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

FINAL PROJECT REPORT

by

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16. Abstract

Autonomous vehicles (AVs) at varying market penetration rates will change traffic flow and highway performance. At AV market penetration rates of between 0 percent and 100 percent, human-driven vehicles (HVs) will be interacting with AVs. However, little is known about how HVs interact with AVs. Using the Oregon State University Driving Simulator, this study measured HV headways when drivers followed an AV and integrated those data into a multi-agent simulation to quantify new highway travel time and flow predictions at varying AV market penetration levels. This study also collected galvanic skin response data to quantify drivers' levels of stress when presented with a hard-braking AV and HV. The driving simulator experiment was successfully completed by 36 participants. The results of this study showed that drivers' levels of stress were 70 percent higher in hard braking scenarios involving HVs versus AVs. Additionally, drivers over the age of 34.5 were found to give AVs 2 percent more headway than HVs, while younger drivers gave AVs 18 percent less headway than HVs. Thirty-six scenarios were tested in the multi-agent simulation using results from the driving simulator. Given the driving simulator results, average travel times were found to increase at most by 2.3 percent, while flow was found to decrease at most by 1.3 percent.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003)

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LIST OF ABBREVIATIONS

ABMS: Agent-based modeling and simulation

ACC: Adaptive cruise control

AV: Autonomous vehicle

CAV: Connected and autonomous vehicle

GIMP: GNU Image Manipulation Program

GSR: Galvanic skin response

HV: Human-driven vehicle

IDM: Intelligent Driver Model

ISA: Internet scene assembler

LMM: Linear mixed effects model

LSD: Least significant difference

MAVS: Multi-agent vehicle simulation

MP: Market penetration

OSU: Oregon State University

PacTrans: Pacific Northwest Transportation Consortium

SAE: Society of Automotive Engineers

EXECUTIVE SUMMARY

Autonomous vehicles (AVs) at varying market penetration rates will change traffic flow and highway performance. At AV market penetration rates of between 0 percent and 100 percent, human-driven vehicles (HVs) will interact with AVs. However, little is known about how HVs interact with AVs. Using the Oregon State University Driving Simulator, this study measured HV headways when drivers followed an AV and integrated those data into a multi-agent simulation to quantify new highway travel time and flow predictions at varying AV market penetration levels. This study also collected galvanic skin response data to quantify drivers' levels of stress when presented with a hard-braking AV and HV. The driving simulator experiment was successfully completed by 36 participants. The results of this study showed that drivers' levels of stress were 70 percent higher in hard braking scenarios involving HVs versus AVs. Additionally, drivers over the age of 34.5 were found to give AVs 2 percent more headway than HVs, while younger drivers gave AVs 18 percent less headway than HVs. Thirty-six scenarios were tested in the multi-agent simulation using results from the driving simulator. Given the driving simulator results, average travel times were found to increase at most by 2.3 percent, while flow was found to decrease at most by 1.3 percent.

CHAPTER 1. INTRODUCTION

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

Headway is a critical parameter in traffic microsimulation and capacity calculations (Pueboobpaphan, et al., 2013), and driving simulators are effective tools for measuring driver headway (Risto & Martens, 2014). This study used a driving simulator to better understand interactions between HVs and AVs in terms of driver level of stress and vehicle headway, noting differences between HV to HV headways and HV to AV headways. Additionally, this study integrated the driving simulator data set into a multi-agent simulation. The simulation tested the effects of new HV to AV headway values on highway travel times and flow.

CHAPTER 2. LITERATURE REVIEW

There are significant challenges and knowledge gaps associated with predicting highway performance given the MP levels of AVs. Significant work has been published on traffic flow simulation with varying MP rates of AVs. However, the assumptions these studies have used to define AV and HV behavior have often lacked empirical justification. This literature review will discuss the work that has been done in predicting highway performance under varying MP levels of AVs, our current understanding of human driver behavior when interacting with AVs, and the role of driving simulators in AV research.

2.1. Autonomous Vehicle Implementation Challenges

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

In comparsion to urban driving, the challenges AVs face driving on highways are significantly less, as highway infrastructure and users tend to be more predictable (Nothdurft, et al., 2011). As a result of this understanding, many transportation agencies are preparing for widespread AV implementation 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 into certain driving environments (Shladover, 2017), which align well with other predictions discussed in this literature review.

Table 2.1 Estimates for when different Society of Automotive Engineering (SAE) levels of AVs will be introduced into 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	-

While significant progress has been made in understanding how AVs will perform under various roadway conditions, not much is known about how HVs will interact with AVs on highways. Specifically, it is not fully understood how the interaction between HVs and AVs will affect highway safety and capacity or 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. Adaptive Cruise Control in Traffic Flow Research

The exploration of how AVs will affect highway capacity began by considering the effects of varying MP levels of vehicles equipped with adaptive cruise control (ACC) (Cui, et al., 2017). Studies exploring the impacts of ACC broadly found that increasing ACC MP rates correlated with increased highway capacity; however, there was variation in estimations of capacity gains. Very early papers on this topic suggested that a low ACC MP level would not affect traffic flow significantly (van Arem, et al., 1996) and found that while vehicles using ACC always helped traffic stability, they could either positively or negatively affect highway capacity (Zwaneveld & van Arem, 1997). "Stability" as used in this paper refers to linear stability theory or flow uniformity, as described by Wilson and Ward (2011). Studies also began to justify parameter values such as desired time headway, finding that ACC systems were capable of safely maintaining time headways of less than 1.0 second (Godbole, et al., 1999). More recent findings on this topic have concluded that ACC could increase highway capacity between 7 percent (Werf, et al., 2002) and 30 percent (or a 0.3 percent increase in capacity per 1 percent increase in MP rate) (Kesting, et al., 2010).

2.3. Autonomous and Connected Autonomous Vehicles in Traffic Flow Research

Like the results of research on ACC's impacts on highway capacity, research on the impacts of AVs has 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, et al., 2017). One microsimulation study found that improvements in traffic flow on highways would only be realized at AV MP rates above 70 percent. The same study recommended that future work develop models that consider HV to AV interactions in mixed traffic. However, the authors recognized that before such a model could be developed, more behavioral work would need 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, et al., 2017).

As innovations in technology and communications have made the introduction of connected and autonomous vehicles (CAVs) more likely, traffic flow and network modeling research has shifted focus away from AVs and toward CAVs. The first paper to distinguish and compare CAVs and AVs in a network model concluded that because CAVs have more information to inform driving behavior than AVs, the potential for highway capacity gains with increasing MP rates of CAVs would be higher than that of AVs by more than 100 percent (Talebpour & Mahmassani, 2016). Rios-Torres (2017) built upon this understanding by finding that increasing MP levels of CAVs could also reduce fuel consumption by up to 70 percent and reduce travel times by more than 100 percent in medium to high congestion scenarios. The study also found that CAVs would be highly effective in stabilizing traffic in very high congestion scenarios (Rios-Torres & Malikopoulos, 2017).

2.4. Human Driver Models

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

Studies that have explored the interaction between HVs and AVs have tended to focus on intersections, as the deployment of traffic control devices that are functional for both HVs and

AVs was identified as a factor limiting 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 by using discrete sequential game theory and found that the more efficient solutions correlated with a higher risk of collision (Fox, et al., 2018).

2.5. Human Trust in Autonomous Vehicles

While the public's perceptions of AVs continue 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 positively affect 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 they 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 technology as younger generations age (Hedlund, 2017). An Australian survey on the topic of trust in AVs 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, et al., 2019).

Empirical studies have also investigated trust in AVs. One 2019 study found that human drivers' level of trust did not change between AVs that were programmed to imitate human driving behavior and AVs programmed to convey the impression of communicating with other AVs and the surrounding infrastructure. This suggested that human drivers' level of trust in AVs is pre-determined and not influenced by AV driving behavior. Additionally, the study found that human drivers trusted AVs more with increased interaction time (Oliveira, et al., 2019).

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 have had to be utilized, such as small-scale vehicles. One study tested humans' intended driving responses against multiple variations of driving maneuvers performed by small-scale AVs. Results showed that HV driving behaviors and perceptions of AVs were strongly related to the AVs' driving maneuvers (Zimmermann & Wettach, 2016). This suggested that AVs can viscerally communicate information to HVs through certain driving maneuvers—the opposite of the findings by Oliveira et al. (2019), as discussed in the previous paragraph.

2.6. Driving Simulators in Autonomous Vehicle Research

Driving simulators are established tools for researching human factors and driver behavior at a nanoscopic level (Fisher, et al., 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 Society of Automotive Engineers (SA)E level 3 to extract participants' levels of trust and perceptions regarding AVs (Buckley, et al., 2018). Another study used a driving simulator to observe how drivers reacted to takeover requests when approaching an intersection, and how proximity to the intersection and in-vehicle tasks affected the 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 previously, headway is a parameter critical to fundamental traffic modeling and simulation (Pueboobpaphan, et al., 2013).

2.7. Research Questions

This literature review revealed that there are significant knowledge gaps related to how human drivers will interact with AVs on highways. This information has the potential to change our understandings of how mixed traffic should be modeled and how varying MP rates of AVs would affect highway capacity. To address these knowledge gaps and issues, the following research questions were developed.

- Research Question 1: How do drivers' levels of stress compare in a hard-braking scenario when they follow an AV or an HV?
- Research Question 2: How do drivers interpret fault from a collision with an AV or an HV?
- Research Question 3: What demographic variables affect drivers' headways when they follow an AV?
- Research Question 4: How do drivers' headways differ when they follow an AV or an HV?
- Research Question 5: How do drivers' headways when they follow an AV compare to headway values currently assumed in mixed traffic models?

- Research Question 6: Do new values for driver headway when an AV is followed have a significant impact on highway travel time and flow predictions for varying market penetration levels of AVs?

These questions guided the methods and analysis of this study, and we sought to produce quantitative data to better understand the interactions between HVs and AVs.

CHAPTER 3. METHODS

This study was approved by the Oregon State University (OSU) Institutional Review Board (Study #2019-0261). The primary experimental tools were the OSU Driving Simulator, used in combination with an iMotions Shimmer3 GSR+, and a custom-built, Python-based multi-agent vehicle simulation (MAVS).

3.1. OSU Driving Simulator

The full-scale OSU Driving Simulator is a high-fidelity, motion-based simulator comprising 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, et al., 2013). Three liquid crystal 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 modeled 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 the 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 room physically separated from the operator workstation to prevent participants in the vehicle from being affected by visual or audible distractions.

3.2. iMotions Shimmer3 GSR+

The Shimmer3 GSR+ measures galvanic skin response (GSR). 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 change the electric flow between the two electrodes. Therefore, GSR data are dependent on sweat gland activity, which is correlated to the participant's level of stress (Bakker, et al., 2011). The Shimmer3 GSR+ sensors attach to an auxiliary input, which is strapped to the participant's wrist, as shown in figure 3.1. Data are wirelessly sent to a host computer running iMotions EDA/GSR Module software, which features data analysis tools such as automated peak detection and time synchronization with other experimental data.

Figure 3.1 Shimmer3 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

3.3. Factorial Design

Two independent variables were selected to explore HV and AV headways—leading vehicle speed and leading vehicle autonomy. A 2x2 factorial design was created to explore each of the two independent variables of the study. Additionally, participants were exposed to two hard-braking scenarios: one with a leading HV (SAE level zero) and one with a leading AV (SAE level five). In total, participants were exposed to each of the four levels and two hard braking scenarios with a total of six unique scenarios (table 3.1). Scenarios presented in the same track were separated by 45 to 60 seconds of driving. Hard braking events included in tracks III and IV did not interfere with the car-following portion of each track.

Table 3.1 Summary of the six scenarios presented in four tracks to participants

Track	Scenario	Leading Vehicle Speed	Leading Vehicle Autonomy	Hard Braking
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

The within-subject design provides the 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," which as 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 can 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 added flexibility and simplicity to the statistical analysis and the number of participants required.

Following their 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.

3.4. Virtual Environment

The virtual environment was developed by 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 by 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 mph and 65 mph. Roadway cross-sections consisted of two 12-foot lanes in each direction of travel.

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 files, 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 replicated the terminology and text position of current SAE level five vehicles being tested on public roads by WAYMO and Uber. The edited image file is shown in figure 3.2. 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 5 mph.

Figure 3.2 Screenshot of the RGBA image file edited with GIMP to modify pre-loaded dynamic vehicles from SimCreator

3.5. Multi-Agent Vehicle Simulation

A MAVS is a variation of agent-based modeling and simulation (ABMS) that features different vehicle types (e.g., both HVs and AVs). 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 simulating real-life situations when empirical data are scarce or difficult to obtain (Sanchez & Lucas, 2002), and it is especially effective at modeling human-involved systems because of the autonomous behavior and interactions of agents preset by the programmer (Bonabeau, 2002).

An agent-based simulation was built to model traffic along a two-lane (per direction), 5-mile highway segment. Agents in the simulation followed the Intelligent Driver Model (IDM), using methodologies similar to those in studies described in section 2.2 of this report. In addition to the IDM, agents could perform simple lane changing behavior. Because of uncertainties in how AVs will be deployed over time (Chang, et al., 2015), the program had to be able to vary AV market penetration as an input. Both inputs to the program and hard-coded parameters are summarized in table 3.2.

Table 3.2 Summary of user inputs and hard-coded parameters in the program. A user input that was randomly generated from a normal distribution used 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

Select parameters were 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 was the total amount of time it took for all vehicles generated in the simulation to traverse the 5-mile highway segment. The total number of vehicles in the simulation could be divided by the total simulation time to give average flow. All vehicles were generated simultaneously and given 2 miles to stabilize their driving behavior before entering the 5-mile highway segment where data were recorded.

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

Using the developed program, three headway conditions were tested: 1) HV to AV headways were equal to HV to HV headways; 2) HV to AV headways were different than HV to HV headways; and 3) HV to AV headways varied by age group and were different from 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 report. Each condition was run with AV market penetration rates varying from 0 percent to 100percent, in 20 percent 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 3,600 iterations.

CHAPTER 4. RESULTS

Driving simulator headway data, GSR data, and MAVS results were reduced and analyzed to answer the study's six research questions (outlined in section 2.7).

4.1. Participant Demographics and Post-Ride Survey Results

Of the 39 participants, 44 percent were female, and 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 data set.

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, the way participants answered this question was not found to have a relationship with participants' headways when following an AV or HV.

Each participant was exposed to two hard braking 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 braking scenarios, they were asked to identify who was at fault for the collision. Of the 78 hard braking scenarios tested in this study, 10 collisions were observed (four with an HV, six with an AV). Half of participants in a collision with an HV placed fault on the leading vehicle, while all of the participants in a collision with an AV placed fault on themselves. However, the sample size was too small to draw a statistical conclusion.

4.2. Galvanic Skin Response Results

GSR measurements were reduced to GSR peaks per minute for the two hard braking scenarios. The analyzed data set began at the start of the lead vehicle's deceleration and ended when the lead vehicle had come to a complete stop. By reducing the data to peaks per minute, the natural variations between participants' peak heights were controlled for. GSR peaks per minute have been used in previous transportation human factors studies (Krogmeier, et al., 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 data set. The software developed a baseline GSR reading for each participant on the basis of their average response throughout the entire experimental drive. Any amplified response above the baseline was classified as a peak and was recorded (iMotions, 2017).

During the experimental drive, GSR data were 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 could vary, with weaker wireless connections degrading the reliability of the data set. Fifteen data sets were removed from the analysis because of weak wireless connections. Figure 4.1 visualizes the two data sets of 21 participants with boxplots; they show that the spread of the participants' GSR response was noticeably wider in the HV hard braking scenario than in the AV hard braking scenario.

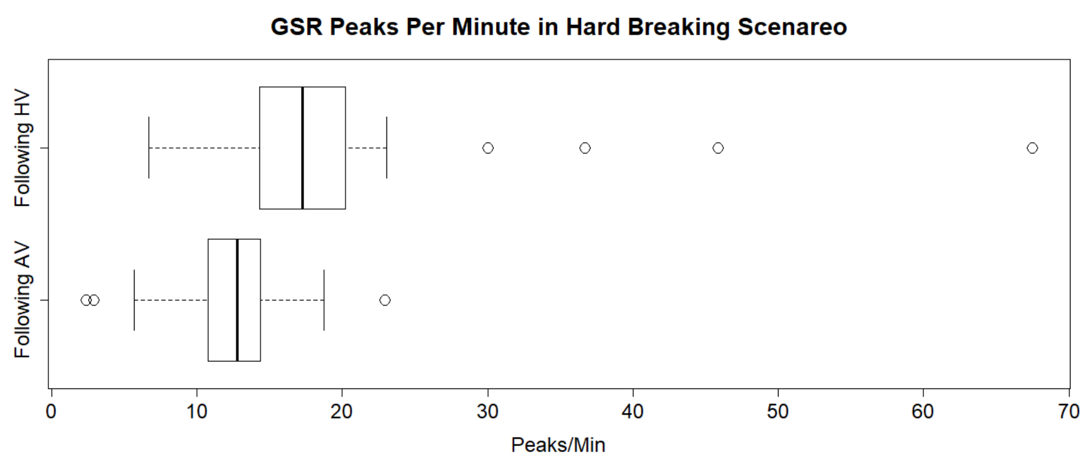

Figure 4.1 Boxplots showing that the spread of the participants' GSR response was noticeably wider in the HV hard braking scenario than in the AV hard braking scenario

The 21 data sets were analyzed with a paired t-test for dependent means (also referred to as a repeated measures t-test) at the 95 percent confidence level. This test was a reliable choice for testing the difference between the two data sets because it accounts for repeated measures (within-subject) data (Jashami, et al., 2017). The test showed that GSR peaks per minute were 70 percent higher in the HV hard braking scenario than in the AV hard braking scenario ($p\text{-value} < 0.01$).

4.3. Experimental Drive Results

Linear mixed effects models (LMM) can account for errors generated from repeated measures, can consider fixed or random effects in its analysis, and can accommodate both categorical and continuous variables (Jashami, et al., 2019). Furthermore, LMMs have a low probability of incurring Type I errors (Jashami, et al., 2020), (Abadi, et al., 2018). Given that this study's sample size exceeded the minimum required for an LMM analysis (Barlow, et al., 2019) and met the required distributional assumptions (Maruyama, 2008), the LMM was a strong candidate for the analysis of the experimental drive data set.

Variables of roadway speed, leading vehicle type, whether the participant was involved in a collision, self-reported level of concern of the participant when following an AV, and age were included in the model as fixed effects. The participant variable was included as a random effect. The driver performance measures evaluated were headways when following either an AV or HV. Instantaneous time headways were recorded when participants followed select vehicles throughout the drive as intended by the experimental design. To find the value closest 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 included headway data points recorded when participants were choosing their preferred headway, which were highly variable across different participants. Instead, the minimum headway value in the recorded segment was used, and it will be referred to as "headway" in the analysis.

The greatest average time headway was observed when participants followed an HV with a 45 mph speed limit (mean = 2.8 sec, SD = 1.9 sec), while the smallest average time headway was observed when participants followed an HV with a 65 mph speed limit (mean = 2.3 sec, SD = 1.2 sec). An LMM was used to estimate the relationship between the independent variables and the participant's time headway. 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 percent confidence level. Restricted maximum likelihood estimates were also used in the development of this model. Table 4.1 shows the results of the model. The random effect was significant (Wald Z = 3.40, $p<0.001$), suggesting that it was necessary to treat the participant as a random factor in the model.

Table 4.1 Mean and standard deviation of time headway (s) at the independent variable level

Variable	Levels	Estimate	DF	P
Participant Random Effect (SD)	-	(0.88)	-	<0.01*
Constant	-	2.39	35	<0.01*
Leading Vehicle Type	AV	-0.21	105	<0.01*
	HV	Base	-	-
Speed Limit	45 mph	0.2	105	<0.01*
	65 mph	Base	-	-
Collision	Yes	-0.99	105	<0.01*
	No	Base	-	-
Age	<34.5	-0.53	105	<0.01*
	>34.5	Base	-	-
Age x Leading Vehicle Type	<34.5 AV	-0.51	105	<0.01*
	>34.5 AV	Base	-	-
Speed Limit x Leading Vehicle Type	45 AV	-0.52	105	<0.01*
	45 HV	Base	-	-
Collision x Leading Vehicle Type	Yes AV	-0.2	105	<0.01*
	Yes HV	Base	-	-
Age x Speed Limit	<34.5 45 mph	-0.3	105	<0.01*
	>34.5 45 mph	-0.1	105	<0.01*
	<34.5 65 mph	-0.8	105	<0.01*
	>34.5 65 mph	Base	-	-
Summary Statistics				
R^2	70%	Observations		144
-2Log Likelihood	402.0	Participants		36
AIC	438.4	Observations/ Participant		4

*Significant at the 95 percent confidence level

Both treatment factors were found to have a significant impact on headway. Regardless of other variables, participants following AVs maintained headways that were 9 percent smaller than when they followed HVs. Similarly, participants selected headways that were 8 percent smaller at 45 mph speeds than at 65 mph speeds. The mean time headways for each level of leading vehicle type and speed limit are shown in the interaction plot presented in figure 4.2.

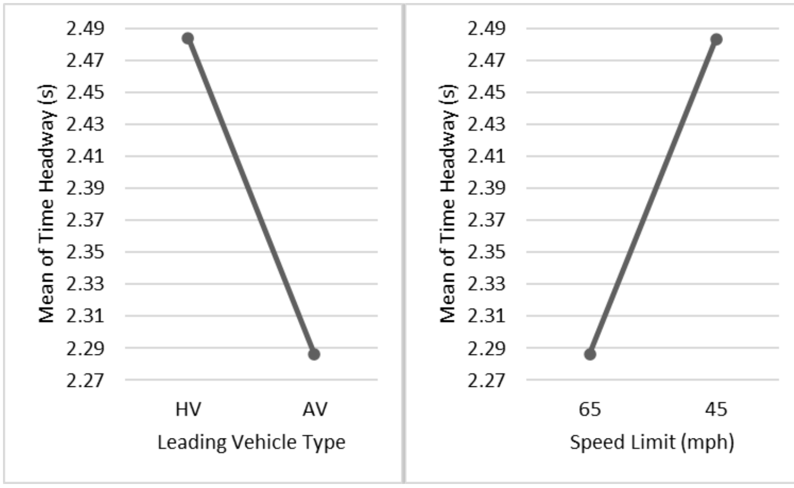

Figure 4.2 Primary effects plot of the leading vehicle type (left) and speed limit (right) on mean lateral position

Figure 4.3visualizes why age was categorized into two groups: below and above 34.5 years of age. In the post-drive survey, participants were asked about the level of concern they felt when following an AV. A clear division was observed between participants in those two age groups. No participants above the age of 34.5 years self-reported being "unconcerned" when following an AV in the post-drive survey, whereas 38 percent of participants under the age of 34.5 did.

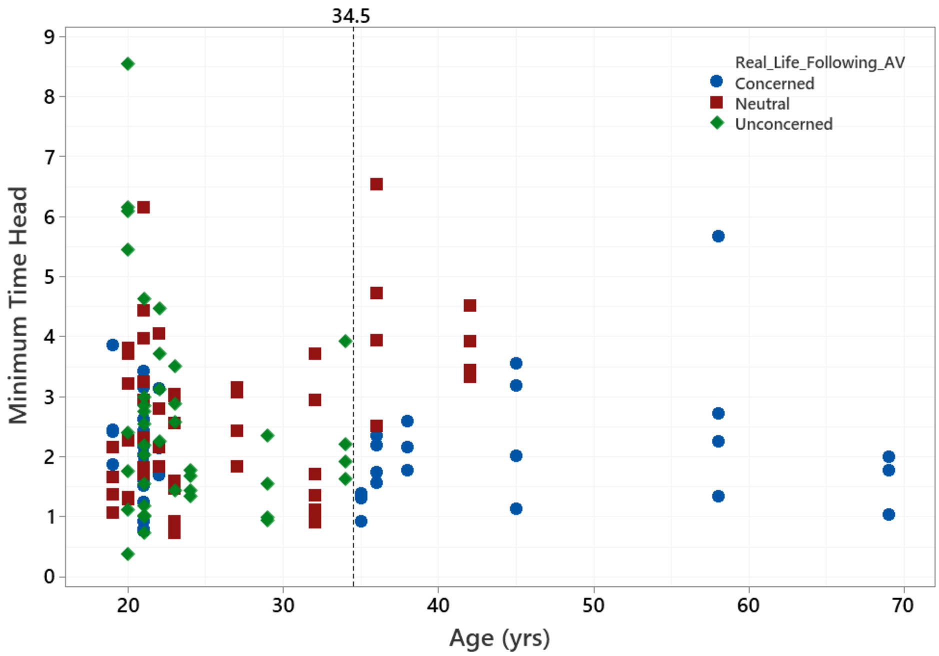

Figure 4.3 Distribution of mean headways and age by level of concern

4.4. Multi-Agent Vehicle Simulation Results

In the multi-agent simulation, AVs in all scenarios followed a time headway of 1 second, while HV time headways varied by scenario. The input values shown in table 4.2 were used by the program to center a normal distribution from which preferred time headway values were randomly assigned to each HV generated in the simulation. Table 4.2 also shows the percentage difference between input time headway values as informed by the driving simulator data set. In the HV2AV*Age Difference condition, Group 1 represented 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 percent of the U.S. population (U.S. Census Bureau, 2019). Therefore, Group 1 agents made up 45 percent of all HV agents, with Group 2 agents making up the remaining 55 percent in the HV2AV*Age Difference condition.

Table 4.2 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 penetration rates were varied from 0 to 100 percent in 20-point increments, and each scenario was iterated 100 times. Figure 4.4 summarizes the results of all simulations.

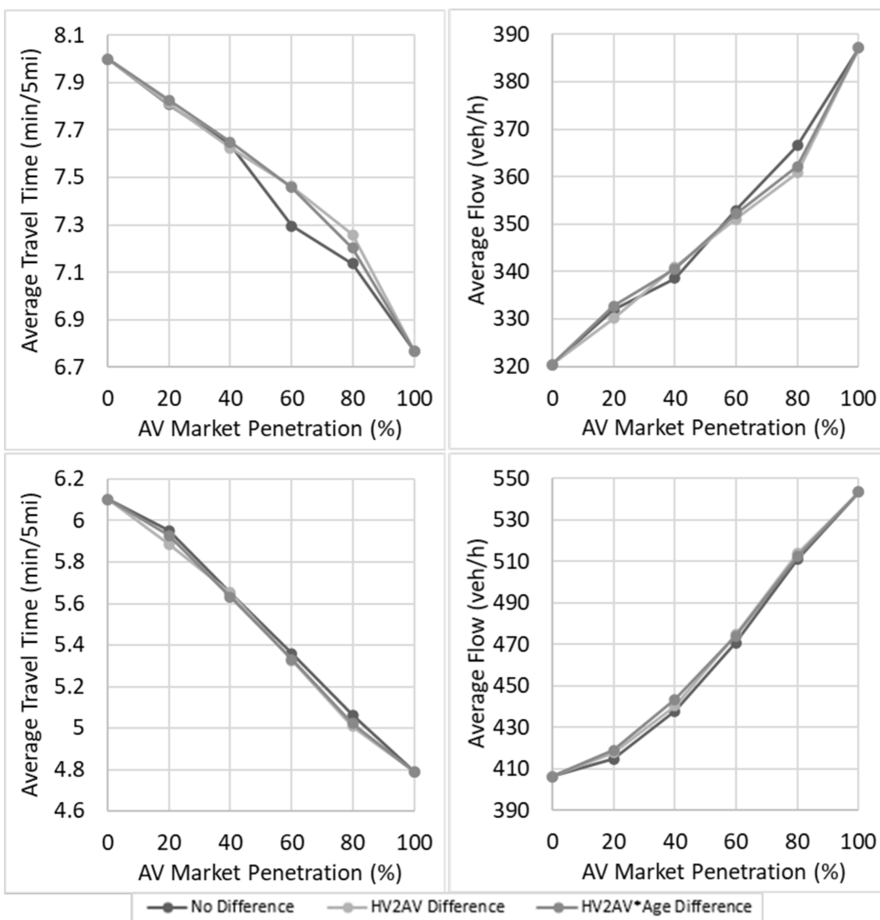

Figure 4.4 Average travel time (left) and average flow (right) across varying AV market penetration rates with 45 mph speed limits (top) and 65 mph speed limits (bottom)

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 lay. Table 4.3 shows the scenarios that had average travel times or average flows different from their respective No Difference scenario at the 99 percent significance level.

Table 4.3 Scenarios found to have different means of travel time or flow at the 99 percent significance level

Measure	Speed Limit	AV Market Penetration	Condition Compared	Percent Difference	Test 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*

*Significant at the 99% confidence level

CHAPTER 5. DISCUSSION

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

5.1. Research Questions 1 and 2

How do drivers' level of stress compare in a hard-braking scenario when they follow an AV or an HV? How do drivers interpret fault from a collision with an AV or an HV?

Driver level of stress was measured by using GSR peaks per minute and was found to be significantly higher in the HV hard braking scenario than in the AV hard braking scenario. On average, GSR peaks per minute were 70 percent higher with HVs than AVs in hard braking scenarios. Of four collisions observed with HVs, two participants blamed the leading HV for the collision and two blamed themselves. In contrast, none of the six participants who collided with an AV blamed the AV for the collision. Given these findings, it is possible that participants had a higher level of confidence in an AV's ability to exhibit safe driving behaviors than in an HV's ability. However, the sample size of driver interpretations of fault was too small to draw a conclusion with confidence.

5.2. Research Question 3

What demographic variables affect drivers' headway when they follow 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 would perceive and interact with AVs. None of the participants over the age of 34.5 reported being "unconcerned" when following an AV, whereas 38 percent of participants under the age of 34.5 reported being unconcerned. In terms of following distance, age was also a strong predictor of how a participant would behave. In general, those over the age of 34.5 maintaned greater headways than those under the age of 34.5, regardless of the vehicle type. This was consistent with what is already known about the impacts of age on driver headways (e.g., (Brackstone, et al., 2009)) and helped to validate the data set produced in this study. In comparison to their respective headways when following an HV, those older than 34.5 increased their headways by over 2 percent when they followed an AV. On the contrary, those younger than 34.5 decreased headways by over 18 percent when they followed an AV. This finding could have substantial impacts on transportation planning.

5.3. Research Questions 4 and 5

How do drivers' headways differ when they follow an AV or an HV? How do drivers' headways when they follow an AV compare to headway values currently assumed in mixed traffic models?

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

5.4. Research Question 6

Do new values for driver headway when an AV is followed have a significant impact on highway travel time and flow predictions for varying market penetration levels of AVs?

The values found for headways when drivers followed an AV without adjusting for age did not seem to have a statistically significant impact on highway travel times or flow predictions. However, adjusting headway values for age did produce statistically significant differences. The greatest difference, seen for average travel times on 45 mph facilities with a 60 percent AV market penetration rate, was a 2.3 percent increase in average travel times. While the difference was statistically significant, nevertheless the practical meaning of this result would be 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 continue to hold the attitudes and behaviors toward AVs that were 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 percent less headway than HVs through time. Given these findings, 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.

5.5. Recommendations

This study made 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 analyses 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.

Analyzed GSR data also suggested that drivers have a smaller physical response to hard braking AVs, which could increase the risk of AVs being rear-ended by human drivers. AVs may be more likely to exhibit hard braking 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 to induce a greater physical response behind hard braking AVs.

The results of this study showed 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, et al., 2009), this could be a potentially dangerous emergent behavior. Education programs and campaigns should reinforce safe following distances regardless of the lead vehicle type.

5.6. Study Limitations

This study serves as an important step in understanding the differences in ways that 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 were limitations to this study, which are addressed below.

- Within-subject study designs have limitations associated with fatigue and carryover effects, which can degrade participant performance and compromise data validity.
- Participants likely had 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 data sets were lost because of 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.

CHAPTER 6. CONCLUSIONS

Each of the six research questions was answered by this study. Drivers' levels of stress were greater in hard braking scenarios involving an HV than an AV, and there was some evidence to suggest that drivers were more likely to blame themselves in a rear-end collision with an AV. In general, drivers gave AVs less headway than HVs. However, age was a compelling indicator of how drivers perceived an AV and how much headway they would give when following an AV. Older drivers followed AVs with slightly greater headways than HVs, while younger drivers followed AVs with significantly smaller headways than HVs. These new headway values could affect highway travel time and flow predictions for lower speed facilities at AV market penetration rates between 0 percent and 100 percent; however, the impact would be small. The greatest impact observed in this study was a 2.3 percent increase in average travel time when headway values were integrated from the driving simulator experiment.

This study justifies the need for a better understanding of how human drivers will interact with AVs. Better understanding of these interactions could improve AV vehicle design and AV policy to increase safety for all roadway users. Calibration of human driver models that considered interactions with AVs would improve the accuracy of facility and network performance predictions for varying AV market penetration rates. The results of this study should be used to inform updates to the HCM.

Building off the results of this study, immediate opportunities for future work could be the following:

1. Continue building upon the multi-agent simulation to model at a network level or to model intersections by using the driving simulator data set produced in this study to inform the model.

2. Expand the driving simulator data set with observations of other human driver to AV interactions. This could include yield behavior and gap acceptance. Use the expanded data set to inform the expanded multi-agent simulation model mentioned above.

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