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Title: INTEGRATING DRIVING SIMULATOR EXPERIMENT DATA WITH MULTI-AGENT CONNECTED AUTOMATED VEHICLE SIMULATION (MA-CAVS) PLATFORM TO QUANTIFY IMPROVED CAPACITY

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Autonomous vehicles (AVs) at varying market penetrations will change traffic flow and highway performance. At AV market penetrations between 0% and 100%, human driven vehicles (HVs) will be interacting with AVs. However, little is known about how HVs interact with AVs. This study attempts to quantify HV headways when following an AV using driving simulator data and integrates that data into a multi-agent simulation to quantify new highway travel time and flow predictions at varying AV market penetrations. This study also collected biometric feedback data to quantify driver level of stress when presented with a hard-breaking AV and HV. The driving simulator experiment was successfully completed by 36 participants. The results of this study show that driver level of stress is 70% higher in hard break scenarios involving HVs versus AVs. Additionally, drivers over the age of 34.5 were found to give AVs 2% more headway than HVs, while younger drivers gave AVs 18% less headway than HVs. Thirty-six scenarios were tested in the multi-agent simulation using results from the driving simulator. Using the driving simulator results, average travel times were found to increase at most by 2.3%.

INTEGRATING DRIVING SIMULATOR EXPERIMENT DATA WITH MULTI-AGENT CONNECTED AUTOMATED VEHICLE SIMULATION (MA-CAVS) PLATFORM TO QUANTIFY IMPROVED CAPACITY

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I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

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Cadell Chand, Author

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1.0 INTRODUCTION

Autonomous Vehicles (AVs) will undoubtedly have a significant impact on transportation networks. Many transportation agencies anticipate that AVs see initial widespread adoption concentrated to highway facilities (KPMG, 2019). In response to this, significant research has been done to better understand how AVs will impact highway performance, especially with varying AV market penetrations. However, these studies use the same interaction model for human vehicle (HV) to HV interactions as for HV to AV interactions. There is evidence that human drivers treat and interact with AVs differently than they would with HVs. Not reflecting these differences when predicting how AVs will impact highway performance under varying AV market penetrations may reduce the accuracy of those predictions.

Headway is a critical parameter in traffic microsimulation and capacity calculations (Pueboobpaphan, Park, Kim, & Choo, 2013), and driving simulators are effective tools for measuring driver headway (Risto & Martens, 2014). This study uses the driving simulator to better understand HV to AV interactions in terms of level of stress and headway, drawing differences between HV to HV headways and HV to AV headways. Additionally, this study integrates the driving simulator dataset into a multi-agent simulation. The simulation tests the effect of new HV to AV headway values on highway travel times and flow.

2.0 LITERATURE REVIEW

This chapter identifies the challenges and knowledge gaps associated with predicting highway capacity when considering the market penetration (MP) of Autonomous Vehicles (AVs). Additionally, literature on human driver behavior when interacting with AVs will be reviewed. Significant work has been published on traffic flow simulation with varying MPs of AVs. However, the assumptions these studies use to define AV and human vehicle (HV) behavior often lack empirical justification. This literature review will end with an overview on the role of driving simulators in transportation research and how that role relates to traffic flow research.

2.1 Autonomous Vehicles

2.1.1 Autonomous Vehicle Classification

Different vehicles have varying degrees of automation, meaning that not all vehicles can be simply categorized as an HV or AV. Guidance from the U.S. Department of Transportation suggests that manufacturers should refer and conform to the Society of Automotive Engineers (SAE) J3016 automation classification system (NHTSA, 2016). Following the publication of this guidance, the SAE J3016 automation classification system has become widely accepted as the industry standard by vehicle manufacturers, state and municipal transportation agencies, and researchers. SAE classifies automation on a scale from zero to five. In summary, the levels are 0) no driving automation, 1) driver assistance, 2) partial driving automation, 3) conditional driving automation, 4) high driving automation, and 5) full driving automation (SAE, 2018). **Figure 2.1** provides more detailed standard definitions of each level. Today, most new vehicles fall under SAE levels 1 and 2. While SAE level 3 vehicles are commercially available, they make up a marginal share of the vehicle market (Hedlund, 2017). There is no consensus on when SAE level 4 or 5 vehicles will be commercially available, however these vehicles are currently being tested on public roads.

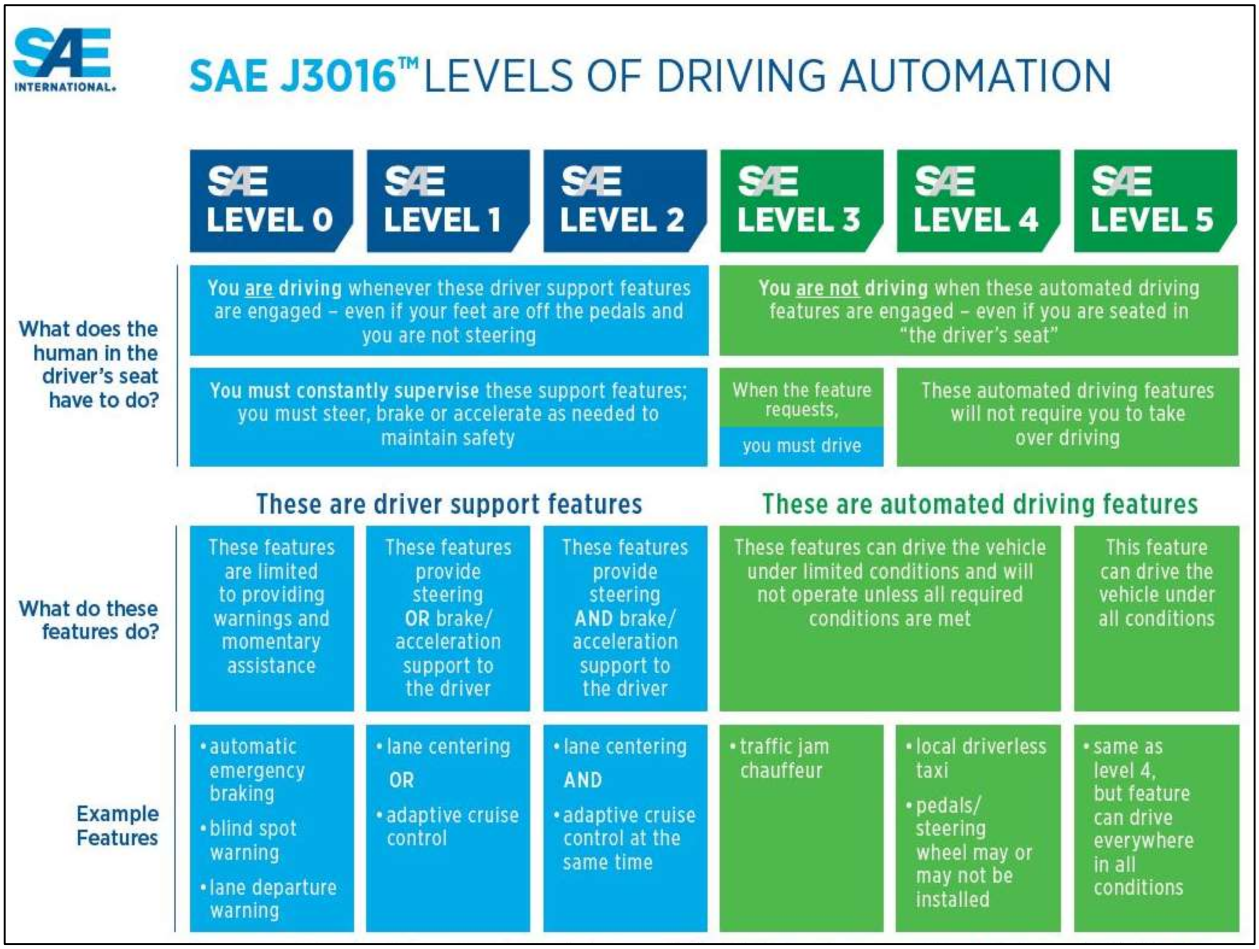

Figure 2.1: SAE's standard definitions for its six levels of driving automation as outlined in "SAE J3016 Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems" (SAE, 2018)

2.1.2 Autonomous Vehicle Implementation Challenges

Leading companies in this field such as General Motors, Waymo (Google), Uber, and Baidu have increased testing of these vehicles significantly in recent years (Bridgelall & Tolliver, 2020). Testing has illustrated the unique safety challenges associated with processing complex movements, interactions, and predictions in urban areas. These challenges have been pushed into the public eye after the tragic and fatal collision in Tempe, AZ involving a pedestrian and an Uber owned AV (CRS, 2020).

Compared to urban driving, the challenges AVs face driving on highways are significantly less, as highway infrastructure and highway users tend to be more predictable (Nothdurft, et al., 2011). As a result of this understanding, many countries at the forefront of AV adoption are preparing for widespread AV adoption on highways (KPMG, 2019). This has increased the urgency for research aimed at solving the set of challenges associated with AV operation on highway infrastructure. **Table 2.1** shows an adoption of Dr. Shladover's (University of California Berkeley) 2017 estimates for when AVs will be introduced to certain driving environments (Shladover, 2017), which align well with other predictions reviewed in this literature review.

Table 2.1: Estimates for when different SAE levels of autonomous vehicles will be introduced to different driving environments, adopted from (Shladover, 2017).

Environment	SAE Level 1	SAE Level 2	SAE Level 3	SAE Level 4	SAE Level 5
Everywhere	2020s	2025s	-	-	2075s
General Urban	2010s	2025s	2030s	2030s	-
Pedestrian Zone	2010s	2020s	2020s	2020s	-
Limited-Access Highway	2010s	2010s	2020s	2025s	-
Separated Guideway	2010s	2010s	2010s	2010s	-

AVs being tested today often use vision systems, which require pavement markings and legible signage to operate. Federal and state agencies in the U.S. who are aware of this trend have subsequently recognized the future need to improve the quality and consistency of highway pavement markings and signage. These agencies have also indicated a desire to ensure that national standards based on the Manual on Uniform Traffic Control Devices (MUTCD) are adequate for AV vision systems before the widespread adoption of AVs on U.S. highways (CRS, 2020).

While significant progress has been made in understanding how AVs will perform under various roadway conditions, not much is known on how HVs will interact with AVs on highways. Specifically, it is not fully understood how the interaction between HVs and AVs will impact highway safety and capacity, and what can be done to mitigate any negative impacts. Work is being done to test the viability of dedicated lanes for AVs, which would limit interactions between HVs and AVs. However, the cost-to-benefit ratio of this infrastructure and policy strategy is still under question (ITS International, 2016). Therefore, it is imperative to understand the dynamics of HV to AV interactions on highways before the widespread adoption of AVs.

2.2 Autonomous Vehicle Impacts on Roadway Capacity

2.2.1 Adaptive Cruise Control

The exploration of how AVs will impact highway capacity began by considering the effect varying MPs of vehicles equipped with Adaptive Cruise Control (ACC) (Cui, Seibold, Stern, & Work, 2017). Many of these studies use the Intelligent Driver Model (IDM), which can be simplified into the differential equations (1) and (2) for vehicle α (Treiber, Hennecke, & Heldbing, 2000):

$$(1) \quad \dot{x}_\alpha = \frac{dx_\alpha}{dt} = v_\alpha$$

$$(2) \quad \dot{v}_\alpha = \frac{dv_\alpha}{dt} = \alpha\left(1 - \left(\frac{v_\alpha}{v_0}\right)^\delta - \left(\frac{s_0 + v_\alpha T + \frac{v_\alpha \Delta v_\alpha}{2\sqrt{ab}}}{s_\alpha}\right)^2\right)$$

Where for each vehicle v_0 is the desired velocity, s_0 is the minimum spacing, T is the desired time headway of vehicle α to its leading vehicle, a is the maximum rate of acceleration, and b is the comfortable deceleration. The method to differentiate between vehicles with autonomous driving capabilities and HVs is to run multiple IDM models (one for each vehicle type, e.g. AV or HV) in the same simulation with parameters that correspond to the vehicle type the model is representing (Cui, Seibold, Stern, & Work, 2017).

Studies exploring the impact of ACC broadly found that increasing ACC MPs correlate with increased highway capacity, however there is variation in estimations of capacity gains. Very early papers on this topic suggested that a low ACC MP does not impact traffic flow significantly (van

Arem, Hogema, Vanderschuren, & Verheul, 1996), and found that while vehicles using ACC help traffic stability, they can either positively or negatively impact highway capacity (Zwaneveld & van Arem, 1997). Studies also began to justify parameter values such as desired time headway, finding that ACC systems are capable of safely maintaining time headways of less than one-second (Godbole, Kourjanskaia, Sengupta, & Zandonadi, 1999). More recent findings on this topic conclude that ACC can increase highway capacity between 7% (Werf, Shladover, Miller, & Kourjanskaia, 2002) and 30% (or a 0.3% increase in capacity per 1% increase in MP) (Kesting, Treiber, & Helbing, 2010).

2.2.2 Autonomous and Connected and Autonomous Vehicles

Many more studies have been done on the impact AVs and Connected and Autonomous Vehicles (CAVs) will have on highway capacity. CAVs are AVs with the ability to communicate with infrastructure and roadway users. CAVs use this information to inform their own decision making, potentially increasing roadway network efficiency and safety. Studies involving CAVs will be discussed later in this section.

Like the results of research in ACC's impact on highway capacity, research on AV's impact on highway capacity have suggested that improvements are possible, but relatively small. By replicating the famous "ring-road" study by Dr. Yuki Sugiyama which provided empirical evidence for the shockwave phenomenon (Sugiyama, et al., 2008) but replacing one HV with an AV, Cui found that AVs can significantly increase local traffic stability without changing HV behavior (Cui, Seibold, Stern, & Work, 2017). One microsimulation study found that improvements in traffic flow on highways will only be realized at AV MP rates above 70%. The same study recommended for future work to develop models that consider HV to AV interactions in mixed traffic. However, the authors recognize that before such a model can be developed, more behavioral work needs to be done to understand how

HVs perceive and interact with AVs. The authors also recognized a need to validate or calibrate their AV driver behavior model (Calvert, Schakel, & van Lint, 2017).

In 2018, Zhu and Zhang attempted to calibrate the predicted impact AVs have on highway capacity and traffic stability ("stability" refers to linear stability theory or flow uniformity as described in (Wilson & Ward, 2011)) by considering AV sensitivity and smoothness. The study found that both highway capacity and traffic stability were significantly impacted by AV sensitivity and smoothness (Zhu & Zhang, 2018). FIGURE 2.2 visualizes how AV sensitivity and smoothness impact the fundamental diagram in mixed traffic.

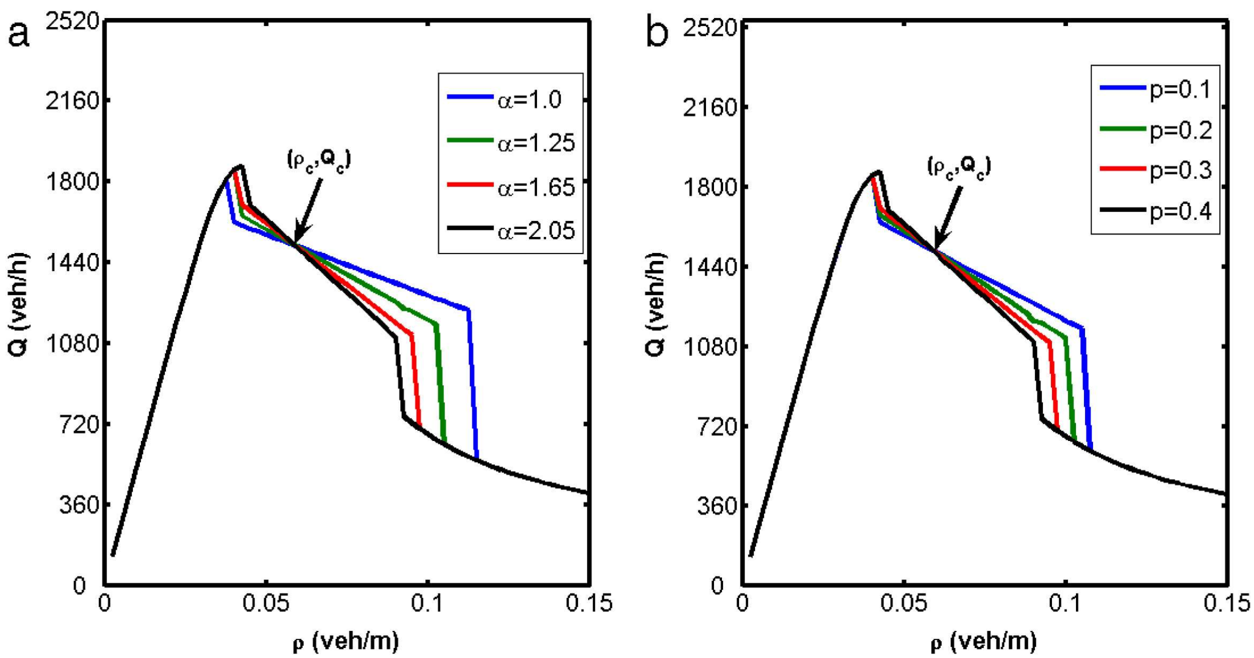

Figure 2.2: The fundamental diagrams for mixed flow traffic (AVs and HVs) for varying sensitivity factors (a) and smoothness factors (b) – note that increases in sensitivity and smoothness lead to increases in flow until the critical point (~0.05 veh/m), at which the opposite is exhibited (Zhu & Zhang, 2018)

As innovations in technology and communications have made the introduction of CAVs more likely, traffic flow and network modelling research has shifted its focus away from AVs towards CAVs. The first paper to distinguish and compare CAVs from AVs in a network model concluded that by the nature of CAVs having more information to inform driving behavior than AVs, the potential for highway capacity gains with increasing MPs of CAVs is higher than that of AVs by more than 100% (Talebpour & Mahmassani, 2016). Rios-Torres built upon this understanding by finding that increasing MPs of CAVs can also reduce fuel consumption by up to 70% and reduce travel times by more than 100% in medium to high congestion scenarios. The study also found that CAVs are highly effective in stabilizing traffic in very high congestion scenarios (Rios-Torres & Malikopoulos, 2017). Similar to Zhu and Zhang's study, "stability" refers to linear stability theory or flow uniformity as described in (Wilson & Ward, 2011).

2.2.3 Human Driver Models

As illustrated by the studies in the previous sections, the HV driver model in many mixed traffic models and simulations is left unchanged from HV driver models used in HV-only traffic analysis. The assumption used in these papers to leave the HV driver model unchanged is that the methods of vehicle to vehicle communication will be unchanged for an AV to an HV from that of an HV to an HV (Wei, Dolan, & Litkouhi, 2013). However, this assumption does not consider potential changes in HV driving behavior due to human drivers' level of trust in or perceptions of AVs. The author of this literature review was unable to find work that justifies the parameters used in network models and simulations for HV to AV interactions. For example, vehicle time headways have been identified as a critical parameter to fundamental traffic simulation and modelling, and is essential to calculate capacity at a microscopic level (Pueboobpaphan, Park, Kim, & Choo, 2013). However, this literature review has identified that headway assumptions for HVs following AVs in traffic and network models are identical to the headway assumptions for HVs following HVs.

Studies that have explored the interaction between HVs and AVs tend to focus on intersections, as the deployment of traffic control devices that are functional for both HVs and AVs was identified as a limiting factor to the widespread adoption of AVs as early as 2007 (Dresner &

Stone , 2007). For example, Dr. Fox developed a model to simulate the negotiation between HVs and AVs at an intersection with no traffic control devices using discrete sequential game theory, and found that the more efficient solutions correlated with higher risk of collision (Fox, et al., 2018).

2.3 Trust in AVs

2.3.1 Surveys

While the public's perception of AVs continues to evolve with time, recent literature can still give a general sense of human drivers' trust in AVs. Five surveys conducted in the United States and Canada found that the general population consistently had considerable doubt in the ability of AVs to have a positive impact on transportation. Most survey respondents reported distrust in AVs' ability to handle unique or edge-case driving scenarios. Those respondents also preferred AVs to have an option for the human operator to take control when the desired. Furthermore, this study found that younger respondents consistently held more trust in AVs than older respondents, suggesting a future shift in public attitudes toward the technology as younger generations age (Hedlund, 2017). Another survey on the topic of trust in AV taken in Australia found similar results, with a significant majority of respondents expressing concerns related to perceived safety, trust, and control issues Males, younger respondents, and respondents with higher levels of education in this survey were also found to hold more favorable views of AVs (Pettigrew, Worrall, Talati, Fritschi, & Norman, 2019).

2.3.2 Empirical Studies

Empirical studies have investigated trust in AVs. One 2019 study found that human drivers' level of trust does not change between AVs that are programmed to imitate human driving behavior and AVs programmed to convey the impression of communicating with other AVs and the surrounding infrastructure. This may suggest that human drivers' level of trust in AVs is predetermined and not influenced by AV driving behavior. Additionally, the study found that human drivers trusted AVs more with increased interaction time (Oliveira, Proctor, Burns, & Birrell, 2019).

2.3.3 Other Data Collection Methods

AVs are significantly more expensive than standard vehicles commercially available today, and are only being tested in a few municipalities across the U.S. (Brownell & Kornhauser, 2014). Therefore, most studies evaluating human interactions with AVs cannot be conducted at any reasonable scale. Instead, other means of data collection must be utilized, such as small-scale vehicles (**Figure 2.3**). This study tested humans' intended driving responses against multiple variations of driving maneuvers performed by small scale AVs. Results show that HV driving behaviors and perceptions of AVs are strongly related to the AVs driving maneuvers (Zimmermann & Wettach, 2016). This suggests that AVs can viscerally communicate information to HVs through certain driving maneuvers.

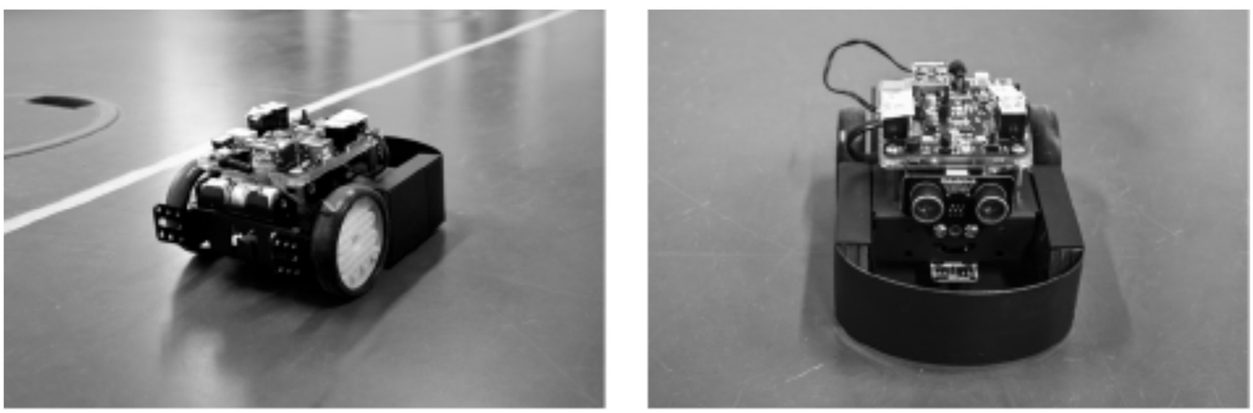

Figure 2.3: Small scale AVs used to observe and study human interactions and perceptions (Zimmermann & Wettach, 2016)

Driving simulators are established tools for researching human factors and driver behavior at a nanoscopic level (Fisher, Rizzo, Caird, & Lee, 2011). Recently, driving simulators have been used to evaluate driver behavior when operating an AV. For example, one study used a driving simulator programmed to simulate automated driving at SAE level 3 to extract participant level of trust in and perceptions of AVs (Buckley, Kaye, & Pradhan, 2018). Another study used a driving simulator to observe how drivers react to takeover requests when approaching an intersection, and how proximity to the intersection and in-vehicle tasks impact risk of collision with bicyclists approaching the same intersection (Fleskes & Hurwitz, 2019).

This literature review found only one study that utilized nanoscopic observations to inform a traffic simulation model in an attempt to explain the sag curve phenomenon (Miska & Kuwahara, 2011). Driving simulators are effective tools to measure headway, as driver headways in virtual driving simulator environments do not vary significantly from driver headways in real road driving (Risto & Martens, 2014). As mentioned in section 2.2.3 of this literature review, headway is a critical parameter to fundamental traffic modelling and simulation (Pueboobpaphan, Park, Kim, & Choo, 2013).

2.4 Research Questions

Based on this literature review, there are significant knowledge gaps related to how human drivers will interact with AVs on highways. This information has the potential to change understandings of how mixed traffic is modelled, and how varying MPs of AVs impact highway capacity. To address these knowledge gaps and issues, the following research questions were identified and guided the development of the experimental procedures.

- Research Question 1 (RQ1): How do driver's level of stress compare in a hard breaking scenario when following an AV or an HV?
- Research Question 2 (RQ2): How do drivers interpret fault from a collision with an AV or an HV?
- Research Question 3 (RQ3): What demographic variables impact driver's headway when following an AV?
- Research Question 4 (RQ4): How do driver headways differ when following an AV or an HV?
- Research Question 5 (RQ5): How do driver headways when following an AV compare to headway values currently assumed in mixed traffic models?

- Research Question 6 (RQ6): Do new values for driver headway when following an AV have a significant impact on highway travel time and flow predictions for varying MPs of AVs?

The author of this paper hypothesizes that older participants will exhibit greater headways when following an AV. Additionally, drivers will interpret fault when in a collision with an AV as their own. This is generally consistent with the findings of the literature summarized in section 2.3.1of this literature review. The author of this paper also hypothesizes that driver headways will be greater when following an AV than an HV and will be different enough from currently assumed headway values in mixed traffic models to have a measurable impact on highway travel time and flow predictions.

3.0 METHODOLOGY

This chapter describes the equipment and experimental design used to evaluate the research questions of this study. The approach used in this study is grounded in accepted practice (Fisher, Rizzo, Caird, & Lee, 2011).

3.1 Experimental Equipment

The study leveraged the unique research capabilities of the Oregon State University (OSU) Driving Simulator. Data was also collected using the iMotions Shimmer3 GSR+, while network analysis was completed using a Python-based multi-agent model. A description of each of these experimental tools are provided in the following sections.

3.1.1 OSU Driving Simulator

The full-scale OSU Driving Simulator is a high-fidelity motion-based simulator comprising of a full 2009 Ford Fusion cab mounted above an electric pitch motion system capable of rotating plus or minus four degrees. The vehicle cab is mounted on the pitch motion system with the driver's eye point located at the center of rotation. The pitch motion system allows for accurate representation of acceleration or deceleration (Swake, Jannat, Islam, & Hurwitz, 2013). Three liquid crystals on silicon projectors with a resolution of 1,400 × 1,050 are used to project a front view of 180 degrees × 40 degrees. These front screens measure 11 feet × 7.5 feet. A digital light-processing projector is used to display a rear image for the driver's center mirror. The two side mirrors have embedded liquid crystal displays. The update rate for all projected graphics is 60 hertz. Ambient sounds surrounding the vehicle and internal vehicle sounds are modelled with a surround sound system.

The computational system includes a quad-core host computer running Realtime Technologies SimCreator Software (Version 3.2) with graphics update rates capable of 60 hertz. The simulator software can capture and output values for multiple kinematic performance measures with high fidelity. These performance measures include position of the subject inside the virtual environment, velocity, and acceleration. Each of these computation components is controlled from the operator workstation. The driving simulator is in a physically separated room from the operator workstation to prevent participants in the vehicle from being affected by visual or audible distractions.

3.1.2 iMotions Shimmer3 GSR+

The Shimmer3 GSR+ measures galvanic skin response (GSR) and photoplethysmogram (PPG) signals. GSR data is collected by two electrodes attached to two separate fingers on one hand. These electrodes detect stimuli in the form of changes in moisture, which increase skin conductance and changes the electric flow between the two electrodes. Therefore, GSR data is dependent on sweat gland activity, which is correlated to participant level of stress (Bakker, Pechenizkiy, & Sidorova, 2011). PPG signals are collected through photodetectors on skin surfaces (usually a finger or ear-lobe) which measure volumetric variations in blood circulation, giving an accurate and non-intrusive method to monitor participant heart rates (Castaneda, Aibhlin, Ghamari, Soltanpur, & Nazeran, 2018). Together, GSR and PPG data produce an accurate depiction of participant level of stress. The Shimmer3 GSR+ GSR and PPG sensors attach to an auxiliary input, which is strapped to the participant's wrist as shown in **Figure 3.1**. Data is wirelessly sent to a host computer running iMotions EDA/GSR Module software, which feature data analysis tools such as automated peak detection and time synchronization with other experimental data.

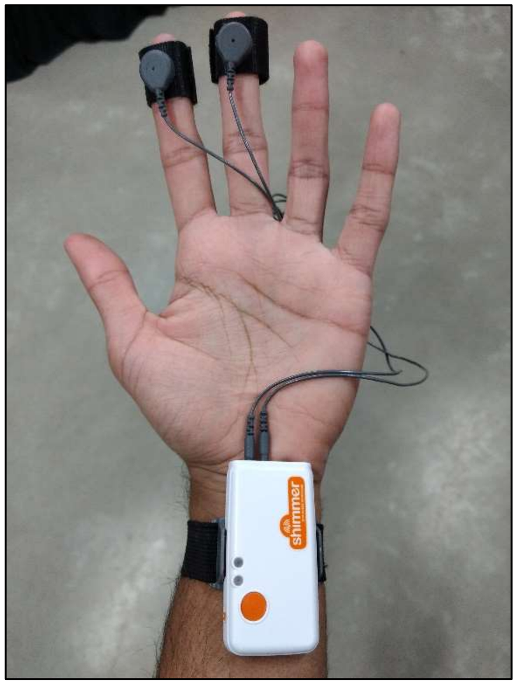

Figure 3.1: Shimmer GSR+ sensors (shown attached to the index and middle finger) send data to a host computer through the wireless transmitter (shown attached to the wrist) in real time

3.1.3 Agent-Based Modeling and Simulation

Agent-based modeling and simulation (ABMS) has a bottom-up structure and can model heterogeneous agents to observe emergent behaviors from interactions among individual agents. ABMS is a popular alternative to simulate real-life situations when empirical data is scarce or difficult to obtain (Sanchez & Lucas, 2002), and is especially effective in modelling human-involved systems due to the autonomous behavior and interactions of agents preset by the programmer (Bonabeau, 2002).

3.2 Experimental Design

3.3 Independent Variables

Two independent variables were included in the experiment: speed of the leading vehicle and the leading vehicle's level of autonomy. These variables were selected by the research team to address the abovementioned research questions.

The speed of the leading vehicle was varied to induce different preferred following distances from participants. This produces a more detailed dataset for determining participant level of comfort. Speeds were varied between 45 mph and 65 mph to reflect high speed facility conditions.

The second independent variable was whether the leading vehicle was fully autonomous or human driven. Fully autonomous vehicles are defined as Society of Automotive Engineers (SAE) level five vehicles, while human driven vehicles are defined as SAE level zero vehicles. Level of autonomy was changed by the researchers to observe differences in participant following behavior and level of comfort between the two vehicle types.

3.4 Factorial Design

A factorial design was created to explore each of the two independent variables of the study. The factorial design, a two by two resulting in four scenarios, is shown in **Table 3.1**. Additionally, participants were exposed to two hard breaking scenarios: one with an SAE level zero and one with an SAE level five vehicle leading. In total, participants were exposed to each of the four levels and two hard breaking scenarios with six unique scenarios.

Table 3.1: Experimental Factors and Levels

Variable	Category	Level Description
Leading Vehicle Speed	Discrete	45 miles per hour
		65 miles per hour
Leading Vehicle Autonomy	Dichotomous (Categorical)	SAE level zero
		SAE level five

The within-subject design provides advantages of greater statistical power and reduced error variance associated with individual differences (Brink & Wood, 1998). However, one fundamental disadvantage of the within-subject design is the potential for "practice effects," caused by practice, experience, and growing familiarity with procedures as participants move through the sequence of conditions. To control for practice effects, the order of the presentation of scenarios to participants needs to be randomized or counterbalanced (Girden, 1992). To account for practice effects, four different track layouts representing six different scenarios were presented in a random order to each participant. This adds flexibility and simplicity to the statistical analysis and number of participants required.

The configuration for each of the six scenarios presented to participants and which track layout they were assigned to are shown in **Table 3.2**. Scenarios presented in the same track were separated by 45 to 60 seconds of driving. Hard braking events were included in tracks III and IV did not interfere with the car-following portion of each track. More information on the design of the virtual environment and tracks can be found in the following sections.

Table 3.2: Six Scenarios Presented in Four Tracks

Track	Scenario	Leading Vehicle Speed	Leading Vehicle Autonomy	Hard Breaking
I	1	65 miles per hour	SAE level five	No
	2	45 miles per hour	SAE level zero	No
II	3	65 miles per hour	SAE level zero	No
	4	45 miles per hour	SAE level five	No
III	5	55 miles per hour	SAE level five	Yes
IV	6	55 miles per hour	SAE level zero	Yes

3.5 Virtual Environment

The virtual environment was developed using the following software packages: Internet Scene Assembler (ISA), SimCreator, and GNU Image Manipulation Program (GIMP). The dynamic elements of the simulations were developed in ISA using JavaScript-based sensors on tracks to engage position dependent events such as hard-braking. The environment was designed to replicate limited-access highway conditions with speed limits between 45 miles per hour and 65 miles per hour. Roadway cross-sections consisted of two 12-foot lanes in each direction of travel. Track layouts, dimensions, and segments of data-collection are shown in **Figure 3.3**.

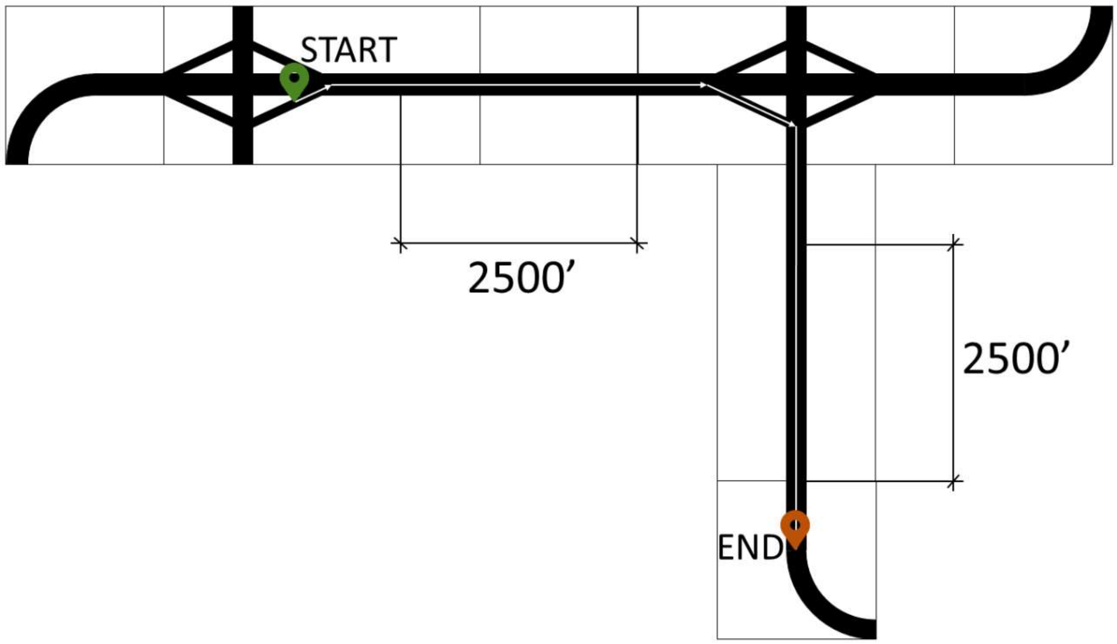

Figure 3.3: Example grid layout with two 2,500-foot segments in which following distances were recorded.

3.5.1 Custom Objects

Pre-loaded dynamic objects from SimCreator were adjusted with GIMP to produce visually identifiable SAE level five vehicles. GIMP is an open-sourced image editing software that is capable of editing RGBA image file types, the file type used to render textures of dynamic objects in SimCreator. The rear of SAE level five vehicles was edited to say “Self-Driving,” which replicates the terminology and position of text of current SAE level five vehicles being tested on public roads by WAYMO and Uber. The edited image file is shown in **Figure 3.4**.

Figure 3.4: Screenshot of RGBA image file edited using GIMP to modify pre-loaded dynamic vehicles from SimCreator

3.5.2 Leading Vehicle Driving Behavior

SAE level five vehicles in the simulation were programmed to have zero fluctuation in speed or lane position. SAE level zero vehicles in the simulation were programmed to have continuous random speed fluctuations plus or minus five mph.

3.5.3 Simulator Sickness

Simulator sickness is a phenomenon where a person exhibits symptoms similar to motion sickness that is caused by a simulator (Fisher, Rizzo, Caird, & Lee, 2011). The symptoms are often like that of motion sickness, and can include headache, nausea, dizziness, sweating, and extreme situations, vomiting. While no definitive explanation for simulator sickness exists, one widely accepted theory is cue conflict theory. Cue conflict theory suggests that simulator sickness arises from the mismatch of visual and physical motion cues, as perceived by the vestibular system (Kolasinski, 1995). Precautions were taken to ensure comfort for all participants in both the experimental design and experimental protocol. Data from participants who experienced simulator sickness during the study were not included in the project's results.

3.6 Experimental Protocol

This section describes the step-by-step procedures of the driving simulator study was conducted for each individual participant. The protocol was approved by the OSU Institutional Review Board (IRB) (Study #2019-0261).

3.6.1 Recruitment

A total of 39 participants, primarily from the Corvallis-Albany metropolitan area, were recruited for the driving simulator study. All participants were required to have at least 1 year of driving experience, not wear glasses or have impaired vision, and be physically and mentally capable of legally operating a motor vehicle. Furthermore, participants needed to be competent to provide written, informed consent. Recruitment for participants was largely done through flyers posted around the Corvallis-Albany metropolitan area and emails sent through different campus organization listservs. An effort to incorporate participants of all ages within the specified range of 18 to 75 years was made to balance the overrepresentation of college-aged students in the Corvallis-Albany metropolitan area.

Researches did not screen interested participants based on gender until the quota for either males or females had been reached, at which point only the gender with the unmet quota could participate. Throughout the entire study, information related to the participants was kept under double-lock security in compliance with accepted IRB procedures. Each participant was randomly assigned a number to remove any uniquely identifiable information from the recorded data.

3.6.2 Informed Consent and Compensation

When the test participant arrived at the laboratory, they received an informed consent document. This document described the reasoning behind the study, the importance of participation, and the risk and benefits of the test for the participant. Participants were also given the opportunity to ask any questions regarding the study and were informed that they could stop the experiment at any time for any reason and still receive full compensation ($10 cash) for participating in an experimental trial. To avoid introducing bias to the experiment, participants were not told the specific research hypotheses.

3.6.3 Prescreening Survey

Participants were administered a prescreening survey before beginning experimental drives. The prescreening survey collected information on the participant's demographics, such as age, gender, ethnicity, driving experience, highest level of education, and prior experience with driving simulators. Furthermore, the survey included questions in the following areas:

- Vision: Participants' vision is crucial for the experiment. Participants were asked if they use corrective glasses or contact lenses when driving. Their abilities to see the driving environment clearly were confirmed during the calibration drive.
- Simulator sickness: Participants with previous driving simulation experience were asked about any simulator sickness that they experienced. If they had previously experienced simulator sickens, they were encouraged not to participate in the experiment.
- Motion sickness: Participants were surveyed about any kind of motion sickness they had experienced in the past. If an individual had a strong tendency towards any kind of motion sickness, they were encouraged not to participate in the experiment.

3.6.4 Calibration Drive

A calibration drive followed the completion of the prescreening survey. The drive was designed to take participants approximately 5-minutes and had the purpose of acclimating the participant to the mechanics of the vehicle and the virtual reality of the simulator. The calibration drive also helps researchers determine if the participant was prone to simulator sickness. Before the calibration drive, participants could adjust the seat, steering wheel, and rearview mirror to maximize comfort and performance while driving. Participants were instructed to drive and follow all traffic laws as they normally would. If the participant reported simulator sickness during or after the calibration drive, they were excluded from the experimental drives. In accordance to accepted practice (Zhao, Wu, Rong, & Zhang, 2015), the calibration effectively introduced participants to horizontal curves, acceleration and deceleration on a stretch of roadway, and turning at intersections.

3.6.5 Biometric Sensors

After the calibration drive was completed, researchers equipped participants with a head-mounted eye-tracker. Participants were directed to look at different locations on a calibration image projected on the forward screen of the driving simulator. Data collected by the eye-tracker was not used for this study.

Participants were also equipped with a GSR sensor. The GSR sensor was placed on the index and middle fingers of the participant's left hand in a way that would not impede normal driving behaviors. The sensors were attached to an auxiliary input, which was strapped to the participant's wrist.

3.6.6 Vehicle Type Briefing

After participants were equipped with the biometric sensors, they were shown the slide in **Figure 3.5**. Researchers verbally explained how SAE level five vehicles would be visually discernable from SAE level zero vehicles in the virtual environment and answered participant questions on the definitions of the SAE levels. Researchers did not answer questions on the driving behavior of different SAE level vehicles.

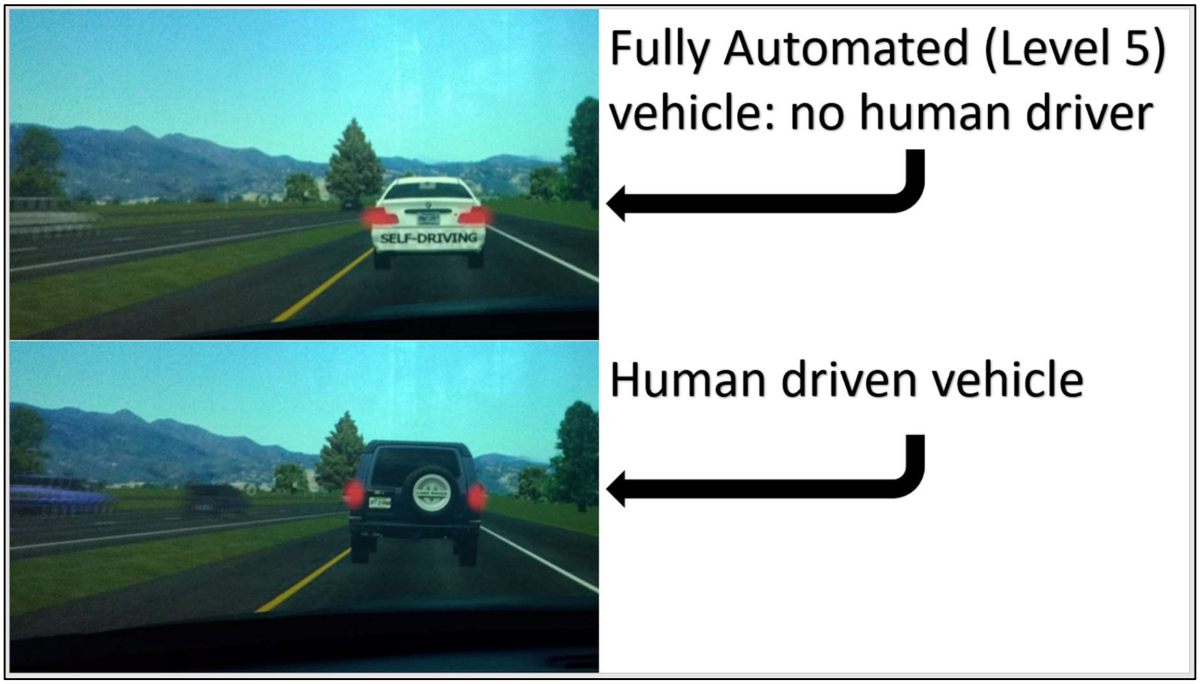

Figure 3.5: Briefing slide shown to participants to assist in explaining how SAE level five vehicles will be visually different than SAE level zero vehicles in the simulated environment

3.6.7 Experimental Drives

Participants were given brief instructions about the test environment and the tasks they would be required to perform. The experiment was divided into four tracks. At the completion of each experimental drive, the researcher instructed the participant to bring the vehicle to a complete stop and ascertained whether the participant was experiencing simulator sickness. The entire experimental portion of the study was designed to take 30 minutes to complete.

3.6.8 Post-Drive Survey

Following the experimental drives, participants were asked to respond to questions in a post-drive survey. The survey included questions about the participant's level of comfort following SAE level five vehicles and SAE level zero vehicles. Additionally, participants were asked to identify fault if they were involved in one or more collisions during the experimental drives.

3.7 Simulator Data Reduction

Simulator data was collected through the SimObserver platform during the experimental drives. A complete data file was generated for each participant for each of the four experimental drives. Files, including collected video data and all output of vehicle performance measures (e.g. lateral position, velocity), were opened and synchronized in the Data Distillery (Version 1.34) software suite. Performance measures when participants were following vehicles of interest were extracted.

JavaScript was also written to extract participant distance headways when the participant was following vehicles of interest. These values were synchronized with the extracted performance measure data and used to calculate the participant's instantaneous time headways with a fidelity of 30 measurements per second. Time headway is a more useful measure as it considers both distance headway and velocity, as shown in equation (3):

$$(3) \quad h_t = \frac{h_d}{v}$$

where h_t is time headway, h_d is distance headway, and v is velocity. Average time headway values were aggregated for each of the six tested scenarios.

3.8 Highway Segment Model

An agent-based simulation was built to model traffic along a two lane (per direction) 5-mile highway segment. Agents in the simulation follow the IDM model, using similar methodologies to studies described in section 2.2 of this paper. In addition to the IDM model, agents can perform simple lane changing behavior. The behavior's logic, as well as the program's overall logic, is presented in **Figure 3.6**.

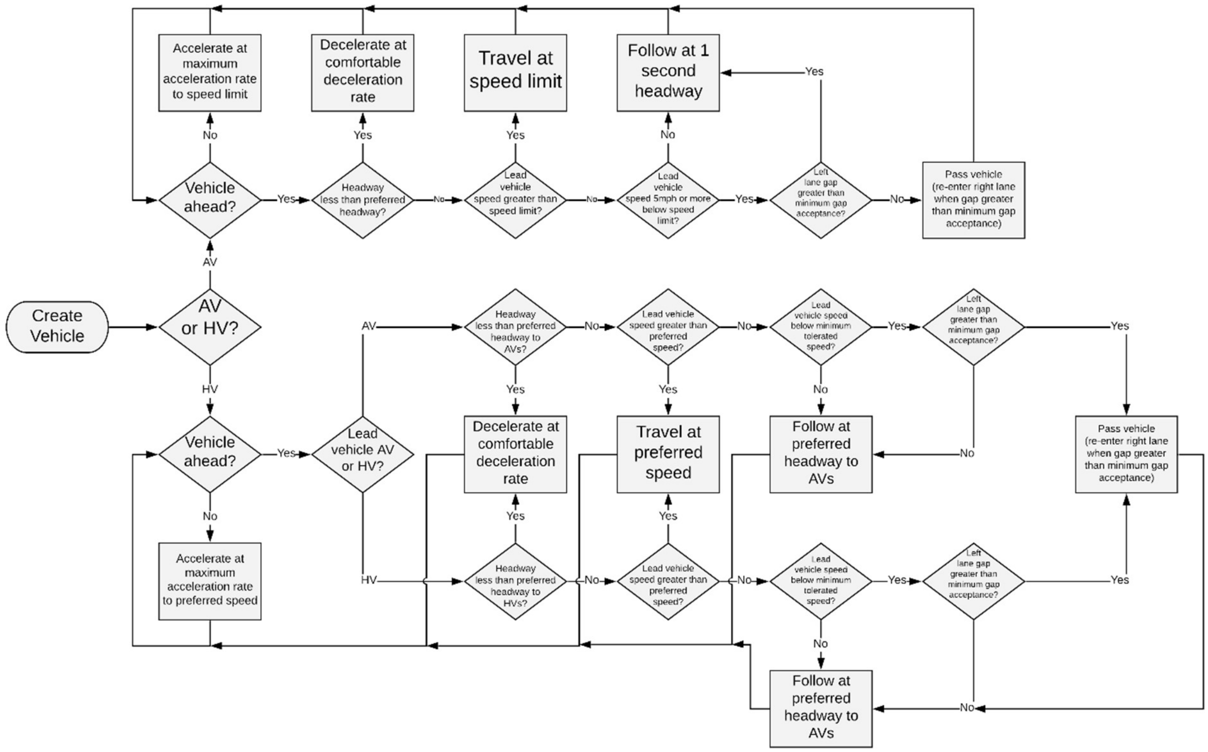

Figure 3.6: Flowchart showing the logic architecture for both AV and HV vehicle-agents

Because of uncertainties in how AVs will be deployed over time (Chang, et al., 2015), the program must be able to vary AV market penetration as an input. Both inputs to the program and hard-coded parameters are summarized in **Table 3.3**. Select parameters are randomly generated from a normal distribution for each agent in the simulation as a part of the Monte Carlo simulation method. More information on the Monte Carlo method used for this study can be found in section 4.4. Program outputs are average vehicle speed, average vehicle travel time, and total simulation time. Total simulation time is the total amount of time it takes for all vehicles generated in the simulation to traverse the 5-mile highway segment. The total number of vehicles in the simulation can be divided by the total simulation time to give average flow. All vehicles are generated simultaneously and given 2-miles to stabilize their driving behavior before entering the 5-mile highway segment where data is recorded.

Table 3.3: Summary of user inputs and hard-coded parameters in the program. A user input that is randomly generated from a normal distribution uses the user input to center the distribution.

Source	Variable	Randomly Generated from Normal Distribution?
User Input	AV Market Penetration	No
	Percentage of HV's in Group 1	No
	Speed Limit	No
	Number of Vehicles	No
	Number of Iterations	No
	HV to AV Headway Group 1	Yes
	HV to AV Headway Group 2	Yes
Hard-Coded	AV Maximum Acceleration	No
	AV Comfortable Deceleration	No
	AV Headway	No
	AV Gap Acceptance	No
	HV Maximum Acceleration	Yes
	AV Comfortable Deceleration	Yes
	HV Preferred Speed	Yes
	HV to HV Preferred Headway	Yes
	HV Gap Acceptance	Yes

The program was developed using Python and utilizes a voxel simulation style. Voxels are like pixels but contain three dimensions of information rather than two, giving it distinct advantages. Relevant to this project, voxels allow for agent's movement to be simulated on a cartesian plane (which requires three dimensions of information) rather than by just vectors (which requires two dimensions of information). Furthermore, voxels are easier to transform and render to perform the kinematic calculations of vehicle-agents and allow for the implementation of lane-changing behavior. However, voxel simulation styles tend to require more computational memory than other simulation styles (Klette & Rosenfeld, 2004). This is not an issue for this project given the relatively small size of the simulated world.

Three headway conditions were tested using the developed program: 1) HV to AV headways are equal to HV to HV headways, 2) HV to AV headways are different than HV to HV headways, and 3) HV to AV headways vary by age group and are different than HV to HV headways. These three conditions will be referred to as "No Difference," "HV2AV Difference," and "HV2AV*Age Difference" respectively for the remainder of this paper. Each condition was run with AV market penetrations varying from 0% to 100% in 20% increments for both 45 mph and 65 mph speed limits. Each of these scenarios was iterated 100 times. In total, 36 scenarios were simulated in 3600 iterations.

4.0 RESULTS

This chapter presents the results of the simulator experiment, which includes demographic summaries of participants, post-drive survey results, analysis of biometric data, and an analysis of experimental drive data. Additionally, this chapter presents the results of the highway capacity sensitivity analysis using a multi-agent simulation platform informed by the experimental drive data.

4.1 Participant Demographics and Post-Drive Survey Results

Information on the participant recruitment and screening process can be found in section 3.6 of this report. Of the 39 participants, 44% were female, while the age of the participants ranged between 18 years and 69 years ($M_{age} = 27.4, SD_{age} = 10.9$). Three participants reported simulator sickness and did not complete the experiment – all responses recorded from participants who reported simulator sickness were excluded from the analyzed dataset. **Table 4.1** summarizes the self-reported demographic information collected from all participants.

Table 4.1: Participant Self-Reported Demographic Information

Question	Possible Responses	Number of Participants	Percentage of Participants
How many years have you been a licensed driver?	1–5 years	21	54%
	6–10 years	7	18%
	11–15 years	3	8%
	16–20 years	3	8%
	20+ years	5	13%
How many miles did you drive last year?	0–5,000 miles	14	36%
	5,000–10,000 miles	9	23%
	10,000–15,000 miles	11	28%
	15,000–20,000 miles	4	10%
	20,000+ miles	1	3%
How often do you drive in a week?	1 time per week	10	26%
	2–4 times per week	15	38%
	5–10 times per week	7	18%
	10+ times per week	7	18%
Do you have previous experience driving an SAE Level 1 vehicle?	Yes	16	41%
	No	23	59%

After the experimental drive, participants were asked if they would prefer AVs to drive in a separate lane from human drivers on highways. Thirty-eight percent of participants indicated that they would prefer separation. However, how participants answered this question was not found to have a relationship with participant's headways when following an AV or HV.

Each participant was exposed to two hard breaking scenarios – one when following an AV and one when following an HV. If the participant was involved in a collision during one or both hard breaking scenarios, they were asked to identify who was at fault for the collision. Of the 78 hard breaking scenarios tested in this study, 10 collisions were observed (4 with an HV, 6 with an AV). **Figure 4.1** visualizes how participants interpreted fault based on the vehicle type they were in a collision with. While those in a collision with an AV did not place fault on the AV, the sample size is too small to draw a statistical conclusion.

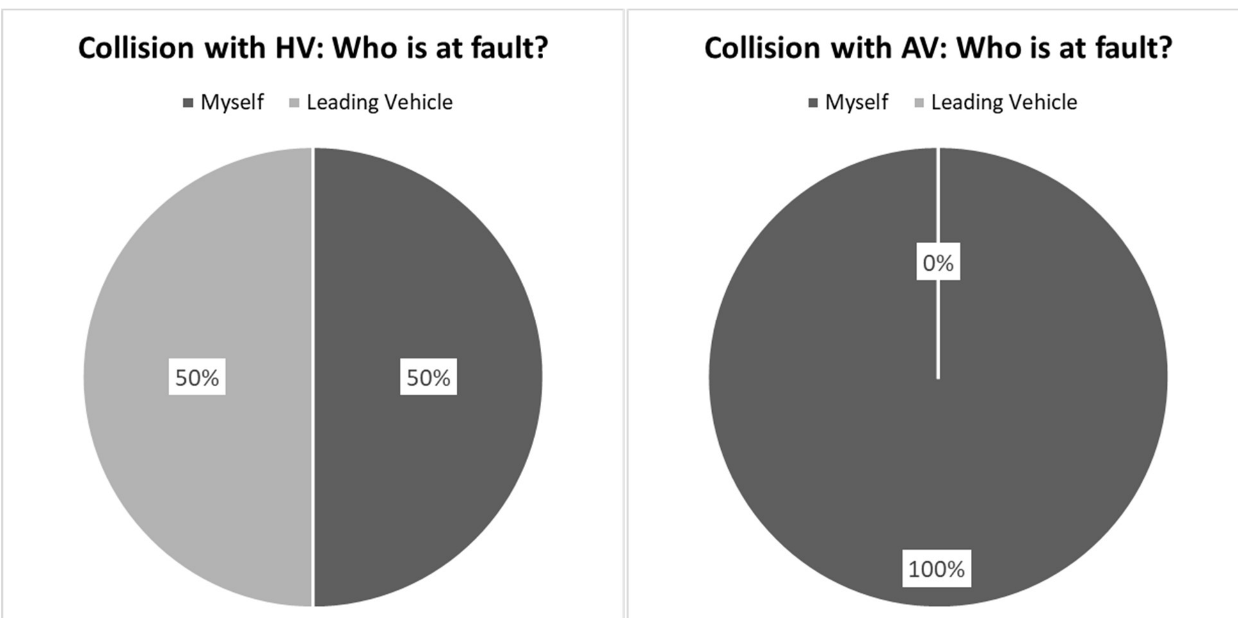

Figure 4.1: Self-reported interpretation of collision fault when in a collision with an HV (left) and when in a collision with an AV (right).

4.2 Biometric Results

GSR measurements were reduced to GSR peaks per minute for the two hard breaking scenarios. The dataset analyzed begins at the start of the leading vehicle's deceleration and ends when the leading vehicle has come to a complete stop. By reducing the data to peaks per minute, the natural variations between participants' peak heights are controlled for. GSR peaks per minute have been used in previous transportation human factors studies (Krogmeier, Mousas, & Whittinghill, 2019). Furthermore, GSR peaks per minute is generally accepted as an indicator of level of stress in human factors studies (Zou & Ergan, 2019). iMotions software was used to segment, compute, and reduce the dataset. The software develops a baseline GSR reading for each participant based on their average response throughout the entire experimental drive. Any amplified response above the baseline, it is classified as a peak and is recorded (iMotions, 2017).

During the experimental drive, GSR data is transmitted wirelessly from the Shimmer+ device attached to the participant in the driving simulator to a host computer in the control room. The strength of wireless connectivity can vary, with weaker wireless connections degrading the reliability of the dataset. Fifteen datasets were removed from the analysis due to weak wireless connections. **Table 4.2** visualizes the two datasets of 21 participants with boxplots.

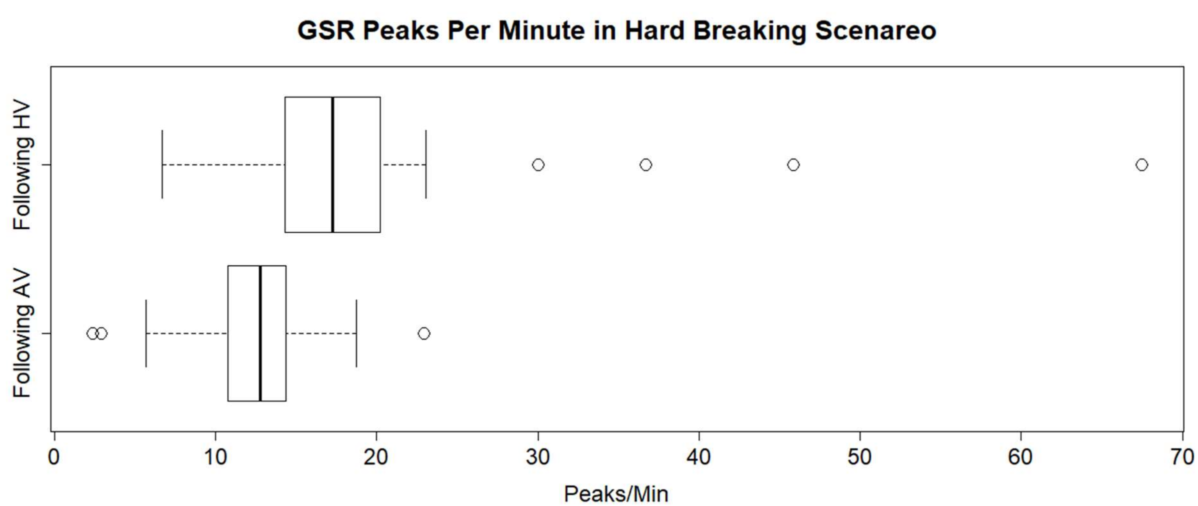

Figure 4.2: Boxplots show that the spread of participant's GSR response is noticeably wider in the HV hard breaking scenario than in the AV hard breaking scenario

The 21 datasets that were analyzed were tested using a two-tailed t-test for dependent means (also referred to as a repeated-measures t-test) at the 95% confidence level. This test is a strong choice to test the difference between the two datasets because it is designed for repeated-measures (within-subject) data. Furthermore, the dataset meets all normalcy assumptions required to conduct a t-test (Jashami H. , Hurwitz, Abdel-Rahim, Bham, & Boyle, 2017). The test shows that GSR peaks per minute is 70% higher in the HV hard breaking scenario than in the AV hard breaking scenario. **Table 4.2** presents the results of the test.

Table 4.2: Results from the two-tailed t-test for dependent means for GSR peaks per minute responses in hard breaking scenarios

Measure	Value
Mean Difference	8.5 peaks/min
[95% Confidence Interval]	[10.6 to 6.4] peaks/min
T-value	2.61
p-value	0.017

4.3 Experimental Drive Results

Linear Mixed Effects Models (LMM) can account for errors generated from repeated measures, considers fixed or random effects in its analysis, and accommodates for both categorical and continuous variables (Jashami H. , Hurwitz, Chris, & Kothuri, 2019). Furthermore, LMMs have a low probability of incurring Type I errors (Jashami, Hurwitz, Monsere, & Kothuri, 2020). Considering that this study's sample size exceeds the minimum required for a LMM analysis (Barlow, Jashami, Sova, Hurwitz, & Olsen, 2019) and meets the required distributional assumptions (Maruyama, 2008), the LMM is a strong candidate for the analysis of the experimental drive dataset.

Variables of roadway speed, leading vehicle type, whether the participant was involved in a collision, the participant's self-reported level of concern when following an AV, and age are included in the model as fixed effects. The participant variable is included as a random effect. The driver performance measures evaluated are headways when following either an AV or HV. Instantaneous time headways are recorded when participants follow select vehicles throughout the drive as intended by the experimental design. To find the closest value to the participant's preferred following distance, the average following distance throughout the entire recorded segment could not be used. This is because the entire recorded segment includes headway datapoints when the participant is choosing their preferred headway, which are highly variable across different participants. Instead, the minimum headway value in the recorded segment was used and will be referred to as "headway" in the analysis.

Mean and standard deviation (SD) values for each independent variable level's time headway are reported in **Table 4.3**. The greatest average time headway was observed when participants followed an HV with a 45 mph speed limit (mean = 2.8 s, SD = 1.9 s), while the smallest average time headway was observed when participants followed an HV with a 65 mph speed limit (mean = 2.3 s, SD = 1.2 s).

Table 4.3: Descriptive statistics for time headways (s) observed in each experimental drive scenario

Leading Vehicle Type	Descriptive Statistics	45 mph Speed Limit	65 mph Speed Limit
AV	Mean	2.4	2.3
	(SD)	(1.4)	(1.3)
HV	Mean	2.8	2.3
	(SD)	(1.9)	(1.2)

An LMM was used to estimate the relationship between the independent variables and the participant's time headway, which is appropriate given the repeated measures nature of the experimental design (Abadi, Fleskes, Jashami, & Hurwitz, 2018). Both fixed and random effects needed to be included in the model. Fisher's Least Significant Difference (LSD) test was run in the case of statistically significant effects to perform post hoc contrasts for multiple comparisons. All statistical analyses were performed at the 95% confidence level. Restricted Maximum Likelihood estimates were also used in the development of this model. **Table 4.4** shows the results of the model. The random effect was significant (Wald Z = 3.56, $p<0.001$), which suggests that it was necessary to treat the participant as a random factor in the model.

Table 4.4: Mean and standard deviation of time headway (s) at the independent variable level

Variable	Levels	Estimate	DF	P
Participant Random Effect (SD)	-	(0.9)	-	<0.001*
Constant	-	2.4	35	<0.001*
Leading Vehicle Type	AV	-0.2	105	<0.001*
	HV	Base	105	<0.001*
Speed Limit	45 mph	0.2	105	<0.001*
	65 mph	Base	105	<0.001*
Collision	Yes	-1.0	105	<0.001*
	No	Base	105	<0.001*
Age	<34.5	-0.5	105	<0.001*
	>34.5	Base	105	<0.001*
Age x Leading Vehicle Type	<34.5 AV	-0.5	105	<0.001*
	>34.5 AV	Base	105	<0.001*
Speed Limit x Leading Vehicle Type	45 AV	-0.5	105	<0.001*
	45 HV	Base	105	<0.001*
Collision x Leading Vehicle Type	Yes AV	-0.2	105	<0.001*
	Yes HV	Base	105	<0.001*
Age x Speed Limit	<34.5 45 mph	-0.3	105	<0.001*
	>34.5 45 mph	-0.1	105	<0.001*
	<34.5 65 mph	-0.8	105	<0.001*
	>34.5 65 mph	Base	105	<0.001*

Summary Statistics			
Adjusted R^2	67%	Observations	216
-2Log Likelihood	402.0	Participants	36
AIC	438.4	Observations/Participant	6

*Significant at the 95% confidence level

Both independent variables were found to have a significant impact on headway. Regardless of other variables, participants following AVs maintained headways that were 9% smaller than when following HVs. Similarly, participants selected headways that were 8% smaller with 45 mph speed limits versus 65 mph speed limits. The mean time headways for each level of leading vehicle type and speed limit are shown in the interaction plot presented in **Figure 4.3**.

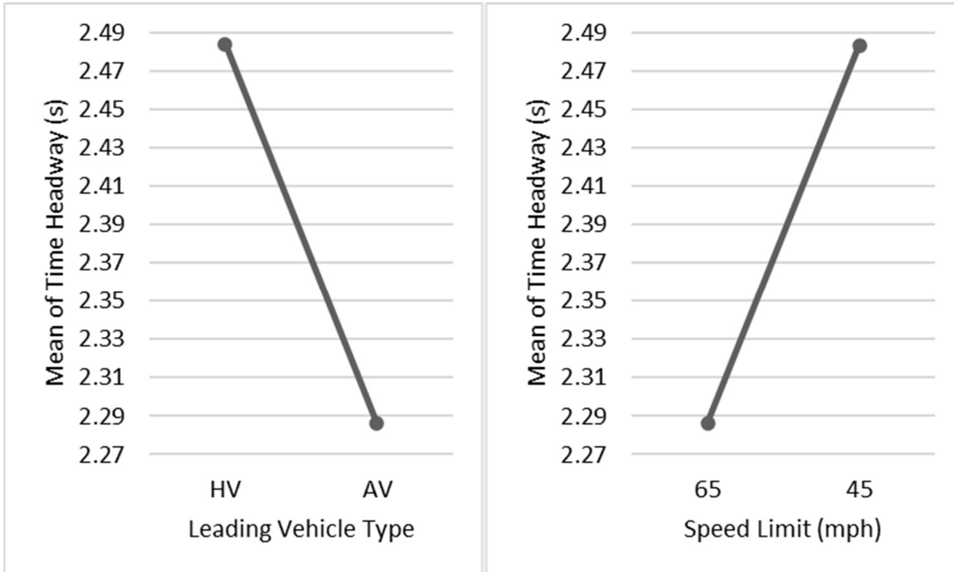

Figure 4.3: Primary effects plot of the leading vehicle type (left) and speed limit (right) on mean lateral position

More interactions relevant to the research questions of this study are shown in **Figure 4.4**. **Figure 4.5** visualizes why age has been categorized into two groups: below and above 34.5 years of age. A clear divide was observed between participants above and below these two age groups. Zero participants above the age of 34.5 years self-reported being "unconcerned" when following an AV in the post-drive survey, while 38% of participants under the age of 34.5 did.

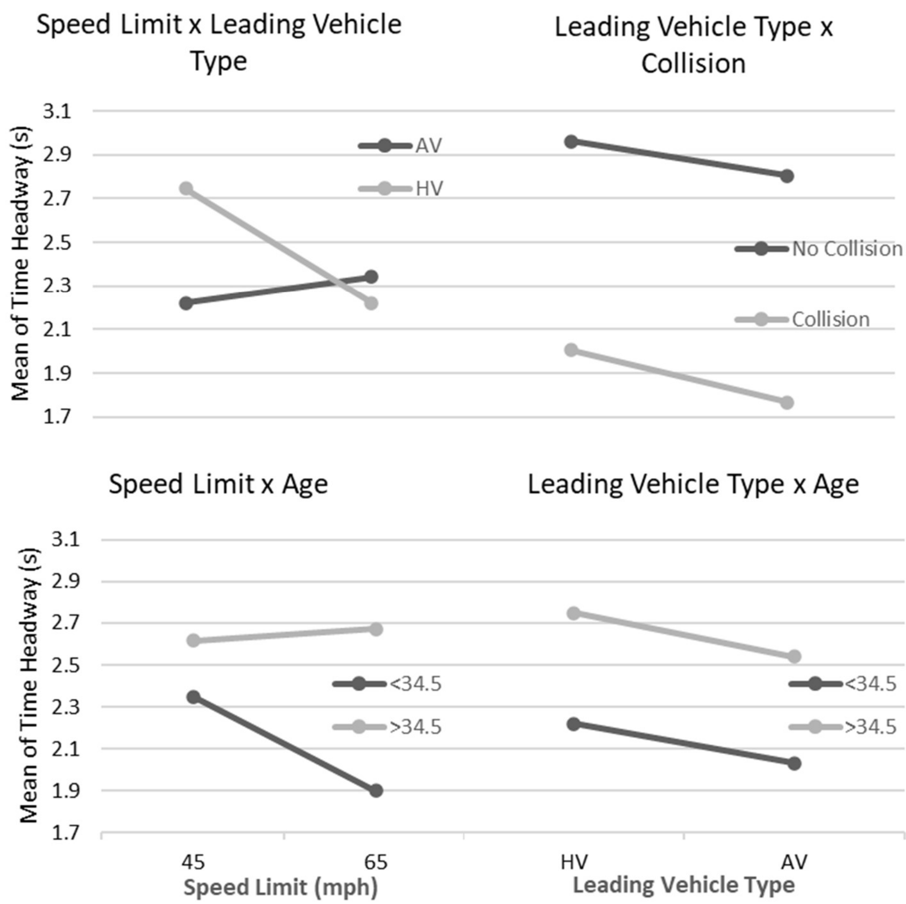

Figure 4.4: Two-way interaction plots of treatment variables on mean time headway between speed limit and leading vehicle type (top left), leading vehicle type and whether or not the participant was involved in a collision during the experimental drives (top right), speed limit and age (bottom left), and leading vehicle type and age (bottom right)

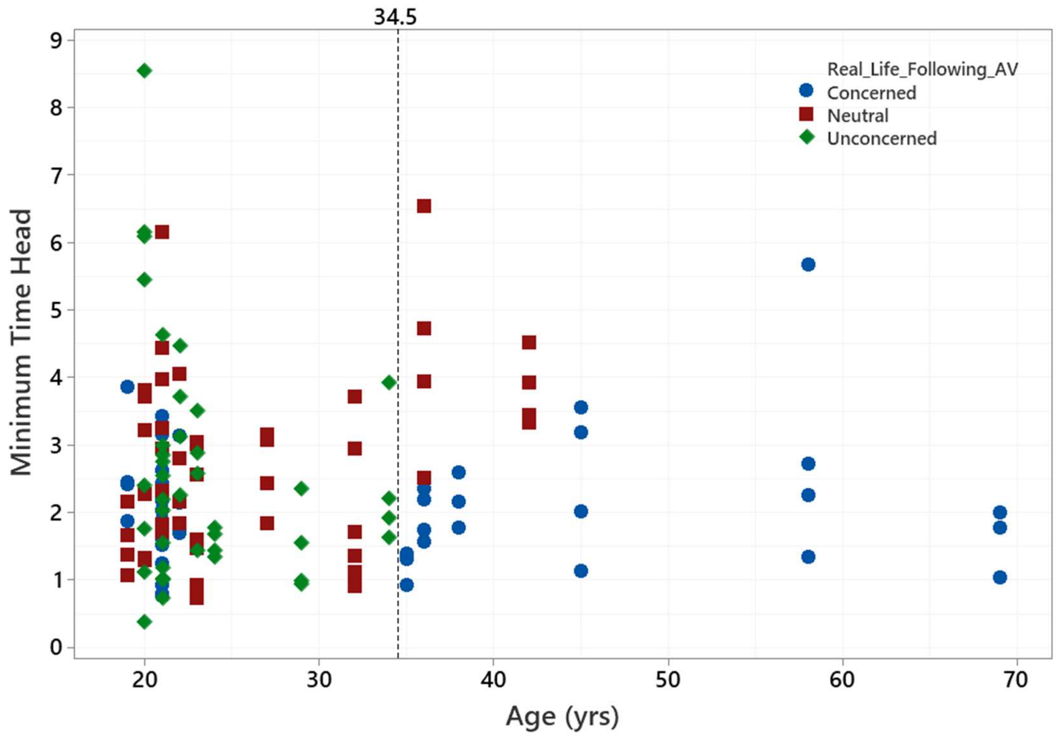

Figure 4.5: Participants were asked about the level of concern they feel when following an AV in the post-drive survey – this plot shows those responses according to the participant's age and corresponding time headways (s) recorded during the experimental drive

4.4 Agent-Based Simulation Results

Information on the development of the agent-based simulation for this study can be found in section 3.8. AVs in all scenarios follow a time headway of 1 s, while HV time headways vary by scenario. The input values shown in **Table 4.5** are used by the program to center a normal distribution from which preferred time headway values are randomly assigned to each HV generated in the simulation. **Table 4.5** also shows the percent difference between input time headway values as informed by the driving simulator dataset. In the HV2AV*Age Difference condition, Group 1 represents drivers under the age of 34.5. According to 2019 data from the U.S. Census Bureau, those under the age of 34.5 make up approximately 45% of the U.S. population (U.S. Census Bureau, 2019). Therefore, Group 1 agents made up 45% of all HV agents, with Group two agents making up the remaining 55% in the HV2AV*Age Difference condition.

Table 4.5: Variation in HV time headway values for the three conditions modeled

Condition	HV Time Headway Group 1	HV Time Headway Group 2	Percentage of HVs in Group 1
No Difference	Base	-	100%
HV2AV Difference	-9%	-	100%
HV2AV*Age Difference	-18%	+2%	45%

The modeling used a Monte Carlo simulation approach to evaluate the emergent collective behaviors and patterns of the traffic flow along the highway segment. AV market penetrations were varied from 0 to 100 percent in 20-point increments and each scenario was iterated 100 times. **Figure 4.6** visualizes convergence after 100 iterations for HV2AV Difference scenarios as an example, while **Figure 4.7** summarizes the results of all simulations.

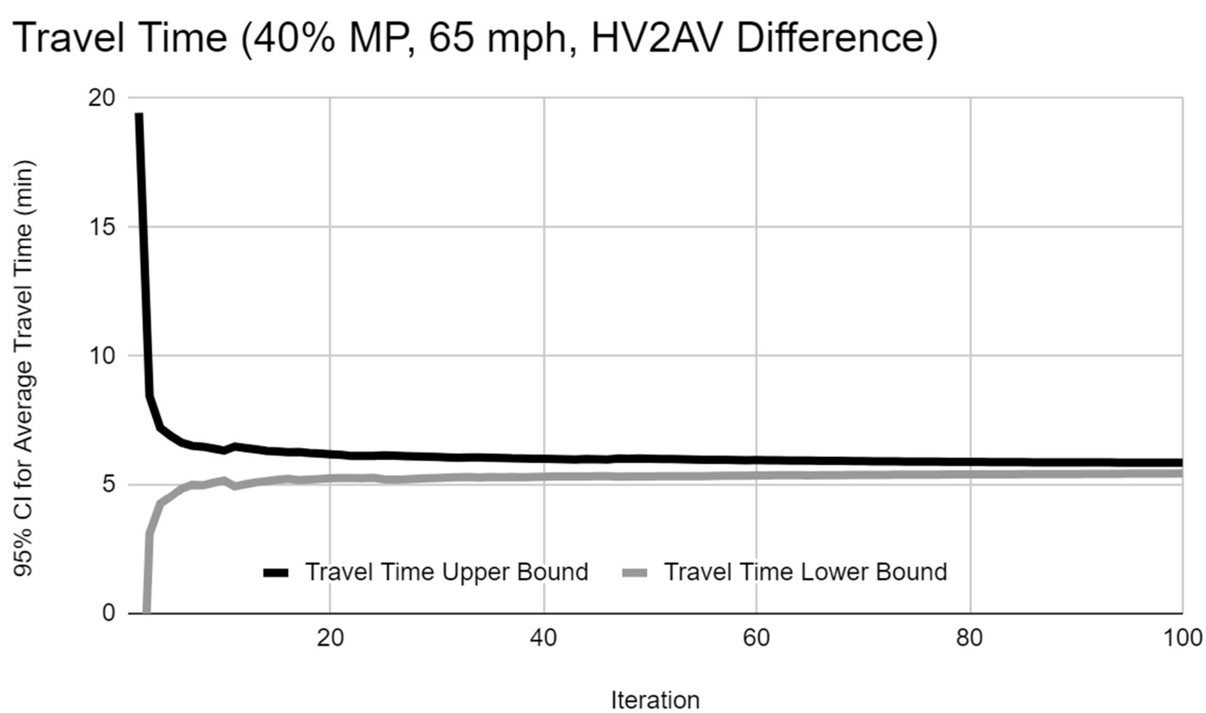

Figure 4.6: The 95% confidence interval of average vehicle travel time (min) through 100 simulation iterations for the 40% AV market penetration 65 mph HV2AV Difference scenario

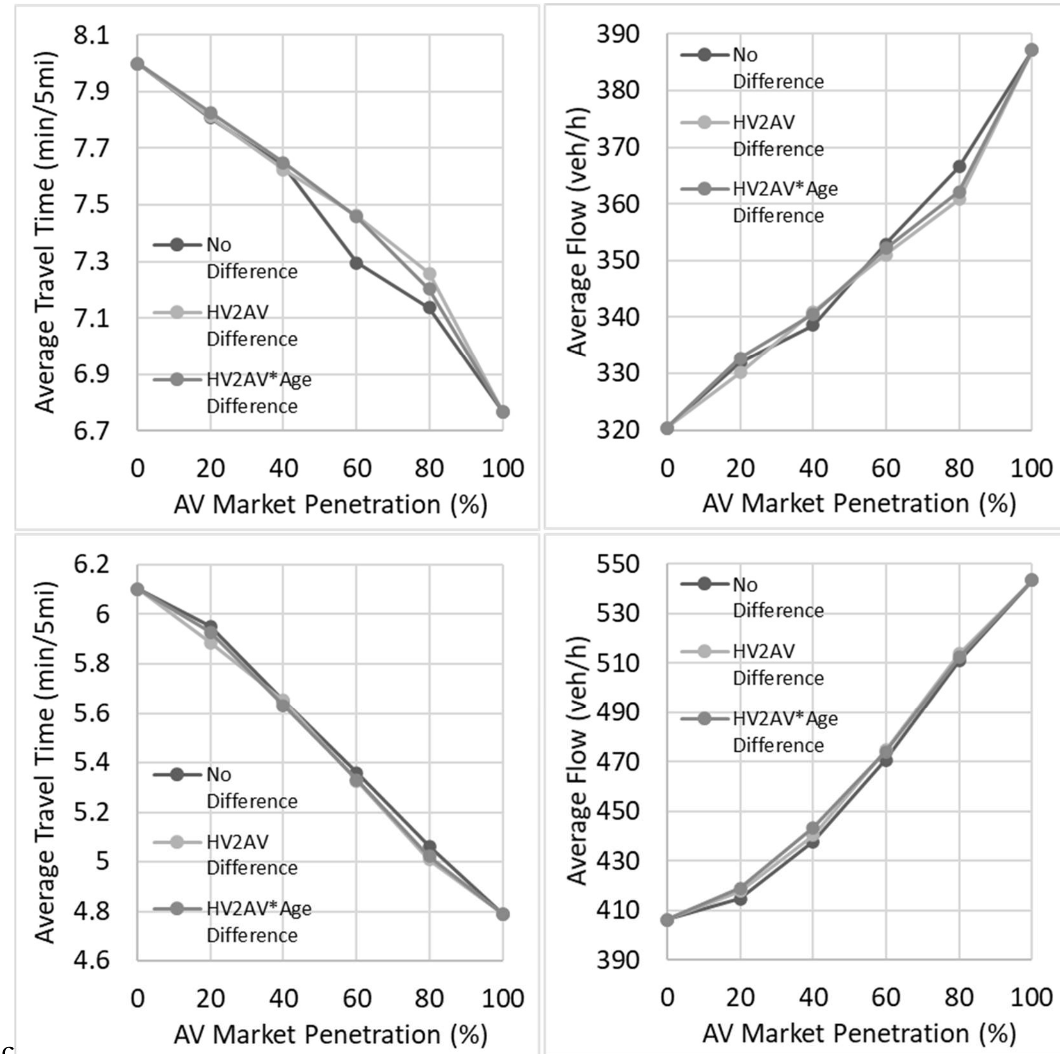

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Figure 4.7: Average travel time (left) and average flow (right) across varying AV market penetrations with 45 mph speed limits (top) and 65 mph speed limits (bottom)

A one-way Analysis of Variance (ANOVA) was conducted between each of the three conditions modeled for each AV market penetration scenario. Separate ANOVAs tested for differences in average travel times and average flow. The Tukey post-hoc test was conducted on each ANOVA analysis to determine where exactly differences lie. **Table 4.6** shows the scenarios that have different average travel times or average flows from its respective No Difference scenario at the 99% significance level.

Table 4.6: Scenarios found to have different means of travel time or flow at the 99% significance level

Measure	Speed Limit	AV Market Penetration	Condition Compared	Percent Difference	Q Statistic	p-Value
Travel Time	45 mph	40%	HV2AV*Age Difference	0.1%	4.88	<0.01
	45 mph	60%	HV2AV Difference	2.3%	16.00	<0.01
	45 mph	60%	HV2AV*Age Difference	2.2%	15.50	<0.01
	45 mph	80%	HV2AV Difference	1.7%	9.35	<0.01
	45 mph	80%	HV2AV*Age Difference	0.9%	5.06	<0.01
Flow	65 mph	40%	HV2AV*Age Difference	-1.3%	5.02	<0.01

5.0 DISCUSSION

This section revisits the research questions of this study and discusses how the study's results answer the research questions. Recommendations, limitations, and suggested future work are also discussed in this section.

5.1 Findings

5.1.1 Research Questions 1 (How do driver's level of stress compare in a hard breaking scenario when following an AV or an HV?) and 2 (How do drivers interpret fault from a collision with an AV or an HV?)

Driver level of stress was measured using GSR peaks per minute and was found to be significantly higher in the HV hard breaking scenario than in the AV hard breaking scenario. On average, GSR peaks per minute were 70% higher with HVs versus AVs in hard breaking scenarios. Of 4 collisions observed with HVs, two participants blamed the leading HV for the collision and two blamed themselves. In contrast, zero of the 6 participants who collided with an AV blamed the AV for the collision. Considering both abovementioned findings, it is possible that participants have a higher level of confidence in an AV's ability to exhibit safe driving behaviors than an HV's. However, the sample size of driver interpretations of fault is too small to draw a conclusion with confidence.

5.1.2 Research Question 3 (What demographic variables impact driver's headway when following an AV?)

Of the demographic information provided by participants (e.g. gender, income, race), age was found to be the best indicator of how a participant perceives and interacts with AVs. None of the participants over the age of 34.5 reported being "unconcerned" when following an AV, compared to 38% of participants under the age of 34.5. In terms of following distance, age was also a strong predictor of how a participant behave. In general, those over the age of 34.5 had greater headways than those under the age of 34.5, regardless of the vehicle type. This is consistent with what is already known about age's impact on driver headways (e.g. (Brackstone, Waterson, & McDonald, 2009)), and helps to validate the dataset produced in this study. Compared to their respective headways when following an HV, those older than 34.5 increased headways by over 2% when following an AV. On the contrary, those younger than 34.5 decreased headways by over 18%. This finding could have important impacts on transportation planning, which will be discussed in section 5.1.4.

5.1.3 Research Questions 4 (How do driver headways differ when following an AV or an HV?) and 5 (How do driver headways when following an AV compare to headway values currently assumed in mixed traffic models?)

The results of this study show that driver headways do differ when following an AV versus an HV. Regardless of any other factors, drivers give HVs 8% more following distance than AVs. This may suggest that participants have a greater level of comfort or trust when following an AV, which is consistent with the findings of research questions 1 and 2. As discussed in the previous section, headways when following an AV can be as much as 18% lower than when following an HV depending on the driver's age. This means a standard 4-second headway would be reduced to a 3.3 s headway. If travelling at 65 mph, a 4-second headway would be reduced nearly 60 feet, or three car lengths.

5.1.4 Research Question 6 (Do new values for driver headway when following an AV have a significant impact on highway travel time and flow predictions for varying MPs of AVs?)

The values found for driver headways when following an AV without adjusting for age do not seem to have a statistically significant impact on highway travel times or flow predictions. However, adjusting headway values for age do produce statistically significant differences. The greatest difference is seen on average travel times for 45 mph facilities with 60% AV market penetrations, with a 2.3% increase in average travel times. While the difference is statistically significant, it appears that the practical meaning of this result is small. At most, the calibrated HV driver model could change a 60-minute travel time prediction to just over 61 minutes.

The impact could become greater as age demographics shift. If younger generations hold their attitudes and behaviors towards AVs as observed in this study as they age, and new generations exhibit similar attitudes and behaviors, then greater portions of the population could give AVs an average of 18% less headway than HVs through time. Based on this study, there is a clear need to fully understand how HVs interact with AVs. Characteristics not analyzed in this study such as gap acceptance combined with the validated headway values found in this study could have an even greater impact on travel time and flow predictions.

5.2 Recommendations

This study makes it clear that there is a difference between how drivers follow HVs and AVs. While these differences have small impacts on highway travel times and flow, they could have more significant impacts on the analysis of other facility types (such as intersections) or on the calculation of other driver behaviors that use headway as an input variable. Therefore, the Highway Capacity Manual (HCM) should include lookup tables with different headway values based on the leading vehicle type and driver age.

GSR data analyzed also suggest that drivers have a smaller physical response to hard breaking AVs, which could increase the risk of AVs being rear-ended by human drivers. AVs may be more likely to exhibit hard breaking behavior at intersections in states with restrictive yellow-light laws and in areas with high inter-modal interaction (e.g. urban areas). States should consider evaluating yellow-light laws and their application to AVs to maximize safety, and vehicle manufacturers should consider ways to communicate to following vehicles of hard breaking that induce a greater physical response.

Results of this study show that younger drivers follow AVs with smaller headways than HVs. Given that younger drivers already tend to follow vehicles with smaller headways than other age groups (Brackstone, Waterson, & McDonald, 2009), this could be a potentially dangerous emergent behavior. Education programs and campaigns should reinforce safe following distances regardless of the lead vehicle type.

5.3 Limitations

This study serves as an important step in understanding the differences in how human drivers interact with and perceive AVs. It is also an important step in developing an effective way to integrate driving simulator data into traffic models. However, there are limitations to this study, which are addressed below.

- Within-subject study designs have limitations associated with fatigue and carryover effects, which can degrade participant's performance and compromise data validity. The magnitude of these effects is mitigated in this study by randomizing the presentation of grids to different participants and minimizing the time spent driving.
- Participants likely have not driven with SAE level 5 vehicles before. Driving behavior and perceptions may change with increased exposure to SAE level 5 vehicles.
- Although efforts were made to recruit a sample of drivers like the driving population of the U.S., the final sample skewed slightly young.
- Fifteen GSR datasets were lost due to weak wireless connectivity between the GSR sensor and host computer. Future studies should find a way to synchronize SimObserver data with GSR data so that the GSR sensor and host computer can be in the same room during data collection.

5.4 Future Work

Additional research is needed to continue developing the HV to AV driver model and to better understand how transportation networks will perform at varying AV market penetrations.

- The headway values produced in this study should be used to calibrate capacity predictions for other facility types and scenarios such as intersections and bottlenecks.

- Driving simulators are effective tools for extracting driver behavior when interacting with AVs. Future studies should explore other driver performance measures such as yielding behavior and gap acceptance when interacting with an AV. Driving simulator studies may also investigate the effectiveness of different ways AVs communicate with HVs.
- This work has attempted to bridge the gap between nanoscopic observations from the driving simulator to microscopic traffic simulation. More work should be done to improve this bridge, such as developing methods to build more detailed driver models from driving simulator data to inform agents in a multi-agent simulation.
- The simulation platform built for this study has high potential for expansion. Future iterations of the simulation should expand to a network level analysis.

6.0 CONCLUSION

Each of the six research questions were answered by this study. Driver level of stress is greater in hard breaking scenarios involving an HV compared to an AV, and there is some evidence to suggest that drivers are more likely to blame themselves if in a rear-end collision with an AV. In general, drivers give AVs less headway than HVs. However, age is a strong indicator of how a driver perceives an AV and how much headway they will give when following an AV. Older drivers may follow AVs with slightly greater headways than HVs, while younger drivers follow AVs with significantly smaller headways than HVs. These new headway values do impact highway travel time and flow predictions for lower speed facilities at AV market penetrations between 0% and 100%, however the impact is small. The greatest impact observed in this study was a 2.3% increase in average travel time when integrating headway values from the driving simulator experiment.

This study justifies the need for a better understanding of how human drivers will interact with AVs. Better understanding these interactions can improve AV vehicle design and AV policy to increase safety for all roadway users. A calibration of the human driver model considering interactions with AVs will improve the accuracy of facility and network performance predictions for varying AV market penetrations. The results of this study should be used to inform updates to the HCM.

Based on the results of this study, immediate opportunities for future work building off this study could:

1. Continue building upon the multi-agent simulation to model at a network level or to model intersections. Use the driving simulator dataset produced by this study to inform the model.
2. Expand the driving simulator dataset with observations of other human driver to AV interactions. This could include yield behavior and gap-acceptance. Use the expanded dataset to inform the expanded multi-agent simulation model mentioned above.

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