified time. The most commonly used are the lognormal, log-logistic, exponential and Weibull distribution functions. In order to select the best fit and most applicable function,

the Akaike information criterion (AIC), which is one of the most well-known approaches for model selection based on their adequacy (Burnham and Anderson 2004, Wagenmakers and Farrell 2004), and log-likelihood values were used. The four distributions were assessed, and it was found that the log-logistic model provides the best fit for the data as it had the lowest AIC values at -382.73 and the highest log-likelihood values at -128.158, among them. The hazard function $h(t)$ of the log-logistic duration model is expressed as (Zhang 2005):

Equation 5: Hazard Function – Log logistic Model

$$h(t) = \frac{\lambda p t^{p-1}}{1 + \lambda t^p}$$

with $p > 0$ and $\lambda > 0$ and the survival function $S(t)$ of the log-logistic duration model is expressed as (Zhang 2005):

Equation 6: Survival Function – Log logistic Model

$$S(t) = \frac{1}{1 + \lambda t^p} \quad \frac{1}{1 + (\lambda^{\frac{1}{p}} t)^p}$$

where λ and p are the location and the scale parameters, while t is the specified time, respectively.

Table 8 shows the descriptive statistics of the different parameters used in the log-logistic model and the speed reduction times of the participants in both the baseline scenario as well as the scenario involving the PCW system.

Table 8. Speed reduction time and Log logistic AFT variable descriptives

Variables	Mean Value (No warning)	Std. Dev (No Warning)	Mean Value (PCW)	Std. Dev (PCW)
V_i (m/s)	11.18	3.11	10.90	3.33
L_{V_i} (m)	50.67	0.44	50.55	0.34
V_{min} (m/s)	1.85	1.92	1.33	1.76

$L_{V_{min}}$ (m)	70.63	9.16	71.77	7.98
d_m (m/s^2)	3.19	1.04	2.99	1.45
Speed Reduction Time(s)	2.53	0.62	3.14	0.95

Moreover, in order to assess the goodness of fit for the log-logistic model, a plot of the cumulative hazard rate was determined from the model estimates and then utilized to build an empirical estimate of the cumulative hazard model. As seen in Figure 28, the points representing the estimate of the cumulative hazard function almost follow the 45° reference line; hence, it can be inferred that the participants' predicted speed reduction time, using the log-logistic model, is a good fit with the observed data.
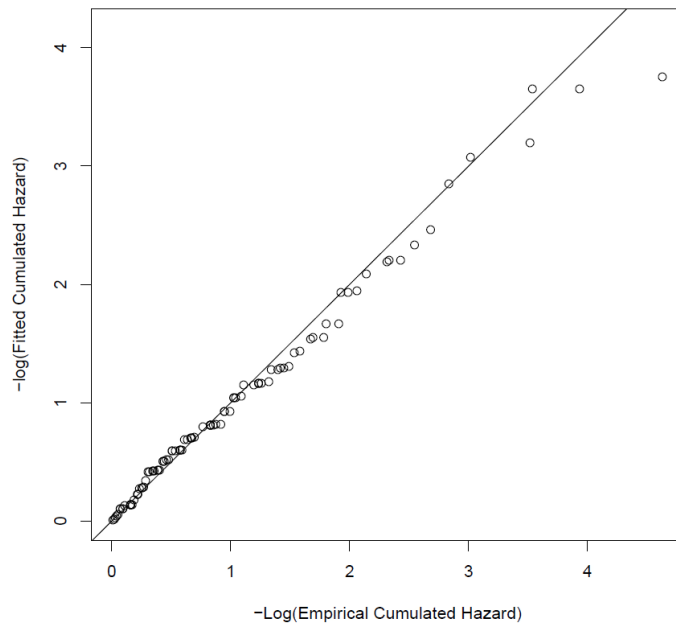
Figure 28. Cox-snell residuals for Log logistic AFT

The estimates from the Log logistic AFT model with the speed reduction times of the participants as the dependent variable are shown in Table 9.

Table 9. Log logistic AFT parameter estimates

Variables	Estimate	Std. Error	z	ρ	Exp (β)
(Intercept)	12.317	70.911	0.173	0.862	223521.809
V_i (m/s)	0.059	0.006	8.892	0.000*	1.062

L_{V_i} (m)	-0.008	0.048	-0.162	0.872	0.992
V_{min} (m/s)	-0.038	0.010	-3.811	0.000*	0.962
Average Deceleration Rate d_m (m/s^2)	-0.245	0.016	-15.343	0.000*	0.782
PCW system	0.074	0.031	2.423	0.010*	1.077
Gender - Male	0.420	0.144	2.914	0.004*	1.522
Not familiar with downtown Baltimore	0.104	0.060	1.723	0.085	1.110
Familiar with CAVs	-0.060	0.042	-1.417	0.156	0.942
Scale Parameter P	2.628	0.085			
AIC	-382.730				
Log-likelihood at convergence	-128.158				
Number of groups	103				

* Statistically significant at 99% CI

Table 9 identifies the variables that are statistically significant to the participants' speed reduction times, in response to the jaywalking pedestrian. The variables significant at a 99% confidence interval were the initial speeds recorded at the waypoint, the minimum speeds reached in the deceleration phase, the average deceleration rates, the PCW system compared to the baseline, and gender. If the initial speed increases, the speed reduction time would also indirectly increase by 6.2% (odds ratio = 1.062), whereas the speed reduction times would decrease by 3.8% (odds ratio = 0.962) and 21.8% (odds ratio = 0.782) if there is a decrease in the minimum speed and the average deceleration rate. In the presence of a PCW system, the participants' speed reduction time increases by 7.7% (odds ratio = 1.077), which infers that the PCW system is the more effective system in improving speed reduction times, i.e., more time to transition to an acceptable speed or come to a stop, to yield to the pedestrian. Odds of male participants having a higher speed reduction time on average was 52.2% more than their female counterparts (odds ratio = 1.522), which implies that the male participants braked aggressively initially, and then proceeded slowly,

until the pedestrian had passed. A scale parameter estimate of 2.628 implies that the survival probability of the speed reduction times decreases with the passage of time.

A representation of the participants' braking patterns can be shown by plotting survival curves of the speed reduction times for the baseline scenario and the scenario involving the PCW system. These predictions were done based on the predict survival regression tool in the R-package (Therneau) and shown in Figure 29.
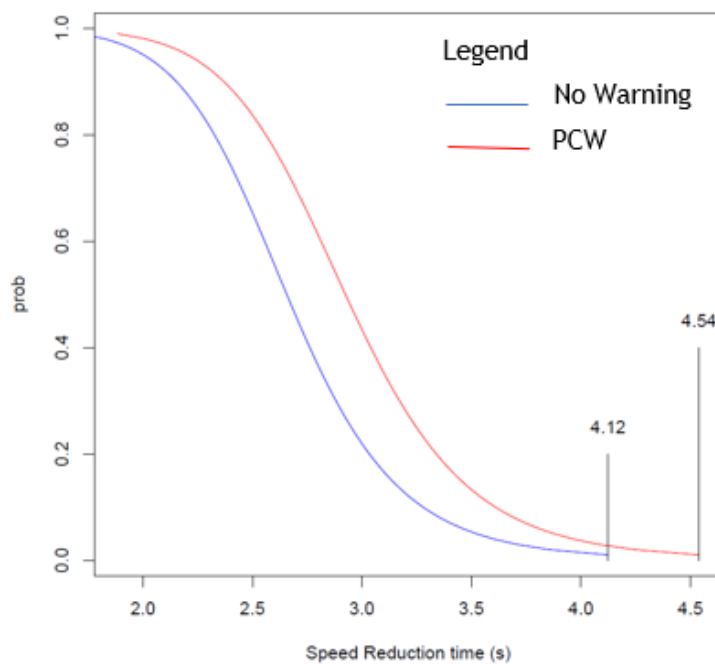
Figure 29. Speed reduction time survival curves

From Figure 29, it can be seen that the speed reduction time survival probability decreases with the passage of time. A lower survival probability was recorded for the baseline scenario as compared to the scenario with the PCW system. At 3 seconds of speed reduction time, the survival probability for the baseline scenario was 21% compared to 43% for the scenario with the PCW system, and it drops even further at 4.5 seconds, to only 5% in the baseline scenario to 13% in the PCW system scenario. The speed reduction

time was 0.42 seconds longer (statistically significant) in the presence of a PCW system, giving the participants longer time to brake and transition to a safe stop.

5.1.4 Eye Gaze Analysis

This study used Tobii Pro Glasses 2 (Tobii 2019), the eye tracking device and its analysis software. Both the scenarios, the baseline and the one with the PCW system, were evaluated, to analyze where the participants glanced while at the waypoint. If the participant glances at any object for a moment, it is captured by the eye tracking device. In this analysis, the glance is recorded at the waypoint, which is when the jaywalking pedestrian first becomes visible. An eye gaze heat map analysis is shown in Figure 30.

Figure 30. Eye tracking gaze analysis

Figure 30 clearly shows that the participants glanced at the PCW and this possibly affected their speed reduction times compared to the baseline scenario in which even though they may not be distracted, it may be difficult to observe the pedestrian at that very

moment. This infers that having a PCW system informs the driver of an oncoming pedestrian, giving them plenty of time to react accordingly. The gaze data also shows that participants who glanced at the PCW popup had longer speed reduction times compared to participants who did not look at the popup.

From the videos recorded using the eye tracker, it was observed that, of the 27% of the participants who did not stop or ran over the jaywalking pedestrian in the baseline scenario, 64% of these participants did actually stop for the pedestrian in the PCW system scenario, confirming the benefits a PCW system. The authors did not find any significant correlation with sociodemographics of the participants and eye gaze analysis.

5.1.5   Findings

This application, a PCW system, was tested on driver braking behavior using a full-scale, medium fidelity driving simulator and an eye tracking device. Ninety-three participants were involved in this study, contributing to 186 simulation sessions. The scenarios were evaluated for the participants' braking behavior at the sudden appearance of a jaywalking pedestrian in the form of speed reduction times using a Log logistic AFT model. It was observed that speed reduction times were higher in the presence of a PCW system and men were more inclined to have a higher speed reduction time compared to women, leading to an initial aggressive braking behavior. This suggests that, the presence of a PCW system sends a clear message to the driver about the presence of a pedestrian, giving the driver ample time to adapt their initial approach speed to yield to the pedestrian. Although, the warning may force the drivers to brake aggressively initially, the objective of the system to protect the pedestrian will be fulfilled. These findings were substantiated

by the jerk analysis, which shows that, jerk is unsafe, in the initial seconds of a PCW, while the scenario without the PCW system, results in a highly uncomfortable jerk, when the pedestrian is closer to the vehicle. The overall analysis also suggested that high initial approach speeds, decrease in minimum speeds during the deceleration phase, and a decrease in average deceleration rates have a significant positive influence on the speed reduction times. An interesting observation from the post simulation survey questionnaire was that 31% of the participants said that a PCW system was their top choice of CAV technology to have in their automobiles. The eye tracking analysis showed that majority of the participants did glance at the PCW as compared to observing other objects; its absence may impact the reaction time needed to stop for the pedestrian. A longer speed reduction time means that, although this may involve aggressive braking initially, the drivers will eventually pace themselves at a speed that will allow the pedestrian to pass safely. This may also be true for drivers who exceed the safe speed limit of the road and may not brake appropriately to stop for the pedestrian in time, if not for the PCW.

5.2 Red Light Violation Warning

Interstate-395, a two-lane highway, south of downtown Baltimore was replicated in the driving simulator for this analysis, where a RLVW is issued to the simulation vehicle, as soon as it enters the dilemma zone, 50 meters from the traffic signal stop line.

5.2.1 Experiments

A total of 186 experiments were conducted; however, in 116 of those experiments, the participants either failed to stop at the red light when it turned yellow or there was a

software glitch which resulted in the RLVW not showing up. Thus, the final data set, used in the analysis, consisted of 70 observations of the driver's braking maneuvers. The braking maneuvers of the participants when they enter the dilemma zone were analyzed, in both the baseline scenario as well as the scenario involving a RLVW system.

The average deceleration rate (d_m) at the instance the participant enters the dilemma zone is stated in Equation (4):

where,

V_i = Participant's initial speed as they approach the dilemma zone

V_{min} = Participant's minimum speed reached during the deceleration phase

L_{V_i} = Distance between the vehicle's location when the initial speed was recorded and the location of the stop line at the red light

$L_{V_{min}}$ = Distance between the vehicle's location when the minimum speed was recorded and the location of the stop line at the red light

The speed reduction time (S) is calculated as the elapsed time between the participant's initial speed (V_i) and the minimum speed (V_{min}) reached before coming to a stop at the red light.

A plot of the participants' speed profile before and after they enter the dilemma zone, where the signal just changed from green to yellow, was generated. Through this plot as shown in Figure 31, several parameters related to the participants' braking maneuvers were calculated. The lowest speeds do not reflect zero values, as this is an interpolation of average speeds over distance i.e. the participants stop at different distances before, at or after the stop line.

83
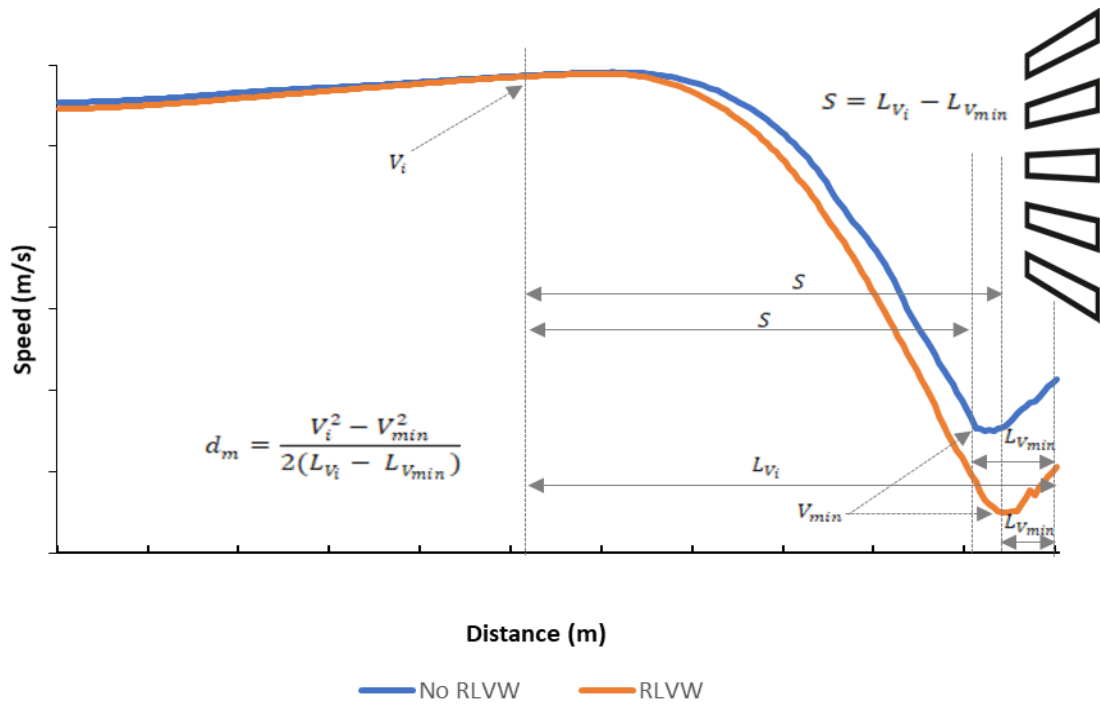
Figure 31. Participant average speed profile comparison

To determine the braking behavior with and without the RLVW, a plot of the average deceleration rates of all participants is plotted in Figure 32.
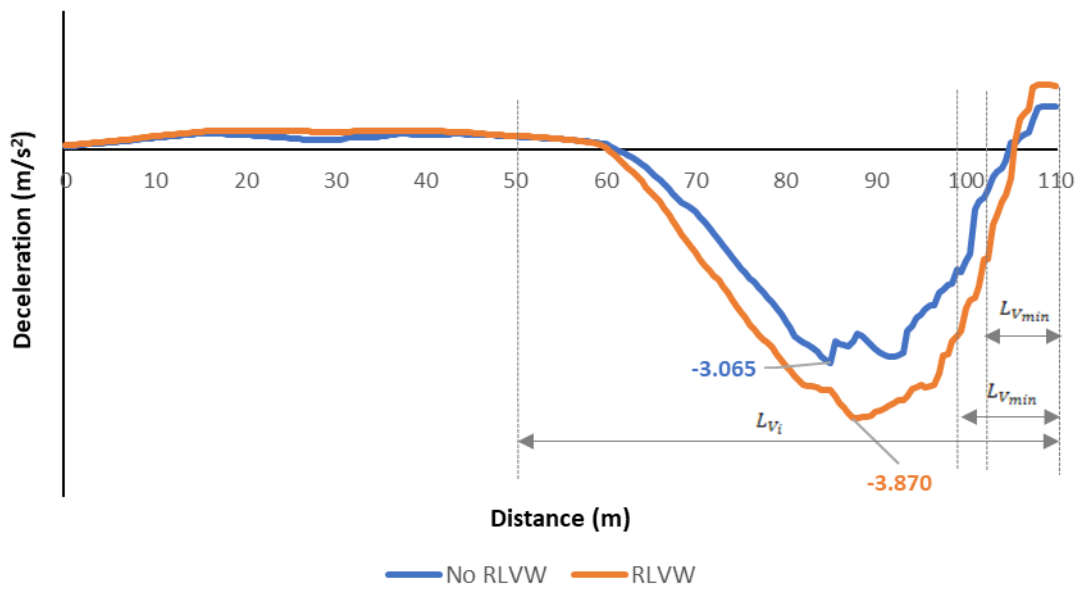
Figure 32. Participant average deceleration

The deceleration rate in Figure 32 shows that, the participants braked earlier, at the onset of the RLVW. Average maximum deceleration (-3.870 m/s^2) for the RLVW scenario is attained at 38 meters from the warning point, while maximum deceleration (-3.065 m/s^2) for the Non-RLVW scenario is attained at 35 meters from the potential warning point. To confirm this braking behavior, once again, the perception reaction time taken to release the throttle and the brake execution time from the moment the throttle is released until the initial brake application, is calculated for each participant. The braking intensity as mentioned before, is calculated, one second after the brakes are pressed to determine the intensity, where on a scale of 0 to 1, 0 is no brake force and 1 is maximum brake force. The average reaction and braking execution time statistics are shown in Table 10.

Table 10. Reaction and braking execution time statistics

	Average Perception Reaction Time (s)	Average Brake Execution Time (s)	Average Time to Reach Max Deceleration (s)	Average Max Braking Intensity	Average Max Speed Change (m/s)
RLVW	0.7	0.31	2.96	0.56	7.57
No RLVW	0.9	0.28	2.61	0.41	4.09

From Table 10, it can be seen that, participants react quicker in the presence of a RLVW system as the participants get the warning before they can anticipate the change in traffic light, and thus start braking early, before gradually coming to a stop at the stop line. The average time to reach maximum deceleration is 2.96 seconds and 2.61 seconds respectively, for the RLVW and Non-RLVW scenario, which confirms the hard-braking behavior. The average maximum braking intensities at these points were 0.56 and 0.41 respectively. The average maximum speed change is the difference in speed from the warning point until the average maximum deceleration is reached. The almost double,

change in speed (7.57 m/s compared to 4.09 m/s) confirms harder braking, between a short time duration of 0.35 seconds. A representation of the numbers shown in Table 10 is presented in Figure 33.
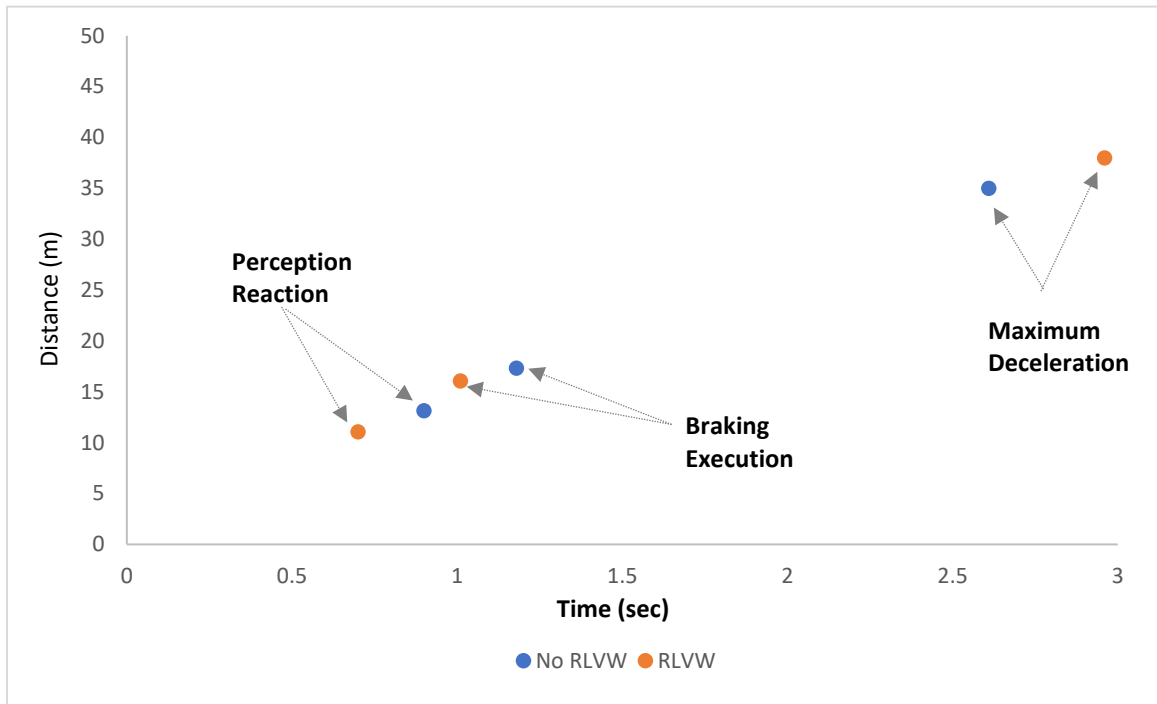
Figure 33. Sequence of events by time

From Table 10 and Figure 33, it can be said that, participants took slightly longer to react in the absence of a RLVW system. From Figure 32 and Figure 33, the hard braking in the RLVW scenario can be confirmed as maximum declaration is reached at 2.96 seconds compared to the 2.61 seconds, in the Non-RLVW scenario, supported by the average maximum braking intensity (0.56 compared to 0.41) from Table 10, at the maximum deceleration points.

5.2.2 Jerk Analysis

Jerk is calculated for each participant and averaged every tenth of a second, from the waypoint where the RLVW is issued. The participants average jerk by time is shown in Figure 34.
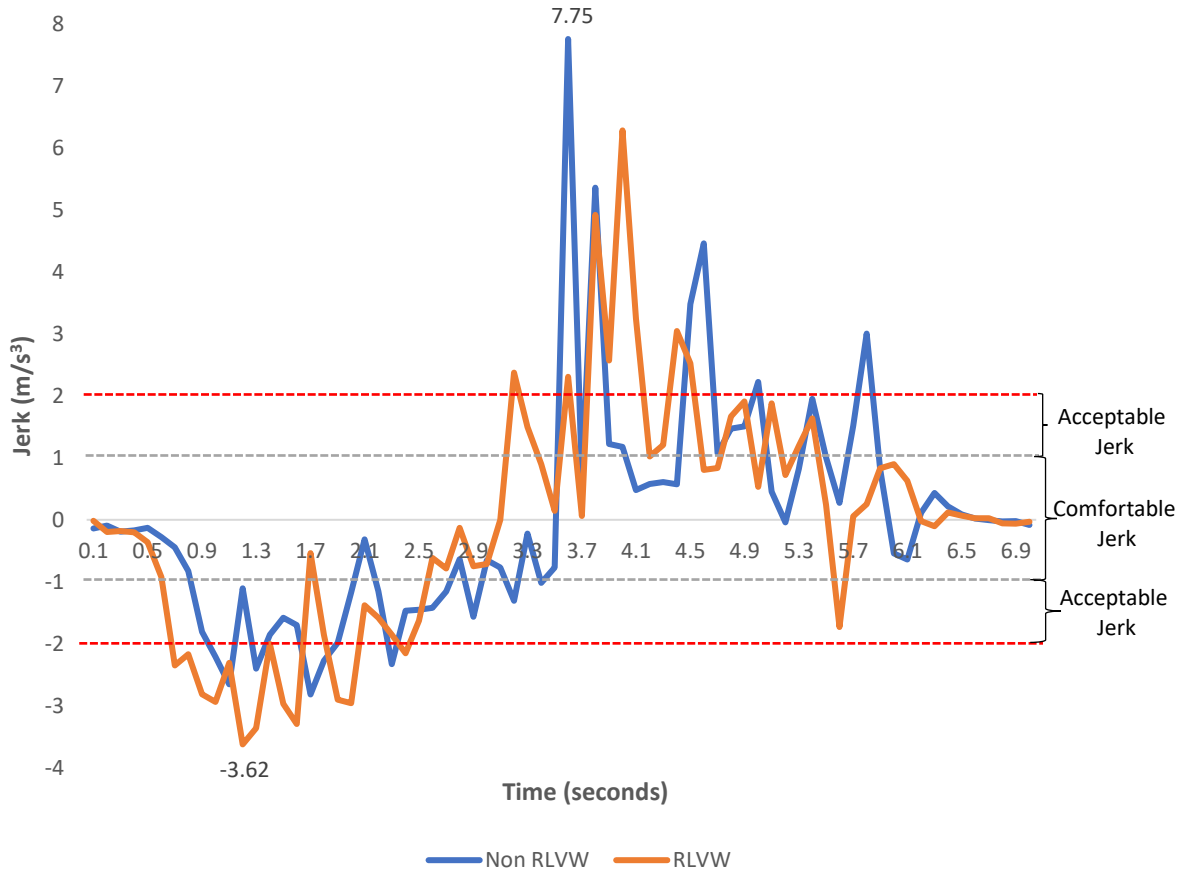
Figure 34. Participants Average Jerk by Time

Negative jerk values are associated with an abrupt release of the throttle, and immediately followed by the pressing of the brakes. It can be seen that, in the scenario with the RLVW, the average initial jerk upto 2 seconds, are over the acceptable jerk limit (Wei and Rizzoni 2004) i.e. it is unsafe. On the other hand, in the scenario without the RLVW, around 3.6 seconds after the waypoint, the jerk is the maximum at 7.75 m/s^3. This being a

positive jerk, it is from the sudden release of the brakes and can be termed as a highly uncomfortable jerk. The jerk drops sharply at 3.6 seconds and is still positive, which means that, the participants in the Non-PCW scenario, press the throttle suddenly. This signifies that the participants slowed down enough initially, and then had to accelerate before coming to a final stop at the red light.

5.2.3 Lognormal AFT model

An ANOVA analysis revealed that there was a statistically significant difference in speed reduction times between the baseline scenario and the scenario with a RLVW system. The speed reduction times were longer in the scenario involving the RLVW system (mean difference in time = 2.41 seconds, $\rho \leq 0.05$) at 6.97 seconds compared to 4.56 seconds in the baseline scenario. This implies that the overall deceleration rate when the RLVW was used, is less compared to when the system was not used (2.40 m/s^2 vs. 2.87 m/s^2). Although like the PCW, this infers a smoother braking maneuver, it is not the case as seen in Figure 30. Since deceleration rate or braking behavior is affected by CAV technology, in this case a RLVW system, a hazard-based duration model was developed to understand the participant's braking behavior in terms of speed reduction times. The aim of this model is to depict the impact of the presence of a RLVW system on the participants' speed reduction times. Consequently, this relationship can be represented by one of the following survival functions: lognormal, log-logistic, exponential and Weibull. As mentioned previously (Burnham and Anderson 2004, Wagenmakers and Farrell 2004), in order to select the best fit and most applicable function, the AIC and log-likelihood values were used. The four distributions were assessed, and it was found that the lognormal model

provides the best fit for the data as it had the lowest AIC values at -88.017 and the highest

log-likelihood values at -150.394, among them.

Therefore, in this research the hazard function of the lognormal duration model will

be used; this function is expressed as (NIST):

Equation 7: Hazard Function – Lognormal Model

$$h(t, \sigma) = \frac{\frac{1}{t\sigma}\emptyset\left(\frac{\ln t}{\sigma}\right)}{\Phi\left(\frac{-\ln t}{\sigma}\right)}$$

where $t > 0$ and $\sigma > 0$ while the survival function $S(t)$ of the lognormal duration model

is expressed as (NIST):

Equation 8: Survival Function – Lognormal Model

$$S(t) = 1 - \Phi\left(\frac{ln(t)}{\sigma}\right)$$

where $t \geq 0$ and $\sigma > 0$ and;

$\emptyset =$ Probability density function of the normal distribution

$\Phi =$ Cumulative distribution function of the normal distribution

$\sigma =$ The shape parameter

$t =$ Specified time

Table 11 shows the descriptive statistics of the different parameters used in the lognormal

model and the speed reduction times in scenarios where both the RLVW system was used

and when the RLVW system was not used.

Table 11. Speed reduction time and Lognormal AFT variable descriptives

Variables	Mean Value (NO RLVW)	Std. Dev (No RLVW)	Mean Value (RLVW)	Std. Dev (RLVW)

V_i (m/s)	16.36	2.82	15.47	2.95
L_{V_i} (m)	2050.96	0.53	2050.77	0.52
V_{min} (m/s)	0	0	0	0
$L_{V_{min}}$ (m)	2098.908	5.58	2102.19	4.01
d_m (m/s^2)	2.87	0.90	2.40	1.02
Speed Reduction Time(s)	4.56	0.98	6.97	3.32

Furthermore, an assessment of the goodness of fit for the lognormal model was conducted by plotting the cumulative hazard rate determined from the model estimates and then utilized to build an empirical estimate of the cumulative hazard model. As seen in Figure 35, the points representing the estimate of the cumulative hazard function almost follow the 45° line; hence, it can be inferred that the participants' predicted speed reduction time, using the lognormal model, can be considered as a good fit with the observed data.
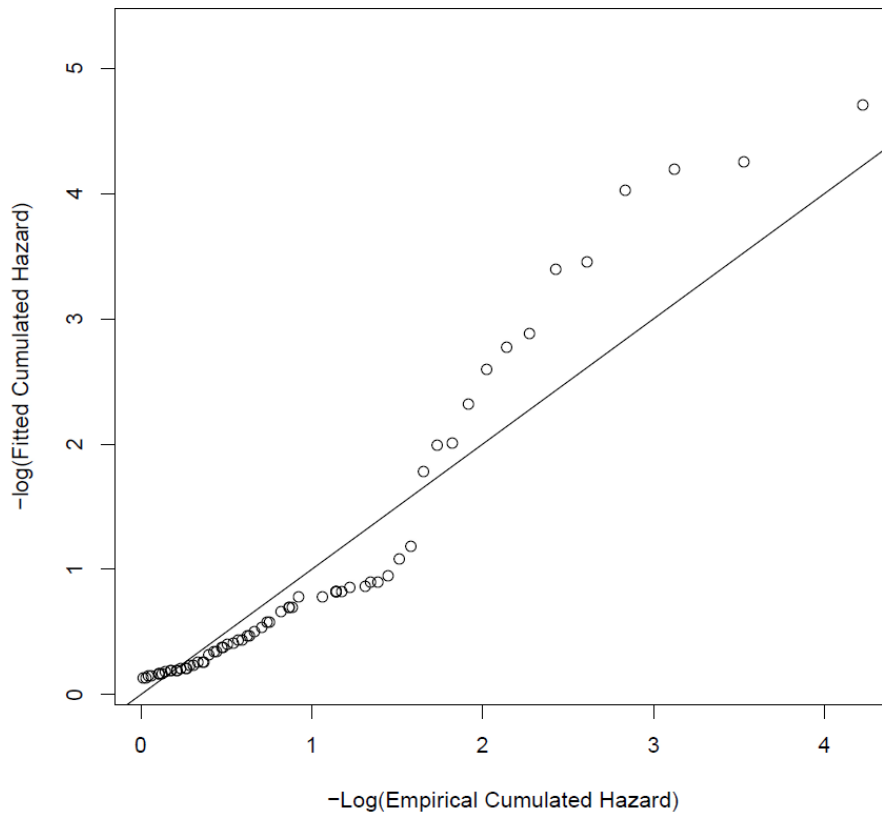
Figure 35. Cox-snell residuals for Lognormal AFT

The estimates from the lognormal AFT model with the speed reduction times of the participants as the dependent variable are shown in Table 12.

Table 12. Lognormal AFT parameter estimates

Variables	Estimate	Std. Error	z-Stat	p-value
(Intercept)	-125.824	181.490	-0.693	0.488
V_i (m/s)	-0.041	0.053	-0.765	0.444
L_{Vi} (m)	0.062	0.089	0.705	0.481
V_{min} (m/s)	0	0	-	-
d_m (m/s^2)	0.023	0.153	0.148	0.882
RLVW	0.373	0.079	4.731	0.000*
Annual mileage> 30,000 miles	-0.152	0.167	-0.913	0.361
Annual mileage 15,001 - 30,000	-0.059	0.129	-0.453	0.651
Annual mileage 8,001 - 15,000 miles	-0.102	0.099	-1.025	0.305
Annual mileage - Not Applicable	-0.259	0.143	-1.812	0.070***
Reaction on getting a RLVW - Ignored it	-0.722	0.358	-2.013	0.044**
Reaction on getting a RLVW - Distracting	-0.056	0.106	-0.529	0.597
Does your car have any CAV application? None	0.274	0.119	2.311	0.020**
AIC	-88.017			
Log-likelihood at convergence	-150.394			
Number of groups	70			

* Significant at 99% CI   ** Significant at 95% CI   *** Significant at 90% CI

Table 12 identifies the variables that significantly influence the participants' speed reduction times while in the dilemma zone. The scenario with the RLVW system was found to be statistically significant in positively influencing speed reduction times at the 99% confidence interval. In the survey questionnaires, participants who stated that they ignored the RLVW had a negative influence on speed reduction times, which infers that they had a lower speed reduction time, compared to the participants who followed the RLVW. Those

who stated that their car does not have, or support CAV applications had a positive influence on speed reduction times. This means that participants who did not have prior experience in getting information while driving, followed the RLVW system, which resulted in longer speed reduction times. This doesn't mean that the braking was smooth, as seen in Figure 32, it means that participants brake harder initially and then gradually proceed towards the signal before, coming to a stop. Participants who stated that annual mileage wasn't applicable to them, i.e., they either do not own a car or drive/rent a vehicle infrequently and had little driving experience compared to the majority. This lack of experience had a negative influence on speed reduction time, resulting in a lower speed reduction time. In a scenario where a driver may run the red light at a high speed, having a RLVW system involving higher speed reduction times may be beneficial as the initial aggressive braking may end up preventing the vehicle from entering the intersection and causing a crash, compared to late braking without a RLVW system and entering the intersection.

A representation of the participants' braking patterns can be shown by plotting survival curves of the speed reduction times for the baseline scenario as well as the scenario involving the RLVW system. These predictions were done based on the predict survival regression tool in the R-package (Therneau) as shown in Figure 36.
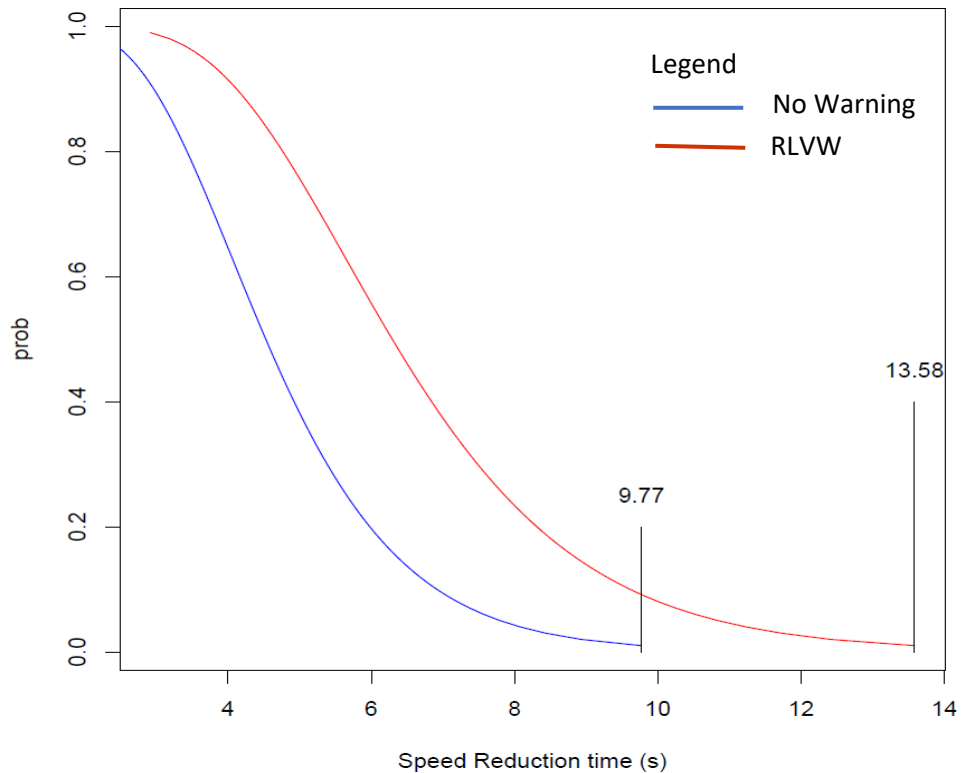
Figure 36. Speed reduction time survival curves

From Figure 36, it can be seen that the speed reduction time survival probability decreases with the passage of time. A lower survival probability was recorded for the scenario with no RLVW as compared to the scenario with the RLVW system. At 5 seconds of speed reduction time, the survival probability for the baseline scenario was 37% compared to 75% for the scenario with the RLVW system, and it drops even further at 7 seconds, to only 9% in the baseline scenario compared to 38% in the RLVW system scenario. Since these values represent the same maneuver performed by the participant to stop at the red light, the longer value (3.81 seconds longer when the RLVW system was used) implies adequate time to come to a stop at the red light. This supports the conclusion that when the RLVW system was used, the participants were able to start their braking maneuver earlier, due to the warning given.

5.2.4 Binary Logit Model

An additional analysis was performed to evaluate the effectiveness of the RLVW application. This analysis used a binary logit model to evaluate the factors, in this case the sociodemographics of the participants and survey questionnaires, influencing stopping at the red light. The output of the model is shown in Table 13.

Table 13. Binary logit model parameter estimates

Violation[a]		B	Std. Error	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
Stopped at Red Light	Intercept	-1.452	1.158	0.210			
	[Gender= Female]	-0.093	0.422	0.826	0.911	0.398	2.084
	[Gender= Male]	0[b]					
	[Age Group= 18 to 25]	0.601	0.898	0.504	1.823	0.314	10.597
	[Age Group= 26 to 35]	-0.069	0.872	0.937	0.933	0.169	5.154
	[Age Group= 36 to 45]	-0.458	1.031	0.657	0.633	0.084	4.777
	[Age Group= 46 to 55]	-1.216	1.051	0.247	0.296	0.038	2.326
	[Age Group= 56 to 65]	0[b]					
	[Familiar with AV Only]	-0.079	0.515	0.878	0.924	0.337	2.534
	[Familiar with both AV and CV]	0.999	0.576	0.083	2.715	0.878	8.388
	[Familiar with CV Only]	0.382	0.887	0.667	1.465	0.258	8.336
	[Familiar with CAV = None]	0[b]					
	[Annual Mileage = < 8000 miles]	2.407	0.777	0.002*	11.103	2.423	50.875

[Annual Mileage => 30,000 miles]	0.874	0.824	0.289	2.397	0.476	12.063
[Annual Mileage =15,001 - 30,000]	0.998	0.731	0.172	2.713	0.648	11.363
[Annual Mileage =8,001 - 15,000 miles]	0.720	0.639	0.260	2.055	0.587	7.189
[Annual Mileage = Not Applicable]	0^b					
[Warning= RLVW]	1.373	0.399	0.001*	3.947	1.806	8.624
[Warning = No RLVW]	0^b					

a. The reference category is: Ran the Red Light

b. This parameter is set to zero because it is redundant.

* Significant at 99% CI

From Table 13, it can be seen that only two factors were found to be statistically significant, influencing the participants to stop at the red light while in the dilemma zone. The scenario involving an RLVW system was found to be more effective as compared to a scenario without an RLVW system. Participants who answered that they drive less than 8,000 miles annually were also found to have a significant impact on stopping at the red light. The odds of participants stopping at the red light are 4 times higher (odds ratio = 3.947) in the presence of an RLVW system, and 11 times higher (odds ratio = 11.103) when participants stated they drive less than 8,000 miles annually. This could possibly mean that participants who drive less tend to drive more cautiously as compared to participants who drive more than 8,000 miles annually, have plenty of driving experience and would be more comfortable accelerating through the dilemma zone.

5.2.5   Eye Gaze Analysis

This analysis used Tobii Pro Glasses 2 (Tobii 2019), the eye tracking device and its analysis software. Both scenarios, the baseline and the one with the RLVW system, were evaluated, to analyze where the participants glanced at the moment when they entered the dilemma zone. An eye gaze heat map analysis is shown in Figure 37.

Gaze Objects	With RLVW	Without RLVW
Buildings		
Automobiles		
RLVW		
Traffic Light		
Trees		
No Distraction, Eyes on Road		
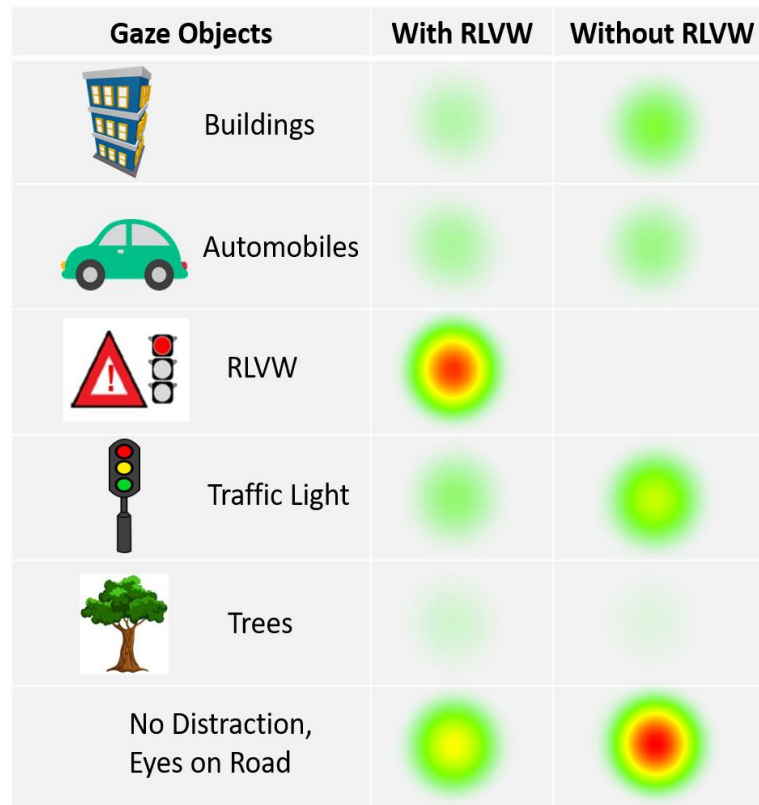
Figure 37. Eye tracking gaze analysis

Figure 37 clearly shows that the participants glanced at the RLVW and this possibly influenced their speed reduction times compared to the baseline scenario, in which even though they may not be distracted, the sudden change in light may have led to aggressive braking at the last moment, considering the speed reduction time was lesser, in this scenario. This infers that having a RLVW system informs the driver of a changing traffic light, giving them plenty of time to react accordingly.

From the videos recorded using the eye tracker, it was observed that, of the 40% of the participants who did not stop for the red light in the baseline scenario, 55% of these participants did actually stop for the red light in the scenario with the RLVW system, confirming the benefits of a RLVW system. The authors did not find any significant correlation between sociodemographics of the participants and eye gaze analysis.

5.2.6 Findings

This application, a RLVW system, was tested on driver braking behavior using a full-scale, medium fidelity driving simulator and an eye tracking device. Ninety-three participants were involved in this study, contributing to 186 simulation sessions. It was found that the participants using the RLVW system braked harder initially when the warning was issued and then gradually proceeded to the stop line. The scenarios were evaluated for the participants' braking behavior at the entrance to the dilemma zone in the form of speed reduction times using a lognormal AFT model. It was observed that speed reduction times were significantly higher in the presence of a RLVW system. This suggests that the presence of a RLVW system sends a clear message to the driver about the change in traffic light and gives the driver ample time to adapt their initial approach speed to stop at the signal, avoiding potential intersection crashes. From the post simulation survey questionnaire, only a small percentage of participants said they would consider a RLVW system among their top choices of CAV technology for their automobiles. A binary logit model showed than having an RLVW system and participants who drive less than 8000 miles annually, are the most important factors influencing participants to stop at the red light, while passing through the dilemma zone. The eye tracking analysis showed that

majority of the participants did glance at the RLVW as compared to other objects, and its absence may impact the reaction time needed to stop for the red light. Similar to the findings of the PCW system, a longer speed reduction time does not necessarily mean a smoother transition, as participants braked aggressively at the onset of the RLVW system but had ample time to come to a stop at the red light, which would potentially help avoid intersection crashes. The aggressive braking at the beginning of the RLVW system was substantiated by the jerk analysis.

5.3 Forward Collision Warning

The FCW was programmed to occur in both the developed scenarios, where only the first stage of an FCW system was replicated for evaluation.

5.3.1 Speed Analysis

Some 104 instances of FCW were detected in 186 experiments in which the participants were approaching the vehicle preceding them at an alarming speed. In this analysis, average speeds were calculated 5 seconds before and after the FCW was issued, to evaluate the impact of the warning in terms of change in speed. The difference in speed change was considered in lieu of average before and after speeds, since the speed limits varied at different segments in the scenario and thus would not be a good measure for this analysis.

5.3.1.1 One sample t-test

A one sample t-test was conducted to determine whether the mean difference in speed change is statistically different from the hypothesized mean difference in speed of zero.

Table 14. One sample t-test

	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
Change in speed	12.990	103	0.000*	15.070	12.769	17.371

* Statistically significant at 99% CI

Table 14 shows that the change in speed is statistically significant at the 95% confidence interval post FCW by an average speed of 15.07 mph. To identify the most appropriate method to evaluate the factors influencing such a change in speed, three models were considered: a decision tree model, a random forest model, and an ordinary least squares regression model. The decision tree and the random forest models are machine learning models and they have a useful tool, called "variable importance," which ranks the variables according to their importance, as they relate to the dependent variable. To select the best model for this FCW dataset across machine learning and statistics, a comparison of R-squared values and Mean squared error (MSE) were considered to be the most appropriate. A higher R-squared value and a lower MSE would suggest the best fit model, out of the models considered for this dataset. The output of the comparison is shown in Table 15.

Table 15. Model Comparison

Model	R-Squared	MSE
Decision Trees	0.268	101.3
Random Forest	0.577	65.4
Linear Regression	0.212	109.1

Based on Table 15, a Random Forest model with the highest R-squared value of 0.577 and the lowest MSE value of 65.4 was considered as the best fit for this dataset.

5.3.1.2 MDG Score

Figure 38 shows the MDG score for all the variables used for the change in speed analysis. It can be seen that "age" and "familiarity with CAVs" stand out and thus are selected as the most important variables that impact change in speed, post FCW. Figure 38 shows the variable importance scores for the respective variables, which means that the variables with the highest importance scores are the ones that give the best prediction and contribute the most to the model. This also means that if the top variables are dropped from the model, the predictive power of the model will be greatly reduced as compared to removing the least important variables.
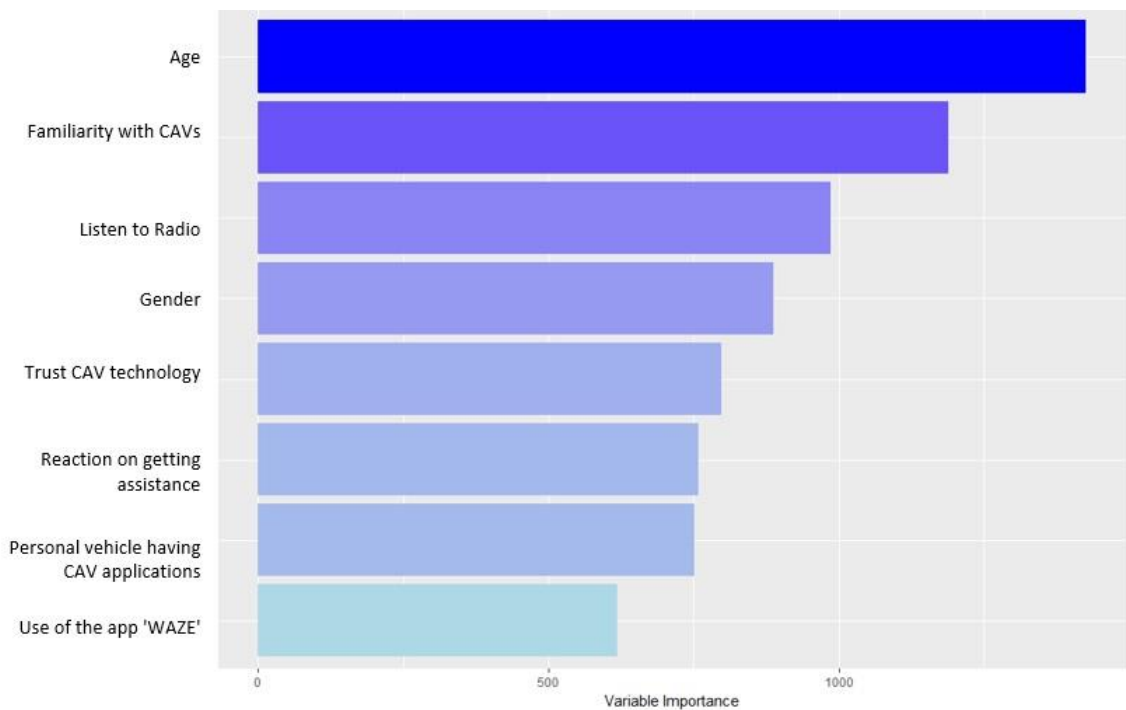
Figure 38. Variable importance based on increasing node impurity (Simulator)

Based on the descriptive statistics, with a change in speed between 15 and 30 mph, more than 66% of the participants were below the age of 35. Thus, it can be inferred that participants in the younger age group tend to slow down more when encountering an FCW, compared to the participants older than 35. Participants' familiarity with CAV technology could also positively or negatively affect speed change, post FCW.

5.3.2 Data from Michigan Field Study

The FCW data obtained from the Michigan study consisted of 106 unique vehicles/participants involved in 12,210 instances of FCW. To obtain metrics similar to the ones observed in the driving simulator, an average change in driving speed was calculated 5 seconds before and after the FCW was issued.

5.3.2.1 One-sample t-test

A one sample t-test was conducted to determine whether the mean difference in speed change is statistically different from the hypothesized mean difference in speed of zero.

Table 16. One sample t-test

	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
Change in speed	55.114	12209	0.000*	8.597	8.291	8.903

* Statistically significant at 95% CI

Table 16 shows that the change in speed is statistically significant at the 95% confidence interval post FCW by an average speed of 8.597 mph. Since sociodemographic variables could not be obtained for this dataset, the influence of the available variables, namely "braking before" and "braking after," could possibly bring some insight to the impact of FCW on speed change behavior. To identify the most appropriate method to evaluate these factors, again, three models were considered: a decision tree model, a random forest model, and an ordinary least squares regression model, in which a comparison of R-squared values and Mean squared error (MSE) were considered to be the most appropriate. The output of the comparison is shown in Table 17.

Table 17. Model Comparison

Model	R-Squared	MSE
Decision Trees	0.505	146.9
Random Forest	0.518	143.9

Linear Regression	0.477	155.1

Based on Table 17, a Random Forest model with the highest R-squared value of 0.518 and the lowest MSE value of 143.9 was considered as the best fit for this dataset.

5.3.2.2 MDG Score

Figure 39 shows the MDG score for all the variables used for the change in speed analysis.
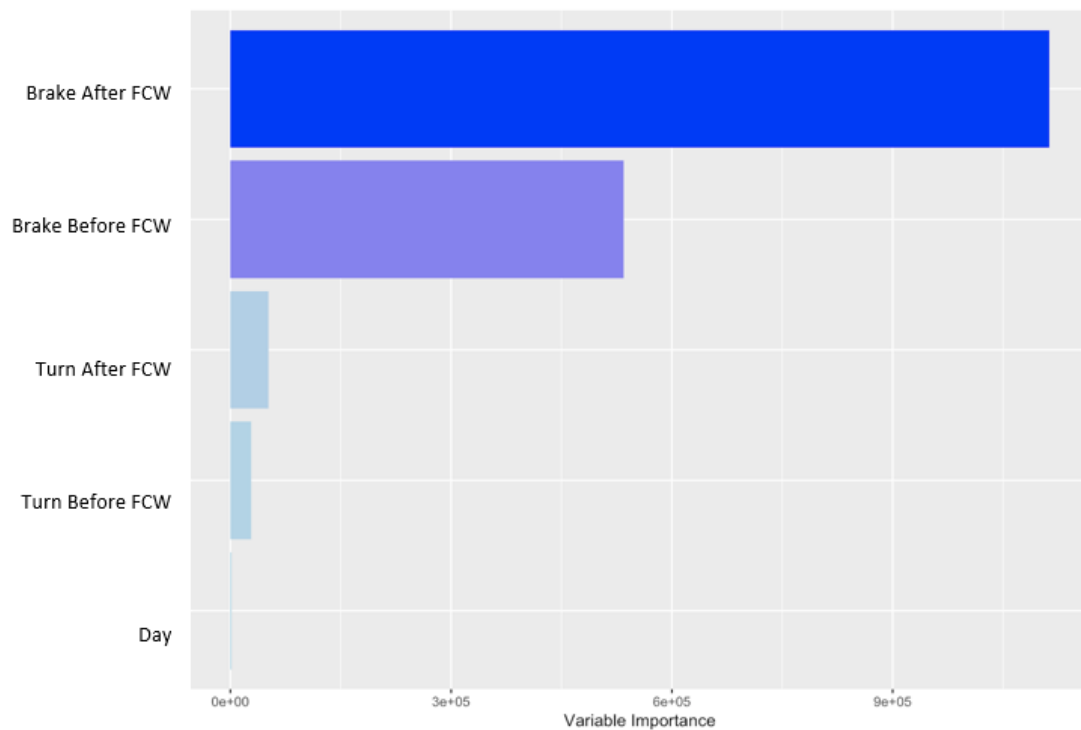
Figure 39. Variable importance based on increasing node impurity (Field Data)

It can be seen that braking after the FCW is the most important variable compared to the others. This means that the majority of the drivers only started braking after receiving

the FCW compared to the drivers who had already started braking before receiving a warning.

5.3.3 Driving Simulator Validation

If a two-sample t-test is performed to compare the changes in speed in both the driving simulator as well as the Michigan field data with regard to the effectiveness of FCW, the change in speeds of 15.07 mph and 8.597 mph will be significantly different. This is mainly due to the different speed limits of the roads in Ann Arbor, compared to the driving simulator. Comparing the mean difference in speeds is not the goal of this validation. This validation simply proves that an FCW system in a driving simulator is as effective as the ones used in the field to induce a speed reduction.

5.4 Curve Speed Warning

Interstate-95, a four-lane highway, south of downtown Baltimore was replicated in the driving simulator for this analysis, where a CSW is issued to the simulation vehicle, as soon as it enters the exit ramp, transitioning from a 55-mph speed limit to a 25-mph speed limit.

5.4.1 Speed Analysis

Some 182 instances of CSW were recorded in 186 experiments, in which the participants were approaching an exit ramp at speeds higher than the safe speed limit for the ramp. In this analysis, once again average speeds were calculated 5 seconds before and after the CSW was issued, to evaluate the impact of the warning in terms of change in speed. The average before and after speeds were considered in this analysis, since the

infrastructure for the V2I technology was present at only one curve, which was at the beginning of the exit ramp.

5.4.1.1 Single Factor ANOVA analysis – CSW scenario

A single factor ANOVA analysis was conducted for the scenario involving a CSW, to determine whether the average before and after speeds are statistically different from the hypothesized average before and after speed difference of zero.

Table 18. Single Factor ANOVA Summary

Groups	Count	Sum	Average	Variance
Speed Before kmph	90	6788.988	75.433	187.380
Speed After kmph	90	6713.018	74.589	137.571

Table 19. Single Factor ANOVA Output

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	32.062	1	32.062	0.197	0.657	3.894
Within Groups	28920.71	178	162.475			
Total	**28952.77**	**179**				

Table 18 shows that the mean speed before the CSW was 75.4 kmph or approximately 20.95 m/s, while the mean speed 5 seconds post CSW was 74.5 kmph or approximately 20.69 m/s, where the safe speed limit to navigate the curve/ramp was 11.17 m/s (25 mph). Table 19 shows that the p-value being 0.657 and statistically insignificant ($\rho > 0.05$), the null hypothesis cannot be rejected, i.e. the CSW did not have an influence on change in speed.

5.4.1.2 Single Factor ANOVA analysis – Non CSW/Baseline scenario

A single factor ANOVA analysis was conducted for the scenario without a CSW, to determine whether the average speed before and after CSW is statistically different from zero.

Table 20. Single Factor ANOVA Summary

Groups	Count	Sum	Average	Variance
Speed Before kmph	92	7352.990	79.924	198.435
Speed After kmph	92	7293.071	79.273	177.315

Table 21. Single Factor ANOVA Output

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	19.513	1	19.513	0.104	0.748	3.893
Within Groups	34193.219	182	187.875			
Total	34212.732	183				

Table 20 shows that the mean speed before the entrance to the ramp was 79.9 kmph or approximately 22.19 m/s, while the mean speed 5 seconds after entering the ramp was 79.2 kmph or approximately 22 m/s, where the safe speed limit to navigate the curve/ramp was 11.17 m/s (25 mph). Table 21 shows that the p-value being 0.748 and statistically insignificant ($\rho > 0.05$), the null hypothesis cannot be rejected, i.e., even without a CSW, the participants did not reduce their speed while entering the curve/exit ramp.

A speed profile for the CSW and Non-CSW scenarios is shown in Figure 40.
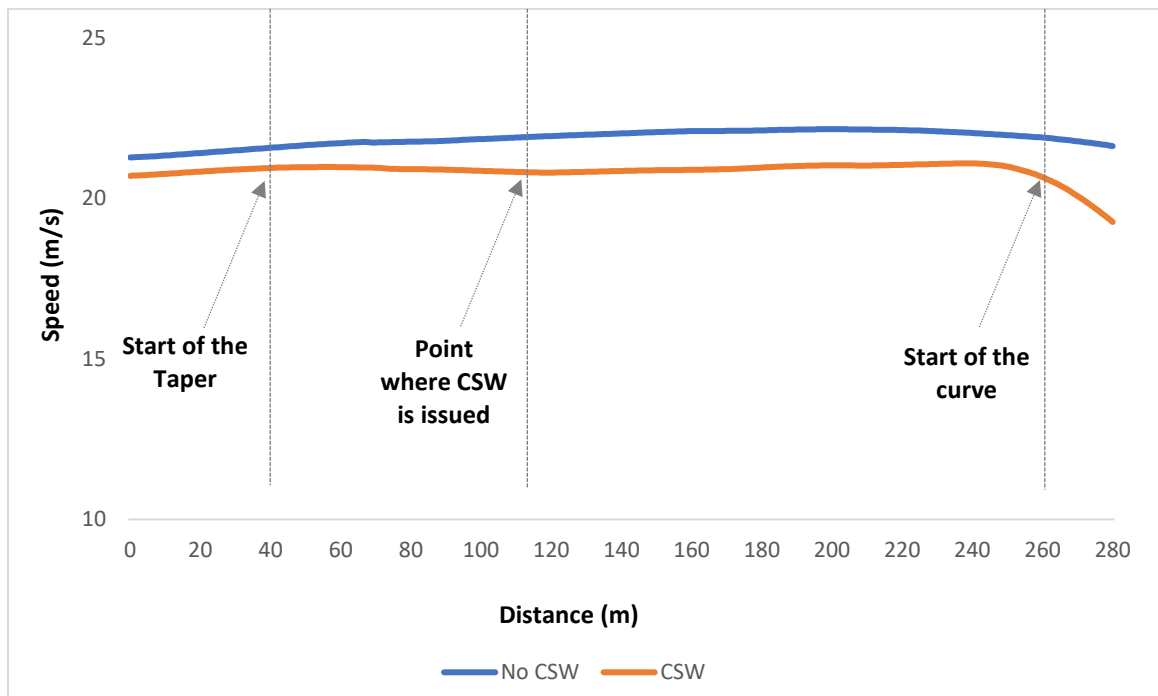
Figure 40. CSW Speed Profile

Figure 40 shows that, there is no immediate effect of the CSW on speed. At the beginning of the curve, the speed drops suddenly, which can be attributed to the entrance to the ramp. The speed drop seems significant compared to the Non-CSW scenario, which may be attributed to the additional speed information provided to the participants in the CSW scenario, on entering the ramp.

5.4.2 Data from Michigan Field Study

The CSW data obtained from the Michigan study consisted of 86 unique vehicles/participants involved in 7,280 instances of CSW. To obtain metrics similar to the ones observed in the driving simulator, the mean speeds 5 seconds before and after the CSW were considered.

5.4.2.1 Single Factor ANOVA analysis – CSW scenario

A single factor ANOVA analysis was conducted for the scenario without a CSW, to determine whether the average before and after speeds are statistically different from the hypothesized average before and after speed difference of zero.

Table 22. Single Factor ANOVA Summary

Groups	Count	Sum	Average	Variance
Speed Before kmph	7280	321959.5	44.225	616.368
Speed After kmph	7280	317193.3	43.571	601.876

Table 23. Single Factor ANOVA Output

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	1560.211	1	1560.211	2.561	0.110	3.842
Within Groups	8867604	14558	609.122			
Total	**8869164**	**14559**				

Table 22 shows that the mean speed before the CSW was 44.2 kmph or approximately 27 mph, while the mean speed 5 seconds post CSW was 43.5 kmph or approximately 27 mph. Information on the road safe speed limits was not available. Table 23 shows that the p-value being 0.110 and statistically insignificant ($\rho > 0.05$), the null hypothesis cannot be rejected, i.e., the CSW did not influence speed.

5.4.3 Driving Simulator Validation

If a single factor ANOVA analysis is performed to compare the changes in speed in both the driving simulator as well as the Michigan field data with regard to the effectiveness of a CSW, the change in speeds of 0.84 kmph and 0.65 kmph was still statistically insignificant. Again, comparing the mean difference in speeds is not the goal

of this validation. This validation simply proves that a CSW is ineffective both in a driving simulator as well as in real world, with regard to inducing a speed reduction.

5.5 Level 3 – Autonomous Mode

Ninety-one instances of Level 3 – Autonomous Mode of driving were recorded in 91 experiments, in which the participants were issued a TOR and expected to regain control of the vehicle. In this analysis, the TORt was calculated for regaining control of the steering wheel as well as the throttle.

5.5.1 Steering Wheel Control TORt

A one sample t-test was conducted to determine whether the difference between the mean steering wheel TORt is significantly different from zero.

Table 24. One sample t-test

| | | | Hypothesized Mean TORt = 0 | | | |
| | | | | Mean | 95% Confidence Interval of the Difference | |
	t	df	Sig. (2-tailed)	TORt	Lower	Upper
Steering Wheel Control	24.045	90	0.000*	2.473	2.269	2.677

* Statistically significant at 99% CI

Table 24 shows that the mean TORt for steering wheel control is statistically significant at the 95% confidence interval post TOR, by a mean TORt of 2.473 seconds. To identify the most appropriate method to evaluate the factors influencing the TORt, three models were considered: a decision tree model, a random forest model, and an ordinary least squares regression model. To select the best model for this TORt dataset across machine learning and statistics, a comparison of R-squared values and MSE was once again considered to be the most appropriate. The output of the comparison is shown in Table 25.

Table 25. Model Comparison

Model	R-Squared	MSE
Decision Trees	0.199	0.762
Random Forest	0.822	0.412
Linear Regression	0.174	0.786

Based on Table 25, a Random Forest model with the highest R-squared value of 0.822 and the lowest MSE value of 0.412 was considered as the best fit for this dataset.

5.5.1.1 MDG Score

Figure 41 shows the MDG score for all the variables used for the TORt analysis. It can be seen that "Age" and "Miles Driven" stand out and thus are selected as the most important variables that impact steering wheel TORt, post a TOR. Figure 41 shows the variable importance scores for the respective variables, which means that the variables with the highest importance scores are the ones that give the best prediction and contribute the most to the model.

Figure 41. Variable importance based on increasing node impurity

The number of miles people drive annually seems to have a direct impact on steering wheel TORt. This implies that driving less or more annually impacts people's TORt abilities. Age also seems to have an influence on steering wheel TORt which disagrees with prior studies (Körber et al. 2016) that say people below and above 36 years old have similar TORts.

5.5.2 Throttle Control TORt

A one sample t-test was conducted to determine whether the mean steering wheel TORt is statistically different from the hypothesized mean TORt of zero.

Table 26. One sample t-test

Hypothesized Mean TORt = 0

	t	df	Sig. (2-tailed)	Mean TORt	95% Confidence Interval of the Difference	
					Lower	Upper
Throttle Control	13.492	90	0.000*	2.948	2.514	3.382

* Statistically significant at 99% CI

Table 26 shows that the TORt for throttle control is statistically significant at the 95% confidence interval post TOR, by a mean TORt of 2.948 seconds. To identify the most appropriate method to evaluate the factors influencing the TORt, once again three models were considered: a decision tree model, a random forest model, and an ordinary least squares regression model. The output of the comparison in terms of R-squared values and MSE is shown in Table 27.

Table 27. Model Comparison

Model	R-Squared	MSE
Decision Trees	0.189	3.48
Random Forest	0.824	1.76
Linear Regression	0.212	3.38

Based on Table 27, a Random Forest model with the highest R-squared value of 0.824 and the lowest MSE value of 1.76 was considered as the best fit for this dataset.

5.5.2.1 MDG Score

Figure 42 shows the MDG score for all the variables used for this TORt analysis. Similar to steering wheel TORt, it can be seen that "Age" and "Miles Driven" stand out as well and are thus selected as the most important variables that impact throttle control TORt, post a TOR. Figure 42 shows the variable importance scores for the respective variables,

which means that the variables with the highest importance scores are the ones that give the best prediction and contribute the most to the model.
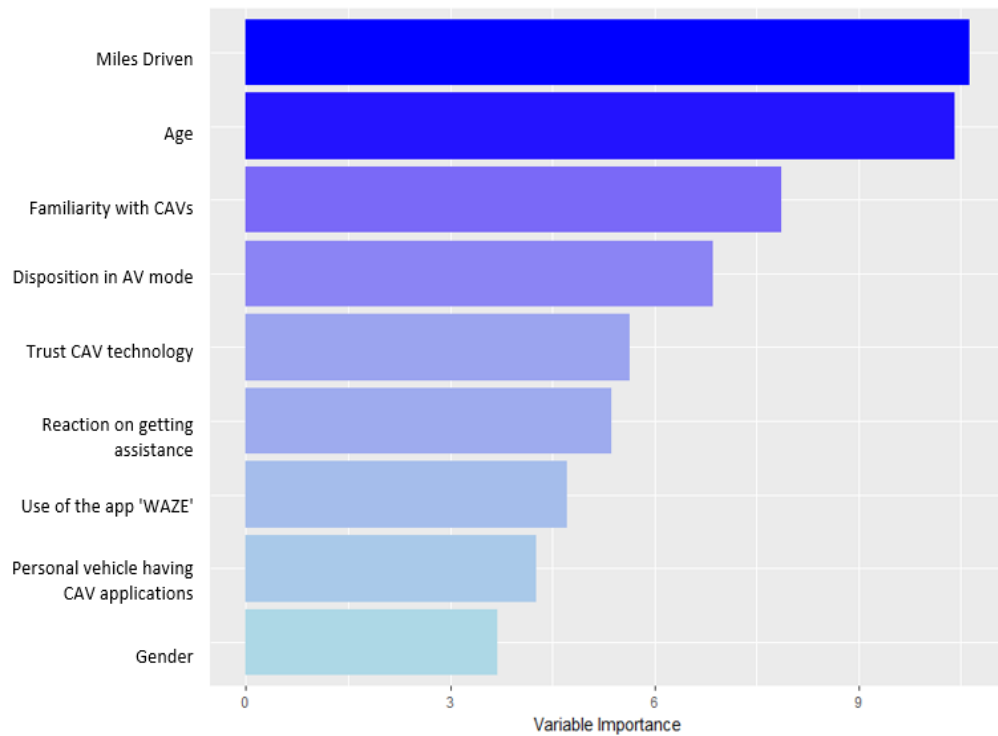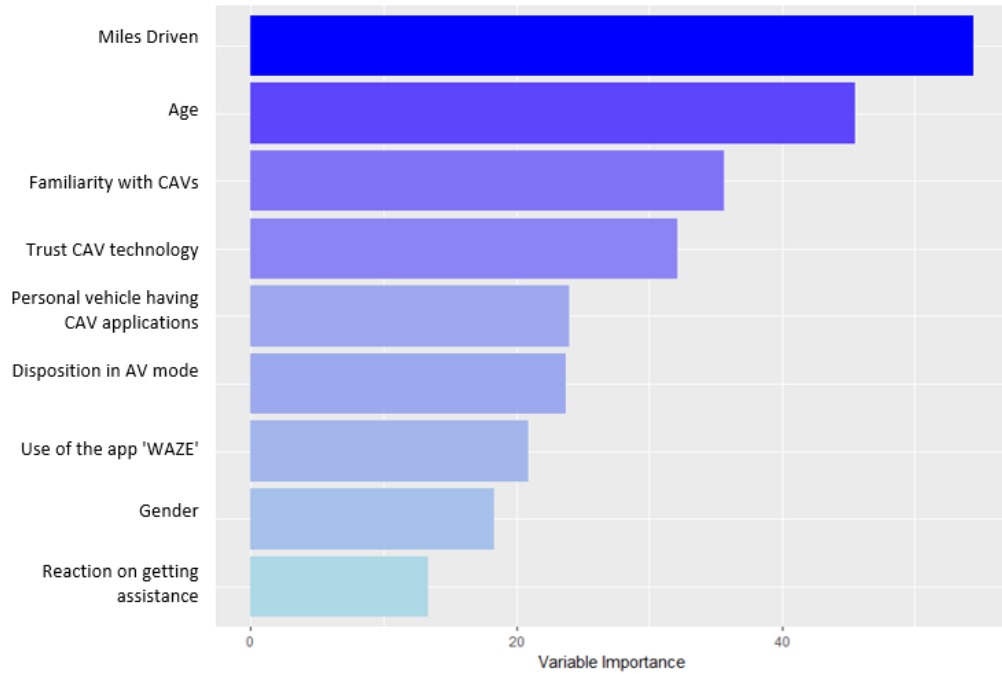

Figure 42. Variable importance based on increasing node impurity

Even though the average throttle TORt varies from the average steering wheel TORt, the factors influencing these TORts are the same. A representation of the TORts is shown in Figure 43.
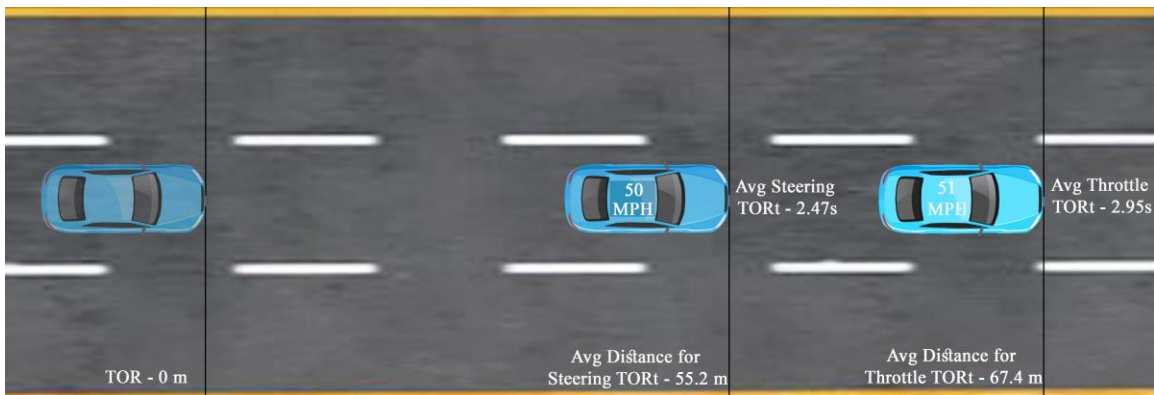
Figure 43. Representation of TORts

5.5.3   Eye Gaze Analysis

This analysis again used Tobii Pro Glasses 2 (Tobii 2019), the eye tracking device and its analysis software. Both scenarios, the baseline scenario without the autonomous mode and the one with the autonomous mode, were evaluated to analyze which objects the participants glanced at the most while the car was in autonomous mode. An eye gaze heat map analysis is shown in Figure 44.
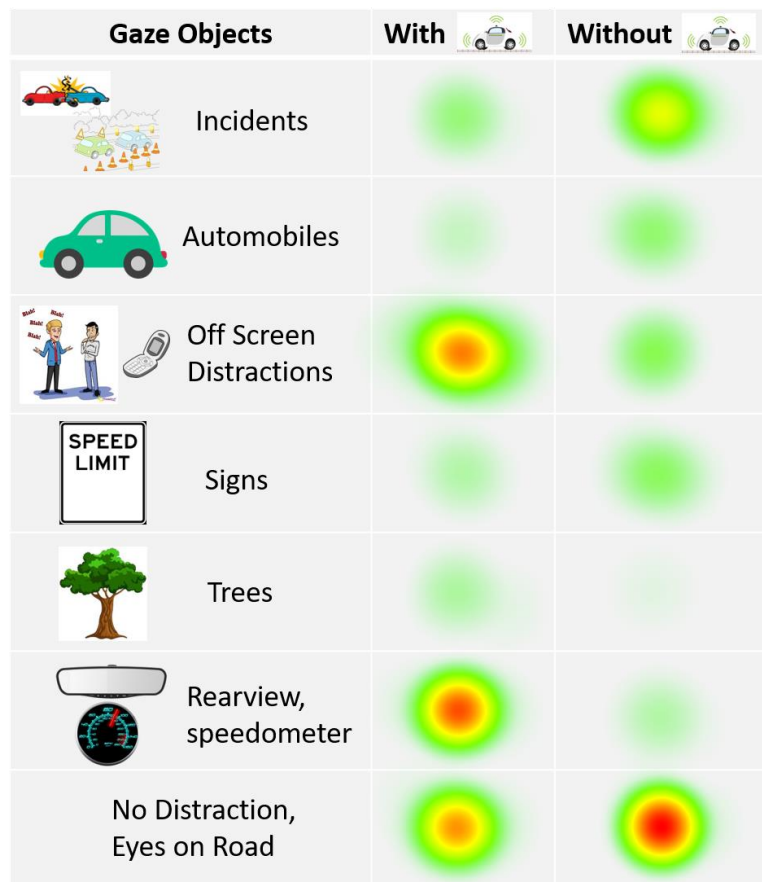
Figure 44. Eye tracking gaze analysis

Figure 44 clearly shows that, while in the Level 3 autonomous mode, most of the participants were distracted, which rejects the hypothesis of the drivers being attentive. A vast majority glanced multiple times at the speedometer as well as the rearview mirror,

which infers that the participants were awed by the new technology and seemed to check out the speed maintained by the vehicle while it drove itself and at the same time kept checking vehicles behind them, possibly to see how close or far they were. The gaze data also shows that while in the non-autonomous mode, the majority of the participants focused on the road and was not as distracted as in the autonomous mode.

The heat map shows that even though a Level 3 autonomous mode is useful in cases where people can let the car drive, there will be situations where a TOR is issued, and people must react fast enough to regain control. This analysis shows that a Level 3 autonomous mode is still in its infancy and it will be a while before people are accustomed to the technology. This study did not find any significant correlation with sociodemographic characteristics of the participants and eye gaze analysis.

Chapter 6. Discussion

This study was designed to examine the effectiveness of five different CAV applications—namely, RLVW, PCW, FCW, CSW—and autonomous driving mode, using both driving simulation experiments and field tests. These evaluations enhance the safety of the road users by assessing the drivers' reactions to these systems and discerning their possible impact, positive or negative, on driving performance. Regarding the RLVW system, the results of our study showed that the presence of a RLVW system significantly impacted the speed reduction time of the driver, requiring a longer period of time to come to a complete stop at the red light. This observation involved initial hard or aggressive braking in the RLVW scenario, but the perception reaction time was faster, which supports our hypothesis. Inferences can be drawn from the jerk analysis that, the RLVW system results in a highly unsafe jerk at the onset of the warning. Without the RLVW system though, a highly uncomfortable positive jerk occurs closer to the signal, which is due to sudden acceleration, as the participants possibly slowed down a lot initially, as can be seen in Figure 34. In addition, these results are in line with the results obtained in the (Nakamura et al. 2016), and (Qi and Mao 2015) studies; however, the results of (Yan, Liu, and Xu 2015) showed that the presence of RLVW had no significant impact on the deceleration rate. Moreover, the eye gaze analysis confirmed that the system was able to attract the drivers' attention, which is similar to the results obtained by (Caird, Chisholm, and Lockhart 2008). Nevertheless, unlike the results of (Yan, Liu, and Xu 2015) which showed that gender and driver's experience had significant impacts on the deceleration rates, our lognormal model showed that none of the drivers' characteristics had a significant impact

on the drivers' performance in terms of both the speed reduction times and deceleration rates.

Concerning the PCW system, like the RLVW, the presence of the PCW system significantly impacted the speed reduction time and deceleration rate, as it increased the former and reduced the latter, which proves the effectiveness of this system in providing an effective driving maneuver by drastically reducing speed and thus, supports our hypothesis. Once again, inferences can be drawn from the jerk analysis that, the PCW system results in a highly unsafe jerk at the onset of the warning. Without the PCW system though, a highly uncomfortable positive jerk occurs closer to the pedestrian, which is due to sudden acceleration, as the participants possibly slowed down a lot initially, as can be seen in Figure 27, to let the pedestrian pass, before accelerating. These results confirm those obtained by (Kim et al. 2018) and (Hakkert, Gitelman, and Ben-Shabat 2002) whose pedestrian warning systems had significant impacts on the drivers' performance; albeit the results from (Lubbe 2017) contradict these findings as this study found no significant impact of the system on the deceleration rate. Furthermore, our gaze analysis also showed that the system was able to attract the attention of the drivers as the majority of the drivers noticed the displayed warning. In addition, the initial and minimum speeds as well as the deceleration rates all had significant impacts on the speed reduction times, with the latter two factors negatively associated with the speed reduction times and the initial speed positively associated. Lastly, the log-logistic model used in our study showed that some characteristics of the drivers had significant impacts on the drivers' speed reduction times. For instance, the familiarity of the driver with the route and connected vehicles reduces the

speed reduction time; gender also can have a significant impact as males tend to have longer speed reduction time.

Comparing the PCW and the RLVW system outcomes, the distance covered, to reach maximum deceleration in the PCW and Non-PCW scenario is 12 – 15 meters while in the Non-RLVW and RLVW scenario, it is between 35 – 38 meters. Thus, from this, it can be inferred that pedestrians are given more importance than the traffic signal, as the initial slow down until maximum deceleration, is achieved quicker as compared to a traffic signal. The jerk analysis in both the PCW and RLVW scenarios, show that warnings result in unsafe jerks initially which could result in a rear-end collision but the early warnings result in early braking maneuvers which could be a lifesaving factor in avoiding a pedestrian collision or preventing a collision at the intersection. The Non-Warning scenarios results in positive uncomfortable jerks, which means that participants braked too hard initially and then released the brakes, resulting in the unsafe positive jerk. The high positive jerk may actually not happen in the real world, as experienced drivers are in much more control of their vehicle and this being a driving simulator, lack of driving simulator experience may have resulted in such braking behavior, and thus, this needs further research.

As for the FCW, our results indicated that this system had a statistically significant impact, at the 95% confidence interval, on the change in speed and the overall speed reduction through calculating the average speeds at 5 seconds before and after the FCW was issued. Again, this finding supports the hypothesis made in this study that these systems impact the drivers' performance positively. This conclusion matches the ones obtained by (Burns, Knabe, and Tevell 2000) and (Ben-Yaacov, Maltz, and Shinar 2002).

Moreover, our simulator experiment's findings proved that the familiarity with CAVs is an important factor that can impact the drivers' change of speed post FCW. This observation is in line with the one deduced by (Koustanaï et al. 2012) who found that familiarity with warning systems has a significant impact on the drivers' performance. The final observation that can be deduced from our simulation experiment is related to the impact of the drivers' ages on the change in speed. Based on our descriptive statistics analysis, more than 66% of the participants who had a change in speed between 15 and 30 mph were below the age of 35; hence, it can be inferred that participants in the younger age group tend to slow down more when encountering an FCW, compared to participants older than 35. Nonetheless, this observation is at odds with most of the previous research studies on the impact of the FCW on the different drivers' behaviors. For instance, (Shinar and Schechtman 2002) found that the drivers' age did not impact their headway when an FCW is present, while (Crump et al. 2015) found that there was no significant difference between younger (below 45 years) and older drivers' (above 45 years) reaction times after receiving a warning from the FCW system. Finally, our real-world findings confirmed the conclusions drawn from the simulation experiment as it was also found that the presence of the FCW had a positive and significant impact on the change of speed, which proves the effectiveness of our simulation experiment. Moreover, this field experiment found that the majority of drivers started pressing the brake pedal after receiving the warning.

Perhaps the most interesting set of results obtained from our five experiments is the one related to the CSW system. Through both the simulation experiment and the field study, the ANOVA analysis showed that this system had no statistically significant impact on the change in the drivers' speed, at the 95% confidence interval; this rejects the

hypothesis made in this research study. The amusing fact about this observation is that the previous research is almost evenly split on the impact of CSW systems on the change in the drivers' speed. On the one hand, our results are in line with those obtained by (Ahmadi and Machiani 2019) and (Lindgren et al. 2009) who found that the presence of the CSW had no significant impact on the drivers' speed while entering the curve and did not lead to a significant reduction in speed. On the other hand, our findings contradict those of (Davis et al. 2018), (Neurauter 2005), (Biral et al. 2010), and (McElheny, Blanco, and Hankey 2006). All of these previous research studies found that the presence of the CSW positively impacted the safety of the drivers as they reduced their speeds significantly before entering a curve.

As a result of the insignificant impact of the CSW on drivers' speed that we observed, our results, expectedly, showed that neither the drivers' age, familiarity with CAVs, or trust in CAVs have any significant impact on the drivers' speed, post CSW. Furthermore, based on the stated preferences, participants had mixed reactions about the CSW. Finally, as with the FCW experiments, the convergence of the results of both the simulation experiment and the field tests shows the accuracy of the former and the reliability of its results.

With regard to the autonomous driving mode, our results showed that the average TORt was found to be 2.47 seconds. That is similar to the take over time observed by (Gold et al. 2016) when there was no traffic density (2.49 seconds), and (Hergeth, Lorenz, and Krems 2017) for experienced drivers (2.48 seconds); slightly higher than the one observed by (Radlmayr et al. 2014) at 2.32 seconds; much higher than the 2.115 seconds recorded by (Feldhütter et al. 2017); and lower than the 2.86 seconds observed by (Lorenz,

Kerschbaum, and Schumann 2014). The gaze analysis rejected the hypothesis that the drivers remain attentive while Level 3 autonomous mode was active.

In addition, our results showed that the average time taken to press the throttle was 2.95 seconds. This parameter is important in determining the quality of the takeover process; albeit no previous studies in literature, to our knowledge, measured this parameter. Finally, the number of miles driven annually, age of the drivers, and familiarity with CAV technology were all found to be influential variables impacting the take over time.

Driving Related Parameters

Very few studies (Jeihani, NarooieNezhad, and Kelarestaghi 2017, Punzo and Ciuffo 2010, Zhao et al. 2016) discuss the integration of a driving simulator and a traffic simulator. Currently driving simulators have the ability to evaluate human driving behavior under different conditions in a simulated environment, where traffic can be sometimes unrealistic, such that traffic can adapt to aggressive and sudden braking, which in the real world may have resulted in a rear-end crash. On the other hand, traffic simulators have the ability to reproduce the macroscopic behavior of the traffic flow, once calibrated. Some of the limitations of such modeling are that lane changing does not affect acceleration and could be quite instantaneous. Thus, these models do not account for high-level tactical tasks that impact driving, such as cooperative behavior in merging tasks (Punzo and Ciuffo 2010). Integrating a driving simulator with a traffic simulator could potentially help bridge the individual limitations of these simulators and may contribute to the enhancement and development of both driving simulator and traffic modeling experiments. Since the integration poses both technical and methodological challenges, it is not used widely.

This study, with the use of a driving simulator, identifies certain driver-related parameters, which could be integrated into a traffic simulator to simulate realistic human driving behavior in mixed traffic, involving both human drivers as well as automated vehicles. The parameters are:

a) Take Over Reaction time (TORt) – The mean steering wheel TORt from autonomous mode was 2.47 seconds while the throttle TORt was 2.95 seconds. These time parameters could possibly be used to simulate realistic TORs, while in autonomous mode using traffic simulation software such as AIMSUN.

b) Deceleration Rate – The mean deceleration rate in the event of an RLVW and a PCW were found to be 2.4 m/s^2 and 2.99 m/s^2 respectively. These deceleration rates could be possibly used to mimic human braking behavior in a traffic simulator, involving other CAV warning based applications.

c) Change in Speed – The average change in speed post an FCW was between 8.5 mph – 15 mph between a real-world study and a driving simulator. This mean change in speed could be appropriately used in a traffic simulator to simulate realistic change in speed behavior at the onset of an FCW.

Chapter 7. Conclusions

Driver behavior while using CAV applications was analyzed in this empirical study, with the help of a medium fidelity, full-scale driving simulator, and validated using real world driving data. The study recruited some 93 participants from a diverse range of sociodemographic backgrounds, and a total of 186 experiments were conducted. A network of downtown Baltimore was built in the driving simulator environment and five CAV applications – PCW, RLVW, FCW, CSW and Level 3 – Autonomous Mode – were developed in the simulated environment.

The experiments conducted to assess the five different applications and systems showed that these systems, with the exception of the CSW system, are effective in improving the safety of the drivers, confirming our hypothesis that these systems positively impact the drivers' performance. Although both the PCW and RLVW systems had longer speed reduction times, the participants braked aggressively initially, at the onset of the warning, before gradually slowing down and coming to a stop. This may not be the ideal scenario in terms of avoiding rear end collisions at the moment, but it will possibly help prevent pedestrian and intersection crashes. Consequently, it is anticipated that these systems will be more widely adopted by the automobile manufacturers and come prebuilt into the vehicles rather than an optional package, as they will help improve the safety of all road users and reduce congestion. As drivers become more accustomed to the technology, they may not need to brake aggressively initially and could be more gradual throughout the deceleration phase. On the other hand, regarding the CSW, it is recommended that further research be conducted in order to examine possible

improvements that could increase the effectiveness of this system. The gaze analysis showed that majority of the participants do glance at the visual pop-ups of the applications, and, as shown in the analysis, react accordingly, mostly in a positive manner. The stated preferences of the participants as seen in Figure 19 show that 77% of the participants are happy to get driving-related input using CAV technology. Thus, the stated preferences, actual driver behavior, and the gaze analysis show the usefulness of these applications, which could potentially help reduce pedestrian crashes, intersection collisions, and rear-end collisions, among others.

Some of the major contributions of this study are as follows:

1) It is one of the few studies that uses a driving simulator to evaluate CAV applications in a realistic network, with an unconventionally large sample of participants. Each of the CAV applications evaluated in this study was developed from the ground up, stretching the capabilities of the driving simulator. The methodology to develop and utilize these applications could be used by researchers employing driving simulators or by companies manufacturing driving simulators, to further the advancements, in the realm of CAV technology.

2) An application has been created (patent pending) to combine the outputs of both the eye tracking device and the driving simulator. For the purposes of this study, the application was programmed to extract specific data for each individual application as well as give outputs for the analysis. This application can be used by researchers who use either a driving simulator, an eye tracking device, or both, to conduct research on upcoming technologies in the future.

3) Three driving-related parameters were identified using a driving simulator which could possibly be used to make the traffic flow more realistically in a traffic simulator. These parameters could improve the outputs of the simulations, which would directly help improve safety.

The deceleration rates, TORts and the change in speed findings, could be potentially used by auto and tech companies to fine tune the CAV applications, to better accommodate human driving behavior, thus enhancing safety.

Future Research

Technology is improving every day. Currently, LIDAR and cameras can detect objects, only at certain distances. This puts a limitation, as to when a warning can be issued to the driver and the driver may or may not react accordingly. This research can be built upon, by evaluating driver braking behavior in a variety of situations at different distances from the object. Although this research shows that, majority of the CAV warnings are useful in terms of driver perception reaction, it also leads the driver to brake aggressively, which may lead to rear end collisions. Thus, future research, can identify the appropriate distances in various situations, which will lead to a smoother braking behavior. This will help auto and technology companies to fine tune the warning issuances for safer driving.

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Appendix A. Pre and Post Simulation Survey Questionnaires

Pre Simulation Survey

Dear Participant,

We are excited and highly appreciative of your interest in our ongoing study aimed at evaluating the potential effects of Connected and Autonomous Vehicle applications on driver behavior. Please fill in the appropriate choice for each question and kindly ensure that the subject number assigned to you (as stated in the subject of the email sent to you) is selected. Thank you once again for your invaluable contribution.

1. Please select your subject number?

…………………………………………………………………………..

2. What is your gender?

☐   Male

☐   Female

3. What is your age group?

☐   18 to 25

☐   26 to 35

☐   36 to 45

☐   46 to 55

☐   56 to 65

☐   Above 65

4. What is your ethnicity?

☐   American or Alaska Native

☐ Asian

☐ Black or African American

☐ White

☐ Other

5. What is your present educational Status?

☐ High School or less

☐ Associate degree

☐ Undergraduate Student

☐ Undergraduate degree (complete)

☐ Post graduate Student

☐ Post graduate degree (completed)

6. Are you currently employed?

☐ No

☐ Part Time

☐ Full Time

7. What type of driving license do you have?

☐ Permanent license for regular vehicles (class C)

☐ Permanent license for all types of vehicles (class A)

☐ Learner's Permit

☐ Don't have a license

8. What is your annual household income?

☐ Less than $20,000

☐ $20,000 to 29,999

☐ $30,000 to $49,999

☐ $50,000 to $74,999

☐ $ 75,000 to $99,999

☐   More than $100,000

9. What is your household size? (If you live away from family/dorm, check '1')

☐   1

☐   2

☐   3

☐   4 or more

10. How many cars does your household own?

☐   1

☐   2

☐   3 or more

☐   None

11. Do your drive a car?

☐   Yes

☐   No

12. What year and model of car do you drive if applicable?

………………………………………………………………..

13. What is the average annual driving mileage on your own car (in miles)?

☐   Less than 8,000 miles

☐   8,001 to 15,000 miles

☐   15,001 to 30,000 miles

☐   More than 30,000 miles

☐   Not applicable

14. Are you familiar with downtown Baltimore?

☐   Yes

☐   No

☐   Somewhat

15. Are you familiar with Connected and Autonomous Vehicles (CAVs)?

☐   Autonomous Vehicles only

☐   Connected Vehicles only

☐   Both Connected and Autonomous Vehicle

☐   None

Please read the following before answering the next set of questions if you are not familiar with CAVs:

Connected vehicles are vehicles that use any of a number of different communication technologies to communicate with the driver, other cars on the road (vehicle-to-vehicle [V2V]), roadside infrastructure (vehicle-to-infrastructure [V2I]), and the "Cloud" [V2C]. This technology can be used to not only improve vehicle safety, but also to improve vehicle efficiency and commute times. Fully automated, autonomous, or "self-driving" vehicles are defined by the U.S. Department of Transportation's National Highway Traffic Safety Administration (NHTSA) as "those in which operation of the vehicle occurs without direct driver input to control the steering, acceleration, and braking and are designed so that the driver is not expected to constantly monitor the roadway while operating in self-driving mode." Connected and Automated vehicles (CAV) are an outcome of the integration of both connected vehicle (CV) and autonomous vehicle (AV) technologies which enable them to reach the next level of efficiency and sophistication by allowing autonomous control of the vehicle as per real-time information provided.

16. Does your personal car inform you about any of the following? Check all that apply

☐ Forward Collision Warning

☐ Curve Speed Warning

☐ Pedestrian Warning

☐ Autonomous Mode

☐ Incident Warning

☐ Red Light Running Warning

☐ None

17. Would you trust CAV application?

☐ Yes

☐ No

☐   Some of them

18. Do you use any app (like "Waze") while driving which alerts you about incidents or other information?

☐   Yes

☐   No

☐   Not applicable

19. Do you usually listen to the radio traffic information when you commute?

☐   All the time

☐   Most of the time

☐   Sometimes

☐   Never

☐   Not applicable to me

Post Simulation Survey

Dear Participant,

Congratulations! We have come to the end of the simulation session. We sincerely hope you had fun! Please, kindly share your driving simulation experience with us by filling the survey below. As with the previous surveys, please ensure that the subject number assigned to you is selected. If in doubt, kindly ask the observer. Thank you.

1. Please select your subject number

    ………………………………………………………………………

2. What was your reaction on encountering a CAV application?

    ☐ It was distracting

    ☐ Happy to get driving related input

    ☐ Ignored it

3. When autonomous mode was activated, you were?

    ☐ Distracted

    ☐ Bored

    ☐ Attentive

4. Please RANK your preference of CAV application importance? (1, 2, 3, 4…. 1 being the highest)

	1	2	3	4	5	6	7
Forward Collision Warning	☐	☐	☐	☐	☐	☐	☐
Curve Speed Warning	☐	☐	☐	☐	☐	☐	☐

Pedestrian Warning	☐	☐	☐	☐	☐	☐	☐
Autonomous Mode	☐	☐	☐	☐	☐	☐	☐
Incident Warning	☐	☐	☐	☐	☐	☐	☐
Red Light Running Warning	☐	☐	☐	☐	☐	☐	☐
Do not care	☐	☐	☐	☐	☐	☐	☐

5. Do you trust CAV applications?

☐ Yes

☐ No

☐ Some of them

6. Would you pay to add any of these applications to your car?

☐ Yes

☐ No

☐ Maybe

7. If you answered "Yes" or "Maybe" to the previous question, how much would you be willing to pay?

☐ Upto $500

☐ Upto $1000

☐ Upto $5000

☐ Above $5000

☐ Not Applicable

8. Did you notice the wider sidewalks and/or bus only lanes in one of the scenarios?

☐ Yes

☐ No

☐ Maybe

9. Please check the intensity of any symptom which applies to you now.

	None	Slight	Moderate	Severe
General discomfort	☐	☐	☐	☐
Fatigue	☐	☐	☐	☐
Headache	☐	☐	☐	☐
Eyestrain	☐	☐	☐	☐
Blurred Vision	☐	☐	☐	☐
Salivation increase/ decrease	☐	☐	☐	☐
Sweating	☐	☐	☐	☐
Dizziness	☐	☐	☐	☐
Nausea	☐	☐	☐	☐

10. Will you return for another simulation run using the driving simulator?

☐ Yes

☐ No

Appendix B. Consent Form for Driving Simulator Study

INFORMED CONSENT FORM   Subject No: _____

You are invited to participate in our Connected and Autonomous Vehicle study. In this project, we would like to study the effect of different in vehicle applications on driver behavior. We hope to learn how effective these applications are and how we can make them more effective for travelers. This project is being conducted by Dr. Mansoureh Jeihani of Morgan State University. You were selected as a possible participant in this study because of your proactive response to our invitation and acceptance to participate.

If you decide to participate, we will ask you to fill out three survey questionnaire forms. You will be given some basic training on how to drive the simulator. Then you will drive the simulator several times in different traffic and driving conditions. It will take no more than 1 hour to complete all scenarios. You will be paid $15 per hour of driving the simulator. When you drive the simulator, you may feel dizzy in the first few experiments until you get used to it. There is no risk of driving the simulator, you just may feel dizzy or fatigue or get headache. You may find it fun to drive the simulator and have some experiences such as crashes that are dangerous in the real world.

Your decision whether or not to participate will not prejudice your future relation with Morgan State University. If you decide to participate, you are free to discontinue participation at any time without prejudice.

Any information that is obtained in connection with this study and that can be identified with you will remain confidential and will be disclosed only with your permission.

If you have any questions, please do not hesitate to contact us. If you have any additional questions later about the study, please contact Dr. Mansoureh Jeihani at 443-885-1873,

who will be happy to answer them. If you have further administrative questions, you may contact the MSU IRB Administrator, Dr. Edet Isuk, at 443-885-3447.

You will be offered to keep a copy of this form.

You are making a decision whether or not to participate. Your signature indicates that you have read the information provided above and have decided to participate. You may withdraw at any time without penalty or loss of any benefits to which you may be entitled after signing this form should you choose to discontinue participation in this study.

……………………………………… ………………………………………………

Signature   Date

……………………………………… ………………………………………………

Signature of Parent/Legal Guardian   Date

 (if necessary)

…………………………………………   ………………………………………………

Signature of the Observer (if appropriate)   Signature of Investigator

Appendix C. Flyer to Recruit Participants for the Study

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