Final Report

Driver's Interactions with Advanced Vehicles in Various Traffic Mixes and Flows (connected and autonomous vehicles (CAVs) electric vehicles (EVs), V2X, trucks, bicycles and pedestrians) - Phase I: Driver Behavior Study and Parameters Estimation

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Date
January 2020

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ACKNOWLEDGMENT

This research was supported by the Urban Mobility & Equity Center at Morgan State University and the University Transportation Center(s) Program of the U.S. Department of Transportation.

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1. Report No.	**2. Government Accession No.**	**3. Recipient's Catalog No.**

4. Title and Subtitle Driver's Interactions with Advanced Vehicles in Various Traffic Mixes and Flows (connected and autonomous vehicles (CAVs) electric vehicles (EVs), V2X, trucks, bicycles and pedestrians) - Phase I: Driver Behavior Study and Parameters Estimation	**5. Report Date** January 2020 **6. Performing Organization Code**
7. Author(s) Mansoureh Jeihani https://orcid.org/0000-0001-8052-6931 Snehanshu Banerjee, Md Muhib Kabir, Nashid K. Khadem	**8. Performing Organization Report No.**
9. Performing Organization Name and Address Morgan State University 1700 E. Cold Spring Lane, Baltimore, MD 21251-0001	**10. Work Unit No.** **11. Contract or Grant No.** 69A43551747123
12. Sponsoring Agency Name and Address US Department of Transportation Office of the Secretary-Research UTC Program, RDT-30 1200 New Jersey Ave., SE Washington, DC 20590	**13. Type of Report and Period Covered** Final January 2018 - October 2019 **14. Sponsoring Agency Code**

15. Supplementary Notes

16. Abstract

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 autonomous systems to assist drivers with certain driving tasks. These technological advances have led to fast tracking the deployment of connected and autonomous vehicles (CAVs), 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.

This study aims to investigate driver behavior in terms of braking, steering and throttle control and change in speed, in the presence of CAV applications, using a driving simulator. The study consisted of 93 participants from diverse socio-economic backgrounds who drove in 186 experiments. 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. Forward Collision Warning had a positive influence on change in speed while Curve Speed Warning had no impact on speed. Lastly, the steering wheel and throttle Take Over Reaction time (TORt) 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. Based on the findings, certain driver-related parameters were identified; TORt, Deceleration Rate and Change in Speed, 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.

17. Key Words: Driver Parameters, CAV, Safety Applications, Driving Simulator, Driver Behavior	**18. Distribution Statement** No restrictions.

19. Security Classif. (of this report): Unclassified	**20. Security Classif. (of this page)** Unclassified	**21. No. of Pages** 117	**22. Price**

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ABSTRACT

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1. INTRODUCTION

Different transportation alternatives equipped with new technologies bring a new era of mobility solutions. Easy and accessible mobility is always preferable for all generations and every aspect of society. Driving paradigms are shifting to introduce safe and stress-free travel. Connected and autonomous vehicles have the potential to reduce crashes due to driver error by up to 90% (NHTSA 2008). Autonomous vehicles (AVs) can reduce traffic congestion and emissions and increase road safety (Mobility and Transport 2011). The introduction of new technologies like connected automated vehicles (CAVs) and social forces are shifting the attitudes toward mobility. The new technologies will change the way people move and profoundly impact transportation safety, efficiency, and accessibility. New technologies like CAV can increase the mobility of disabled and underserved people.

CAV is a combination of a connected vehicle (CV) and an autonomous vehicle (AV). An AV is capable of taking a course of action in response to any incidents, such as braking for a pedestrian without human intervention. AVs potentially will increase driving safety, operating efficiency, and environmental sustainability. Today's cars feature different AV levels, some of which are commercially available. The levels range from 1 to 4, in which 1 means no autonomy and 4 represents a driverless car (CAAT 2019). On the other hand, a CV is capable of using different communication technologies to connect with drivers, other cars on the road (vehicle to vehicle — V2V), roadside infrastructure (vehicle to infrastructure – V2I) and with the cloud (vehicle to cloud – V2C). It is assumed that CV technology will improve not only vehicle safety but also efficiency and commuting time. However, the connected automated vehicle (CAV) is the newest robust invention of transportation, resulting from artificial intelligence, robotics, information technologies, and automotive design. CAV technology can empower the car to take control by calculated decision and perfect the craft of driving. According to U.S. Department of Transportation research, 94% of serious crashes occurred due to human error (CAAT 2019). One wrong decision at the wrong time can lead to a life-ending collision. The CAV can monitor the surrounding environment continuously and alert the driver to avoid a crash. CAV technologies (V2V, V2C, and V2I) can reduce travel time uncertainty and give real-time updates to travelers. CAVs will reduce driving tasks and help drivers use that time productively.

New technologies always face hurdles to get accepted in people's lives. Researchers found that a lack of knowledge, less interest in adopting new technologies, high initial cost, and low consumer risk tolerance are reasons behind people's reluctance to accept new technology (Jaffe and Stavins 1994, Diamond 2009). Attitudes toward the new technology, which is a psychological factor, have a reasonable influence on the consumer's adoption of the technology (Payre, Cestac, and Delhomme 2014). The adaptation rate of autonomous and connected vehicles also depends on different factors such as their safety, reliability, legislation for insurance or tax, and people's socio-demographic characters. People are also concerned about technology and software safety issues such as hacking (Pinto 2012, Casley, Jardim, and Quartulli 2013, Kyriakidis, Happee, and de Winter 2015). The connected vehicle market is expected to reach $131.9 billion in 2019 (Lu et al. 2014). However, there is also no appropriate prediction about future driverless technologies, which are an unprecedented revolution in how people move. Most new cars come pre-equipped with these applications that assume the behavior of drivers (Hoogendoorn, van Arerm, and Hoogendoom 2014). In this case, evaluating the driver's interaction with automated systems and responses to safety-critical events is essential. Research shows that drivers using the automated systems performed more poorly than those manually driving regarding reaction time, lane departure duration, and maximum steering wheel angle to an induced lane departure event (Shen and Neyens 2017). Policymakers also need appropriate tools to plan for and analyze the significant impacts of novel navigation systems.

This research project aims to evaluate driver behavior while using CAV applications. The project also involves estimating driver related parameters using a medium-fidelity, full scale driving simulator. The parameters that are identified from this research, can be incorporated into a traffic simulator, to make the traffic flow more realistic.

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 in which 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 that is developed to have the capability to safely complete journeys without requiring 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 those in which, at a minimum, certain aspects of the control functions critical to safety such as 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 on the road such as the internet, global positioning systems (GPS), local area networks (LAN), wireless technology, etc., thereby assisting drivers and navigation (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.

With V2D, variations such as V2P (Vehicles-to-Pedestrian mobile devices) and V2C (Vehicle-to-Cloud) are definite possibilities.

.

Some developers of autonomous vehicles, such as Google, are dedicated to 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 past research studies related to connected vehicles identify available applications and investigate the feasibility of such applications (NHTSA 2011). The U.S. Department of Transportation (USDOT) has been 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 were selected; they were perceived to have great prospective benefits for further research. These scenarios were:

(a) curve speed warning,

(b) pre-crash warning,

(c) traffic signal violation 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 and 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 congested routes.

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, event-driven applications require a shorter interval for updates as opposed 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 fourth among the causes of fatalities in the U.S. In 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 the Texas Transportation Institute, in 2011 highway users on urban roads in the U.S. lost 5.5 billion hours of their time because of traffic congestion (TTI 2012). Various traffic management and operation programs consider travel delays due to traffic congestion to be one of the top priorities that needs to be addressed. Mobility applications in connected vehicles potentially could 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 such as mobile devices, infrastructure, and connected vehicles. The data can be utilized to manage 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 that includes I-SIG (Intelligent Traffic Signal System), TSP (Transit Signal Priority), 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), and 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 2011 congestion wasted 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 that can improve the environment by bypassing congested routes, leading to fewer emissions and opting for green transportation 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.

The 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, and 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

Using the available types of measurement fulfills the requirement to measure the feasibility of connected vehicle systems and applications. Certain studies have used information propagation through wireless technologies to assess the V2V performance. A widespread and quick propagation of information related to traffic incidents is crucial for managing them as such incidents lead to secondary incidents, which account for 20% of all incidents (FHWA). If a vehicle is disabled due to an incident or mechanical failure, that 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 that 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) using an NS-2 communication network simulator. The study found that the average maximum distance of information propagation increases when there is an increase in the transmission range as low traffic density and a shorter transmission range negatively impact the message propagation in IVC over several vehicles. But it needs to be noted that (Jung et al. 2010) considered equipped vehicle market penetration of only one level, i.e., 10%. (Yang and Recker 2005) tested the probability of communication success and traffic information propagation in arterial networks and freeways in a simulation framework. This study used a hypothetical area with a simple grid network. The researchers evaluated the measurement of the maximum distance of information propagation 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.

2.3 *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 full 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 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 responsibility 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 the vehicle's control functions between 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 can detect 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 active blind spot monitor uses a camera or radar to detect when a different vehicle is in the blind spot, and the driver of the vehicle is notified if a vehicle is detected (Kockelman et al. 2017). (Reports 2019) noted that specific conditions, such as inclement weather, reduce the effectiveness of the blind spot technologies.

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. A camera detects 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 both visual and audible sound alerts, and sophisticated applications of LDW can 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 the driver might miss. 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 precise systems have been created 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 used 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 for 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 use laser or radar headway sensors and processors for digital signals to determine the 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, is capable of reducing the severity and volume of collisions by automatically braking when an imminent collision is predicted. 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 using 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. When the camera finds that the driver is starting to leave the lane without using the turn signal, a warning sound will 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 can provide full-speed range Adaptive Cruise Control in addition to lane keeping. Radars and cameras are employed for sensing, and this system automatically accelerates, steers, and applies 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 aims 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 such as 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 investigates potentially allowing a human driver to drive the lead vehicle which is pursued by a platoon of fully automated vehicles. SATRE from Europe developed a prototype of this technology using 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 engineering in the form of a pedal or lever that 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 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.

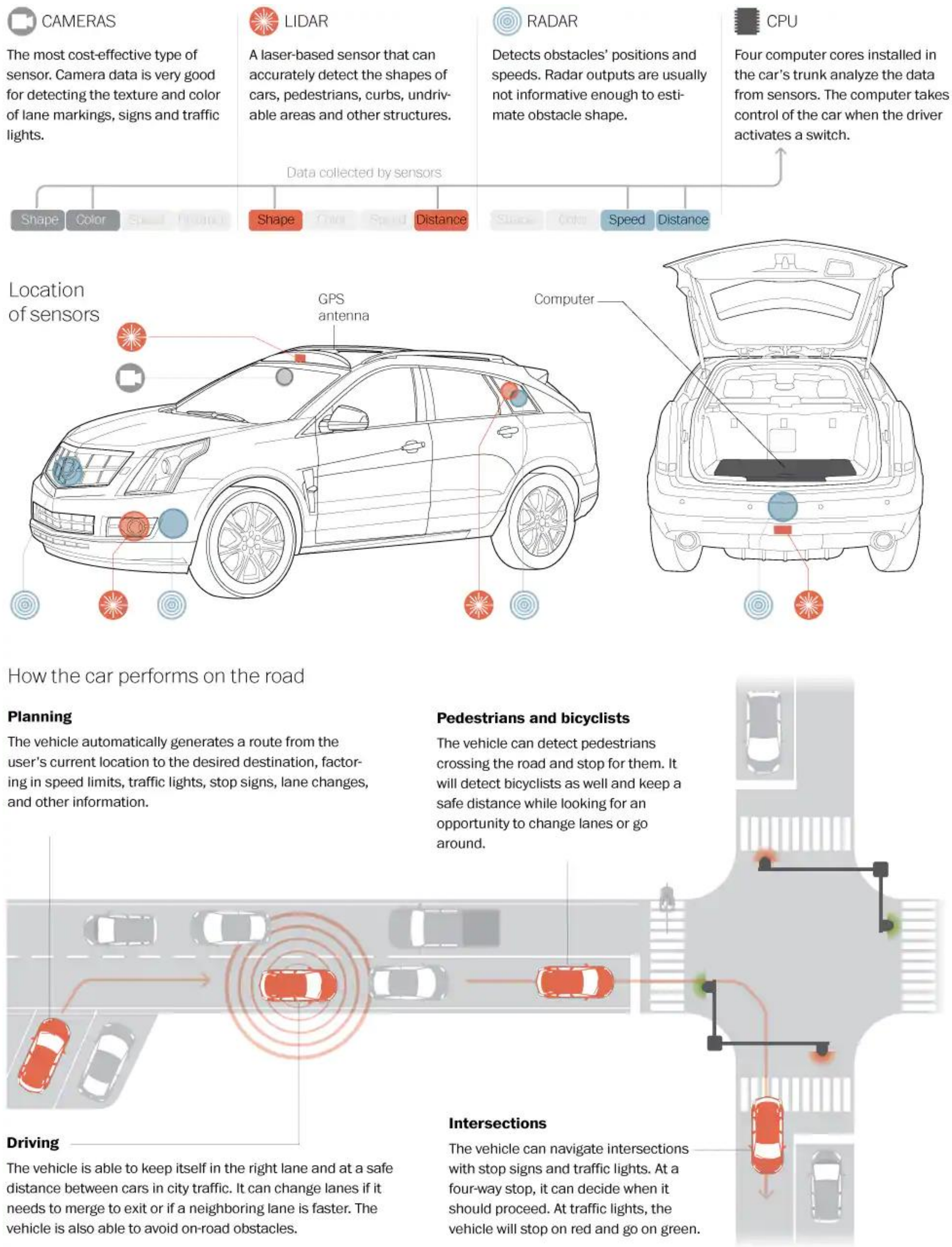

Figure 1. Autonomous Car by Carnegie Mellon (source: Gibson, 2017)

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 DARPA Urban Challenge (Buehler, Iagnemma, and Singh 2009) and the V-Charge project (Furgale et al. 2013) accelerated the research work in autonomous vehicle driving on urban roads for several organizations. According to (Pendleton et al. 2017), an 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, such as 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 are 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).

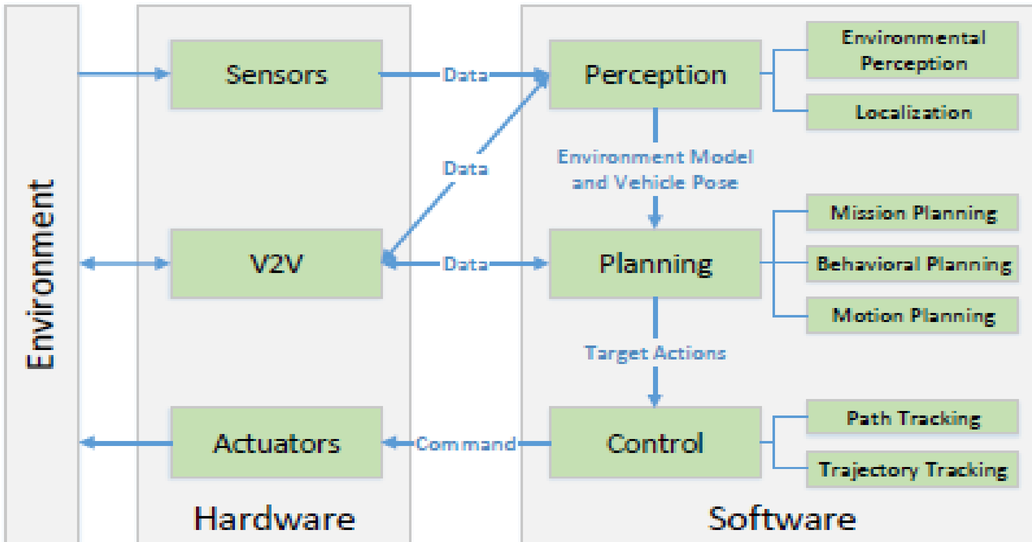

Figure 2. A Typical Autonomous Vehicle Overview, Showcasing Core Competencies Source: (Pendleton et al. 2017)

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 using cameras, LIDARs, or a fusion of both. The conventional sources for environmental perception may also entail applying both short- and long-range radars as well as ultrasonic sensors. Irrespective of the sensors used, two central components of the perception task are:

(a) on-road object detection and

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

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.

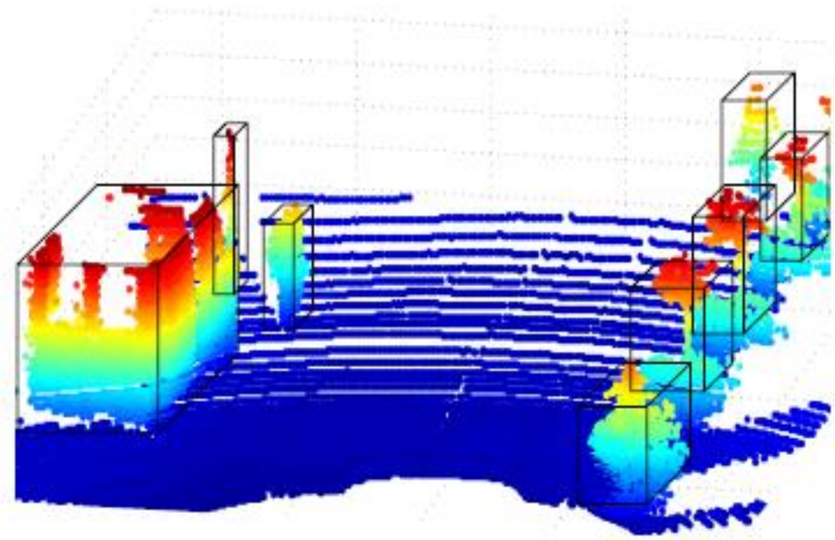

Figure 3. An Ideal Detection Result from a 3D LIDAR

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 vehicle's control system. 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, faded lane markings 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. Deep learning has performed better 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 determining the vehicle's position and estimating 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). Using 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 are dependable, which may require 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) proving that a better and more 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 that 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 used to estimate 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).

2.4 *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 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 that 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 that 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, a DS provides human-in-loop capability for the evaluation of technologies that are yet to be proven. Within the diverse area of study on driving support systems, the vehicle's longitudinal control is among the aspects that 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 relate 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, several examples 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 that 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.

3. METHODOLOGY

3.1 *Driving Simulator*

This study uses 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 is capable 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 captures 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*

The authors developed two survey questionnaires (Appendix A), a pre-simulation sociodemographic survey and a post-simulation, driving simulation-related experience survey, 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 is 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. The authors designed two scenarios in this virtual network, as shown in the study area map in Figure 5.

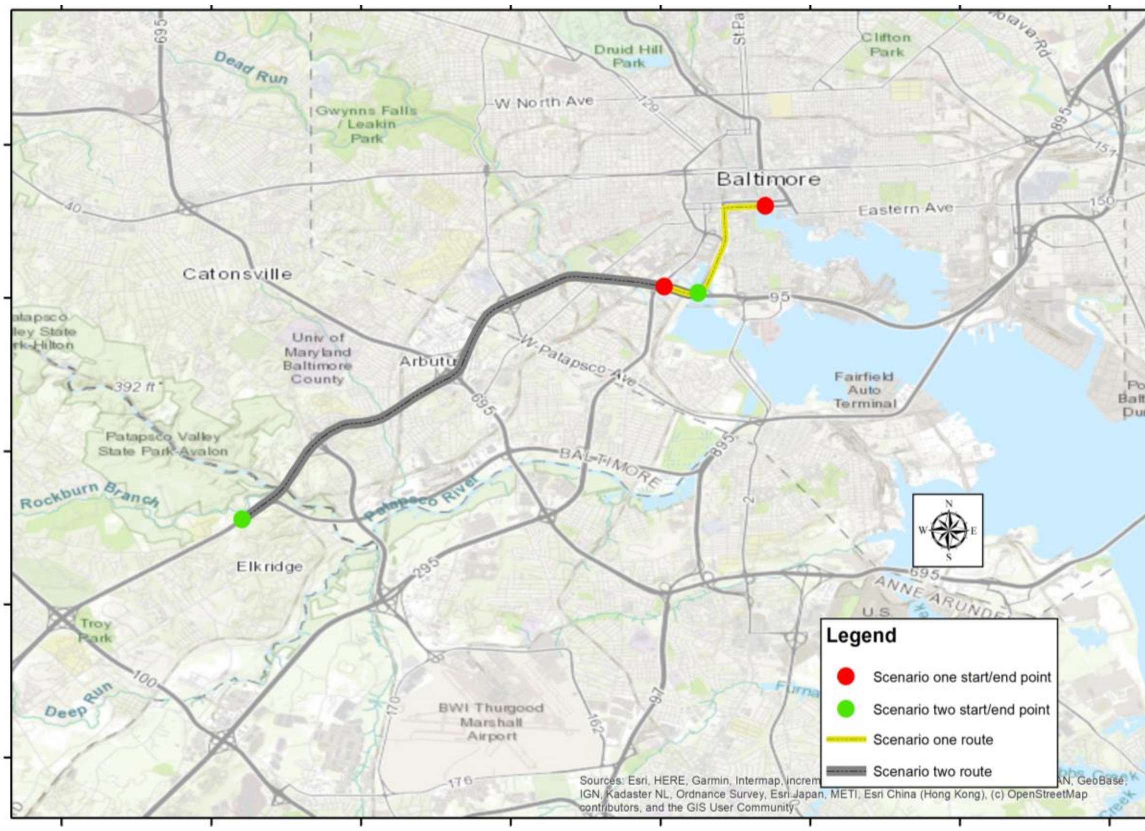

Figure 5. Study Area

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.

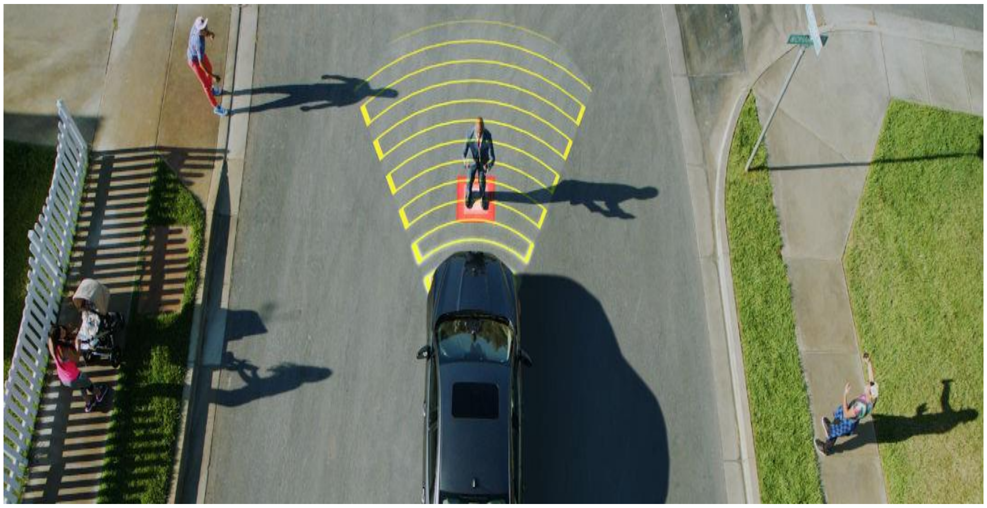

Figure 6. Pedestrian Alert

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, especially 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 volume, which otherwise might have created 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 PCW 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, in this case 40 meters.

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 researchers recreated 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. 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 RLVW Driving Simulator Environment

To evaluate the RLVW system, the participant always received the RLVW as soon as they enter the dilemma zone, 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.

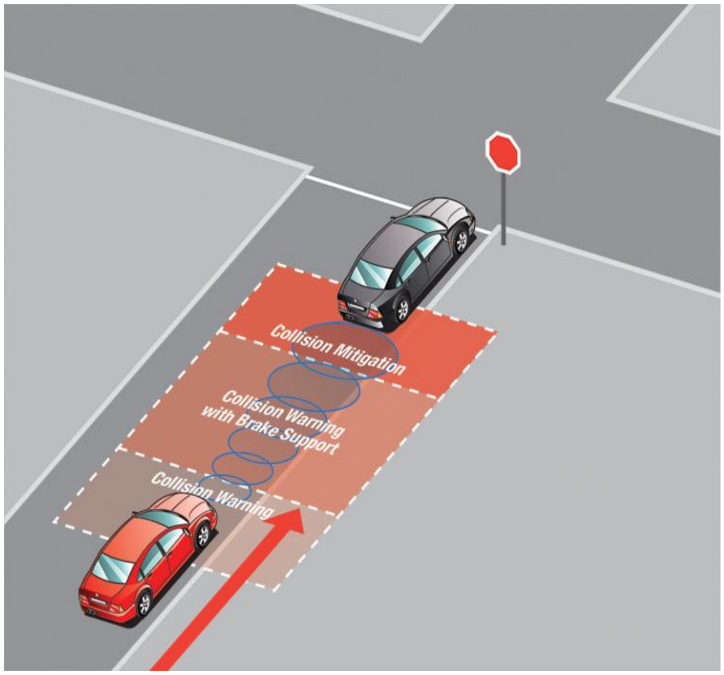

Figure 9. Forward Collision Warning

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, the researchers used a perception reaction distance as defined by the National Association of City Transportation Officials (NACTO) 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 2.

Table 2. 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 2.

3.4.4 Curve Speed Warning (CSW)

This application uses 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 researchers replicated a segment of the four-lane highway Interstate 95 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 on 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.

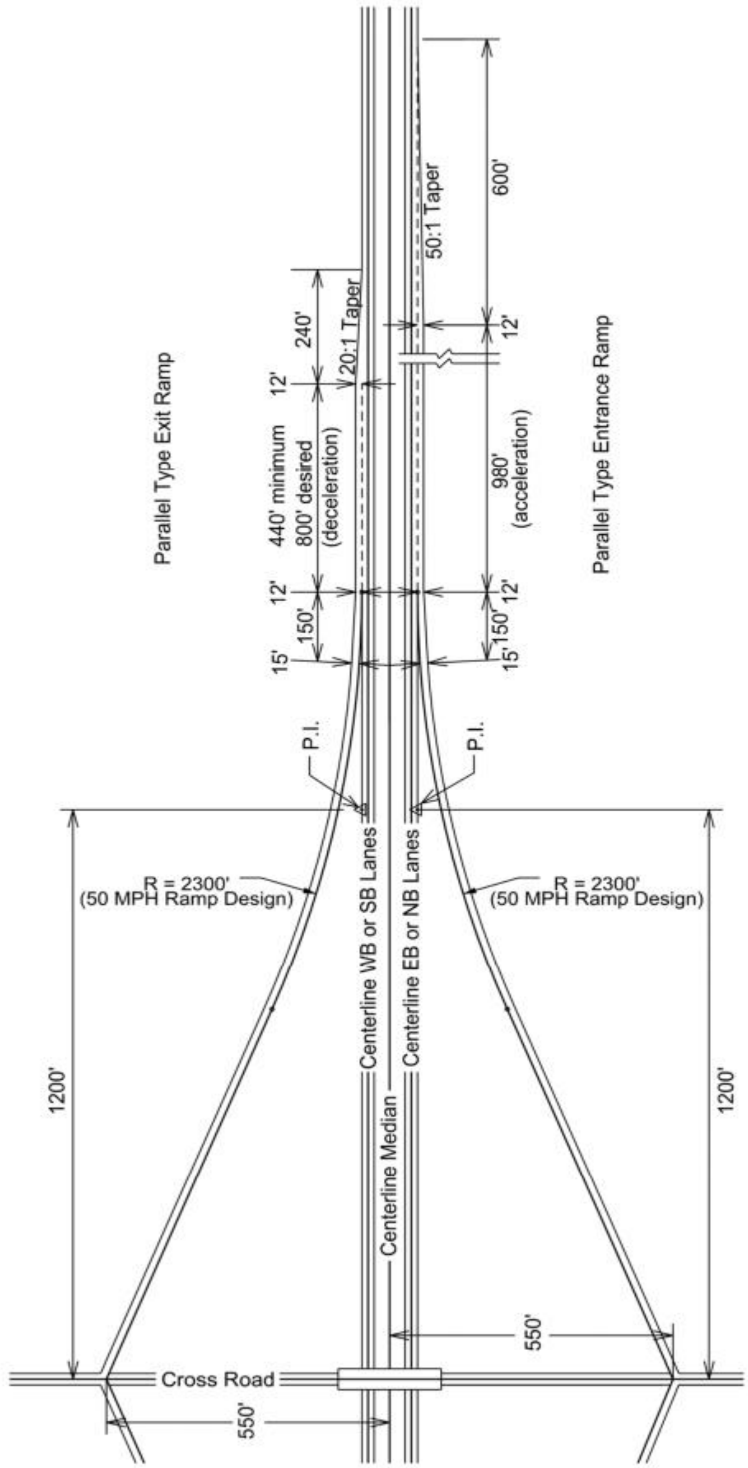

Figure 11. Diamond Interchange Dimensions

Source: (SDDOT, 2013)

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

Figure 12. CSW Snapshot in the Driving Simulator

This study attempted to evaluate another application informing drivers about their current speeds in tandem with the CSW application. Although the warning was used in the scenario, the evaluation was scrapped because the exit 53 ramp is a steep curve, and 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 participants drove in this scenario, they received a brief explanation of SAE Level 3 technology and how it works. A snapshot of the event is shown in Figure 13.

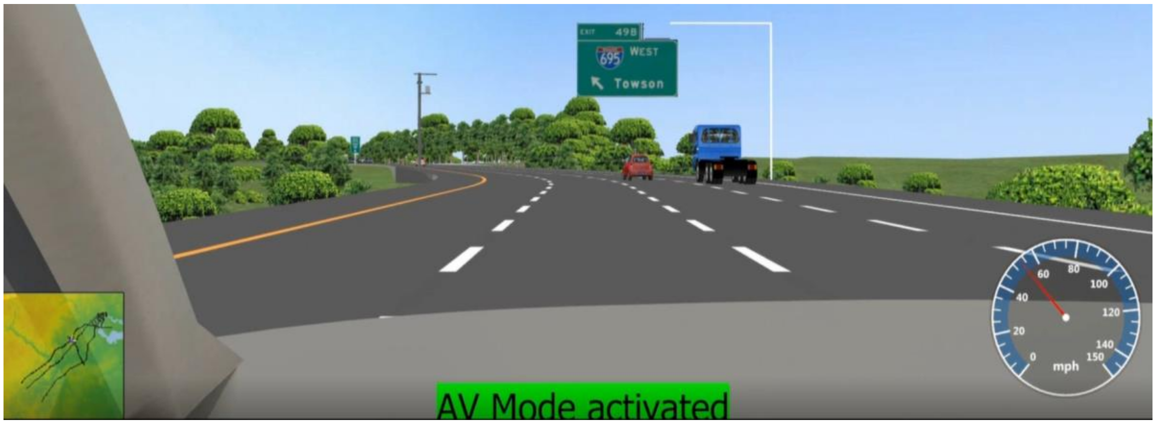

Figure 13. Autonomous Mode Snapshot in the Driving Simulator

3.4.6 Control Scenarios

In addition to the two scenarios 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 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 Random Forest model

Random forest is a supervised learning algorithm that 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.

3.5.3 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 3 (Eriksson and Stanton 2017), either involve a limited number of driving simulator participants or only consider steering wheel control when measuring TORt.

Table 3. 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 3, 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.

4. DATA

4.1 *Recruitment Process*

Institutional Review Board (IRB) approval was received before human participants were recruited. A total of 93 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 (Appendix C). Participants signed a consent form (Appendix B) before participating in the study and were paid at the rate of $15 per hour of driving. 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 93 participants consisted of a balanced group of male and female individuals. Table 4 presents some of the sociodemographic statistics of the participants.

Table 4. 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 14 through 20 highlight the stated preferences of the participants, which they offered through the pre and post simulation survey questionnaires.

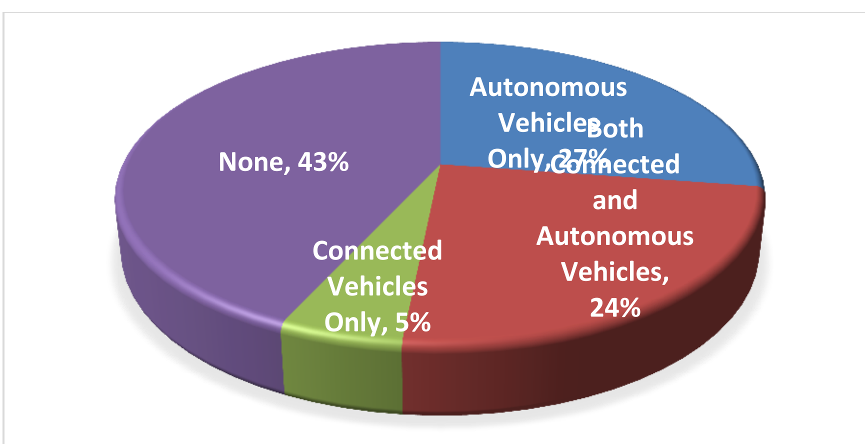

Figure 14. Familiarity with CAV

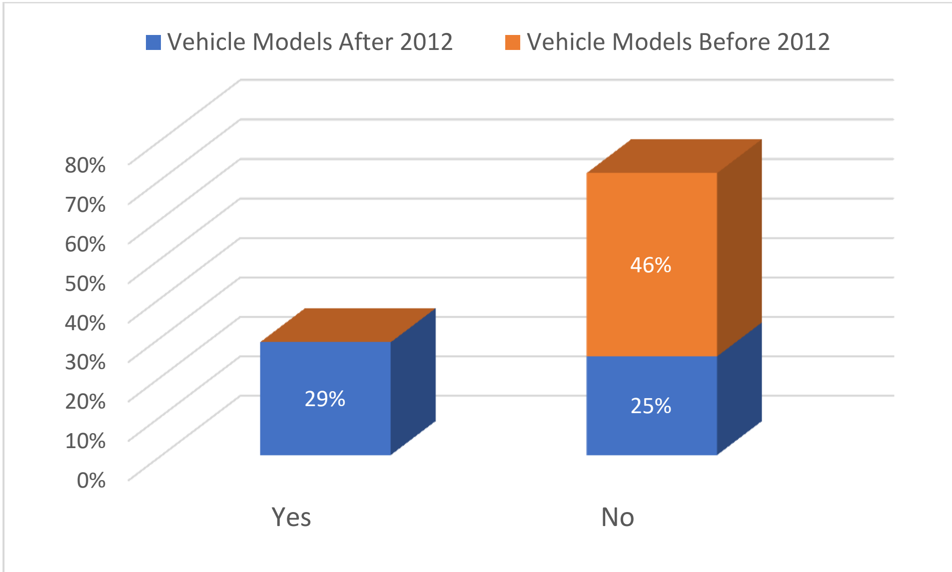

Figure 15. Experience using CAV Applications

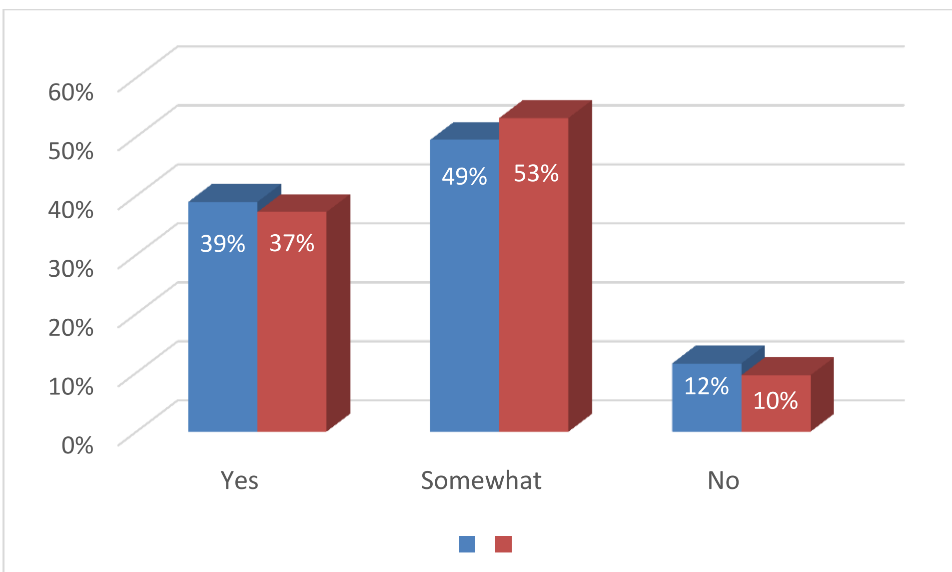

Figure 16. Trust in CAV Applications

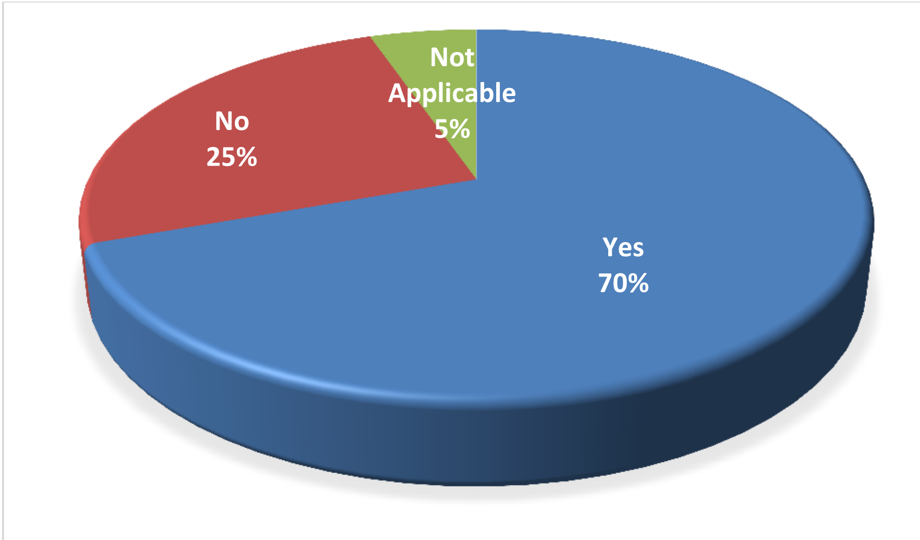

Figure 17. Participants Who Use 'Waze' while Driving

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.

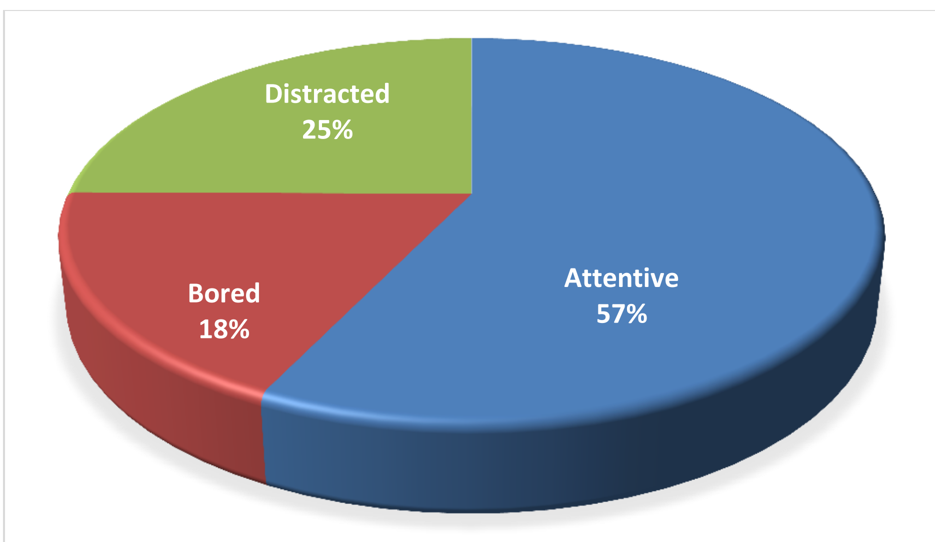

Figure 18. Participant Disposition during Autonomous Driving

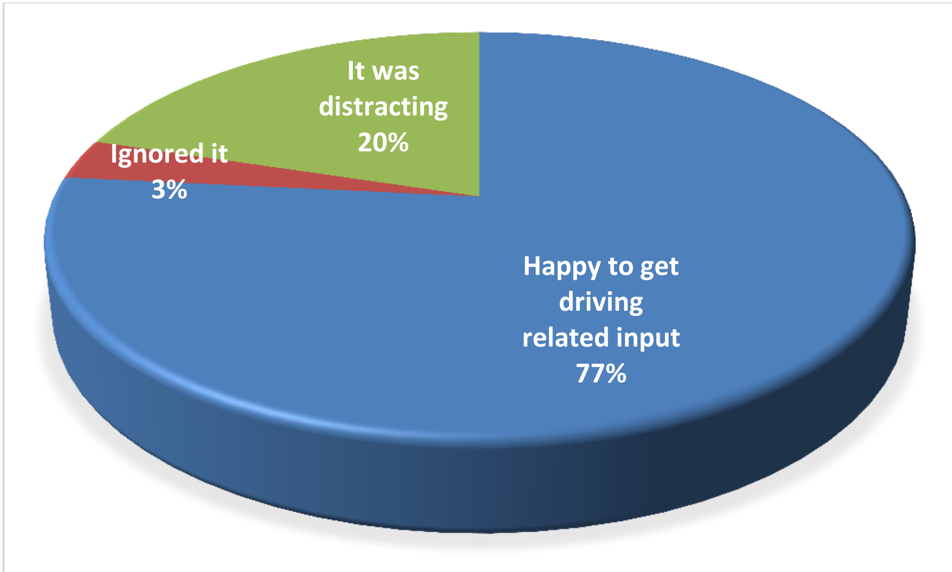

Figure 19. Participant Reaction on Using CAV Technology

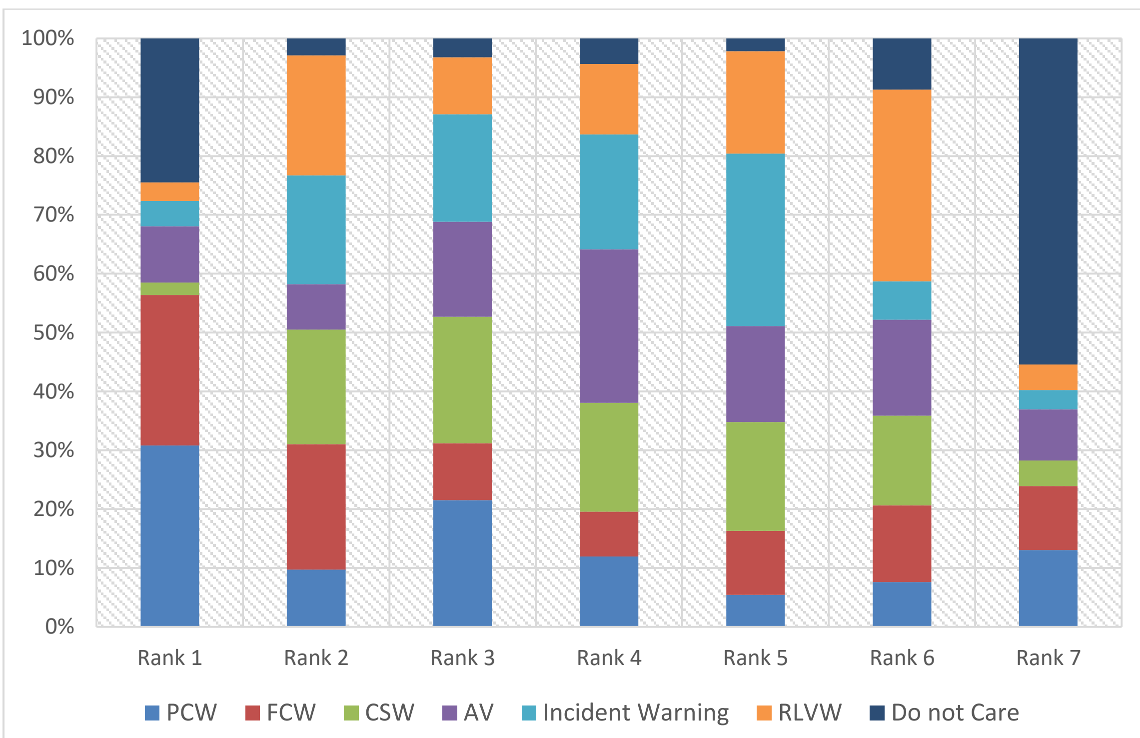

Figure 20. Ranked Preferences of Potential Application Importance

5. ANALYSIS

5.1 Pedestrian Collision Warning

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

5.1.1 *Experiments*

A total of 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. This study analyzed the braking maneuvers of the participants the moment they encounter the jaywalking pedestrian, 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 2: 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 21, several parameters related to the participants' braking maneuvers were calculated. Clearly, participants braked harder when they receive a PCW, compared to when they do not receive a warning.

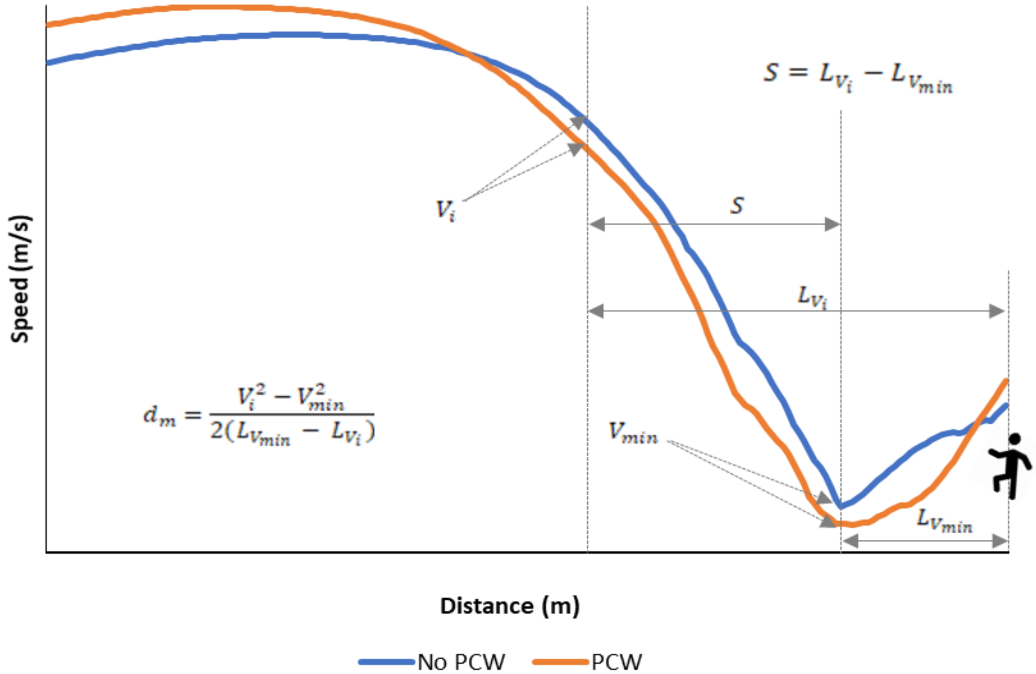

Figure 21. Participant Speed Profile Comparison

To determine the braking behavior with and without the PCW, the average deceleration rates of all participants are plotted in Figure 22.

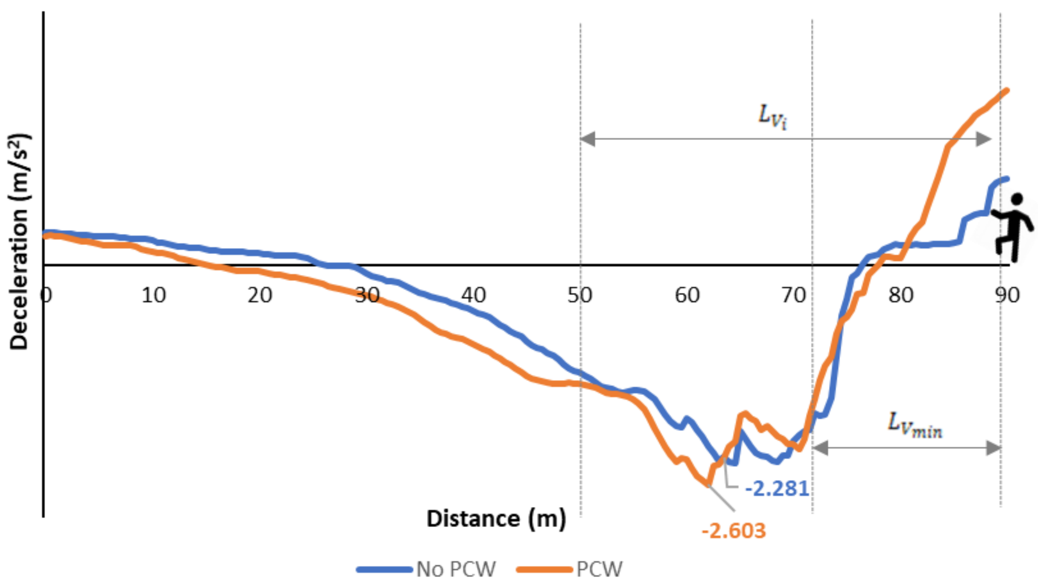

Figure 22. Participant Average Deceleration

The deceleration rate in Figure 22 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 are calculated for each participant. The braking intensity is calculated, one second after the brakes are pressed, to determine the intensity, using 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 5.

Table 5. 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

Table 5 reveals that participants react more quickly 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.

5.1.2 *Log logistic AFT model*

An ANOVA analysis revealed 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 than when it 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 22. Since deceleration rate or braking behavior is affected by CAV technology, in this case a PCW system, the researchers developed a hazard-based duration model 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 authors used the Akaike information criterion (AIC), 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. The four distributions were assessed, and the log-logistic model provided 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 3: Hazard Function – Log logistic Model

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

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

Equation 4: Survival Function – Log logistic Model

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

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

Table 6 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 6. 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	2.53	0.62	3.14	0.95

Time(s)

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 used to build an empirical estimate of the cumulative hazard model. As seen in Figure 23, the points representing the estimate of the cumulative hazard function almost follow the 45° reference line; it can be inferred that the participants' predicted speed reduction time, using the log-logistic model, is a good fit with the observed data.

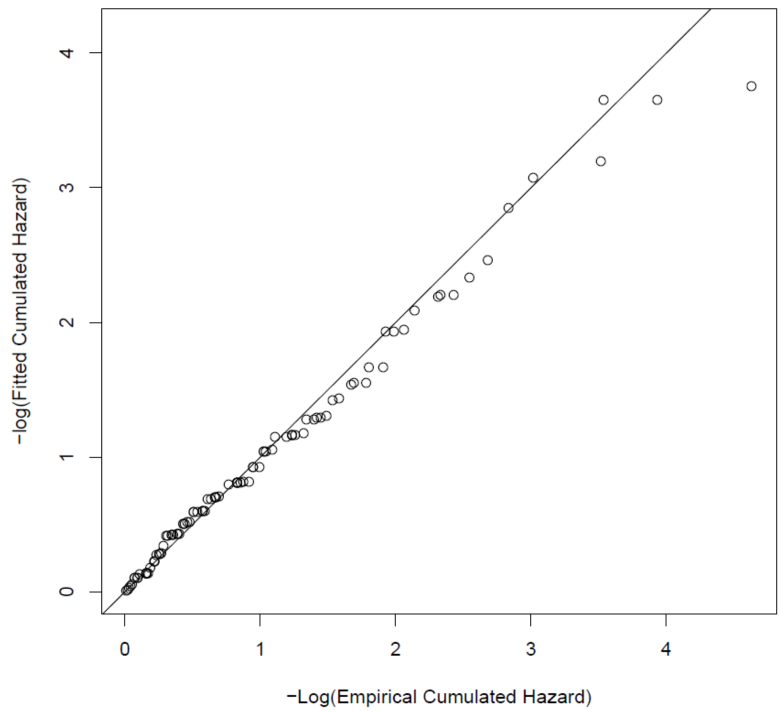

Figure 23. Cox-snell Residuals for Log logistic AFT

The estimates from the Log logistic AFT model with the speed reduction times of the participants as the dependent variable are shown in Table 7.

Table 7. 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 7 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. The odds of male participants having a higher speed reduction time on average were 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 24.

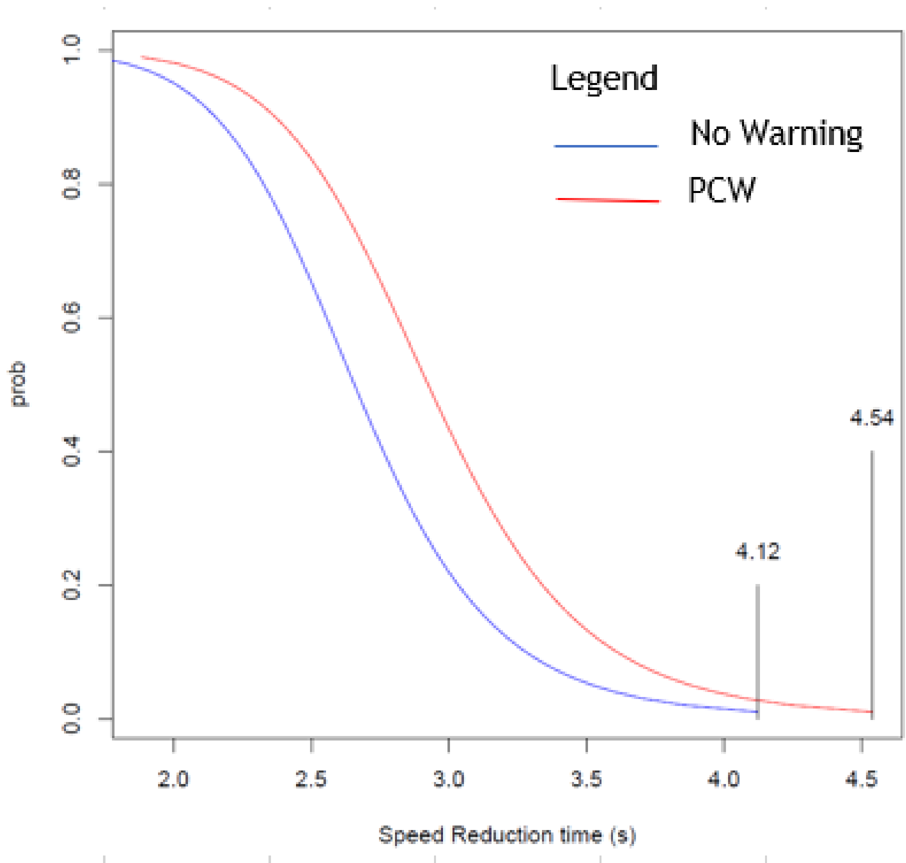

Figure 24. Speed Reduction Time Survival Curves

Figure 24 shows 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 compared 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.

5.2 Red Light Violation Warning

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

5.2.1 *Experiments*

The researchers conducted a total of 186 experiments; however, in 116 of those experiments, the participants either failed to stop at the red light when it turned yellow or the participants were below the road speed limit of 30 mph, which did not trigger the changing of the signal light from green to yellow, at the beginning of the dilemma zone. The final data set used in the analysis consisted of 70 observations of the drivers' braking maneuvers. The researchers analyzed the participants' braking maneuvers when they entered the dilemma zone in both the baseline scenario as well as the scenario involving an RLVW system.

The average deceleration rate (d_m) at the instant the participant enters the dilemma zone is stated in (2):

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 25, 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.

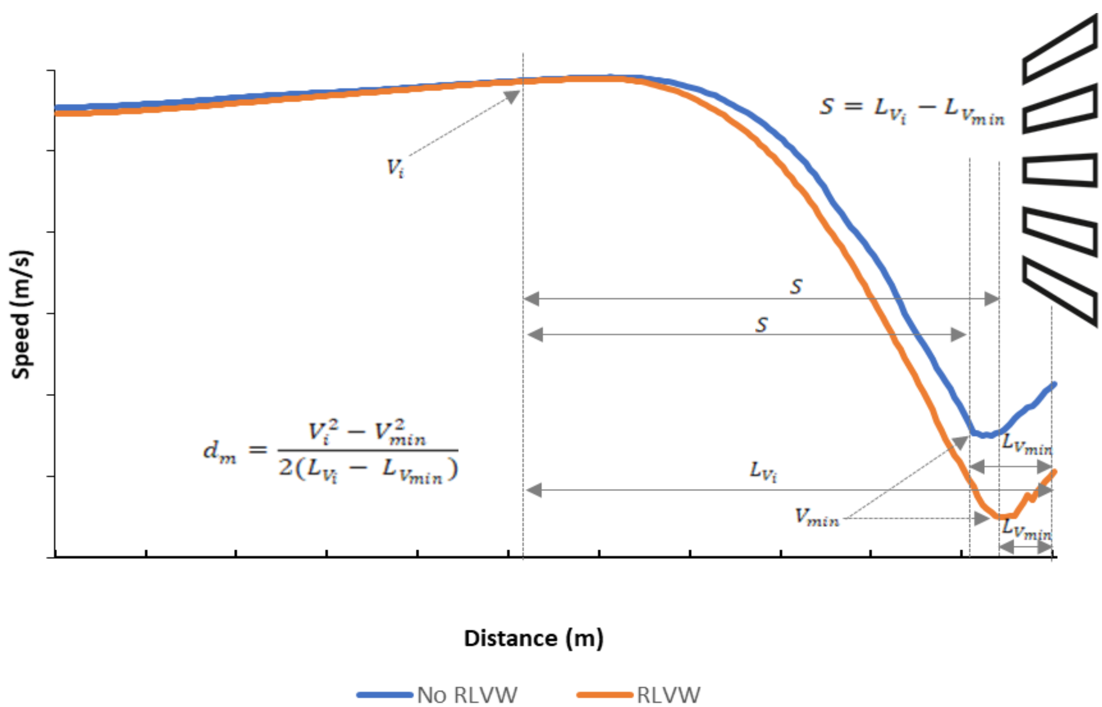

Figure 25. Participant Average Speed Profile Comparison

To determine the braking behavior with and without the RLVW, a plot of the average deceleration rates of all participants is plotted in Figure 26.

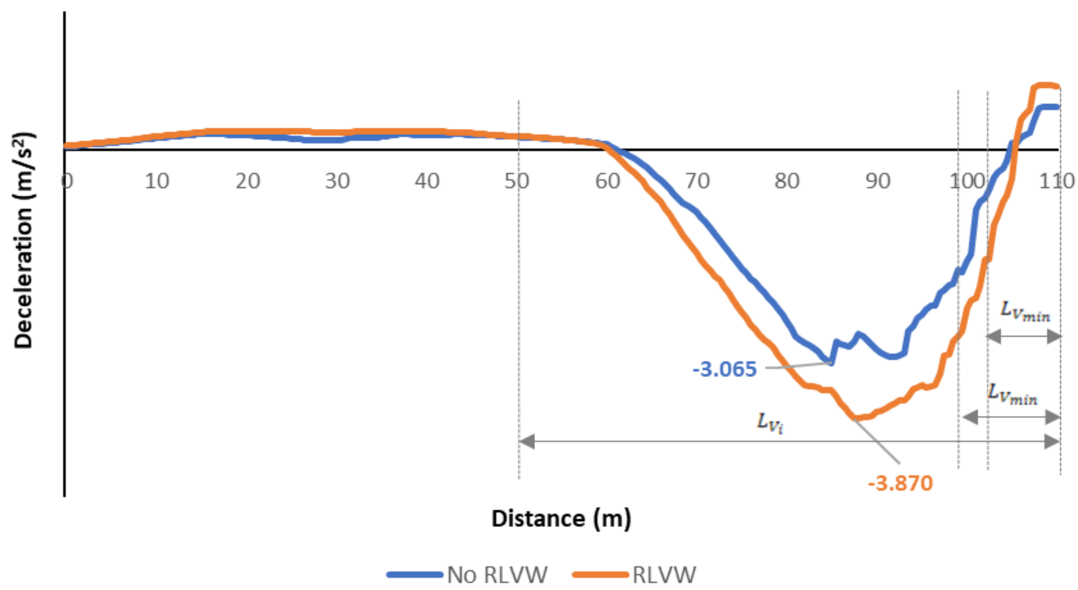

Figure 26. Participant Average Deceleration

The deceleration rate in Figure 26 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 are calculated for each participant. The braking intensity, as mentioned before, is calculated one second after the brakes are pressed to determine the intensity, using a scale of 0 to 1 in which 0 is no brake force and 1 is maximum brake force. The average reaction and braking execution time statistics are shown in Table 8.

Table 8. 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

Table 8 shows that participants react more quickly in the presence of an 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 scenarios, 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, with a time difference of 0.35 seconds.

5.2.2 *Lognormal AFT model*

An ANOVA analysis revealed a statistically significant difference in speed reduction times between the baseline scenario and the scenario with an 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 than 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 26. Since deceleration rate or braking behavior is affected by CAV technology, in this case an RLVW system, the researchers developed a hazard-based duration model to understand the participants' braking behavior in terms of speed reduction times. This model depicts 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), researchers used the AIC and log-likelihood values to select the best fit and most applicable function. The four distributions were assessed, and the lognormal model provided 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 5: Hazard Function – Lognormal Model

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

where t > 0 and σ > 0 while the survival function $S(t)$ of the lognormal duration model is expressed as (NIST):

Equation 6: Survival Function – Lognormal Model

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

where $t \geq 0$ and σ > 0 and;

ϕ = Probability density function of the normal distribution

Φ = Cumulative distribution function of the normal distribution

σ = The shape parameter

t = Specified time

Table 9 shows the descriptive statistics of the different parameters used in the lognormal model and the speed reduction times in scenarios with and without the RLVW system.

Table 9. 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, researchers assessed the goodness of fit for the lognormal model by plotting the cumulative hazard rate determined from the model estimates and then used it to build an empirical estimate of the cumulative hazard model. As seen in Figure 27, the points representing the estimate of the cumulative hazard function almost follow the 45° line; 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.

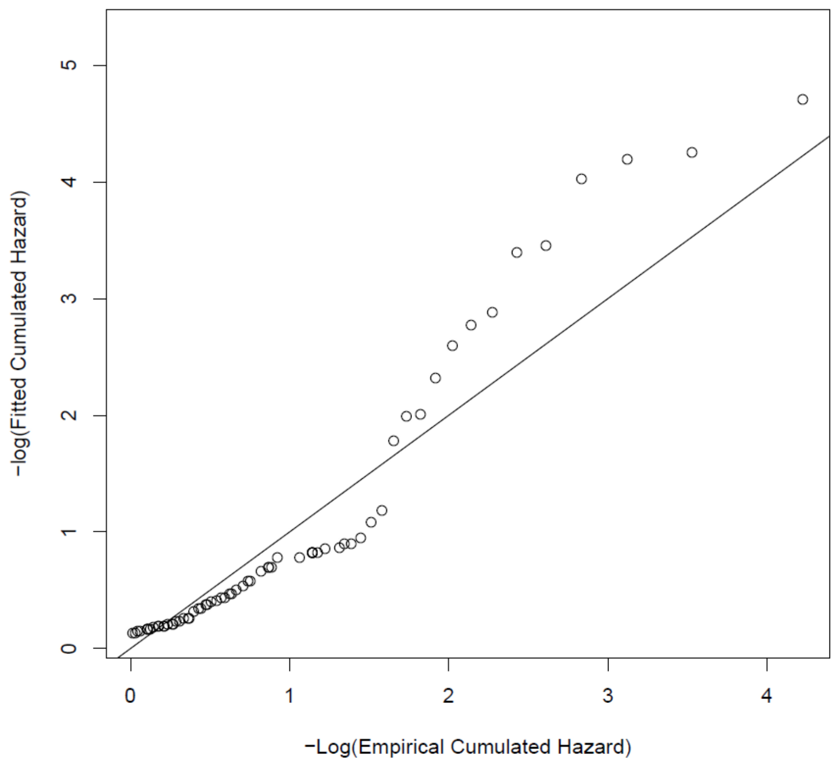

Figure 27. Cox-snell Residuals for Lognormal AFT

The estimates from the lognormal AFT model with the speed reduction times of the participants as the dependent variable are shown in Table 10.

Table 10. 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 10 identifies the variables that significantly influence the participants' speed reduction times while in the dilemma zone. The scenario with the RLVW system was 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 negatively influenced 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 positively influenced 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 26, it means that participants brake harder initially and then gradually proceed toward 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, had little driving experience compared to the majority. This lack of experience negatively influenced speed reduction time, resulting in a lower speed reduction time. In a scenario in which a driver may run the red light at a high speed, having an RLVW system involving higher speed reduction times may be beneficial as the initial aggressive braking may prevent the vehicle from entering the intersection and causing a crash, compared to late braking without an 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 for the scenario involving the RLVW system. These predictions were based on the predict survival regression tool in the R-package (Therneau) as shown in Figure 28.

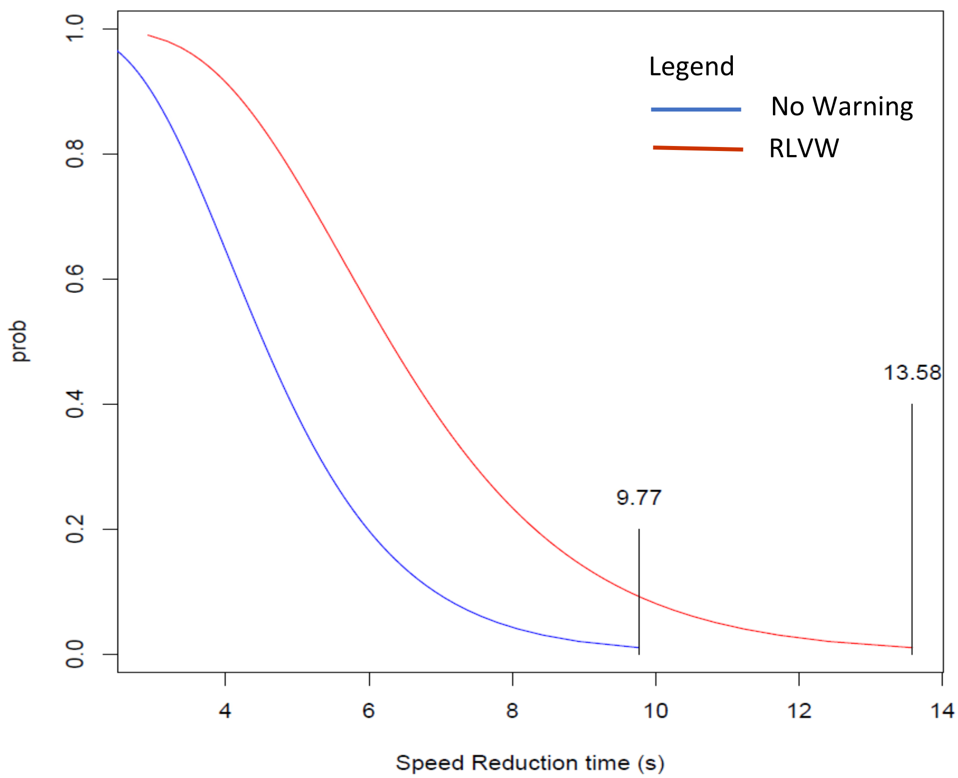

Figure 28. Speed Reduction Time Survival Curves

Figure 28 illustrates 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.

5.3 Forward Collision Warning

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

Speed Analysis

A total of 104 instances of FCW were detected in 186 experiments in which the participants approached 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 warning's impact 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.

One sample T-test

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

Table 11. One Sample T-test

	Hypothesized Mean Difference = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
Change in speed	12.990	103	0.000*	15.070	12.769	17.371

* Statistically significant at 99% CI

Table 11 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, the researchers considered three models: 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 that 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) was 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 12.

Table 12. 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 12, 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.

MDG Score

Figure 29 shows the MDG score for all the variables used for the change in speed analysis. “Age” and “familiarity with CAVs” stand out and thus are selected as the most important variables impacting change in speed, post FCW. Figure 29 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.

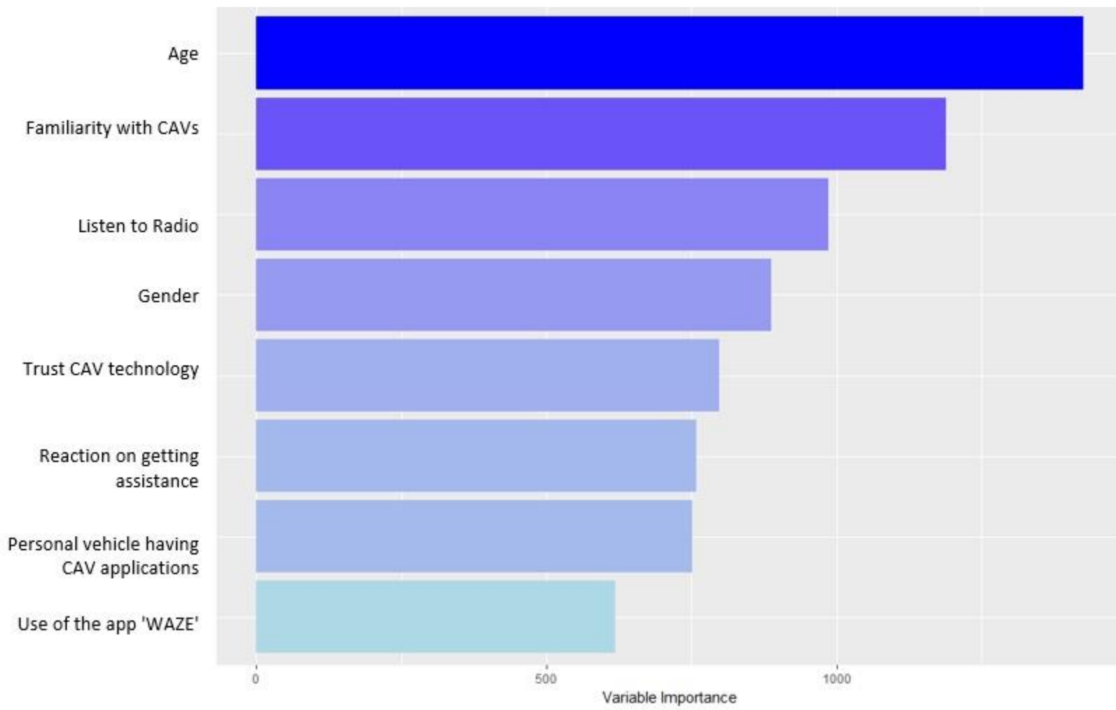

Figure 29. Variable Importance Based on Increasing Node Impurity (Simulator)

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.

5.4 Curve Speed Warning

Interstate 95, a four-lane highway south of downtown Baltimore, was replicated in the driving simulator for this analysis, which issues a CSW 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.

Speed Analysis

Some 182 instances of CSW were recorded in 186 experiments, in which the participants approached 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 warning's impact 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.

Single Factor ANOVA Analysis – CSW Scenario

For the scenario involving a CSW, a single factor ANOVA analysis determined whether the average before and after speeds are statistically different from the hypothesized average before and after speed difference of zero.

Table 13. 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 14. 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 13 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, whereas the safe speed limit to navigate the curve/ramp was 11.17 m/s (25 mph). Table 14 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 influence change in speed.

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 the CSW is statistically different from zero.

Table 15. 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 16. 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 15 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, whereas the safe speed limit to navigate the curve/ramp was 11.17 m/s (25 mph). Table 16 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 30.

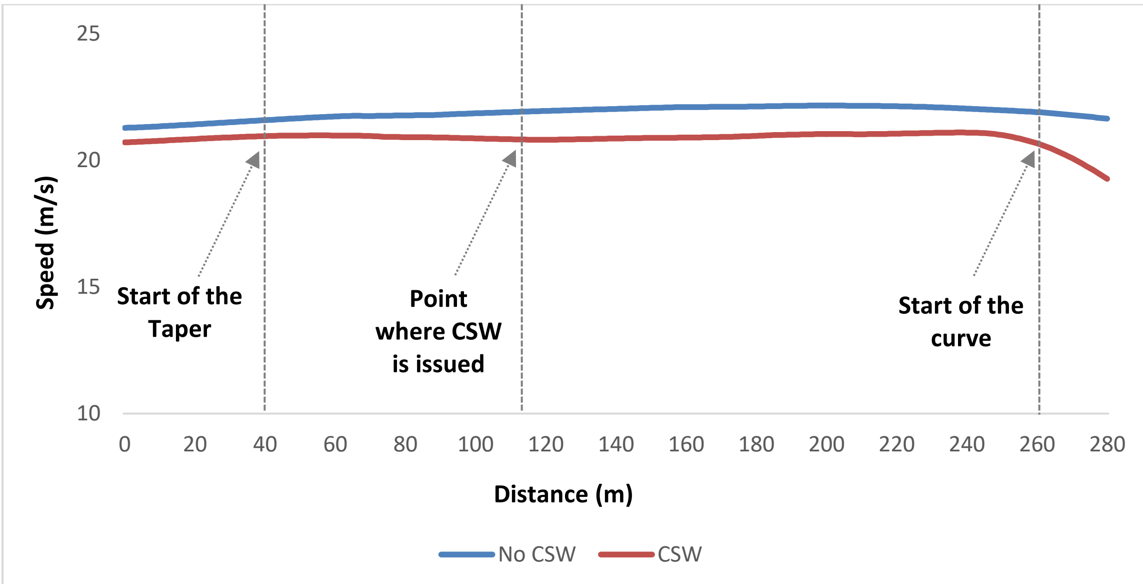

Figure 30. CSW Speed Profile

Figure 30 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.

5.5 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 authors calculated the TORt 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 hypothesized mean steering wheel TORt is significantly different from zero.

Table 17. One Sample T-test

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

* Statistically significant at 99% CI

Table 17 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, the researchers considered three models: 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 18.

Table 18. 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 18, 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 31 shows the MDG score for all the variables used for the TORt analysis. "Age" and "Miles Driven" stand out and thus are selected as the most important variables that impact steering wheel TORt, post a TOR. Figure 31 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.

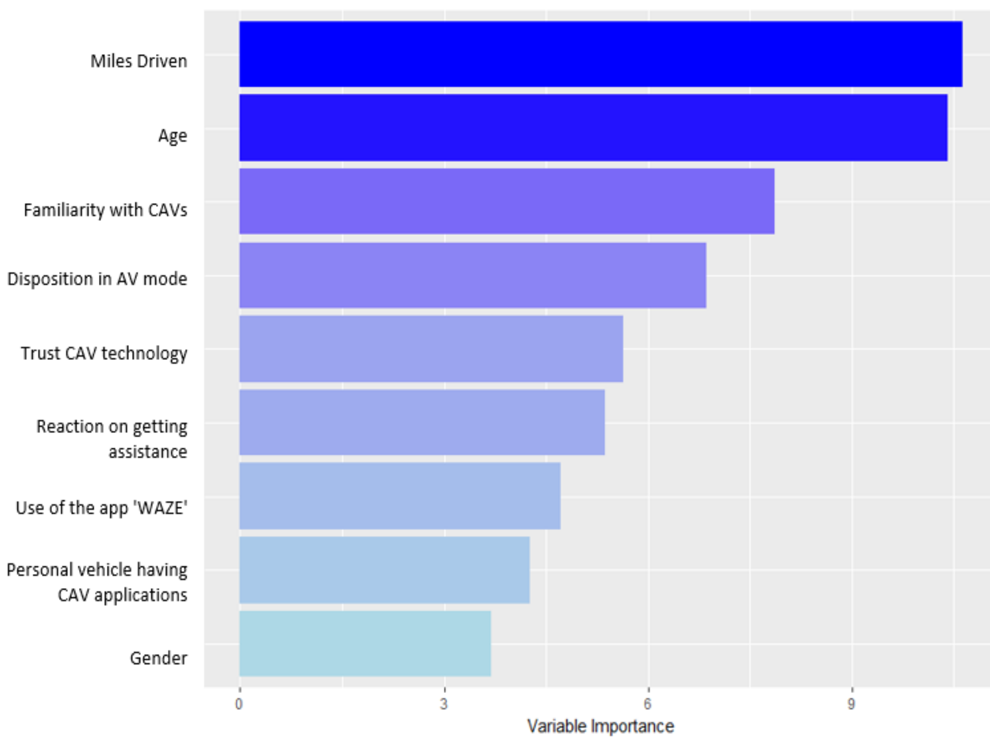

Figure 31. Variable Importance Based on Increasing Node Impurity

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 influence 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 determined whether the mean steering wheel TORt is statistically different from the hypothesized mean TORt of zero.

Table 19. One Sample T-test

	Hypothesized Mean TORt = 0					
				Mean	95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	TORt	Lower	Upper
Throttle Control	13.492	90	0.000*	2.948	2.514	3.382

* Statistically significant at 99% CI

Table 19 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 20.

Table 20. 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 20, 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 32 shows the MDG score for all the variables used for this TORt analysis. Like steering wheel TORt, “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 32 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.

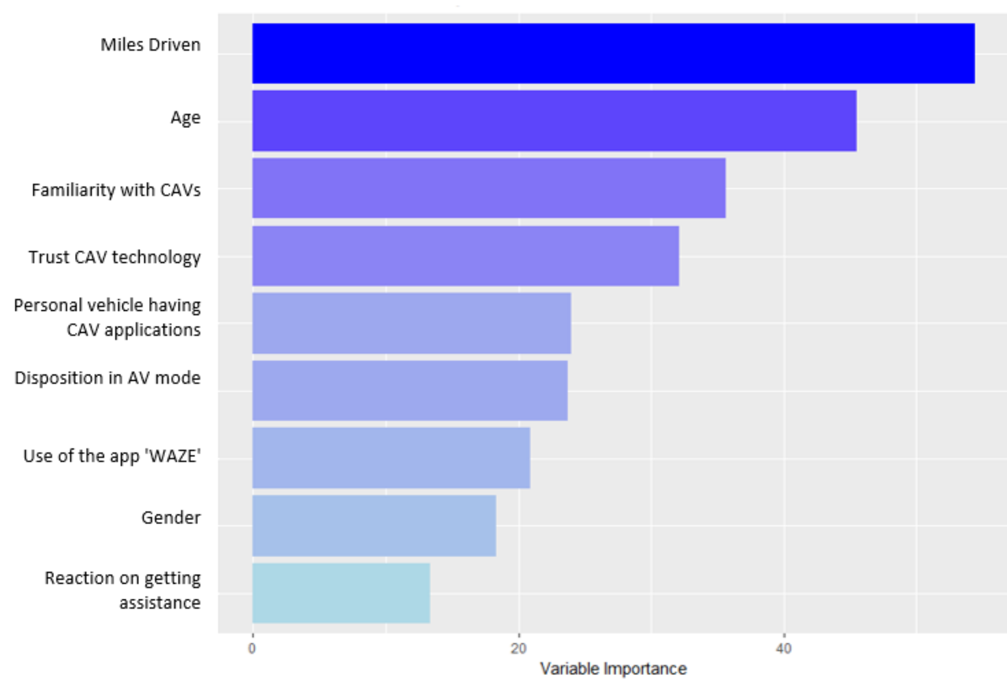

Figure 32. Variable Importance Based on Increasing Node Impurity

Even though the average throttle TORt varies from the average steering wheel TORt, the factors influencing these TORts are the same.

7. DISCUSSION

This study was designed to examine the effectiveness of five different CAV applications — namely, RLVW, PCW, FCW, CSW and autonomous driving mode, using driving simulation experiments. 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 an RLVW system significantly impacted the speed reduction time of the driver, requiring a longer period 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. 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. Nevertheless, unlike the results of (Yan, Liu, and Xu 2015) which showed that gender and driver's experience significantly impacted the deceleration rates, our lognormal model showed that none of the drivers' characteristics significantly impacted the drivers' performance in either speed reduction times or deceleration rates.

Concerning the PCW system, like the RLVW, the presence of the PCW 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 and supports our hypothesis. 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. In addition, the initial and minimum speeds as well as the deceleration rates all significantly impacted 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 significantly impacted 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 times.

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 positively impact the drivers' performance. This conclusion matches those of (Burns, Knabe, and Tevell 2000) and (Ben-Yaacov, Maltz, and Shinar 2002). Moreover, our simulator experiments' findings proved that 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 significantly impacts 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; 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 no significant difference between younger (below 45 years) and older drivers' (above 45 years) reaction times after receiving a warning from the FCW system.

Perhaps the most interesting set of results obtained from our five experiments is the one related to the CSW system. Through the simulation experiment, 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 studies found that the presence of the CSW positively impacted the safety of the drivers since they reduced their speeds significantly before entering a curve. Furthermore, based on the stated preferences, participants had mixed reactions to the CSW.

Finally, regarding 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).

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 the 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

Understanding driver reaction time is critical to modeling driver behavior in simulator studies. Driver reaction time depends on several factors like- simulator characteristics, participant age and mental state (Kosinski 2008). Driver reaction time has impacts on both traffic safety and traffic flow, as it has time-bound implications for a driver response, in different traffic situations (Gartner, Messer, and Rathi 2002, van der Horst 2007, Kesting and Treiber 2008). Traffic simulator safety evaluation studies dealing with emergency brakes and red-light violations, face several limitations involving unrealistic traffic flows (Barceló and Casas 2004, Cunto 2008, Saunier and Sayed 2008).

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 can 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 result in a rear-end crash. On the other hand, traffic simulators can 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 possibly be 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.

8. CONCLUSIONS

The shifting driving paradigms aim to introduce safe and stress-free travel. The new technology equipped CAVs have potential to fulfill the vision to have a stress-free, safe, and secure travel for everyone and also mitigate crash rates due to driver error. CAV technology also raises hopes to shift the attitude towards mobility. New technologies like CAV can help increase the mobility of disabled and underserved people. However, establishing a new technology in people's daily life is not an easy task. Technologies need to go through different testing/phases before being accepted by society.

This empirical study analyzed driver behavior while using CAV applications with the help of a medium fidelity, full-scale driving simulator, and used real-world driving data to validate it. The study recruited a total of 93 participants from a diverse range of sociodemographic backgrounds and conducted a total of 186 experiments. The researchers built a network of downtown Baltimore in the driving simulator environment and developed five CAV applications – PCW, RLVW, FCW, CSW and Level 3 – Autonomous Mode –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 as an optional package, since 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 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 and actual driver behavior show the usefulness of these applications, which could potentially help reduce pedestrian crashes, intersection collisions, and rear-end collisions.

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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.EdetIsuk, 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 (if necessary)	…………………………………………… Date
………………………………………… Signature of the Observer (if appropriate)	…………………………………………… Signature of Investigator

APPENDIX C. FLYER TO RECRUIT PARTICIPANTS FOR THE STUDY

MORGAN STATE UNIVERSITY
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Department of Transportation & Urban Infrastructure Studies

Do you want to do something new and exciting ?!?

GET PAID HAVING FUN!!

Drive One of The Most Advanced Driving Simulators
and
Get $15 for Each Hour You Drive!

Department of Transportation & Infrastructure Studies
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- Applicants will be expected to drive the simulator about 1 hour and must have a valid driving license.
- Driving simulators are used for variety of educational and research purposes. They provide fairly realistic driving environment by enabling the users to drive in a virtual highway system!

Contact: msudrivingsimulator@gmail.com, Mansoureh.Jeihani@morgan.edu / (443) 707-0361