

MODELING DRIVER BEHAVIOR AND I-ADAS IN INTERSECTION TRAVERSALS

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Thesis submitted to the faculty of the Virginia Polytechnic Institute and State University
in partial fulfillment of the requirements for the degree of

Master of Science

In

Biomedical Engineering

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November 2nd, 2023

Blacksburg, VA

Keywords: Advanced Driver Assist Systems, crashes, driver behavior, intersection, real-
world data.

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Modeling Driver Behavior and I-ADAS in Intersection Traversals

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ABSTRACT

Intersection Advance Driver Assist Systems (I-ADAS) may prevent 25 to 93% of intersection crashes. The effectiveness of I-ADAS will be limited by driver's pre-crash behavior and other environmental factors. This study will characterize real-world intersection traversals to evaluate the effectiveness of I-ADAS while accounting for driver behavior in crash and near-crash scenarios. This study characterized real-world intersection traversals using naturalistic driving datasets: the Second Strategic Highway Research Program (SHRP-2) and the Virginia Traffic Cameras for Advanced Safety Technologies (VT-CAST) 2020. A step-by-step approach was taken to create an algorithm that can identify three different intersection traversal trajectories: straight crossing path (SCP); left turn across path opposite direction (LTAP/OD); and left turn across path lateral direction (LTAP/LD). About 140,000 intersection traversals were characterized and used to train a unique driver behavior model. The median average speed for all encounter types was about 7.2 m/s. The driver behavior model was a Markov Model with a multinomial regression that achieved an average 90.5% accuracy across the three crash modes. The model used over 124,000 total intersection encounters including 301 crash and near-crash scenarios. I-ADAS effectiveness was evaluated with realistic driver behavior in simulations of intersection traversal scenarios based on proposed US New Car Assessment Program I-ADAS test protocols. All near-crashes were avoided. The driver with I-ADAS overall helped avoid more crashes. For SCP and LTAP the collisions avoided increased as the field

of view of the sensor increased in I-ADAS only simulations. There were 18% crash scenarios that were not avoided with I-ADAS with driver. Among near-crash scenarios, where NHTSA expects no I-ADAS activation, there were fewer I-ADAS activations (58.5%) due to driver input compared to the I-ADAS only simulations (0%).

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GENERAL AUDIENCE ABSTRACT

Intersection Advance Driver Assist Systems (I-ADAS) may prevent 25-93% of intersection crashes. I-ADAS can assist drivers in preventing or mitigating these crashes using a collision warning system or automatically applying the brakes for the driver. One way I-ADAS may assist in crash prevention is with automatic emergency braking (AEB), which will automatically apply braking without driver input if the vehicle detects that a crash is imminent. The United States New Car Assessment Program (US-NCAP) has also proposed adding I-ADAS with AEB tests into its standard test matrix. The US-NCAP has proposed three different scenarios. All the tests have two crash-imminent configurations where the vehicles are set up to collide if no deceleration occurs and a near-miss configuration where the vehicles are set up to barely miss each other. This study will use intersection traversals from naturalistic driving data in the US to build a driver behavior model. The intersection travels will be characterized by their speed, acceleration, deceleration, and estimated time to collision. The driver behavior model was able to predict the longitudinal and lateral movements for the driver. The proposed US-NCAP test protocols were then simulated with varied sensors parameters where one vehicle was equipped with I-ADAS and a driver. The vehicle with I-ADAS with a driver was more successful than a vehicle only equipped with I-ADAS at preventing a crash.

ACKNOWLEDGEMENTS

First and foremost, I would like to thank my advisor and mentor, Dr. Luke Riexinger. I appreciate your guidance (and reassurance at times) to get me to the finish line. I will forever admire your work ethic, leadership, and poise. Although I did not become Dr. Kleinschmidt, you have taught me lessons that will last a lifetime.

A big thank you to Dr. Clay Gabler who introduced me to this crazy world of vehicle safety when I was 18. I will cherish the time in Kelly 440 forever. Like many others, you inspired my whole career, and I am forever thankful for that.

I would also like to thank the rest of my committee: Dr. Samantha Haus and Dr. Warren Hardy. People like you are who inspire me to continue to work in the field of Vehicle Safety.

Thank you to Toyota Collaborative Research Center for funding this work. Especially, Rini Sherony, Toshiaki Ishikawa, and Takashi Hasegawa for their guidance and technical insight.

The SAFTEY IMPACT Lab also deserves a big thanks for their help and laughs throughout my second round at VT.

Last, to my friends and family, for always being there for me during the ups and downs.

- To Liz - Thank you for always picking up the phone.
- To Abby - I will cherish the summer we had together. I am so proud of you!
- To my Parents- Thank you for your unconditional love and support.
- To Allyson & Maddie – Thank you for always putting a smile on my face.
- To Austin - Thank you for your service.
- To my Grandma- Thank you for forever being my biggest fan and #1 supporter.
- To Eric & friends - Mega-Couch Forever!

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1 INTRODUCTION

1.1 Intersection Crashes

From 2019 to 2020, 25% of all traffic fatalities in the USA occurred at an intersection [2]. Intersection crashes also cause about half of all traffic injuries in the USA [3]. Crossing-path crash scenarios make up one-third of nationally represented police-reported tow-away crashes. The top three most common crossing-path pre-crash scenarios are: straight crossing path (SCP); left turn across path lateral direction (LTAP/LD); and left turn across path opposite direction (LTAP/OD) [4]. The SCP scenario is when both vehicles are traversing straight and the vehicles are travelling on crossing streets (Figure 1). The LTAP/LD scenario is when one vehicle is traversing straight and another vehicle is intending to turn left from a crossing street. The LTAP/OD scenario is when one vehicle is traversing straight and the other vehicle is intending to turn left from the opposite direction as the vehicle traversing straight. A typical intersection encounter (no crash or near-crash) will have one vehicle waiting at the start of the intersection, which in this study will be called the subject vehicle (SV), and a vehicle traversing through the intersection, which will be called the principal other vehicle (POV). These pre-crash scenarios can lead to near-side crashes, a side-impact crash on the same side as the occupant, or far-side crashes, a side-impact crash on the opposite side from the occupant. These side impact crash modes have been found to lead to a greater risk of serious injury compared to the front and rear crash modes at the same delta-V [5]. The serious injury severity is based on an occupant receiving a 3 or higher out of 6 on the maximum abbreviated injury scale (MAIS). Therefore, intersection crashes are not only common, they also are more severe than other crash modes.

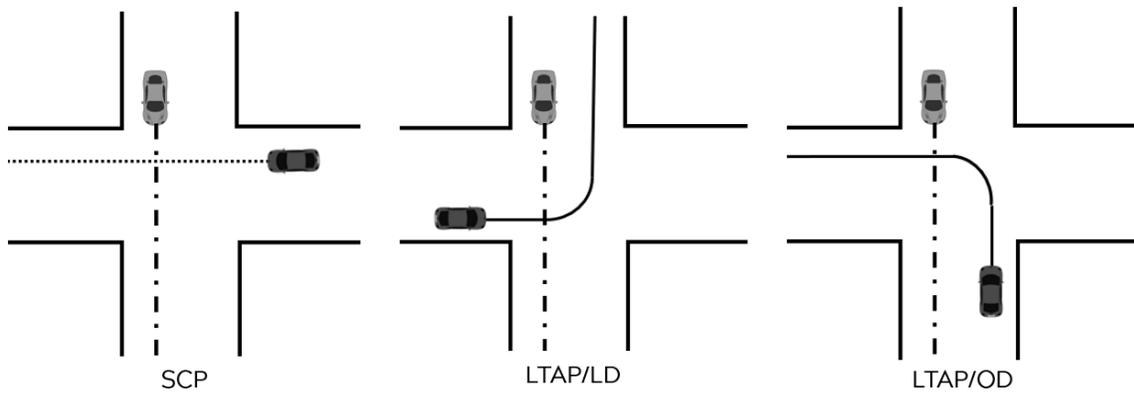


Figure 1. Example of each of the top three pre-crash scenarios.

1.2 Intersection Advanced Driver Assist Systems

Intersection Advanced Driver Assist Systems (I-ADAS) can assist drivers in preventing or mitigating these crashes using a collision warning system or automatically applying the brakes for the driver. One way I-ADAS may assist in crash prevention is with automatic emergency braking (AEB), which will automatically apply braking without driver input if the vehicle detects that a crash is imminent. I-ADAS with AEB uses sensors to detect objects around it including permanent fixtures like stop lights and moving objects like other vehicles traversing the roadways. The information from the sensors is then interpreted by onboard computers to determine how far the objects are away from the vehicle and how fast they are moving. Calculations are continually being done to determine if any of these objects are a threat for collision. Every I-ADAS has activation thresholds based on the distance and dynamics of the vehicle in relation to other vehicles, pedestrians, and objects. If this threshold is met, the vehicle will automatically apply the brakes for the driver in an attempt to avoid the crash. While the I-ADAS is activated, the driver can intervene by also applying the brakes, applying the accelerator (disabling I-ADAS), or steering.

Currently, AEB is an effective method for preventing front-to-rear crashes, with estimated crash reduction benefits up to 56% [6]. I-ADAS uses similar technology, but instead of trying to prevent rear-end crashes, I-ADAS is for intersection crash modes. Intersection crash modes have an extra layer of difficulty adding the lateral and longitudinal distances and velocities to the equations.

There are many different sensors used to detect objects, such as radar, lidar and cameras [5]. Counterfactual simulation studies have been conducted using hypothetical I-ADAS systems with ideal detection systems and real-world crashes to predict the percentage of intersection crashes that could have potentially been avoided.

The study conducted by Tan et al. used a safety impact methodology that considered real-world crashes from around the world as well as a driver behavior model created through participants in a driver simulator. This study looked at SCP and LTAP/OD configurations. The study used MATLAB and a miniSim to simulate the crashes as well as a Monte Carlo analysis. I-ADAS in this study had latencies from 0 to 0.3 s, braking time-to-collision thresholds from 0.5 to 1.5 s, and braking peak magnitudes of 0.3 to 0.8 g. The study evaluated two systems for SCP, which were called Intersection Management Assist Warning and Intersection Management Assist Braking. The warning system was able to prevent 23 to 35% of crashes, and the braking system was able to prevent 42 to 67% of crashes. The LTAP/OD portion of the study used the same simulation technique but evaluated Left Turn Assist Warning and Left Turn Across Braking. The warning system was able to prevent 32% of crashes, and the braking system was able to prevent 55 to 60% of crashes. This study is unique because it uses real-world crashes from around the world and drivers from China compared to this study that uses more driver data from certain regions of the US to create the driver behavior model [7].

The study conducted by Bariess et al. reconstructed 501 LTAP/OD crashes from National Motor Vehicle Crash Causation Survey (NMVCCS). These reconstructed crashes were then simulated with one vehicle equipped with I-ADAS. Two different I-ADAS were simulated one with only an alert and another with automatic emergency braking (AEB). There were varied sensor parameters: 5 time-to-collision activation thresholds, 3 latency times, 2 lines of sight, and 2 different response types. The alert/warning was found to prevent 0 to 32% of crashes, and the AEB I-ADAS was found to prevent 18 to 84% of crashes [8].

The study conducted by Saunder and Lubbe evaluated 792 SCP crashes from German In-Depth Accident Study (GIDAS). The study evaluated two different field of view sensors (120 and 180 degrees). The pre-crash simulations were conducted in MATLAB. The crashes were simulated with no vehicles equipped with I-ADAS, one vehicle equipped, and both vehicles equipped. The final evaluation looked at crashes prevented as a function of predictive market penetration. The vehicles where I-ADAS has reached 100% market penetration and 180 degree field of view had a 79% crash prevention [9].

The study conducted by Scanlon et al. in 2017 evaluated 448 SCP crashes from NMVCCS. The crashes were reconstructed in PC crash. One vehicle was equipped with I-ADAS. Two I-ADASs were evaluated: a warning system and AEB. The sensors for both I-ADAS types were varied. There were 5 different TTC thresholds, 3 latency times, and 2 response modalities. The crashes simulated with a warning I-ADAS was able to prevent 0 to 23% of crashes. The crashes simulated with I-ADAS AEB was able to prevent 25 to 59% of crashes [10].

The study conducted by Scanlon et al. in 2016 evaluated 459 SCP crashes from NMVCCS. The crashes were reconstructed to determine the vehicles velocity and trajectory pre-crash. The crashes

were then simulated with both vehicles being equipped with I-ADAS. The I-ADAS used AEB to avoid the crash. The sensors were evaluated at three different TTC activation thresholds. The model predicted that 19 to 35% of the real-world crashes could be prevented with this system [11].

The last study conducted by Chen et al. used 32 participants in a Driver Simulator with Intersection Crash Warning System. The drivers were put in three different scenarios: a violating vehicle crossing from the left, a violating car crossing from the right, and an LTAP/OD scenario. The vehicle the participant was driving was equipped with an I-ADAS warning system. This study found that 40 to 50% of crashes were prevented with this system [12].

I-ADAS with AEB could potentially be a viable option for preventing intersection crashes (Table 1). With limitations to the studies, the crash preventability will potentially decrease as driver behavior, weather conditions, and other environmental factors could play a role in the AEB system's effectiveness.

Table 1. Previous Studies on I-ADAS Effectiveness

Author, Year	Design Type	Crash Type	Study Population	Benefit
Tan 2021[7]	Safety Impact Methodology (Intersection Management Assist Warning)	SCP	459-770 Crashes	23-35%
Tan 2021[7]	Safety Impact Methodology (Intersection Management Assist Braking)	SCP	792-84 Crashes	42-67%
Tan 2021[7]	Safety Impact Methodology (Left Turn Assist Warning)	LTAP/OD	501 Crashes	32%
Tan 2021[7]	Safety Impact Methodology (Left Turn Assist Braking)	LTAP/OD	501-96 Crashes	55-60%
Bareiss 2019[8]	Ideal Sensors with collision alert (1 vehicle equipped)	LTAP/OD	501 Crashes (NMVCCS)	0-32%
Bareiss 2019[8]	Ideal Sensors with AEB (1 vehicle equipped)	LTAP/OD	501 Crashes (NMVCCS)	18-84%
Saunders & Lubbe 2018 [9]	Ideal Sensors with AEB (Both Vehicles Equipped)	SCP	792 Crashes (GIDAS)	79%
Scanlon 2017 [10]	Ideal Sensors with collision alert (1 vehicle equipped)	SCP	448 Crashes (NMVCCS)	0-23%
Scanlon 2017 [10]	Ideal Sensors with AEB (1 vehicle equipped)	SCP	448 Crashes (NMVCCS)	25-59%
Scanlon 2016 [11]	Ideal Sensors with AEB (Both Vehicles Equipped)	SCP	459 Crashes (NMVCCS)	19-35%
Chen 2011[12]	Driver Simulator with Intersection Crash Warning System	SCP & LTAP/OD	32 Participants	40-50%

1.3 Scenario-Based Testing

The European New Car Assessment Program (Euro NCAP) has added test protocols for I-ADAS to test the capability of this type of feature [13]. The protocol tests two different scenarios. One is a straight crossing path scenario, and the other is a left turn across path opposite direction scenario [13]. The straight crossing path tests have the target vehicle travelling from the left of the test vehicle on the crossing street. The speeds of each vehicle vary: the test vehicle speed will range from 0 kph to 60 kph and the target vehicle speed will range from 20 kph to 60 kph. There is a total of 30 tests for SCP. The test is designed such that if no deceleration occurs, the center front

of the test vehicle will collide with the side of the target vehicle. The left turn across path opposite direction scenario tests have the target vehicle travelling straight and the test vehicle making a left turn from the opposite direction. The radius of the turn varies based on the speed of the test vehicle. The test vehicle's speed ranges from 10 kph to 20 kph, and the target vehicle's speed ranges from 30 kph to 60 kph. The tests are set up such that the front center of the test vehicle will impact the front left corner of the target vehicle. The test ends if at least one of the three scenarios occurs: the test vehicle has a velocity of 0 kph without entering into the path of the target vehicle; the test vehicle and target vehicle collide; or the target vehicle has left the path of the test vehicle [13]. The target vehicle is vehicle replica that is controlled by a robot driver. This vehicle replica when contacted collapses in order to prevent any damage to the test vehicle.

In Asia, I-ADAS test protocols have been introduced. The China New Car Assessment Program in 2025 is going to add AEB car-to-car turn across path tests as well as crossing tests[14]. China Insurance Automobile Safety Index has turn across path tests that are in the test protocol now [15] Last, Japan NCAP plans to add turn across path tests in 2024 [15].

The United States New Car Assessment Program (US-NCAP) has also proposed adding I-ADAS with AEB tests into its standard test matrix. The US-NCAP has proposed three different scenarios. All the tests have two crash-imminent configurations where the vehicles are set up to collide if no deceleration occurs and a near-miss configuration where the vehicles are set up to miss each other by 2 meters [1]. The first scenario is a straight crossing-path scenario where both the test vehicle and the target vehicle are traversing straight from crossing roads, with the approach side of the test vehicle changing from being on the right or left side of the target vehicle. There are three different proposed speed combinations, which include both vehicles traveling at 25 mph, the test vehicle

travelling at 25 mph and the target vehicle travelling from 0 mph to 25 mph, and the test vehicle travelling from 0 mph to 25 mph and the target vehicle traveling at 25 mph.

The SCP crash scenarios are configured such that the front center of the subject vehicle (SV), equipped with I-ADAS will impact the principal other vehicle (POV) at its longitudinal center line [16] (Figure 2). The near-miss SCP scenario was setup such that the SV would be 2 meters behind the rearmost part of the POV when the SV crosses into the POV's lane of travel lane [16] (Figure 2).

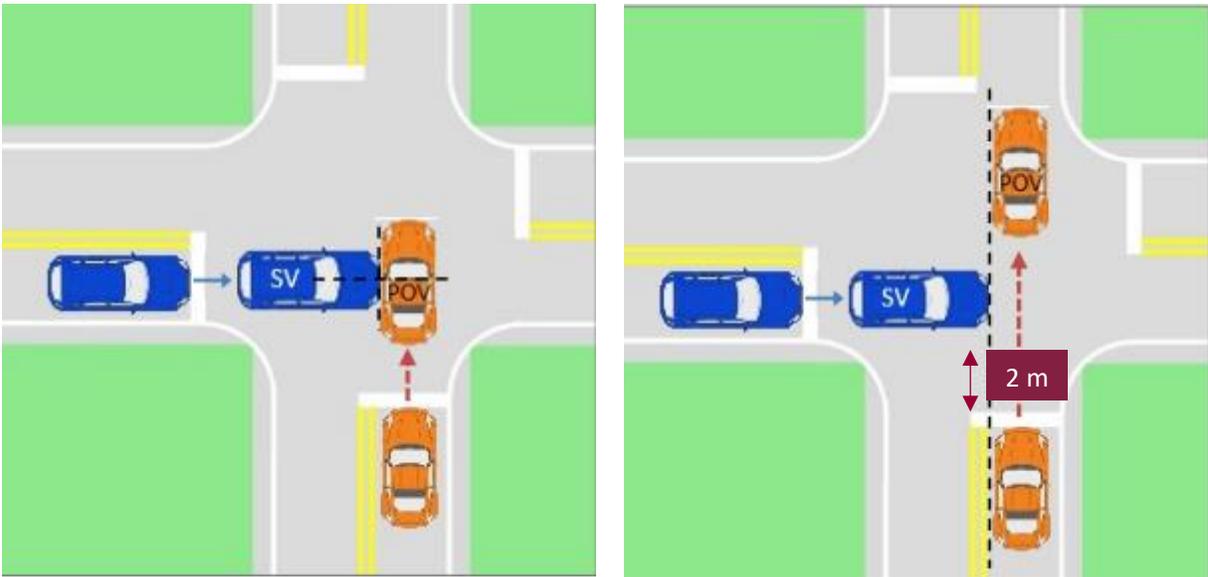


Figure 2. Crash Imminent Impact Point and Near-Miss[16]

There are three different combinations of approach speeds for the SV and POV: SV 25mph and POV 25mph, SV 0mph to 25 mph and POV 25mph, and SV 25mph and POV 0mph to 25 mph. Each combination is tested in both a crash imminent and near-miss configuration. The NHTSA proposed I-ADAS tests contain 6 different SCP scenarios [16] (Table 2).

Table 2. NHTSA SCP Test Scenario Matrix

Test Number	Crash or Near-Miss	Subject Vehicle Velocity	Principal Other Vehicle Velocity
1	Crash	25 mph	25 mph
2	Near-Miss	25 mph	25 mph
3	Crash	0 mph → 25 mph	25 mph
4	Near-Miss	0 mph → 25 mph	25 mph
5	Crash	25 mph	0 mph → 25 mph
6	Near-Miss	25 mph	0 mph → 25 mph

The second scenario is a LTAP/OD test scenario where the test vehicle is travelling straight and the target vehicle is turning left. There are also three different proposed test combinations for this scenario: the test vehicle is travelling at 25 mph and the target vehicle is travelling at 15 mph, the test vehicle is travelling at 25 mph and the target vehicle is travelling from 0 mph to 25 mph, and the test vehicle is travelling from 0 kph to 25 mph and the target vehicle is travelling at 15 mph. The third scenario is also a LTAP/OD scenario, but the test vehicle is turning left and the target vehicle is travelling straight. There are also three speed combinations for this scenario: the test vehicle is travelling at 15 mph and the target vehicle is travelling at 25 mph, the test vehicle is travelling at 15 mph and the target vehicle is traveling from 0 mph to 25 mph, and the test vehicle is travelling from 0 mph to 25 mph and the target vehicle is travelling at 25 mph. The crash scenarios are configured such that the left front corner of the subject vehicle (SV), equipped with I-ADAS will impact the principal other vehicle (POV) at left front corner [16] (Figure 3). The near-miss LTAP/OD scenario was setup such that the POV would be 2 meters behind the rearmost part of the SV when the POV crosses into the SV's lane of travel lane [16] (Figure 3). The situation is then reversed when the POV is the turning vehicle.

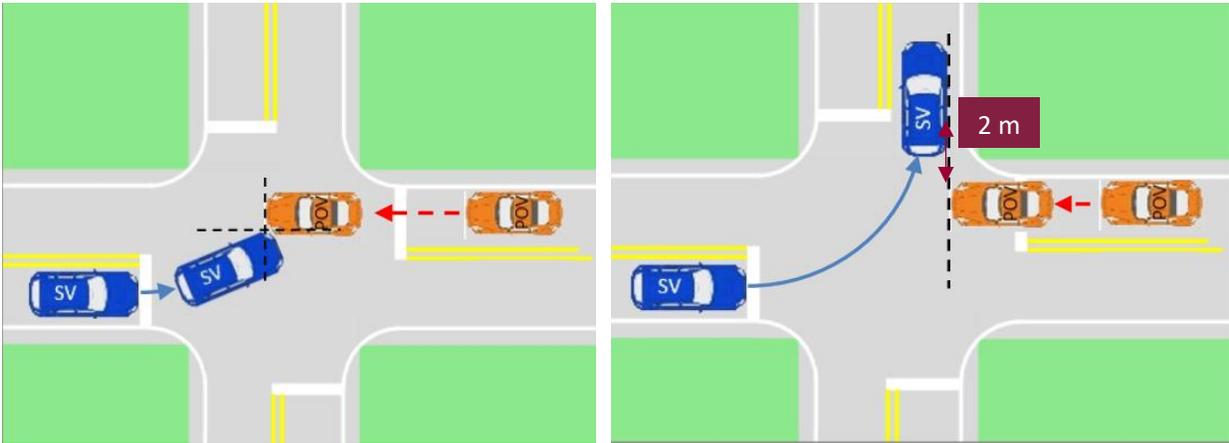


Figure 3. Crash Imminent Impact Point and Near-Miss [16]

There are six different combinations of approach speeds for the SV and POV. Each combination is tested in both a crash imminent and near-miss configuration. The NHTSA proposed I-ADAS tests contain 12 different LTAP/OD scenarios [16] (Table 3). The test protocol currently does not contain LTAP/LD scenarios and turn into path scenarios.

Table 3. NHTSA LTAP/OD Test Scenario Matrix

Test Number	Turning Vehicle	Crash or Near-Miss	Subject Vehicle Velocity	Principal Other Vehicle Velocity
1	POV	Crash	0 mph → 25 mph	15 mph
2	POV	Near-Miss	0 mph → 25 mph	15 mph
3	POV	Crash	25 mph	0 mph → 25 mph
4	POV	Near-Miss	25 mph	0 mph → 25 mph
5	POV	Crash	25 mph	15 mph
6	POV	Near-Miss	25 mph	15 mph
7	SV	Crash	0 mph → 25 mph	25 mph
8	SV	Near-Miss	0 mph → 25 mph	25 mph
9	SV	Crash	15 mph	0 mph → 25 mph
10	SV	Near-Miss	15 mph	0 mph → 25 mph
11	SV	Crash	15 mph	25 mph
12	SV	Near-Miss	15 mph	25 mph

While the EU NCAP and the proposed US-NCAP tests evaluate the object detection and decision-making of the system, they do not incorporate any potential actions of the driver. The effectiveness of I-ADAS will be limited by driver's pre-crash behavior and other environmental factors. The objective of this study was to characterize real-world intersection traversals using naturalistic driving datasets to provide driver behavior context to I-ADAS development which could potentially affect crash reduction/mitigation benefits of such systems. Evaluating driver behaviors intersections can give insight how vehicles behave in crash and near-crash scenarios compared to standard driving in intersections. Analyzing I-ADAS with a driver in the I-ADAS tests will give understanding on how these systems will operate in more realistic driving scenarios.

2 DEVELOPMENT OF A DRIVER BEHAVIOR MODEL FOR INTERSECTION TRAVERAL

2.1 Introduction

In this chapter, intersection traversals were characterized to create a unique driver behavior model for simulating crash and near-crash scenarios.

2.2 Data Sources

2.2.1 SHRP-2

The real-world intersection traversals were selected from the Second Strategic Highway Research Program (SHRP-2). SHRP-2 is a database that is comprised of vehicle kinematics, radar, and camera data from all trips taken by volunteering participants [17]. The naturalistic driving study conducted from 2010 to 2013 across six cities in the US. The database contains more than 4,300 years and 80 million kilometers of driving data across 3,516 instrumented participant vehicles. Vehicles were instrumented to collect vehicle speed, acceleration, yaw rate, and gas and brake pedal positions, and other vehicle characteristics at varied sampling frequencies. The SHRP2 database contains approximately 1,900 crashes and 6,900 near-crashes, in addition to normal/baseline driving data. Multiple SHRP2 sub-datasets exist for easy extraction depending on the use case.

For this study, only trips that involve a crash or near-crash in an intersection were analyzed. SHRP-2 crashes and near-crashes were obtained from the Research of Driver Assist System Dataset using event severity and incident type [17]. The dataset also specified which vehicle in the encounter was at fault. Event severity describes whether the event was a crash, near-crash, or normal/baseline driving. Incident type describes the configuration of the vehicles when the event severity is a crash

or near-crash according to NHTSA’s Crash Type variable (Figure 4) [3]. Turn across path: initial opposite directions describes the LTAP/OD configuration. Turn into path: turn into opposite direction describes the LTAP/LD configuration. Both straight paths describe the SCP configuration.

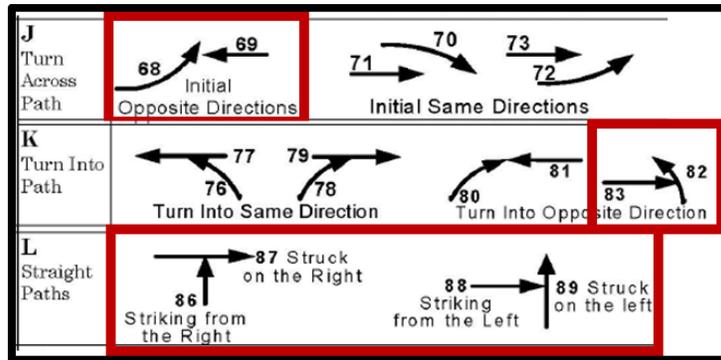


Figure 4. Crash diagrams used to code the incident type variable in the RDAS data. The red boxes indicate which encounter types are of interest for this study.

After applying the event severity and incident type selection criteria, 797 cases were selected for manual inspection: 62 crashes and 735 near-crashes. Across all 797 cases, 5,148 targets were identified by the radars mounted on the participant vehicles. Among these targets, 351 were identified as being involved in one of the three encounter types with the participant vehicle. More LTAP/ODs were found than SCPs and LTAP/LDs. This is because the radars picked up vehicles involved in LTAP/ODs better than vehicles involved in the other two encounter types since they remained within the radar’s range for a longer length of time.

2.2.2 VT-CAST

The source of the Virginia Traffic Camera for Advanced Safety Technologies (VT-CAST) database is from Virginia Tech Transportation Institute [18]. The data is comprised of stored traffic camera footages from the Virginia Department of Transportation (VDOT) Virginia Traffic Information System. The Virginia Traffic Information System provides livestream video to the public throughout the state of Virginia. There was a total of 1,263 cameras recorded from December 17th, 2019 to December 31st, 2020 resulting in 6,779,726 hours of video data captured in the VT-CAST dataset. The dataset had 93% of cameras with a resolution of 320x240 pixels, and 77% of the dataset capturing images at 15 frames per second [18]. The video was analyzed to determine the trajectories of each passenger vehicle and heavy vehicle. In order to do this the capture video was fed through a pipeline. The first step of the pipeline was to determine the main points of the vehicles in each video frame. The coordinates of the vehicle were then transformed into real-world coordinates. The most likely time-series trajectory was determined for each vehicle using a Kalman filter [18]. The trajectories, velocities, and headings for each vehicle were stored in hour segments in parquet files.

For each camera, an aerial view of the location, latitude and longitude, of the camera using Google maps (Figure 5 and Figure 6) was used to determine the camera is located near an intersection. There were 352 cameras noted to be near an intersection. The camera doesn't always show the full intersection. It may even show a partial of the intersection (Figure 5). Every video feed for cameras near an intersection and determine if the camera was looking at an intersection. If the camera is only looking at one leg of the intersection, it would not be counted in the study because the encounters between two vehicles could not be seen. However, if the camera shows multiple paths

a vehicle could take in the camera view, even if the complete paths are not in the view, it would be counted as a potential intersection in this study (Figure 6). There were 126 cameras in VT-CAST that look at an intersection and could be used to properly characterize trajectories. A low pass filter was used on vehicles position points to smooth vehicles trajectory.



Figure 5. Aerial view and camera view of vabeachcam002.



Figure 6. Aerial view and camera view of vabeachcam056.

2.3 Methods - Encounter Characterization

Once the trajectories at intersections were gathered, an algorithm needed to be created in order to determine which vehicles were in an encounter as well as what type of encounter the vehicles were

in. An encounter was defined as two vehicles being in or around an intersection at the same time for at least 1 second. In VT-CAST, each vehicle is near the beginning of the intersection during the start of the vehicle's trajectory. We defined a physical zone to capture the time range within which the vehicle was in this zone near the start of the intersection. When the vehicle was within this zone, it was determined to be the waiting vehicle. The zone is 10 m in length and is measured from the center of the closest lane perpendicular to the lane of the vehicle's trajectory (Figure 7). Once the vehicle exits this zone, it is considered to be traversing through the intersection.

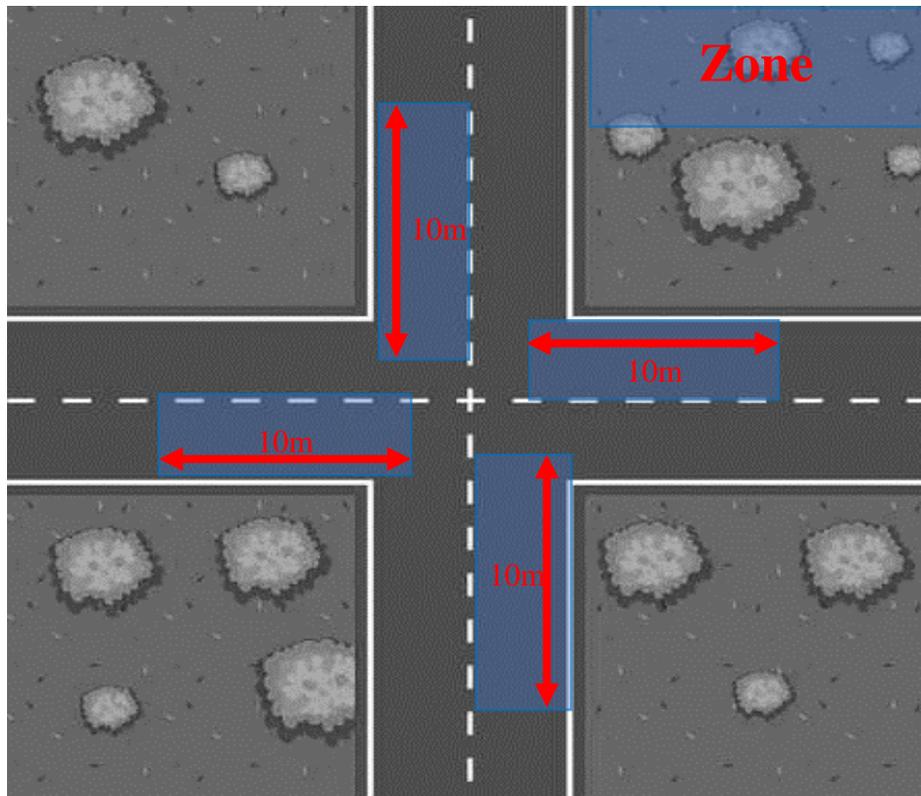


Figure 7. Visual zones for all four directions of travel in the intersection.

Once the encounters are determined, they were then categorized into encounter types.

2.3.1 Algorithm Development

Testing and iteration steps of increasing complexity were employed to develop an algorithm that could determine which vehicles were in an encounter and the encounter type (Figure 8). The first step was to create an ideal intersection with 4 legs intersecting at 90°. The vehicle trajectories were manually chosen to have the three target scenarios occur. An algorithm was created to parse through the trajectories and categorize the encounters. The next step applied the algorithm to simulated vehicle traversal data in a real intersection geometry. The simulated data added complexity by having 200 vehicles driving through a road system compared to 5 vehicles in the ideal intersection. The final step applied the algorithm to the VT-CAST dataset and improved the algorithm performance. The VT-CAST dataset has an extra layer of challenges since not all cameras captured the whole intersections. Therefore, the algorithm needed to be robust to partial vehicle trajectories. Each step of the process came with its own challenges, which made iterating the algorithm at each step crucial to be able to capture every encounter found in the VT-CAST dataset (Table 4).

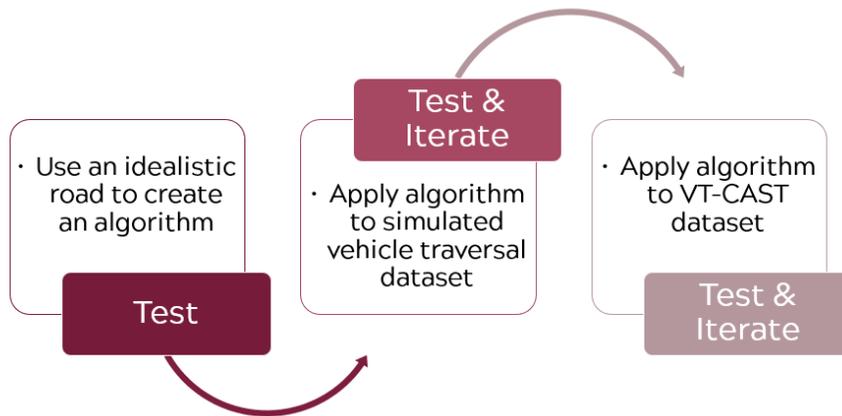


Figure 8. Algorithm development process.

Table 4. Characteristics of the datasets used in each step of the process.

Ideal Intersection	Simulated Vehicle Trajectories	VT-CAST Dataset
<ul style="list-style-type: none"> • Vehicles moving at constant speed and ideal trajectories • Simple intersection geometry • Complete trajectory known for each vehicle • 5 vehicles 	<ul style="list-style-type: none"> • Vehicles moving at constant speed with ideal trajectories • One real-world intersection geometry • Complete trajectory known for each vehicle • 200 vehicles 	<ul style="list-style-type: none"> • Vehicles moving at various speeds and trajectories • Many varying intersection geometry • Some trajectories maybe partial due to camera angle • Unknown number of vehicles

2.3.2 Encounter Classification Algorithm

To capture every possible interaction between vehicles, the algorithm will select a subject vehicle, then check the trajectory with all possible vehicle partners. The algorithm can then select another subject vehicle, eventually shifting to the perspective of every possible vehicle. The time range when the subject vehicle was near the intersection until the subject vehicle left the intersection was identified. This time range was then compared to all the other vehicle trajectories in this time range in the dataset. If there was any overlap in the time ranges, the vehicle was considered in potential conflict with the subject vehicle. The next step was to categorize each conflict. For characterization, the starting point of the subject vehicle was defined as (0,0) and the heading as 0° (Figure 9). All other vehicles' points and headings for each timestep were rotated based on the subject vehicles initial point and heading. The following equations are used to rotate the potential conflict vehicles:

$$x_{New} = (x_{SV} - x_{CV}) \cos(\theta + 90) - (y_{SV} - y_{CV}) \sin(\theta + 90) \quad (1)$$

$$y_{New} = (x_{SV} - x_{CV}) \sin(\theta + 90) + (y_{SV} - y_{CV}) \cos(\theta + 90) \quad (2)$$

$$\theta_{New} = \theta_{SV} - \theta_{CV} \quad (3)$$

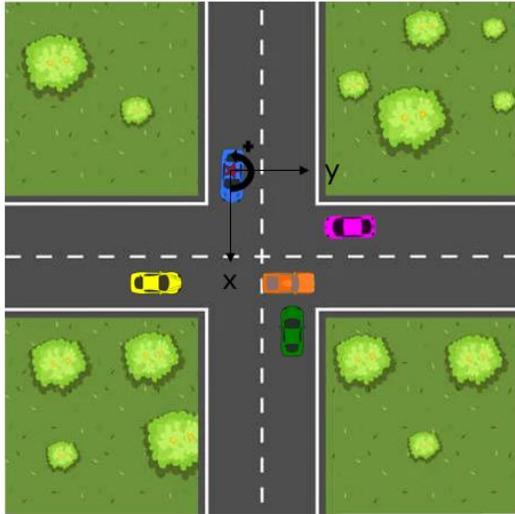


Figure 9. Coordinate system based on the initial point and heading of the subject vehicle, depicted with the star.

The new coordinate points and headings were passed through a decision tree to determine if the encounter is SCP, LTAP/LD, LTAP/LD, or other. For an encounter to be SCP, the conflict vehicle must begin its traversal with a heading of about 90° or 270° and finish its traversal with a similar heading. With the intersection legs being at a 90° angle from each other, the x-coordinate staying constant stands to be true for a SCP encounter. However, if the intersection legs are not at a 90° angle the x-coordinate does not stay constant, so the x-coordinate staying constant cannot be a criterion to determine a SCP encounter. For an encounter to be LTAP/LD, the conflict vehicle must begin its traversal with a heading of about 270° . The conflict vehicle will end its traversal at about 180° . Last, for an encounter to be LTAP/OD, the conflict vehicle must begin its traversal with a heading of about 180° and end the traversal with a heading of about 90° . All other encounters, such as LTAP/Turn-into-Path or right turns, were considered an ‘other’ encounter, and were excluded from this study (Figure 10).

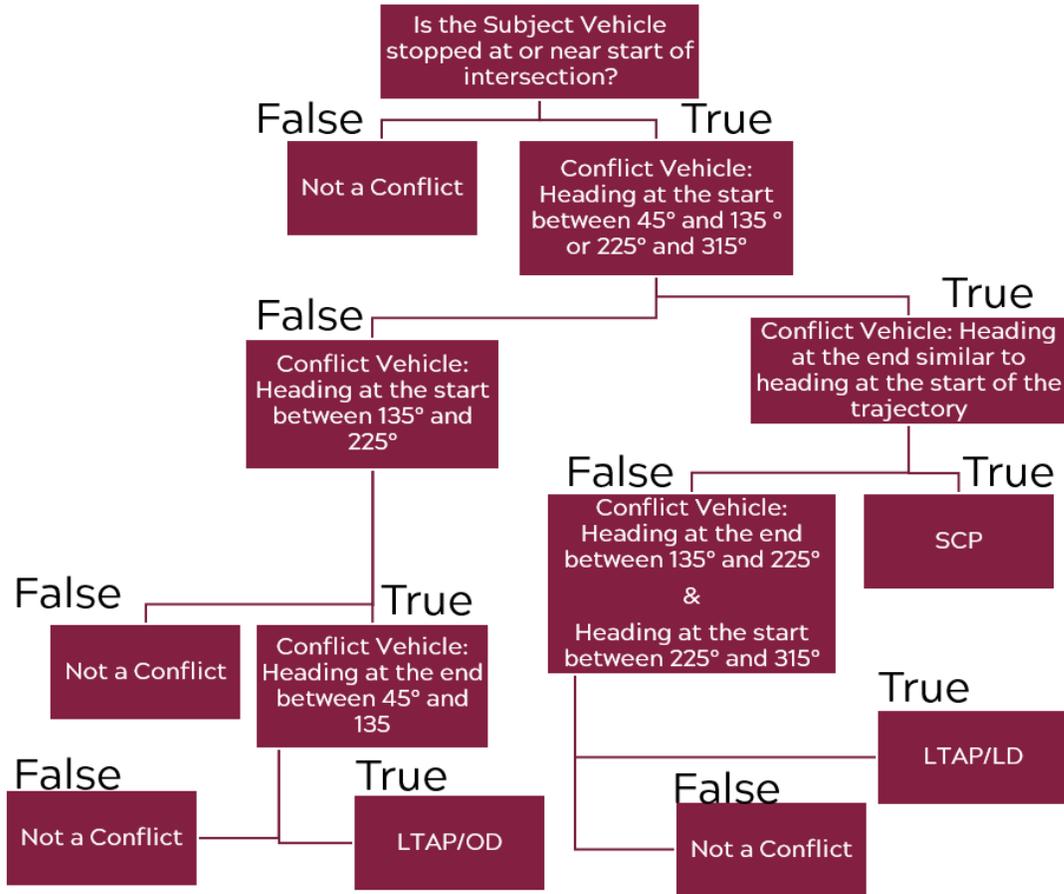


Figure 10. Algorithm Decision Tree

2.3.3 Encounter Characterization

The two datasets were analyzed separately due to the data format and overall layout of the data. At the end of the task both datasets were reformatted and combined into one dataset. Only the time both vehicles were in or near the intersection at the same were analyzed (Figure 11) to capture the behavior during the encounter. Any time in or near the intersection when the vehicle was not in an encounter was disregarded.

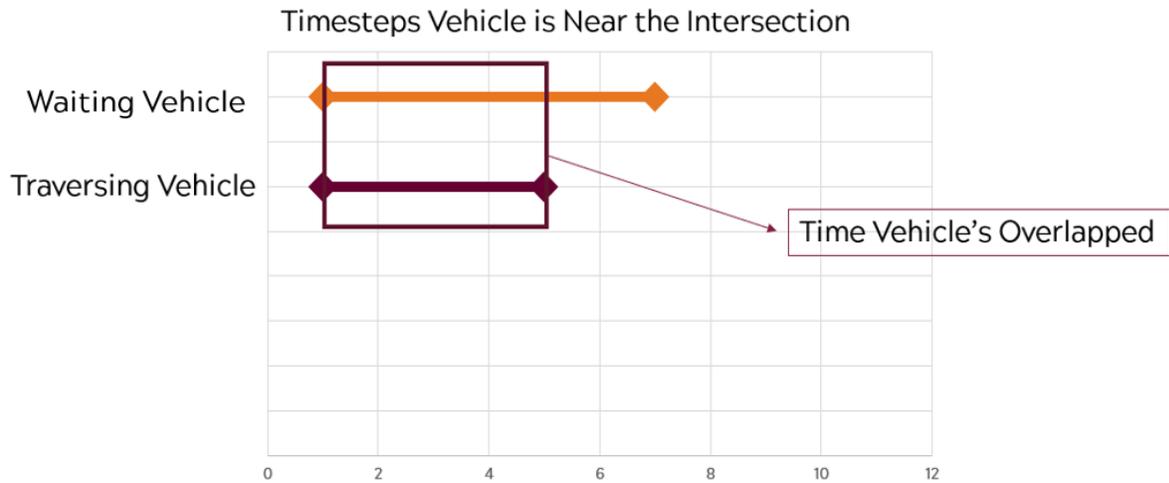


Figure 11. Time overlap for encounter analysis.

The total speed for each vehicle over time was analyzed from the beginning to the end of the encounter. The absolute difference in speed was calculated using equation 4. Each difference in speed was found by subtracting the total speed of vehicle 2 from the total speed of vehicle 1 at each timestep arbitrary of direction (Figure 12).

$$\text{Absolute Difference in Speed} = |v_2 - v_1| \quad (4)$$



Figure 12. Vehicle encounter speed vectors used to compute speed difference.

The estimated time to collision point was calculated by using known path knowledge and path prediction to determine an intersect point. If the exact intersect point was not captured by the camera, path prediction was used to determine the intersect point. For SCP, the slope of the traversing vehicle's trajectory was determined based the known trajectory. The waiting vehicle's full trajectory was not always known, so the trajectory was then assumed to be perpendicular to that of the traversing vehicle's slope (Figure 13). Creating two point-slope equations, the intersection point can be determined and used to determine the estimated time to collision.

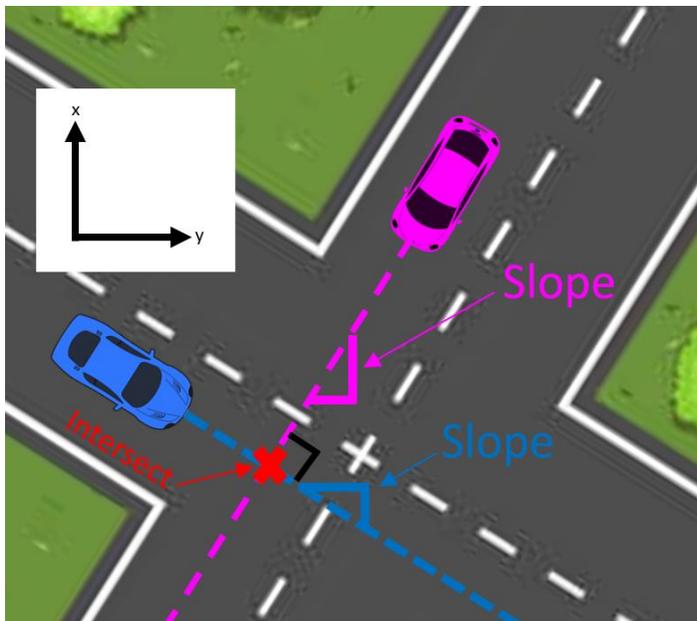


Figure 13. Methodology for finding the intersect point of the two vehicles' trajectories.

The instantaneous speed and instantaneous distance to the intersect point were used to determine how long the vehicle would take to reach the intersect point of the vehicle's trajectories (Figure 14).

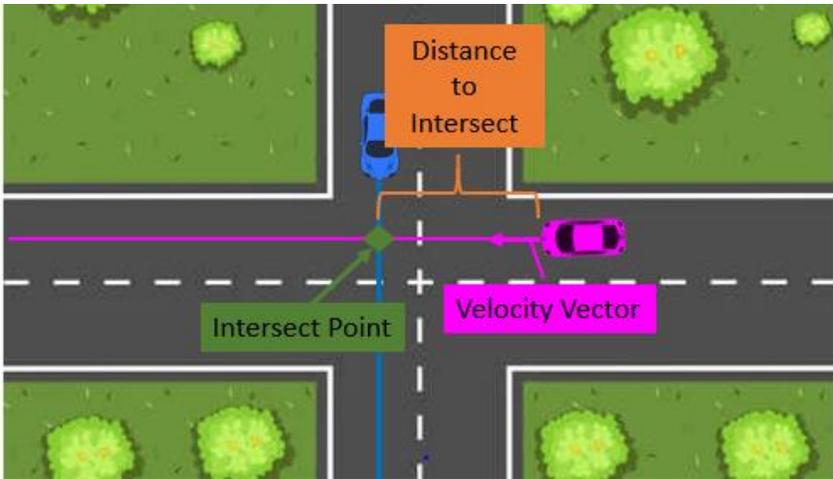


Figure 14. Methodology to determine the estimated time to collision for the vehicles in the SCP encounter.

The estimated collision point in LTAP encounters was found by finding the slope of the waiting vehicle’s trajectory to then create a predicted path straight forward (Figure 15). The traversing vehicle will pass through the point of the trajected path of the waiting vehicle.

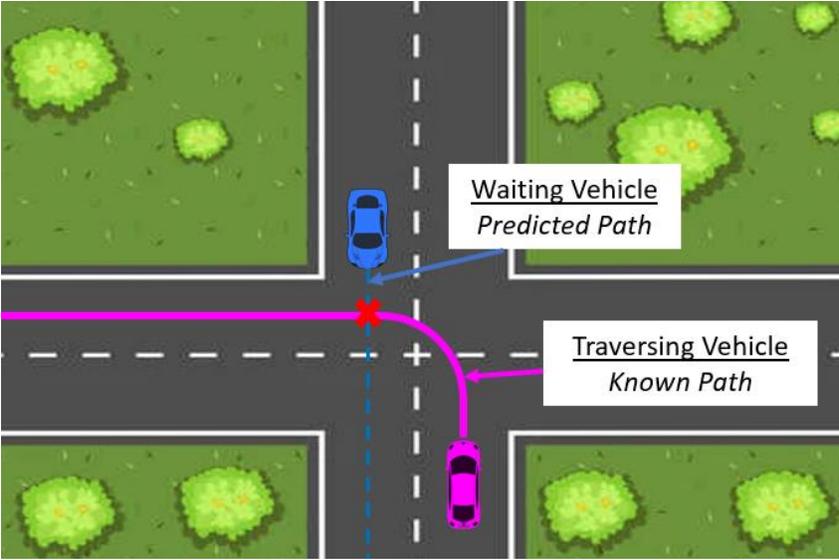


Figure 15. Methodology for finding the intersect point of the two vehicles' trajectories (LTAP encounters).

The absolute distance from the vehicle's instant position to the intersect point was divided by the absolute instantaneous speed vector to equate the estimated time to collision (eTTC) (Equation 5).

$$\textit{Estimated Time to Collision} = \frac{|\textit{Distance to Intersect}|}{|\textit{Velocity Vector}|} \quad (5)$$

The maximum acceleration was determined for each vehicle at each time step. The acceleration was determined between each time point by calculating the change in speed divided by the change in time.

$$\textit{acceleration} = \frac{v_2 - v_1}{t_2 - t_1} \quad (6)$$

2.4 Methods - Driver Behavior Model Construction

The encounters characterized by the algorithm were then used to create three different driver behavior models: SCP model, LTAP/LD model, and LTAP/OD model. The three crash modes were randomly divided into a training dataset that makes up 70% of the original dataset and was used to train the model. The remaining 30% of the original dataset was used for testing the accuracy of the model.

2.4.1 Markov Chain Model

A Markov chain model considers the current state of the vehicle and then predicts which state the next time step will be [19]. The Markov chain model is a timestep based model, but the model only takes into consideration the state of the previous timestep. The probability of transition from state to state is unique to the vehicle's current predictive variables. The next state can transition back to the current state or transition to a different state (Figure 16). Each possible transition option was assigned a probability of occurring.

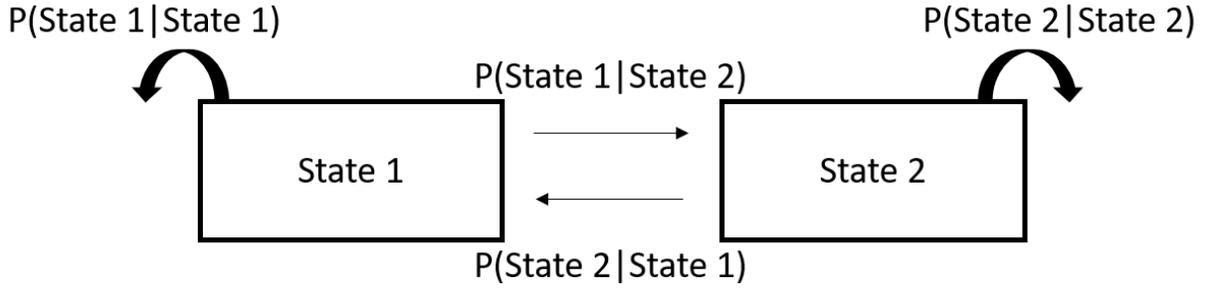


Figure 16. Markov Model Example

For our specific application, the probabilities are constantly changing based on the subject vehicle and POV current state and the predictive variables. The predictive variables for the longitudinal model were current speed, eTTC, and the speed, acceleration, and eTTC of the other vehicle in the encounter. The vehicles waiting at an intersection had an infinite eTTC, to counteract the infinite eTTCs an eTTC over 10 seconds was set to 10 seconds. The current state is denoted as X_n [19]. The probability of the current state being braking and the next state being accelerating was determined by previous states (Equation 7).

$$P\{X_{n+1} = accelerating | X_n = braking\} = P_{braking-accelerating} \quad (7)$$

This probability equation was then repeated for the probability of each state transitioning to another state or staying at the same state until a transition matrix is formed (Equation 8). This was repeated for every vehicle for each time timestep. Each state is abbreviated as braking (b), accelerating (a), waiting (w), and constant speed (c).

$$\mathbf{P} = \begin{bmatrix} P_{aa} & P_{ab} & P_{aw} & P_{ac} \\ P_{ba} & P_{bb} & P_{bw} & P_{bc} \\ P_{wa} & P_{wb} & P_{ww} & P_{wc} \\ P_{ca} & P_{cb} & P_{cw} & P_{cc} \end{bmatrix} \quad (8)$$

The transition probabilities using a multinomial logistic regression model that was trained using predictive variables from the training dataset.

2.4.1.1 Longitudinal Driver Behavior Model

Each time point in the trajectory was determined to be in one of 4 states: accelerating, braking, waiting, and constant speed (Table 5). The vehicle was determined to be accelerating if the instantaneous acceleration was greater than 0.1 m/s^2 . The vehicle was determined to be braking if the vehicle had an instantaneous acceleration of less than -0.1 m/s^2 . The vehicle was determined to be waiting if the acceleration is less than 0.1 m/s^2 and greater than -0.1 m/s^2 and the speed is less than 1 m/s . The vehicle was determined to be at a constant speed if the acceleration is less than 0.1 m/s^2 and greater than -0.1 m/s^2 and the speed is greater than 1 m/s .

Table 5. Markov Model State Definitions

Waiting $-0.1 \text{ m/s}^2 < \text{Acceleration} < 0.1 \text{ m/s}^2$ $\text{Speed} < 1 \text{ m/s}$	Accelerating $\text{Acceleration} > 0.1 \text{ m/s}^2$
Braking $\text{Acceleration} < -0.1 \text{ m/s}^2$	Constant Speed $-0.1 \text{ m/s}^2 < \text{Acceleration} < 0.1 \text{ m/s}^2$ $\text{Speed} > 1 \text{ m/s}$

The model was trained on 70% of the dataset. The training dataset was comprised of 70% of the crashes, near-crashes, and normal driving encounters. A Markov chain model was used to determine the probability of a vehicle to transition to a different state or stay in the same state between time steps (Figure 17). It is not physically possible to go from waiting to constant speed without accelerating and going from constant speed to waiting without braking first.

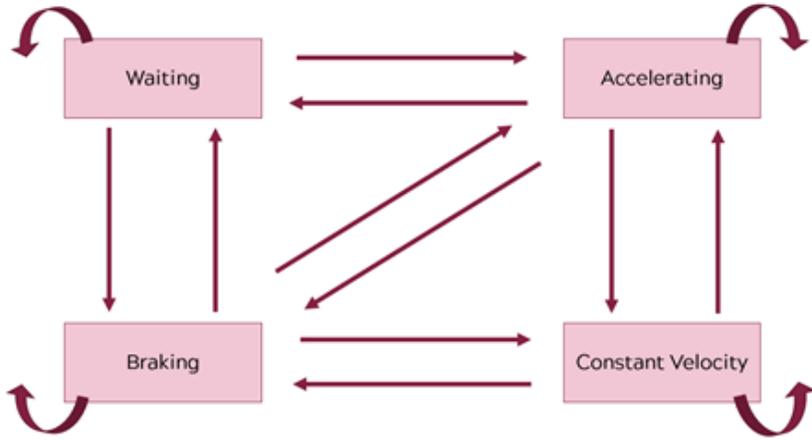


Figure 17. Markov chain model for longitudinal driver behavior model

The SCP encounter transition probabilities were determined using a multinomial logistic regression equation (Equation 9).

$$\ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1(\text{Speed}) + \beta_2(\text{eTTC}) + \beta_3(\text{POV Vel}) + \beta_4(\text{POV Acc}) + \beta_5(\text{POV eTTC}) \quad (9)$$

The coefficients, β , were determined after running the training dataset through the multinomial function in R. Acceleration being the next state is considered the baseline in the model. The baseline creates a comparison for the transition probability. Each state going to the next state will have its own equation. There was a total of 10 equations. There were not 12 equations because it is not physically possible to go from waiting to constant speed without accelerating and going from constant speed to waiting without braking first. The model consisted of 6 input predictive variables and outputs 1 variable (Figure 18).

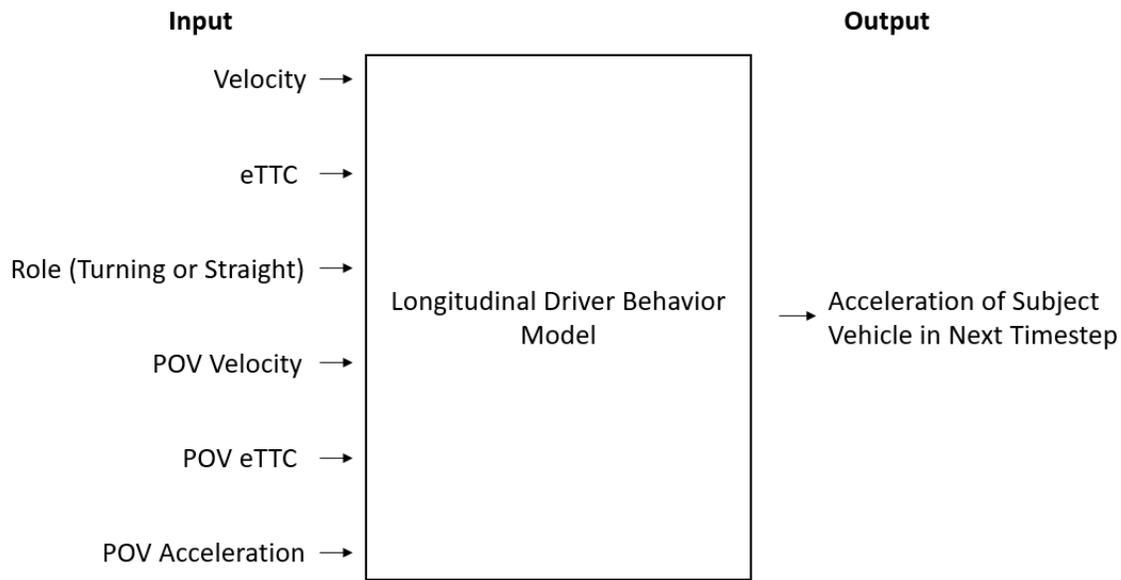


Figure 18. Inputs and Output of the Longitudinal Driver Behavior Model

The transition probabilities for LTAP encounter types were determined using a multinomial logistic regression equation (Equation 10). The role predictive variable was added for the LTAP encounter types in order to differentiate between a vehicle turning versus traversing straight.

$$\ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1(\text{Speed}) + \beta_2(\text{eTTC}) + \beta_3(\text{Role}) + \beta_4(\text{POV Vel}) + \beta_5(\text{POV Acc}) + \beta_6(\text{POV eTTC}) \quad (10)$$

2.4.1.2 Lateral Driver Behavior Model

The lateral driver behavior was setup similarly to the longitudinal driver behavior model. The lateral driver behavior model has three states: path following, evasive steering to the left, and evasive steering to the right (Table 6). The states were determined by a 4 degree/second threshold that determines if a vehicle is completing an evasive maneuver as determined by previous studies [20]. The yaw rate was the absolute value of the yaw rate. The absolute value of the yaw rate allowed for the model to evaluate changes of the vehicle turning left or right the same.

Table 6. Markov Model State Definitions for Lateral Driver Behavior Model

Path Following	Evasive Steering (Left)	Evasive Steering (Right)
$\leq 4 \text{ deg/s} \ \& \ \geq -4 \text{ deg/s}$	$< -4 \text{ deg/s}$	$> 4 \text{ deg/s}$

The angle of the vehicle was determined relative to the vehicle's direction of travel. The angle was calculated by finding the difference in heading between each timestep for each vehicle. Zero degrees was determined by the initial heading of the subject vehicle. All other angles of the vehicles in the encounter were based off of the initial heading. The yaw rate was calculated by dividing the change in the angle by the change in time for every timestep per vehicle.

The model was trained on 70% of the dataset. The training dataset was comprised of 70% of the crashes, near-crashes, and normal driving encounters. A Markov chain model was used to determine the probability of a vehicle to transition to a different state or stay in the same state between time steps. The transition probabilities are determined using a multinomial logistic regression equation (Equation 11).

$$\ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1(\text{Speed}) + \beta_2(\text{eTTC}) + \beta_3(\text{Acceleration}) + \beta_4(\text{Vehicle Angle Difference}) + \beta_5(\text{POV Vel}) + \beta_6(\text{POV Acc}) + \beta_7(\text{POV eTTC}) + \beta_8(\text{POV Yaw Rate}) \quad (11)$$

The coefficients, β , were determined after running the training dataset through the multinomial function in R. The baseline for the multinomial logistic regression was the evasive maneuver. The predictive variables were the speed, acceleration, eTTC, angle difference between the vehicles, the role the vehicle had in the encounter, and the POV vehicle in the encounter's speed, acceleration, eTTC, and yaw rate (Figure 19). The angle difference between the vehicles is linearized using a sine function.

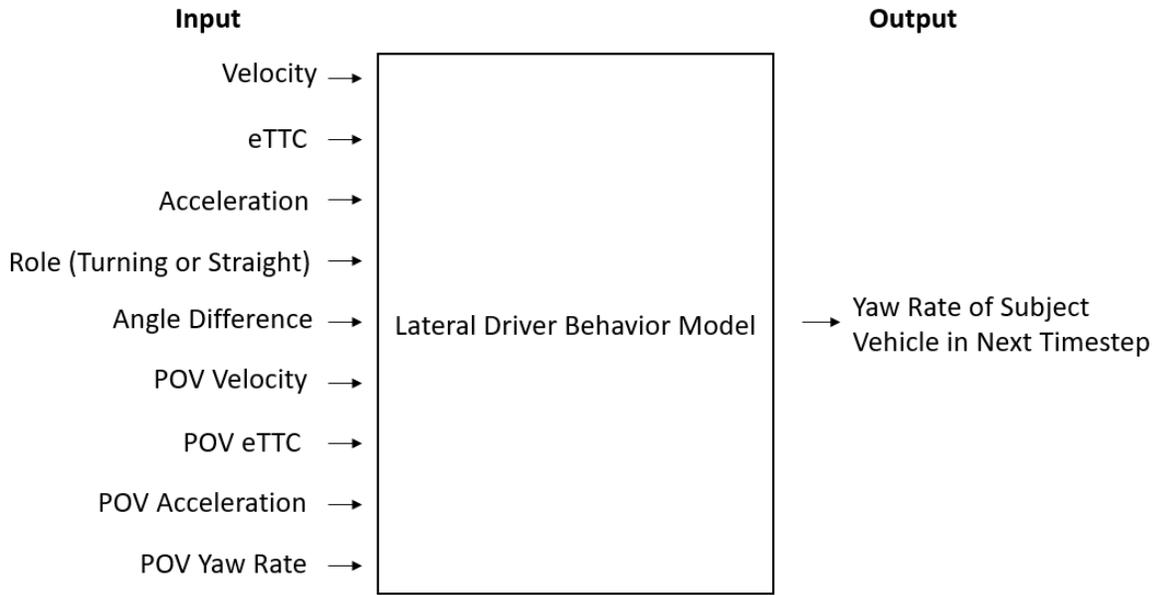


Figure 19. Lateral Driver Behavior Inputs and Output

The LTAP encounter transition probabilities were determined using a multinomial logistic regression equation (Equation 12). The role predictive variable was added for the LTAP encounter types in order to differentiate between a vehicle turning versus traversing straight.

$$\ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1(\text{Speed}) + \beta_2(\text{eTTC}) + \beta_3(\text{Acceleration}) + \beta_4(\text{Vehicle Angle Difference}) + \beta_5(\text{Role}) + \beta_6(\text{POV Vel}) + \beta_7(\text{POV Acc}) + \beta_8(\text{POV eTTC}) + \beta_9(\text{POV Yaw Rate}) \quad (12)$$

The coefficients, β , were determined after running the training dataset through the multinom function in R. The baseline for the multinomial logistic regression was the evasive maneuver.

2.5 Results

2.5.1 Encounter Characterization

There were 64 SCP encounters found in the SHRP-2 database, which were crashes and near-crashes. There were 35,879 SCP encounters found in VT-CAST. Between the two databases, there were a total of 35,943 SCP encounters to be analyzed. There were 94 LTAP/LD encounters found

in the SHRP-2 database, which were crashes and near-crashes. There were 52,957 LTAP/LD encounters found in VT-CAST. Between the two databases, there were a total of 53,051 LTAP/LD encounters to be analyzed. There were 143 LTAP/OD encounters found in the SHRP-2 database, which were crashes and near-crashes. There were 54,506 LTAP/OD encounters found in VT-CAST. Between the two databases, there were a total of 56,649 LTAP/OD encounters to be analyzed.

Table 7. Total Encounters

Encounter Type	SCP	LTAP/LD	LTAP/OD
Crash (SHRP 2)	7	4	8
Near-Crash (SHRP 2)	57	90	135
Encounter (VT-CAST)	35,879	52,957	54,506
TOTAL	35,943	53,051	54,649

The average speed was calculated for each vehicle type in the datasets. The waiting vehicles in VT-CAST SCP encounters had a low average speed of 1.18 m/s (Table 8). The speed of the waiting vehicles in VT-CAST was greater than zero due to the speed of a vehicle starting its traversal through an intersection directly after the vehicle is waiting at a stopping mechanism. On an average, the average acceleration and deceleration was much higher for the crash and near-crash encounters compared to the than the VT-CAST vehicles, except the acceleration of the vehicles at fault in crash scenarios. The encounters that were not characterized as at fault or not at fault made up approximately 6.3% of the SHRP 2 cases and were disregarded from the results.

Table 8. SCP Encounter Characteristics

<i>Median</i>	<i>Crashes</i>		<i>Near-Crashes</i>		<i>Encounter</i>	
	Not at Fault	At Fault	Not at Fault	At Fault	Waiting	Traversing
Average Speed (m/s)	10.74	13.35	5.03	4.42	1.18	7.19
Average Acceleration (m/s²)	0.37	0.08	0.69	0.45	0.15	0.28
Maximum Deceleration (m/s²)	6.04	10.18	7.94	7.86	0.23	0.28

The minimum, median, and maximum eTTC was consistently lower for the crash and near-crash in SHRP 2 compared to VT-CAST traversing vehicles (Figure 20). The VT-CAST eTTC leveled off around 10 seconds, and these larger eTTCs were most likely caused by slower velocities. Due to the small number of crashes, the eTTCs for crashes and near-crashes were plotted together.

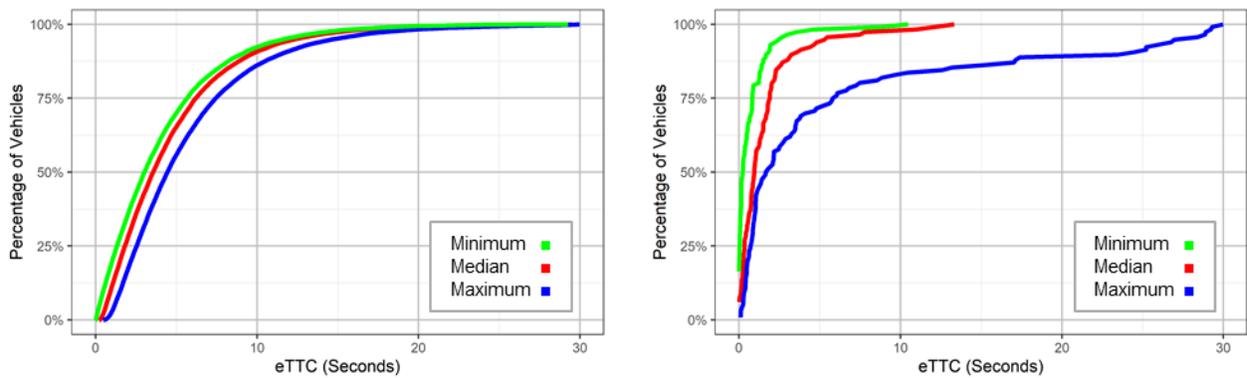


Figure 20. The cumulative distribution of eTTC maximum, median, and minimum for SCP traversing vehicles in VT-CAST (left), and SHRP 2 (right).

The average speed for crashes and near-crashes was higher than the VT-CAST LTAP/LD traversing vehicles (Table 9). There are 3% of cases in SHRP 2 that fault was not defined, so these cases were removed from the calculations.

Table 9. LTAP/LD Encounter Characteristics

<i>Median</i>	<i>Crashes</i>		<i>Near-Crashes</i>		<i>Encounters</i>	
	Not at Fault	At Fault	Not at Fault	At Fault	Waiting	Traversing
Average Speed (m/s)	10.74	6.96	8.71	7.85	0.63	7.30
Average Acceleration (m/s²)	0.20	0.48	0.47	0.58	0.15	0.65
Maximum Deceleration (m/s²)	17.75	4.93	8.33	7.47	0.28	0.19

The VT-CAST vehicle eTTCs leveled off around 15 seconds (Figure 21). The minimum and median eTTC for VT-CAST have a very similar distribution and start to fully converge at about 15 seconds. The crashes and near-crashes all had a minimum eTTC of less than 5 seconds (Figure 21). About 75% of the maximum eTTCs for crash and near-crashes were less than 2.5 seconds.

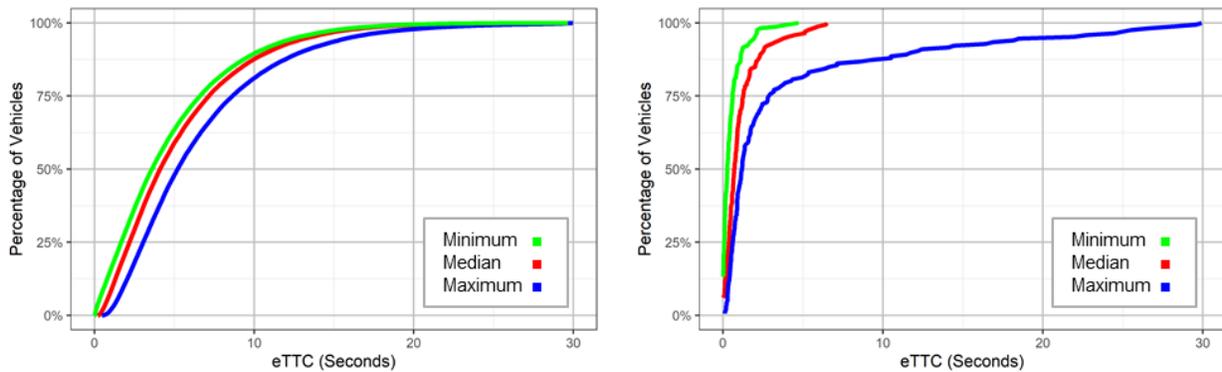


Figure 21. The cumulative distribution of eTTC maximum, median, and minimum for LTAP/LD traversing vehicles in VT-CAST (left), and SHRP 2 (right).

The average speed of the crashes in an LTAP/OD scenario was almost 10 m/s greater than the other scenario crashes (SCP and LTAP/OD) (Table 10). Similar to the other scenarios, the crash maximum deceleration was high, which is caused by a limitation and accuracy of the radars that captured the trajectories. About 5.6% of SHRP 2 encounters did not have fault defined by the SHRP 2 reductionist and were not included in the calculations.

Table 10. LTAP/OD Encounter Characteristics

<i>Median</i>	<i>Crashes</i>		<i>Near-Crashes</i>		<i>Encounters</i>	
	Not at Fault	At Fault	Not at Fault	At Fault	Waiting	Traversing
Average Speed (m/s)	17.67	17.85	11.98	11.04	0.66	7.20
Average Acceleration (m/s²)	0.33	0.00	0.36	0.51	0.16	0.61
Maximum Deceleration (m/s²)	19.08	15.63	8.33	8.86	0.30	0.21

The VT-CAST traversing vehicles had a linear distribution for the minimum, median, and maximum eTTC until about 6 seconds in LTAP/OD encounters (Figure 22). The minimum eTTC for crashes and near-crashes stayed close to 0 for 75% of the vehicles before it started to level off (Figure 22). The same for the maximum eTTC for crashes and near-crashes, but the maximum eTTC slowly leveled off at about 3.5 seconds.

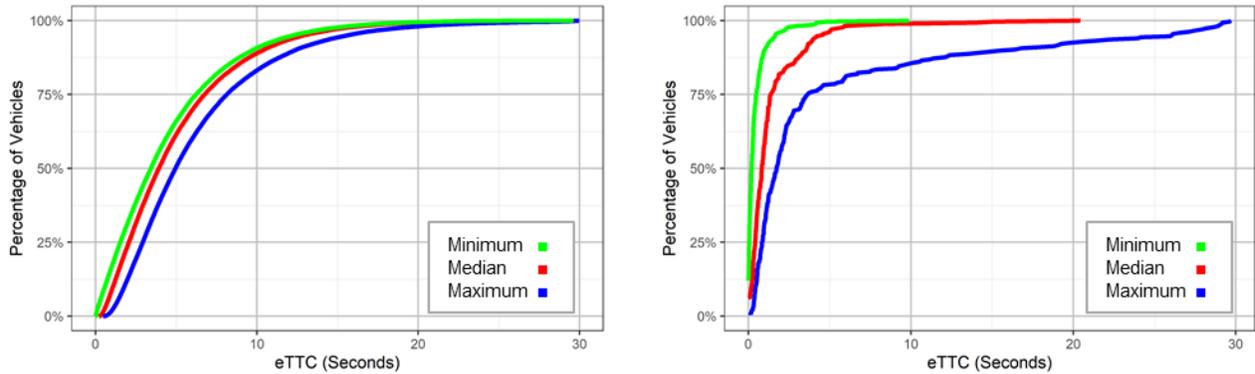


Figure 22. The cumulative distribution of eTTC maximum, median, and minimum for LTAP/OD traversing vehicles in VT-CAST (left), and SHRP 2 (right).

2.5.2 SCP Driver Behavior Model

The models predicted the next state by calculating the probabilities at every time step based on the current state and the predictive variables for both the training dataset and the test dataset.

2.5.2.1 SCP Longitudinal Driver Behavior Model

The multinomial linear regression model had 10 equations (Table 11). The speed played an important role in the probability of transition for the transitions to constant speed or braking because the higher the speed the more likely the vehicle is the transition to a constant speed or braking rather than accelerating more. The speed coefficient had an opposite effect on the probability of transition to waiting. The higher the speed the more likely the vehicle is accelerating rather than waiting. The lower the POV eTTC, the more likely the vehicle was to transition to a state that is not accelerating. The exception was if the vehicle was already accelerating, it was more likely to stay accelerating rather than transition to braking. The higher the POV vehicle's speed the less likely the subject vehicle was to accelerate. The exceptions were when the vehicle was waiting and potentially transitioning to braking and when the vehicle was accelerating to transition to constant speed.

Table 11. Model Weights (β)

Current State	Next State	Intercept	Speed	eTTC	POV Speed	POV Acc	POV eTTC
Constant Speed	Braking	-0.19	0.19	0.001	0.05	0.03	0.01
	Constant Speed	2.48	0.16	0.007	0.06	-0.14	0.03
	Waiting	-----	-----	-----	-----	-----	-----
Braking	Braking	3.17	0.65	0.05	0.06	0.01	0.01
	Constant Speed	-0.01	0.67	0.02	0.01	-0.04	0.03
	Waiting	1.72	-2.24	0.04	0.09	-0.10	0.02
Accelerating	Braking	-6.74	0.12	-0.10	0.04	0.02	-0.05
	Constant Speed	-3.14	0.02	-0.02	0.009	-0.02	0.02
	Waiting	-2.26	-2.38	-0.002	0.04	-0.12	0.01
Waiting	Braking	-1.35	1.28	0.02	-0.002	0.07	0.006
	Constant Speed	-----	-----	-----	-----	-----	-----
	Waiting	2.48	-0.02	0.008	0.06	-0.11	0.005

The transition probabilities were changed at each timestep as the two vehicles traverse the intersection. The maximum, average, and minimum probability of transitioning based on the current state was determined. On average the vehicle was most likely to stay in the state it currently is in based on the model results (Table 12). The results with N/A in the table were due to the vehicle not being physically able to go from constant speed to waiting without braking first and going from waiting to constant speed without accelerating first.

Table 12. Maximum, Average, and Minimum Probability of Transition

Current State		Probability for Next State			
		Constant Speed	Braking	Accelerating	Waiting
Constant Speed	Maximum	97.6%	30.3%	9.7%	N/A
	Average	92.4%	5.4%	2%	
	Minimum	53.6%	1.5%	0%	
Braking	Maximum	13.6%	99.3%	2.4%	31.9%
	Average	3.2%	94.7%	0.3%	1.8%
	Minimum	0.4%	67.1%	0%	0%
Accelerating	Maximum	8.5%	3.7%	97.3%	29.8%
	Average	4.7%	0.1%	94.6%	0.6%
	Minimum	2.3%	0%	67%	0%
Waiting	Maximum	N/A	11.9%	10.3%	99.0%
	Average		2.9%	4.3%	92.6%
	Minimum		0.2%	0.5%	24.4%

The longitudinal driver behavior model was validated on both the training and test dataset. The model had greater than a 92% accuracy for predicting the next state in all 4 current states (Table 13). The accuracy was based on the percent of timesteps in the data that correctly predicted the next state by comparing it to the actual next state.

Table 13. Model Validation Results

Current State	Training	Test
Constant Speed	92.44%	92.12%
Braking	94.74%	94.68%
Accelerating	94.61%	94.52%
Waiting	92.67%	92.84%

2.5.2.2 Lateral Driver Behavior Model

There are nine equations that represent the natural log of the odds ratio comparing path following to evasive steering (Table 14). The positive coefficients represent the odds of the vehicle transitioning to evasive steering in the next state to be greater than transitioning to path following.

An increase in the vehicle’s speed made the next state more likely to be following the path except when the vehicle was evasively steering right or left it is more likely to stay in the current state. The POV’s acceleration increased the probability of the vehicle performing an evasive steering maneuver, specifically an evasive steering maneuver to the right also increased. When the vehicle was performing an evasive steering maneuver to the left, an increase in acceleration made the vehicle more likely to evasively steer to the right rather than follow the path. An increase in the vehicle’s acceleration made the vehicle more likely to transition to evasive steering. There were exceptions to this. If the vehicle was evasively steering to the right, it is more likely to path follow than evasively steer to the left when the acceleration increased. Same for if the vehicle was evasively steering to the left, then an increase in acceleration was associated with a transition to path following rather than continuing to evasively steer left.

Table 14. Model Weights (β)

Current State	Path Following		Evasive Steering (Left)		Evasive Steering (Right)	
	Evasive Steering (Left)	Evasive Steering (Right)	Evasive Steering (Left)	Evasive Steering (Right)	Evasive Steering (Left)	Evasive Steering (Right)
Intercept	-2.65	-2.3	2.9	-0.29	-0.81	3.04
Speed	-0.26	-0.35	-0.01	-0.82	-0.56	-0.06
eTTC	0.02	0.014	0.002	-0.1	-0.1	0.004
Acceleration	0.1	0.08	-0.01	0.62	-0.79	0.04
Angle Difference	0.01	-0.03	0.0064	-0.14	-0.14	-0.02
POV Speed	-0.04	-0.06	-0.02	-0.06	-0.003	-0.03
POV eTTC	-0.04	-0.04	-0.006	0.007	0.03	-0.007
POV Acceleration	0.14	0.18	0.08	0.19	-0.11	0.1
POV Yaw Rate	-0.008	-0.002	-0.003	-0.01	0.011	-0.002

Similar to the longitudinal driver behavior model results, the next state the vehicle will be in is most likely to be the vehicles current state (Table 15). When a vehicle is in an evasive steering

state it is more likely to transition to the path following state compared to a vehicle in a path following state transitioning to an evasive steering state.

Table 15. Maximum, Average, and Minimum Probability of Transition

Current State		Probability for Next State		
		Path Following	Evasive Steering (Left)	Evasive Steering (Right)
Path Following	Maximum	100%	10.1%	14.0%
	Average	96.8%	1.6%	1.6%
	Minimum	76.3%	0%	0%
Evasive Steering (Left)	Maximum	12.2%	97.4%	12.0%
	Average	5.9%	93.8%	2.6%
	Minimum	2.5%	82.3%	0%
Evasive Steering (Right)	Maximum	31.5%	69.5%	97.2%
	Average	6.1%	0.3%	93.6%
	Minimum	2.8%	0%	24.2%

The lateral driver behavior model performed better than the longitudinal driver behavior model.

The lowest accuracy was 93% for the test dataset (Table 16). The lowest accuracy was from the evasive steering state.

Table 16. Model Validation Results

Current State	Training	Test
Path Following	96.8%	96.8%
Evasive Steering (Left)	93.64%	93.68%
Evasive Steering (Right)	93.84%	93.94%

2.5.3 LTAP/LD Driver Behavior Model

The models predicted the next state by calculating the probabilities at every time step based on the current state and the predictive variables for both the training dataset and the test dataset.

2.5.3.1 LTAP/LD Longitudinal Driver Behavior Model

The multinomial linear regression model had 10 equations (Table 17). The speed played an important role in the probability of transition to waiting, the higher the speed the more likely the vehicle was to transition to accelerating rather than waiting for all current states. The role the vehicle was in played a big part in the probability to transition to accelerate for all transitions besides the current state being constant speed or accelerating and transitioning to constant speed. The higher the POV's acceleration the more likely the vehicle was to transition to a state that was not accelerating.

Table 17. Model Weights (β)

Current State	Next State	Intercept	Speed	eTTC	Role	POV Speed	POV Acc	POV eTTC
Constant Speed	Braking	1.32	0.20	-0.3	-1.21	-0.05	-0.01	0.02
	Constant Speed	2.94	0.13	0.02	0.37	-0.02	-0.10	0.04
	Waiting	-----	-----	-----	-----	-----	-----	-----
Braking	Braking	5.06	0.45	-0.13	-1.80	0.05	0.32	0.11
	Constant Speed	0.87	0.43	-0.21	-0.33	0.06	0.40	0.13
	Waiting	4.00	-2.74	-0.14	-0.41	0.02	0.31	0.08
Accelerating	Braking	-6.64	0.19	-0.16	-1.08	0.10	-0.37	-0.10
	Constant Speed	-3.51	0.002	-0.07	0.46	0.02	0.09	0.03
	Waiting	-2.66	-1.79	0.03	-0.75	-0.003	-0.05	-0.002
Waiting	Braking	-1.50	1.69	0.005	-0.71	0.05	0.005	0.03
	Constant Speed	-----	-----	-----	-----	-----	-----	-----
	Waiting	2.20	-0.28	0.04	-0.82	0.05	-0.05	0.03

The transition probabilities were changed at each timestep as the two vehicles traversed the intersection. The maximum, average, and minimum probability of transitioning based on the current state was determined. On average the vehicle was most likely to stay in the state it currently is in based on the model results (Table 18). The results with N/A in the table were due to the

vehicle not being physically able to go from constant speed to waiting without braking first and going from waiting to constant speed without accelerating first.

Table 18. Maximum, Average, and Minimum Probability of Transition

	Current State		Probability for Next State			
			Constant Speed	Braking	Accelerating	Waiting
Traversing Straight	Constant Speed	Maximum	92.6%	27.3%	13.9%	N/A
		Average	87.0%	9.7%	3.3%	
		Minimum	46.9%	4.9%	0.3%	
	Braking	Maximum	12.2%	99.1%	53.4%	20.0%
		Average	0.8%	94.8%	0.7%	3.7%
		Minimum	0.1%	46.4%	0%	0%
	Accelerating	Maximum	6.8%	29.7%	98.4%	9.3%
		Average	2.2%	0%	95.0%	2.8%
		Minimum	1.1%	0%	67.1%	0%
	Waiting	Maximum	N/A	15.6%	7.1%	95.9%
		Average		3.1%	4.1%	92.8%
		Minimum		1.2%	2.7%	73.4%
Turning	Constant Speed	Maximum	97.6%	21.3%	4.7%	N/A
		Average	95.2%	4.0%	0.8%	
		Minimum	78.6%	1.3%	0%	
	Braking	Maximum	16.8%	98.0%	8.7%	22.0%
		Average	5.6%	94.2%	0.2%	0%
		Minimum	0.9%	68.4%	0%	0%
	Accelerating	Maximum	70.3%	45.7%	98.0%	7.0%
		Average	0.5%	0%	95.0%	0%
		Minimum	1.8%	0%	27.9%	0%
	Waiting	Maximum	N/A	12.8%	23.7%	86.7%
		Average		9.5%	19.0%	71.5%
		Minimum		2.3%	10.9%	64.8%

The longitudinal driver behavior model was validated on both the training and test dataset. The model had greater than an 86% accuracy for predicting the next state in all 4 current states (Table 19). The accuracy was based on the percent of timesteps in the data that correctly predicted the next state by comparing it to the actual next state.

Table 19. Model Validation Results

	Current State	Training	Test
Traversing Straight	Constant Speed	86.95%	86.89%
	Braking	94.75%	94.7%
	Accelerating	94.88%	95.29%
	Waiting	92.76%	93.08%
Turning	Constant Speed	95.15%	95.2%
	Braking	94.44%	94.46%
	Accelerating	94.94%	95.3%
	Waiting	N/A	N/A

2.5.3.2 Lateral Driver Behavior Model

There are two equations that represent the natural log of the odds ratio comparing path following to evasive steering (Table 20). The positive coefficients represent the odds of the vehicle transitioning to evasive steering as the next state to be greater than transitioning to path following. An increase in the vehicle's speed made the next state more likely to follow the path. An increase in acceleration increased the probability of the vehicle performing an evasive steering maneuver except when the vehicle's current state was evasive steering to the right and then transitioning to evasive steering the left. An increased POV vehicle acceleration was associated with a greater likelihood that the subject vehicle evasively steered. The role of the vehicle had the biggest impact and favored path following. The POV's yaw rate had a very small association with transition probability.

Table 20. Model Weights (β)

Current State	Path Following		Evasive Steering (Left)		Evasive Steering (Right)	
Next State	Evasive Steering (Left)	Evasive Steering (Right)	Evasive Steering (Left)	Evasive Steering (Right)	Evasive Steering (Left)	Evasive Steering (Right)
Intercept	-2.07	-1.98	-0.42	3.52	3.40	-0.44
Speed	-0.24	-0.27	-0.52	-0.08	-0.05	-0.75
eTTC	0.02	0.01	0.06	0.01	0.02	0.06
Acceleration	0.12	0.39	0.27	0.07	-0.04	0.09
Angle Difference	-0.01	0.11	-0.41	0.1	-0.15	0.33
Role	-1.03	-0.86	0.52	-0.36	-0.25	1.50
POV Speed	-0.05	-0.06	-0.03	-0.02	-0.02	-0.03
POV eTTC	-0.03	-0.05	-0.04	-0.001	-0.007	-0.02
POV Acceleration	0.08	0.09	0.06	0.08	0.16	0.1
POV Yaw Rate	-0.00005	-0.0002	0.00003	0.00002	-0.0002	-0.00007

Similar to the longitudinal driver behavior model results, the next state the vehicle will be in is most likely to be the vehicles current state (Table 21). When a vehicle was in an evasive steering state, it was more likely to transition to the path following state compared to a vehicle in a path following state transitioning to an evasive steering state.

Table 21. Maximum, Average, and Minimum Probability of Transition

	Current State		Probability for Next State		
			Path Following	Evasive Steering (Left)	Evasive Steering (Right)
Traversing Straight	Path Following	Maximum	98.1%	12.4%	18.0%
		Average	87.7%	6.8%	5.5%
		Minimum	71.7%	1.3%	0.5%
	Evasive Steering (Left)	Maximum	13.6%	99.0%	8.7%
		Average	2.6%	96.0%	1.4%
		Minimum	0.7%	85.5%	0%
	Evasive Steering (Right)	Maximum	9.0%	8.5%	97.5%
		Average	3.0%	2.3%	94.7%
		Minimum	1.6%	0.2%	87.7%
Turning	Path Following	Maximum	100%	2.9%	6.0%
		Average	98.9%	0.5%	0.6%
		Minimum	91.8%	0%	0%
	Evasive Steering (Left)	Maximum	24.9%	98.5%	10.6%
		Average	6.2%	93.5%	0.3%
		Minimum	1.4%	75.1%	0%
	Evasive Steering (Right)	Maximum	38.2%	4.9%	96.6%
		Average	6.2%	0.3%	93.5%
		Minimum	2.3%	0%	61.8%

The lateral driver behavior model performed better than the longitudinal driver behavior model. The lowest accuracy was 87% for the test dataset (Table 22). The lowest accuracy was from the evasive steering state. Evasive steering is a very rare event, so it makes sense that those states are more difficult to predict.

Table 22. Model Validation Results

	Current State	Training	Test
Traversing Straight	Path Following	87.69%	87.44%
	Evasive Steering (Left)	95.98%	96.06%
	Evasive Steering (Right)	94.82%	94.43%
Turning	Path Following	98.82%	98.91%
	Evasive Steering (Left)	93.32%	93.47%
	Evasive Steering (Right)	93.35%	93.46%

2.5.4 LTAP/OD Driver Behavior Model

The models predicted the next state by calculating the probabilities at every time step based on the current state and the predictive variables for both the training dataset and the test dataset.

2.5.4.1 Longitudinal Driver Behavior Model

The multinomial linear regression model had 10 equations (Table 23). The speed of the subject vehicle has a relatively large weight when it comes to transitioning to waiting. As speed increased, the subject vehicle was more likely to transition to acceleration rather than waiting from all current states. Role of the subject vehicle being turning made the probability of transition more likely to transition be acceleration except if the vehicle was braking transitioning to constant speed or accelerating transitioning to constant speed. The POV speed increasing caused the odds ratio to be more in favor to transition to accelerating besides constant speed transitioning to braking and accelerating transitioning to braking.

Table 23. Model Weights (β)

Current State	Next State	Intercept	Speed	eTTC	Role	POV Speed	POV Acc	POV eTTC
Constant Speed	Braking	0.64	0.00005	-0.006	-1.41	-0.03	0.07	-0.01
	Constant Speed	2.00	-0.04	0.006	-0.15	0.005	0.02	0.01
	Waiting	-----	-----	-----	-----	-----	-----	-----
Braking	Braking	2.85	-0.03	-0.009	-0.13	0.02	-0.01	0.03
	Constant Speed	-0.47	-0.03	-0.08	0.76	0.02	-0.05	0.05
	Waiting	1.61	-2.42	-0.03	-0.0027	0.03	-0.03	0.03
Accelerating	Braking	-2.87	0.02	0.006	-1.29	-0.003	-0.16	-0.05
	Constant Speed	-3.08	-0.02	-0.04	0.70	0.007	0.02	0.009
	Waiting	-1.95	-1.88	0.01	-1.37	0.02	-0.08	0.005
Waiting	Braking	-0.63	0.99	0.014	-0.67	0.007	-0.05	-0.01
	Constant Speed	-----	-----	-----	-----	-----	-----	-----
	Waiting	2.54	-0.80	0.02	-1.79	0.003	-0.03	0.006

The transition probabilities were changed at each timestep as the two vehicles traverse the intersection. The maximum, average, and minimum probability of transitioning based on the current state was determined. On average the vehicle was most likely to stay in the state it currently is in based on the model results (Table 24). If the vehicle's current state was braking or accelerating, it was more likely to transition to constant speed while turning compared to traversing straight. The results with N/A in the table were due to the vehicle not being physically able to go from constant speed to waiting without braking first and going from waiting to constant speed without accelerating first.

Table 24. Maximum, Average, and Minimum Probability of Transition

		Probability for Next State				
Current State			Constant Speed	Braking	Accelerating	Waiting
Traversing Straight	Constant Speed	Maximum	87.7%	36.0%	25.0%	N/A
		Average	76.7%	13.5%	9.5%	
		Minimum	47.5%	3.8%	7.3%	
	Braking	Maximum	6.1%	94.4%	10.6%	22.8%
		Average	1.7%	88.2%	4.5%	5.6%
		Minimum	0.8%	71.8%	1.9%	0%
	Accelerating	Maximum	5.1%	45.5%	95.2%	34.0%
		Average	2.9%	3.9%	88.7%	4.6%
		Minimum	1.2%	0.9%	53.3%	0%
	Waiting	Maximum	N/A	18.9%	13.5%	92.7%
		Average		5.7%	6.3%	97.9%
		Minimum		2.5%	4.2%	67.2%
Turning	Constant Speed	Maximum	85.6%	17.4%	38.5%	N/A
		Average	78.7%	5.8%	15.5%	
		Minimum	44.1%	1.5%	10.8%	
	Braking	Maximum	19.3%	91.3%	16.4%	24.9%
		Average	7.0%	87.3%	5.7%	0.02%
		Minimum	2.4%	68.1%	3.2%	0%
	Accelerating	Maximum	10.5%	7.5%	95.0%	4.2%
		Average	6.7%	1.0%	92.3%	0%
		Minimum	1.0%	0.2%	88.4%	0%
	Waiting	Maximum	N/A	17.8%	40.3%	67.3%
		Average		10.4%	35.5%	54.2%
		Minimum		4.7%	27.9%	42.8%

The longitudinal driver behavior model was validated on both the training and test dataset. The model had greater than a 78% accuracy for predicting the next state in all 4 current states (Table 25). The accuracy was based on the percent of timesteps in the data that correctly predicted the next state by comparing it to the actual next state. The accuracy for the longitudinal driving behavior model for LTAP/OD was about 15% lower than the accuracy of SCP and LTAP/LD. The drop in accuracy could be caused by the dynamic maneuver of a vehicle turning. A vehicle turning

was much more likely to change states than a vehicle going straight, and an LTAP/OD event may be an unprotected left causing even more transitions from state to state. More transitions and variability in driving technique caused the accuracies of LTAP/OD to be lower than LTAP/LD and SCP.

Table 25. Model Validation Results

	Current State	Training	Test
Traversing Straight	Constant Speed	76.59%	76.59%
	Braking	88.28%	88.09%
	Accelerating	88.65%	88.71%
	Waiting	87.92%	87.73%
Turning	Constant Speed	78.88%	78.82%
	Braking	87.23%	87.02%
	Accelerating	92.23%	92.3%
	Waiting	N/A	N/A

2.5.4.2 Lateral Driver Behavior Model

There are nine equations that represent the natural log of the odds ratio comparing path following to evasive steering (Table 26). The positive coefficients represented the odds of the vehicle transitioning to evasive steering as the next state to be greater than transitioning to path following. An increase in the vehicle’s speed made the next state more likely to evasively steer except when the vehicle was evasively steering right or left it is more likely to stay in the current state if transitioning to the opposite direction evasive steering. An increase in acceleration when the vehicle’s current state was path following decreases the probability of the vehicle performing an evasive steering maneuver. An increased POV vehicle acceleration was associated with a greater likelihood that the subject vehicle evasively steered except state if transitioning to the opposite

direction evasive steering. The role of the vehicle had the biggest impact and favored path following. The POV's yaw rate had a very small associated with transition probability.

Table 26. Model Weights (β)

Current State	Path Following		Evasive Steering (Left)		Evasive Steering (Right)	
Next State	Evasive Steering (Left)	Evasive Steering (Right)	Evasive Steering (Left)	Evasive Steering (Right)	Evasive Steering (Left)	Evasive Steering (Right)
Intercept	-1.94	-2.23	3.58	0.70	1.22	3.26
Speed	-0.02	-0.007	-0.07	-0.1	-0.07	-0.08
eTTC	0.02	0.03	-0.005	0.02	-0.02	0.007
Acceleration	-0.12	-0.12	-0.03	0.004	-0.01	0.07
Angle Difference	0.08	0.09	-0.05	-0.01	-0.12	0.009
Role	-0.85	-0.67	-1.25	-0.8	-1.59	-0.98
POV Speed	-0.02	-0.03	-0.008	-0.002	0.01	-0.006
POV eTTC	-0.03	-0.03	0.004	-0.014	-0.009	-0.006
POV Acceleration	0.03	0.03	0.05	-0.007	-0.03	0.03
POV Yaw Rate	0.0004	-0.0003	-0.0002	-0.0004	0.000009	0.0001

Similar to the longitudinal driver behavior model results, the next state the vehicle will be in is most likely to be the vehicles current state (Table 27). When a vehicle was in an evasive steering state it is more likely to transition to the path following state compared to a vehicle in a path following state transitioning to an evasive steering state. The probabilities for transition on average were similar for a vehicle traversing straight compared to a vehicle turning.

Table 27. Maximum, Average, and Minimum Probability of Transition

	Current State		Probability for Next State		
			Path Following	Evasive Steering (Left)	Evasive Steering (Right)
Traversing Straight	Path Following	Maximum	97.9%	54.7%	48.3%
		Average	91.0%	4.5%	4.5%
		Minimum	44.4%	0.2%	0.3%
	Evasive Steering (Left)	Maximum	98.3%	95.3%	27.4%
		Average	5.5%	88.7%	5.8%
		Minimum	0.7%	1.6%	0.01%
	Evasive Steering (Right)	Maximum	94.0%	25.7%	94.7%
		Average	7.5%	7.9%	84.5%
		Minimum	1.6%	0.6%	5.4%
Turning	Path Following	Maximum	97.9%	48.3%	54.7%
		Average	91.1%	4.5%	4.5%
		Minimum	44.4%	0.3%	0.2%
	Evasive Steering (Left)	Maximum	78.7%	94.4%	28.2%
		Average	5.5%	88.8%	5.8%
		Minimum	0.8%	20.1%	0.3%
	Evasive Steering (Right)	Maximum	85.1%	21.8%	95.4%
		Average	7.6%	7.9%	84.5%
		Minimum	1.6%	1.5%	13.4%

The lateral driver behavior model performed better than the longitudinal driver behavior model. The lowest accuracy was 84% for the test dataset (Table 28). The lowest accuracy was from the evasive steering state. Evasive steering is a very unpredictable event, so it makes sense that those are next states more difficult to predict.

Table 28. Model Validation Results

	Current State	Training	Test
Traversing Straight	Path Following	81.29%	80.93%
	Evasive Steering (Left)	91.16%	91.11%
	Evasive Steering (Right)	87.17%	87.25%
Turning	Path Following	93.02%	93.11%
	Evasive Steering (Left)	81.26%	81.41%
	Evasive Steering (Right)	79.16%	78.95%

2.6 Discussion

The driver behavior characteristics that were generated in this study provide insight as to what drivers do in the top three most frequent intersection scenarios. Most of the normal driving encounters occurred at intersections with traffic light, while most of the crashes and near-crashes occurred at intersections without any type of traffic control for all three scenario types. The infrastructure differences can contribute to the differences seen in the driver behavior characteristics, such as speed. The median average speed for crashes and near-crashes (SHRP2 data) was consistently higher than that of the normal driving encounters (VT CAST data). This could be due to the traffic lights present at the encounters. For example, vehicles at intersections with stop light tend to have a lower speed with a similar acceleration compared to the vehicles in intersections without a traffic-control device. Speeding is typically closely linked to crashes [11]. Speeding could be the cause for the increased median average speed in crashes and near-crashes compared to normal encounters in all three scenario types [12].

Currently, the Euro NCAP and proposed US-NCAP only cover SCP and LTAP/OD scenarios. Although LTAP/LD crashes are not as frequent as LTAP/OD and SCP crashes in the US, the

LTAP/LD scenarios still pose a risk to drivers, unprotected left turns, and a challenge to I-ADAS [2]. The LTAP/LD encounters can be unprotected lefts where there is no traffic control to tell the driver when to turn and only relies on the driver's perception to make a safe turn. The maximum speed for the US-NCAP SCP tests (40.2 kph) is 1.5 times higher than the median average velocities found for traversing vehicles in VT-CAST (about 26 kph). However, the distribution of average velocities from in each scenario falls below 54 kph except for LTAP/OD crashes and near-crashes that had on average higher velocities with most of the average velocities being less than 72 kph. Although the US-NCAP tests have a higher speed than the average encounter in the study, it does not represent all encounters found. The average speed for the LTAP/OD scenarios for traversing vehicles in VT-CAST was lower than the maximum test speed for the LTAP/OD scenarios for the proposed US-NCAP tests (40.2 kph). However, the median average velocities in crash and near-crash scenarios in SHRP-2 were higher and closely matched the Euro NCAP test speeds (20–60 kph). The maximum Euro NCAP test speed (60 kph) is greater than all the median average velocities found for each scenario except LTAP/OD crashes and near-crashes. The NCAP test scenarios also only has roads with a 90-degree difference between the legs and no obstructed view. In this study, it was observed that the road infrastructure is not as perfect as this which may affect driver behavior. The combination of drivers driving faster and intersections different than those that the systems were tested on could pose a problem for AEB systems that depend on its perception system to detect hazards in time to activate and prevent or mitigate the imminent crash.

Table 29. Summary Table

	Euro NCAP	US-NCAP (Proposed)	SHRP-2 (Crash & Near Crashes)	VT-CAST (Only Traversing)
Intersection Type	4-Legged	4-Legged	Many	99% 4-Legged
SCP Max. Median Speed	60 kph	40.2 kph	48.06 kph (13.35 m/s)	25.88 kph (7.19 m/s)
LTAP/LD Max. Median Speed	N/A	N/A	38.66 kph (10.74 m/s)	26.28 kph (7.3 m/s)
LTAP/OD Max. Median Speed	60 kph	40.2 kph	64.26 kph (17.85 m/s)	25.92 kph (7.2 m/s)

The analysis of intersection driving data can provide insights into real-world intersection normal driving encounters, crashes, and near-crashes. Since VT-CAST and SHRP 2 contain observations of real-world driving behaviors in intersections (distance, speed, heading, etc.), this data is relevant for the development of I-ADAS systems. In addition to generating I-ADAS activation criteria, the estimated parameters from the encounters could allow for a driver behavior prediction model to be developed. The driver behavior model may be able to predict the longitudinal and lateral behaviors of drivers based on the data collected and characterized in this study to improve interactions with other vehicles on the road.

Some limitations to this chapter were that the SHRP-2 dataset uses radar data to collect information about other vehicles in the roadway. The radar has a limited field of view, therefore the target vehicle for the SCP and LTAP/LD scenarios was recorded for only a short amount of time. The whole traversal is not known, but the known trajectories are long enough to assess driver behaviors in crash and near-crash scenarios. The radars are also limited by the inaccuracies in detecting

another vehicle's speed, which caused some of the accelerations to be higher than the vehicles' capabilities. The VT-CAST dataset was limited by the camera quality of the traffic cameras from which it was collected, as well as by the angles of those cameras. In some cases, the camera was not angled to capture the whole intersection, which meant only partial trajectories were recorded. Similar to SHRP-2, the vehicles were filtered based on the length of time the camera was able to capture the vehicle's trajectory.

The Markov chain with the multinomial logistic regression model performed well in predicting the next state for each of the current states in the model. SCP performed the best, likely because the two vehicles behave similarly. The acceleration and speed consistently had the highest weights in the model while the other predictors fluctuated based on the state and next state in the equation. In future work, the model could be trained after separating the LTAP cases by whether the vehicle is turning or travelling straight.

The role predictive variable was created to inform the transition probabilities and to adjust for vehicles turning left at an intersection instead of traversing straight. A predictive variable alone was chosen instead of creating two models: one for traversing straight and one for turning left. The predictive variable was sufficient based on the accuracy of the models for LTAP/LD and LTAP/OD being greater than 76% at predicting the next state.

The longitudinal and lateral driver behavior models were not able to 100% predict the next state for every timestep in the dataset. The slight inaccuracies may be caused by the unpredictability of humans and how they react in various driving scenarios. The inaccuracies could also be caused by limitations in the radar and cameras of the two datasets which could cause parameters to change quicker than expected. The radar in the SHRP 2 dataset did not always track the vehicle for the

entire trajectory, and the radar had inaccuracies when it came to knowing the position and speed of the POV. The camera is limited by the field of view, so the full trajectory of the vehicle was not always captured.

In both models, the next state was most likely to be the current state. If a vehicle goes through each of the stages, it will most commonly only transition 3 times to a state that is not the vehicles initial state. For example, a vehicle may brake for a red light then transition to waiting at the red light. Once the light turns green, the vehicle will transition to accelerating and finally transition to a constant speed once up to the wanted speed. If the vehicle takes 4 seconds to complete all these transitions which is a total of 60 timesteps. Of those 60 timesteps, only 3 have a transition to a different state that is not the current state. In the example, 95% of the transitions are the next state being the current state which is close to the average results found by the model. The example is for the longitudinal driver behavior model, but the lateral model is more unique since the transition between the two states is less common in normal driving. Evasive steering maneuvers are not very common, and the maneuver is most likely caused by an imminent crash scenario or inattention causing a diverge from the intended path. The training dataset for both of the models was comprised of mostly normal driving behavior with crash and near-crashes being very rare.

The human aspect of driving is built into the model. Reaction latency can be assumed as the amount of time before the transition happens. For example, if a driver is at a constant speed and then applies braking at a certain timestep, the time the driver decides to brake is at a previous timestep while the vehicle was still braking.

Modeling longitudinal and lateral movements of the vehicle caused limitations to the driver behavior model because the two movement directions can be closely related. However, modeling

them separately allowed for a simplified and accurate driver behavior model with a minimized amount of states.

3 INVESTIGATION OF INTERACTIONS BETWEEN DRIVERS AND I-ADAS

3.1 Methods

The SCP scenarios were simulated in OpenPass. The driver behavior models were integrated using a functional mockup unit. The simulations were verified and visualized in Open Visualization (Figure 23).

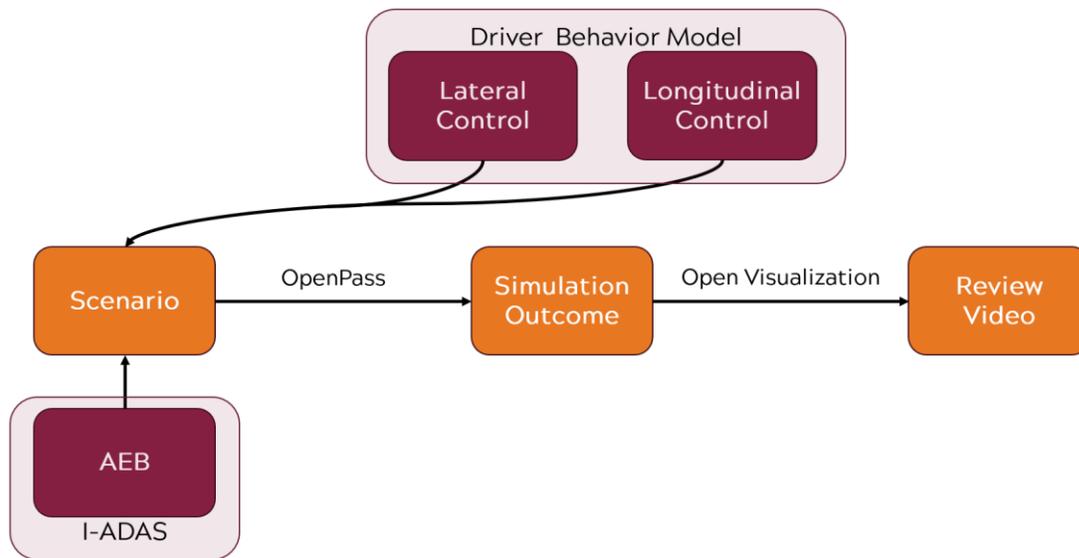


Figure 23. Simulation Creation Flowchart

The test matrix reflects that proposed by NHTSA to test I-ADAS. Each scenario had the time to collision, field of view, range, and latency of I-ADAS varied. Each variation for each test was run 100 times to cover the probability distribution of the driver behavior model in order to observe less probable driver behavior.

3.1.1 I-ADAS Parameters and Set Up

I-ADAS was varied using 4 different parameters: the range the sensor can see, the field of view of the sensor, the time to collision (TTC) threshold for I-ADAS activation, and the latency of the

system. Each parameter had three different levels (Table 30). The camera ranges were 100 meters, 200 meters, and 300 meters. The sensor field of views were +/- 45°, +/- 70°, and +/- 110°. The I-ADAS TTC activation thresholds were 1.0 seconds, 1.5 seconds, and 2.0 seconds. The latencies were 50 milliseconds, 120 milliseconds, and 200 milliseconds.

Table 30. Parameter Lists

Range	Field of View	TTC Threshold	Latency
100m	+/- 45°	1.0s	50ms
200m	+/- 70°	1.5s	120ms
300m	+/- 110°	2.0s	200ms

Every combination of I-ADAS parameters was tested leading to a total of 81 combinations of parameters. All 81 combinations were run for each scenario and severity and each set of parameters was run 100 times to cover the range of possible driver responses. In total, there were 48,600 SCP vehicle simulations (Table 31).

Table 31. Total Number of SCP Simulation Combinations

Type	Number of Combinations	Options
Severity	2	Crash or Near-Miss
Approach	3	25 mph, 0 mph → 25 mph (SV), 0 mph → 25 mph (POV)
Range	3	100m, 200m, 300m
Field of View	3	+/- 45°, +/- 70°, +/- 110°
TTC Threshold	3	1.0s, 1.5s, 2.0s
Latency	3	50 ms, 120 ms, 200 ms
Behavior Variation	100	
Total	48,600	

Every combination of I-ADAS parameters was tested leading to a total of 81 combinations of parameters. All 81 combinations were run for each scenario and severity and each set of parameters

was run 100 times to cover the range of possible driver responses. In total, there were 97,200 LTAP/LD & LTAP/OD vehicle simulations (Table 32).

Table 32. Total Number of LTAP/LD & LTAP/OD Simulation Combinations

Type	# of Combinations	Options
Severity	2	Crash or Near-Miss
Approach	6	POV Turning 0 mph→25 mph (SV) - 15 mph (POV), 25 mph (SV) - 0 mph→25 mph (POV), 25 mph (SV) – 15 mph (POV)
		SV Turning 0 mph→25 mph (SV) - 25 mph (POV), 15 mph (SV) - 0 mph→25 mph (POV), 15 mph (SV) – 25 mph (POV)
Range	3	100m, 200m, 300m
Field of View	3	+/- 45°, +/- 70°, +/- 110°
TTC Threshold	3	1.0s, 1.5s, 2.0s
Latency	3	50 ms, 120 ms, 200 ms
Behavior Variation	100	
Total	97,200	

3.1.2 OpenPass Simulations

OpenPass (Open Platform for Assessment of Safety Systems) is a newly developed open-source vehicle simulation software. OpenPass allows for flexible and personalized driving scenarios [21]. For the SCP scenarios, a 2D intersection was created in Blender [22](Figure 24). The intersection was created following the intersection and road dimensions specified in NHTSA’s I-ADAS proposed test protocol [16](Figure 25).

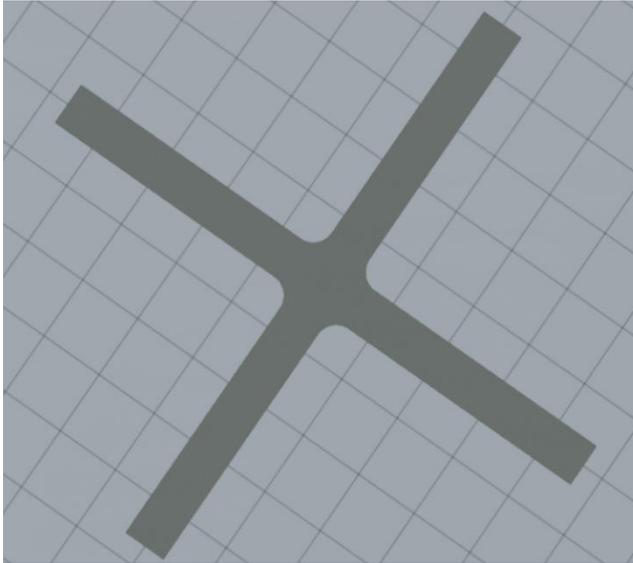


Figure 24. Intersection Schematic in Blender.

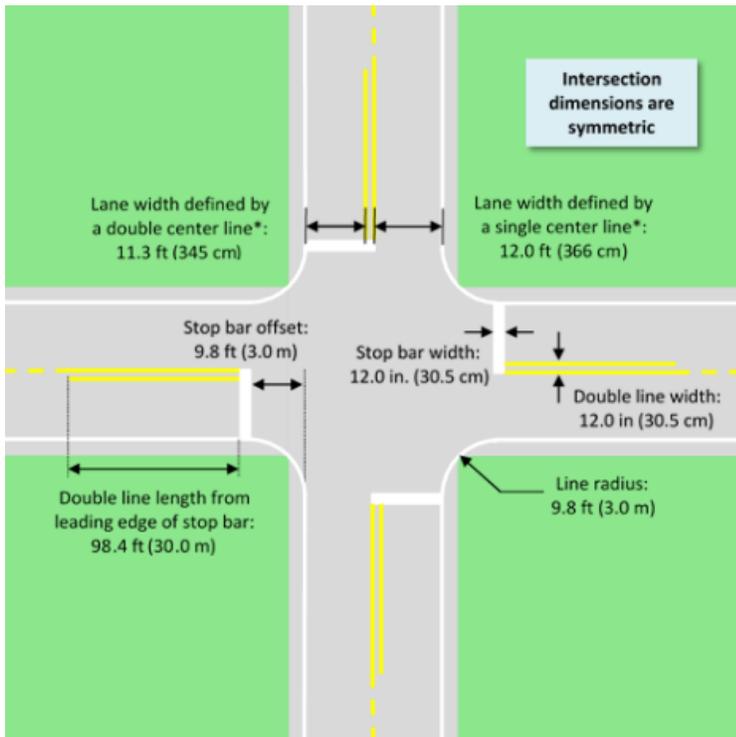


Figure 25. NHTSA Test Protocol Intersection Dimensions [16].

Each scenario was created to reflect the correct speed and impact point (or near-miss) designated by NHTSA without I-ADAS or the driver behavior model in OpenPass without I-ADAS nor the driver behavior FMU (Functional Mockup Unit). Once the scenario was validated to reflect the test in the NHTSA test proposal, I-ADAS was added as an OpenPass component. The I-ADAS was constructed based on the built-in OpenPass AEB system that uses vehicle sensors to detect other vehicles and objects. In this task, the TTC threshold and sensor parameters were varied as reflected in the scenario parameters (Table 30). There was only one sensor at the front center of the vehicle for the I-ADAS component (Figure 26).

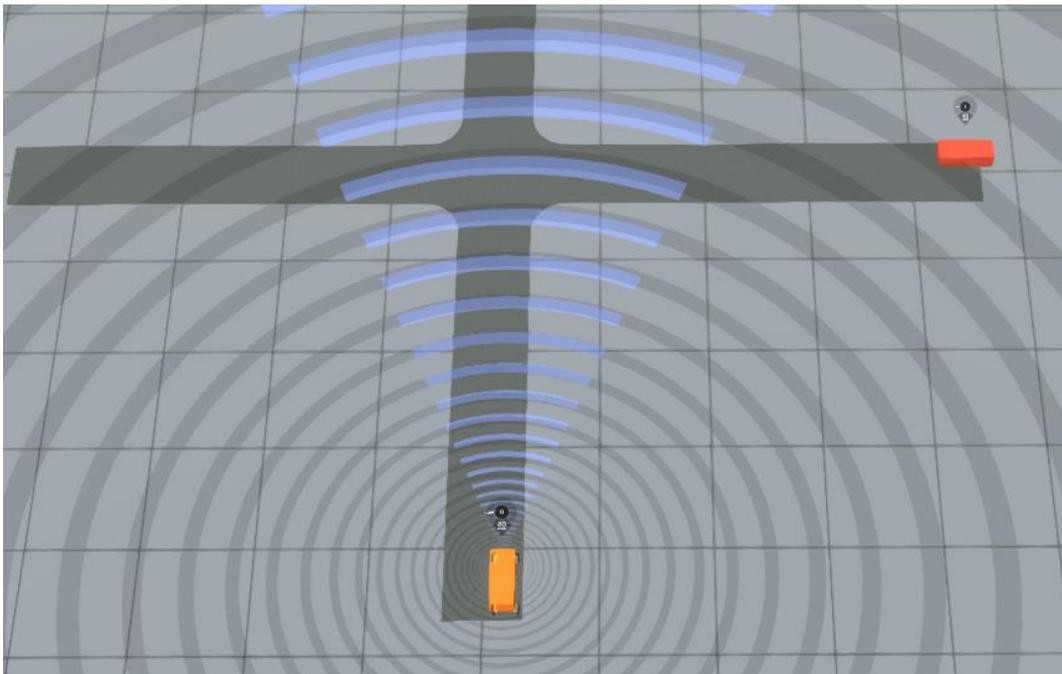


Figure 26. Subject Vehicle Equipped with Front Center Sensor for I-ADAS.

The I-ADAS feature was verified with the largest range and field of view and no latency for each scenario to verify the system activated at the appropriate time based on the set parameters in the simulation. The scenarios were checked in OpenVisualizer. From the built-in AEB system, the

system configuration needed to be changed to have the AEB be more important than the OpenPass driver to allow the system to activate and apply braking at the appropriate time instead of proceeding along the path with the initialized speed and acceleration. The maximum deceleration for the AEB was set to 9.81 m/s^2 for all simulations.

Once I-ADAS was functioning and verified, the longitudinal and lateral driver behavior model FMU was incorporated into the OpenPass simulation. Similar verification steps to I-ADAS were taken. All variations were run with only the driver behavior model equipped and no I-ADAS to verify the output of the driver behavior model was reflected in the output of the simulation, acceleration, and steering angle. In addition, the I-ADAS and driver behavior FMU were verified to function together in the simulation.

All 48,600 simulations needed a unique OpenPass simulation file to reflect to correct parameter configuration, and scenario configuration. A python script was built to automatically create the proper simulation files. Once all files were generated, another would run each simulation in OpenPass. Each simulation completed in approximately 500 ms on average. Each test scenario, consisting of 8,100 simulations, could run to completion in about 1 hour and four test scenarios were operating simultaneously. All SCP simulations were completed in about 2 hours on our machines.

To analyze the effects of the driver behavior model, each scenario was run with a vehicle equipped with only I-ADAS and compared to simulations with I-ADAS with driver. This comparison between I-ADAS with the driver and I-ADAS only allowed for analyzation of vehicle behavior and the effects of a normal driver.

The goal was to analyze the unintended outcomes of the system. The intended outcome for a crash imminent scenario was for I-ADAS to activate so that the crash was avoided. The intended outcome for the near-crash scenarios was for I-ADAS to never activate, and the vehicle to travel along the intended trajectory at the intended speed. The NHTSA tests are divided into two separate test configurations: crash and near-crash. The crash configuration is when the vehicles trajectory and speed are setup to crash if there is no braking or accelerating. A near-crash is setup so the vehicles' trajectory and speed with no extra acceleration or braking will allow the vehicles to pass through the intersection without a collision. The intended outcome of the crash configuration is for I-ADAS to activate and the crash to be avoided. The near-crash configuration is for I-ADAS to not activate and the vehicle continues at the same speed and acceleration. For each scenario, crash, or near-crash, I-ADAS will activate or not activate in the simulation. The other outcome for all simulations is whether the vehicles crashed or did not crash (Table 33).

Table 33. Driver with I-ADAS Outcomes (All)

	Crash Scenario		Near-Crash Scenario	
Outcome	I-ADAS Not Activated	I-ADAS Activated	I-ADAS Not Activated	I-ADAS Activated
Crash	Incorrect System Activation	System & Driver Interaction	Driver Intervened	System & Driver Interaction
No Crash	Driver Intervened	Intended Outcome	Intended Outcome	False Activation

Not all unintended outcomes are negative. This report will also analyze the effects of a normal driver behavior model, and how those decisions can affect the outcome of the simulation.

3.2 Results of Simulation Outcomes

3.2.1 SCP

The simulations with I-ADAS (AEB) and the driver behavior model (48,600 simulations) as well as the same scenarios with varying parameters without the driver behavior model and only I-ADAS. The simulations performed better with the driver behavior model in crash scenarios where the SV or POV are accelerating from stop (Table 34). The scenario where both vehicles were traveling at 25 mph performed about the same.

Table 34. Percent of Collisions Avoided Based on Scenario (All configurations of I-ADAS are averaged)

	25 mph (SV)	25 mph (SV)	0-25 mph (SV)	0-25 mph (SV)	25 mph (SV)	25 mph (SV)
	25 mph (POV)	25 mph (POV)	25 mph (POV)	25 mph (POV)	0-25 mph (POV)	0-25 mph (POV)
	Crash	Near	Crash	Near	Crash	Near
I-ADAS Only	29.3%	100%	11%	100%	66.6%	100%
Driver Behavior Model + I-ADAS	29.7%	100%	0%	100%	100%	100%

The field of view was shown to have the biggest influence on crash avoidance due to limitations in detecting the other vehicle quick enough to be able to avoid the crash has no effect on crash avoidance. There was a difference in I-ADAS only simulations comparing the 45-degree FOV compared to 110-degree FOV, 58.8% and 74.1% respectively (Table 35). The TTC activation threshold did affect the percent of crashes avoided when it was greater than 1 second. There was no difference in outcome between 2.0 second TTC threshold and a 1.5 second TTC threshold (Table 35). With a TTC of 1 second, the I-ADAS was not able to avoid the scenario where both vehicles travelled 25 mph. The latency also had a large impact on crash avoidance. There was a

difference between a 50ms and a 120 ms in the I-ADAS only simulations, 82.4% and 50.0% respectively. There was not as large of a difference between the same latencies for the driver behavior and I-ADAS simulations (Table 35). The range of the sensor had little to no effect on the percent avoidance. As the range increased there was no effect on the crash avoidance performance for all of the scenarios (Table 35).

Table 35. Percent of Collisions Avoided Based on Parameters

FOV	% of Collisions Avoided	
	I-ADAS Only	Driver Behavior Model + I-ADAS
45 Degrees	58.8%	62.5%
70 Degrees	64.8%	67.6%
110 Degrees	74.1%	71.2%

TTC Threshold	% of Collisions Avoided	
	I-ADAS Only	Driver Behavior Model + I-ADAS
1.0 s	60.6%	66.0%
1.5 s	68.5%	67.6%
2.0 s	68.5%	67.4%

Latency	% of Collisions Avoided	
	I-ADAS Only	Driver Behavior Model + I-ADAS
50 ms	82.4%	74.2%
120 ms	64.8%	65.5%
200 ms	50.0%	61.1%

Range	% of Collisions Avoided	
	I-ADAS Only	Driver Behavior Model + I-ADAS
100 m	65.4%	68.1%
200 m	66.0%	68.9%
300 m	66.0%	68.9%

The crash scenarios that had the POV go from 0 mph to 25 mph had no I-ADAS activation in any of the combinations in the driver behavior model and I-ADAS simulations (Table 36). This is due to the SV evasively steering away from the POV changing the orientation of the sensor.

Table 36. Percent of Simulations with I-ADAS Activation

Collisions Avoided	25 mph (SV) 25 mph (POV)	25 mph (SV) 25 mph (POV)	0-25 mph (SV) 25 mph (POV)	0-25 mph (SV) 25 mph (POV)	25 mph (SV) 0-25 mph (POV)	25 mph (SV) 0-25 mph (POV)
	Crash	Near	Crash	Near	Crash	Near
I-ADAS Only	100%	100%	100%	100%	100%	0%
Driver Behavior Model + I-ADAS	100%	100%	0%	100%	0%	0%

The field of view did not have an effect on I-ADAS activation (Table 37). Similar to latency TTC threshold did not have a large effect on I-ADAS activation (Table 37). The latency had no effect on I-ADAS activation for I-ADAS only simulations (Table 37). The sensor range did not have any effect on I-ADAS activation in I-ADAS only simulations (Table 37).

Table 37. Effect of FOV on I-ADAS Activation

FOV	% Cases with I-ADAS Activated	
	I-ADAS Only	Driver Behavior Model + I-ADAS
45 Degrees	83.3%	43.8%
70 Degrees	83.3%	41.6%
110 Degrees	83.3%	40.1%

TTC Threshold	% Cases with I-ADAS Activated	
	I-ADAS Only	Driver Behavior Model + I-ADAS
1.0 s	83.3%	42.6%
1.5 s	83.3%	41.7%
2.0 s	83.3%	41.2%

Latency	% Cases with I-ADAS Activated	
	I-ADAS Only	Driver Behavior Model + I-ADAS
50 ms	83.3%	42.2%
120 ms	83.3%	41.8%
200 ms	83.3%	41.7%

Range	% Cases with I-ADAS Activated	
	I-ADAS Only	Driver Behavior Model + I-ADAS
100 m	83.3%	43.8%
200 m	83.3%	45.2%
300 m	83.3%	37.5%

The I-ADAS could activate and deactivate based on the TTC threshold. If the I-ADAS never deactivated by the time the simulation was complete the activation time was assumed to be 10 seconds. If I-ADAS never activated the I-ADAS activation time was 0 seconds. The I-ADAS activation time was grouped by the scenario type. The scenario where the POV accelerated from stop never activated. The crash scenarios mostly never activated or activated and stayed on throughout the simulation. The near miss scenario where the POV accelerates from stop stayed active the longest compared to the other near-miss scenarios (Table 38). The activation times were also determined for the I-ADAS only simulations. I-ADAS was active longer for crash simulations in I-ADAS only simulations. I-ADAS was also active for less time for near-miss simulations in

the I-ADAS only simulations (Table 38). Indicating that the driver lessened the need of I-ADAS and/or shortened necessary activation time.

Table 38. I-ADAS Activation Duration

I-ADAS Median Activation Duration (Seconds)	25 mph (SV) 25 mph (POV)	25 mph (SV) 25 mph (POV)	0-25 mph (SV) 25 mph (POV)	0-25 mph (SV) 25 mph (POV)	25 mph (SV) 0-25 mph (POV)	25 mph (SV) 0-25 mph (POV)
	Crash	Near	Crash	Near	Crash	Near
I-ADAS Only	5.96	1.54	8.30	10.0	4.4	0.0
Driver Behavior Model + I-ADAS	5.66	1.47	0.0	9.61	0.0	0.0

3.2.2 LTAP/LD

The simulations with I-ADAS (AEB) and the driver behavior model (97,200 simulations) as well as the same scenarios with varying parameters without the driver behavior model and only I-ADAS. The simulations performed better with the driver behavior model in crash scenarios especially when the SC is traveling at 25 mph and the POV is turning (Table 34). All near scenarios in both I-ADAS only and I-ADAS and driver behavior model simulations were all avoided.

Table 39. Percent of Collisions Avoided Based on Scenario (All configurations of I-ADAS are averaged)

Collisions Avoided	SV (I-ADAS Equipped) Straight Travelling					
	0-25 mph (SV) 15 mph (POV)	0-25 mph (SV) 15 mph (POV)	25 mph (SV) 0-25 mph (POV)	25 mph (SV) 0-25 mph (POV)	25 mph (SV) 15 mph (POV)	25 mph (SV) 15 mph (POV)
	Crash	Near	Crash	Near	Crash	Near
I-ADAS Only	45.5%	100%	45.5%	100%	33.3%	100%
Driver + I-ADAS	100%	100%	100%	100%	100%	100%
Collisions Avoided	SV (I-ADAS Equipped) Turning					
	0-25 mph (SV) 25 mph (POV)	0-25 mph (SV) 25 mph (POV)	15 mph (S V) 0-25 mph (POV)	15 mph (SV) 0-25 mph (POV)	15 mph (SV) 25 mph (POV)	15 mph (SV) 25 mph (POV)
	Crash	Near	Crash	Near	Crash	Near
I-ADAS Only	0%	100%	89.9%	100%	0%	100%
Driver + I-ADAS	100%	100%	100%	100%	0%	100%

The field of view was shown to have very little to no impact on crash avoidance in either simulation. The TTC activation threshold increasing caused the number of crashes avoided to increase in I-ADAS only simulations. There was no difference in outcome between TTC thresholds in driver with I-ADAS simulations (Table 40). The latency also had a large impact on crash avoidance in I-ADAS only simulations. As the latency decreased the percent of collisions avoided increased. There was no difference in collisions avoided based on latency for driver with I-ADAS simulations (Table 40). The range of the sensor had no effect on the percent avoidance. As the range increased there was no effect on the crash avoidance performance for all of the scenarios, which is likely due to the vehicle’s approach from the lateral direction (Table 40).

Table 40. Percent of Collisions Avoided Based on Parameters

FOV	% of Collisions Avoided	
	I-ADAS Only	Driver Behavior Model + I-ADAS
45°	64.7%	91.6%
70°	64.7%	91.6%
110°	64.7%	91.6%

TTC Threshold	% of Collisions Avoided	
	I-ADAS Only	Driver Behavior Model + I-ADAS
1.0 s	59.2%	91.6%
1.5 s	64.9%	91.6%
2.0 s	70.6%	91.6%

Latency	% of Collisions Avoided	
	I-ADAS Only	Driver Behavior Model + I-ADAS
50 ms	79.4%	91.6%
120 ms	62.0%	91.6%
200 ms	53.1%	91.6%

Range	% of Collisions Avoided	
	I-ADAS Only	Driver Behavior Model + I-ADAS
100 m	64.7%	91.6%
200 m	64.7%	91.6%
300 m	64.7%	91.6%

I-ADAS only simulations had more I-ADAS activation compared to driver with I-ADAS simulations (Table 41).

Table 41. Percent of LTAP/LD Simulations with I-ADAS Activation

	POV Turning					
	0-25 mph (SV) 15 mph (POV)	0-25 mph (SV) 15 mph (POV)	25 mph (SV) 0-25 mph (POV)	25 mph (SV) 0-25 mph (POV)	25 mph (SV) 15 mph (POV)	25 mph (SV) 15 mph (POV)
	Crash	Near	Crash	Near	Crash	Near
I-ADAS Only	100%	100%	100%	100%	100%	100%
Driver + I-ADAS	100%	100%	100%	66.6%	100%	100%
	SV Turning					
	0-25 mph (SV) 25 mph (POV)	0-25 mph (SV) 25 mph (POV)	15 mph (SV) 0-25 mph (POV)	15 mph (SV) 0-25 mph (POV)	15 mph (SV) 25 mph (POV)	15 mph (SV) 25 mph (POV)
	Crash	Near	Crash	Near	Crash	Near
I-ADAS Only	33.3%	33.3%	100%	34.1%	67.1%	28.2%
Driver + I-ADAS	0%	0%	0%	0%	0%	0%

As field of view increased the number of cases with I-ADAS activation increased in I-ADAS on simulations. The field of view at 110 degrees increased the number of simulations that had I-ADAS activate in driver with I-ADAS simulations (Table 42). TTC threshold did not have an effect on I-ADAS for either simulation type (Table 42). Varying latencies showed no effect on AEB activation in I-ADAS only simulations. However, the latency at 200 ms showed a degradation in I-ADAS activation in driver with I-ADAS simulations (Table 42). The sensor range did not have any effect on I-ADAS activation in either simulation type (Table 42).

Table 42. Effect of Parameters on I-ADAS Activation

FOV	% Cases with I-ADAS Activated	
	I-ADAS Only	Driver Behavior Model + I-ADAS
45°	61.1%	46.2%
70°	70.6%	46.2%
110°	100%	46.2%

TTC Threshold	% Cases with I-ADAS Activated	
	I-ADAS Only	Driver Behavior Model + I-ADAS
1.0 s	76.9%	44.4%
1.5 s	76.9%	47.2%
2.0 s	77.4%	47.2%

Latency	% Cases with I-ADAS Activated	
	I-ADAS Only	Driver Behavior Model + I-ADAS
50 ms	77.2%	49.9%
120 ms	77.2%	47.2%
200 ms	77.2%	41.7%

Range	% Cases with I-ADAS Activated	
	I-ADAS Only	Driver Behavior Model + I-ADAS
100 m	33.3%	25.9%
200 m	33.3%	25.9%
300 m	33.3%	25.9%

The I-ADAS could activate and deactivate based on the TTC threshold. If the I-ADAS never deactivated by the time the simulation was complete the activation time was assumed to be 10 seconds. If I-ADAS never activated the I-ADAS activation time was 0 seconds. The I-ADAS activation time was grouped by the scenario type. The scenario where the POV accelerated from stop never activated. When I-ADAS did activate in driver with I-ADAS simulations it was activated for less than 2.5 seconds (Table 43). The activation times were also determined for the

I-ADAS only simulations. I-ADAS was active longer for crash simulations in I-ADAS only simulations. I-ADAS was also active for less time for near-miss simulations in the I-ADAS only simulations. Indicated driver removed the need of I-ADAS and/or shortened necessary activation time.

Table 43. I-ADAS Median Activation Duration

	POV Turning					
	0-25 mph (SV) 15 mph (POV)	0-25 mph (SV) 15 mph (POV)	25 mph (SV) 0-25 mph (POV)	25 mph (SV) 0-25 mph (POV)	25 mph (SV) 15 mph (POV)	25 mph (SV) 15 mph (POV)
	Crash	Near	Crash	Near	Crash	Near
I-ADAS Only	5.43	2.43	3.76	2.06	2.69	2.07
Driver Behavior Model + I-ADAS	1.83	2.40	4.34	8.91	1.73	1.24
	SV Turning					
	0-25 mph (SV) 25 mph (POV)	0-25 mph (SV) 25 mph (POV)	15 mph (SV) 0-25 mph (POV)	15 mph (SV) 0-25 mph (POV)	15 mph (SV) 25 mph (POV)	15 mph (SV) 25 mph (POV)
	Crash	Near	Crash	Near	Crash	Near
I-ADAS Only	0.15	0.08	2.25	0.59	6.70	0.04
Driver Behavior Model + I-ADAS	0.0	0.0	0.0	0.0	0.0	0.0

3.2.3 LTAP/OD

The simulations with I-ADAS (AEB) and the driver behavior model (97,200 simulations) as well as the same scenarios with varying parameters without the driver behavior model and only I-ADAS. The simulations performed better with the driver behavior model in crash scenarios especially when the SV is traveling at 25 mph and the POV is turning (Table 44). All near scenarios in both I-ADAS only and I-ADAS and driver behavior model simulations were all avoided.

Table 44. Percent of Collisions Avoided Based on Scenario (All configurations of I-ADAS are averaged)

Collisions Avoided	POV Turning					
	0-25 mph (SV) 15 mph (POV)	0-25 mph (SV) 15 mph (POV)	25 mph (SV) 0-25 mph (POV)	25 mph (SV) 0-25 mph (POV)	25 mph (SV) 15 mph (POV)	25 mph (SV) 15 mph (POV)
	Crash	Near	Crash	Near	Crash	Near
I-ADAS Only	33.3%	100%	66.6%	100%	33.3%	100%
Driver + I-ADAS	100%	100%	100%	100%	100%	100%
Collisions Avoided	SV Turning					
	0-25 mph (SV) 25 mph (POV)	0-25 mph (SV) 25 mph (POV)	15 mph (SV) 0-25 mph (POV)	15 mph (SV) 0-25 mph (POV)	15 mph (SV) 25 mph (POV)	15 mph (SV) 25 mph (POV)
	Crash	Near	Crash	Near	Crash	Near
I-ADAS Only	0.0%	100%	100%	100%	100%	100%
Driver + I-ADAS	100%	100%	100%	100%	100%	100%

The field of view was shown to have very little to no impact on crash avoidance in either simulation. (Table 45). The TTC activation threshold increasing had little to no effect on crashes

avoided in both simulations. (Table 45). The latency also had a large impact on crash avoidance in I-ADAS only simulations. As the latency decreased below 120 ms the percent of collisions avoided increased. There was no difference in collisions avoided based on latency for driver with I-ADAS simulations (Table 45). The range of the sensor had little to no effect on the percent avoidance. As the range increased there was no effect on the crash avoidance performance for all of the scenarios (Table 45).

Table 45. Percent of Collisions Avoided Based on Parameters

FOV	% of Collisions Avoided	
	I-ADAS Only	Driver Behavior Model + I-ADAS
45°	75%	100%
70°	75%	100%
110°	75%	100%

TTC Threshold	% of Collisions Avoided	
	I-ADAS Only	Driver Behavior Model + I-ADAS
1.0 s	75%	100%
1.5 s	75%	100%
2.0 s	75%	100%

Latency	% of Collisions Avoided	
	I-ADAS Only	Driver Behavior Model + I-ADAS
50 ms	90.6%	100%
120 ms	69.3%	100%
200 ms	63.0%	100%

Range	% of Collisions Avoided	
	I-ADAS Only	Driver Behavior Model + I-ADAS
100 m	75%	100%
200 m	75%	100%
300 m	75%	100%

I-ADAS only simulations had more I-ADAS activation compared to driver with I-ADAS simulations (Table 46).

Table 46. Percent of Simulations with I-ADAS Activation

	POV Turning					
	0-25 mph (SV) 15 mph (POV)	0-25 mph (SV) 15 mph (POV)	25 mph (SV) 0-25 mph (POV)	25 mph (SV) 0-25 mph (POV)	25 mph (SV) 15 mph (POV)	25 mph (SV) 15 mph (POV)
	Crash	Near	Crash	Near	Crash	Near
I-ADAS Only	100%	100%	100%	100%	100%	100%
Driver + I-ADAS	0%	33.3%	0%	0%	0%	0%
	SV Turning					
	0-25 mph (SV) 25 mph (POV)	0-25 mph (SV) 25 mph (POV)	15 mph (SV) 0-25 mph (POV)	15 mph (SV) 0-25 mph (POV)	15 mph (SV) 25 mph (POV)	15 mph (SV) 25 mph (POV)
	Crash	Near	Crash	Near	Crash	Near
I-ADAS Only	100%	100%	100%	100%	100%	30.9%
Driver + I-ADAS	0%	1000%	22.2%	89.9%	0%	29.7%

The field of view did not have an effect on either of the simulation types (Table 47). This is most likely due to the POV being in front of the SV for most of the encounter. TTC threshold did not have an effect on I-ADAS for either simulation type (Table 47). Varying latencies showed little to no effect on I-ADAS activation in I-ADAS simulations (Table 47). The sensor range did not have any effect on I-ADAS activation in either simulation type (Table 47).

Table 47. Effect of Parameters on I-ADAS Activation

FOV	% Cases with I-ADAS Activated	
	I-ADAS Only	Driver Behavior Model + I-ADAS
45°	94%	23.1%
70°	94%	21.3%
110°	94%	21.3%

TTC Threshold	% Cases with I-ADAS Activated	
	I-ADAS Only	Driver Behavior Model + I-ADAS
1.0 s	95.4%	16.7%
1.5 s	95.4%	23.1%
2.0 s	95.4%	25.9%

Latency	% Cases with I-ADAS Activated	
	I-ADAS Only	Driver Behavior Model + I-ADAS
50 ms	97.0%	33.3%
120 ms	93.6%	18.5%
200 ms	91.7%	13.9%

Range	% Cases with I-ADAS Activated	
	I-ADAS Only	Driver Behavior Model + I-ADAS
100 m	93.0%	21.9%
200 m	93.0%	21.9%
300 m	96.4%	21.9%

The I-ADAS could activate and deactivate based on the TTC threshold. If the I-ADAS never deactivated by the time the simulation was complete the activation time was assumed to be 10 seconds. If I-ADAS never activated the I-ADAS activation time was 0 seconds. The I-ADAS activation time was grouped by the scenario type. The scenario where the POV accelerated from stop never activated. When I-ADAS did activate in driver with I-ADAS simulations, it was activated for less than 2.5 seconds (Table 48). The activation times were also determined for the I-ADAS only simulations. I-ADAS was active longer for crash simulations in I-ADAS only simulations. I-ADAS was also active for less time for near-miss simulations in the I-ADAS only

simulations (Table 48). Indicated driver removed the need of I-ADAS and/or shortened necessary activation time.

Table 48. I-ADAS Activation Duration Median

Median Activation Duration (seconds)	POV Turning					
	0-25 mph (SV) 15 mph (POV)	0-25 mph (SV) 15 mph (POV)	25 mph (SV) 0-25 mph (POV)	25 mph (SV) 0-25 mph (POV)	25 mph (SV) 15 mph (POV)	25 mph (SV) 15 mph (POV)
	Crash	Near	Crash	Near	Crash	Near
I-ADAS Only	6.13	2.17	3.17	1.54	6.02	1.58
Driver Behavior Model + I-ADAS	0.0	0.25	0.0	0.0	0.0	0.0

Median Activation Duration (seconds)	SV Turning					
	0-25 mph (SV) 25 mph (POV)	0-25 mph (SV) 25 mph (POV)	15 mph (SV) 0-25 mph (POV)	15 mph (SV) 0-25 mph (POV)	15 mph (SV) 25 mph (POV)	15 mph (SV) 25 mph (POV)
	Crash	Near	Crash	Near	Crash	Near
I-ADAS Only	4.43	1.80	1.20	2.69	1.30	0.05
Driver Behavior Model + I-ADAS	0.0	2.16	1.20	2.43	0.0	0.05

3.3 Results of I-ADAS Unintended Simulation Outcomes

When the crash scenarios were only equipped with I-ADAS, I-ADAS did not activate for 6.6% of the simulations. The crashes avoided made up 48.1% of crash scenarios. The rest were crashes where I-ADAS activated, but due to parameter limitations there was not enough time for the crash to be avoided. Almost one-fourth of near-crashes had the intended outcome of the I-ADAS not activating. The rest of the near-crash scenarios did have I-ADAS activate, however, there are limitations with intersection TTC calculations because of difficulty in path planning (Table 49). There was also only a 2-meter gap, per the NHTSA proposed test, between the vehicles at their closest distance. This close of a distance could put the TTC below the threshold of activation and cause I-ADAS to activate despite it being a near-crash scenario.

Table 49. Outcomes for I-ADAS Only

Outcome	Crash Scenario		Near-Crash Scenario	
	I-ADAS Not Activated	I-ADAS Activated	I-ADAS Not Activated	I-ADAS Activated
Crash	6.6%	45.3%	0%	0%
No Crash	0%	48.1%	24.9%	75.1%

The I-ADAS with driver outcomes differed greatly from the I-ADAS only simulation outcomes. I-ADAS with the driver avoided more crashes. The driver either braked prior to I-ADAS to avoid the collision or made an evasive steering maneuver to avoid the other vehicle. There were 18% crash scenarios that were not avoided (Table 50). There were also less near-crash scenarios that had the unintended outcome of I-ADAS activating compared to the I-ADAS only simulations. This could be due to the driver braking prior to the I-ADAS activation threshold allowing for the

system to have to activate less frequently and maximizing the minimum distance between the vehicles.

Table 50. Outcomes for I-ADAS with Driver

Outcome	Crash Scenario		Near-Crash Scenario	
	I-ADAS Not Activated	I-ADAS Activated	I-ADAS Not Activated	I-ADAS Activated
Crash	13.3%	4.7%	0%	0%
No Crash	58.5%	23.5%	41.3%	58.7%

3.3.1 SCP

I-ADAS always activated as intended in the crash scenarios in an SCP configuration. About one-third of near-crash scenarios had the intended outcome (Table 51).

Table 51. SCP I-ADAS Only Outcomes

Outcome	Crash Scenario		Near-Crash Scenario	
	I-ADAS Not Activated	I-ADAS Activated	I-ADAS Not Activated	I-ADAS Activated
Crash	0%	64.4%	0%	0%
No Crash	0%	35.6%	33.3%	66.7%

The SCP simulations in crash scenarios had less I-ADAS activation, but more slightly more crashes avoided than the I-ADAS only simulations (Table 52). In the simulations with no I-ADAS activation the driver made an evasive maneuver to avoid the crash.

Table 52. SCP Outcomes for I-ADAS with Driver

Outcome	Crash Scenario		Near-Crash Scenario	
	I-ADAS Not Activated	I-ADAS Activated	I-ADAS Not Activated	I-ADAS Activated
Crash	33.3%	23.4%	0%	0%
No Crash	33.3%	9.9%	66.7%	33.3%

The unintended incomes were investigated further to evaluate driver action in these scenarios. The driver was evaluated prior to the collision or prior to exiting the intersection if there was no collision. In the crash scenarios that had an outcome of a crash and I-ADAS did not activate there was both deceleration and acceleration from the driver. The crashes where I-ADAS did activate the vehicle still crashed, the driver also decelerated most of the time, but neither was enough to avoid the crash completely (Table 53).

Table 53. Driver Behavior for SCP Crash Scenarios (Blank Spaces were not Observed)

Outcome		Crash Scenario							
		I-ADAS Not Activated				I-ADAS Activated			
		Accelerate	Decelerate	Neither	Both	Accelerate	Decelerate	Neither	Both
Crash	Evasive Steering								
	No Steering			0.4%	99.6%		99.7%	0.3%	
No Crash	Evasive Steering			99.7%					
	No Steering			0.3%			99.4%	0.6%	

For near-crash scenarios, no crashes occurred. For simulations that had no I-ADAS activation, the driver did evasive steering maneuvers. For simulations that did have I-ADAS activation, the driver accelerated and evasively steered half of the time (Table 54). Among the remainder of the simulations, the driver either accelerated or decelerated with no evasive steering.

Table 54. Driver Behavior for SCP Near-Crash Scenarios (Blank Spaces were not Observed)

		Near-Crash Scenario							
Outcome		I-ADAS Not Activated				I-ADAS Activated			
		Accelerate	Decelerate	Neither	Both	Accelerate	Decelerate	Neither	Both
Crash	Evasive Steering								
	No Steering								
No Crash	Evasive Steering			99.5%		50.9%			
	No Steering			0.5%		25.1%	23.8%	0.2%	

3.3.2 LTAP/LD

The left turn across path scenarios were avoided at a similar frequency as SCP scenarios, however, the LTAP scenarios had more simulations have no I-ADAS activation compared to SCP that had 100% activation in crash simulations. These no activation cases were from the scenarios where the subject vehicle was making the left turn. As the subject vehicle turns the field of view then shifts with the orientation of the vehicle, potentially putting the POV farther from the sight of the sensor. By the time the POV was seen by the sensor with some sensor parameters, the vehicles have either already collided or the system latency was too long to fully activate the system in time. LTAP/LD crash scenarios were avoided 35.7% of time (Table 55).

Table 55. LTAP/LD Outcomes with I-ADAS Only

Outcome	Crash Scenario		Near-Crash Scenario	
	I-ADAS Not Activated	I-ADAS Activated	I-ADAS Not Activated	I-ADAS Activated
Crash	16.6%	47.7%	0%	0%
No Crash	0%	35.7%	34.1%	65.9%

The LTAP/LD simulations with I-ADAS with a driver had similar results to the I-ADAS only simulations for crash scenarios where I-ADAS did not activate and the outcome was a crash, about 17% of LTAP/LD crash scenarios (Table 56). However, the difference was there no simulations where I-ADAS activated and the crash was not avoided, so 100% of simulations where I-ADAS activated with a driver were avoided. There was also one-third of crash scenarios where there was no I-ADAS activation and the crash was still avoided. These simulations were solely avoided by the driver without the need of I-ADAS intervention.

Table 56. LTAP/LD Outcomes with I-ADAS with Driver

Outcome	Crash Scenario		Near-Crash Scenario	
	I-ADAS Not Activated	I-ADAS Activated	I-ADAS Not Activated	I-ADAS Activated
Crash	16.7%	0%	0%	0%
No Crash	33.3%	55.0%	55.6%	44.4%

LTAP scenarios had 3 different steering options. First, the vehicle had no steering and decided to proceed straight. Second, the driver made a normal steering maneuver as expected. Third, the vehicle evasively steered. The scenarios where the SV traversed straight, I-ADAS activated for all scenarios. In two-thirds of the scenarios, the driver decelerated. In the remaining simulations the I-ADAS alone avoided the collision (Table 57).

Table 57. Driver Behavior for SV Traversing Straight LTAP/LD Crash Scenarios (Blank Spaces were not Observed)

Outcome		Crash Scenario							
		I-ADAS Not Activated				I-ADAS Activated			
		Accelerate	Decelerate	Neither	Both	Accelerate	Decelerate	Neither	Both
Crash	Evasive Steering								
	Steering								
	No Steering								
No Crash	Evasive Steering								
	Steering								
	No Steering						66.5%	33.5%	

The scenarios that had no I-ADAS activation and were avoided almost all had evasive steering to avoid the crash. In the simulations that were not avoided, the driver took no evasive maneuvers and I-ADAS did not activate (Table 58).

Table 58. Driver Behavior for SV Turning LTAP/LD Crash Scenarios (Blank Spaces were not Observed)

Outcome	Crash Scenario								
		I-ADAS Not Activated				I-ADAS Activated			
		Accelerate	Decelerate	Neither	Both	Accelerate	Decelerate	Neither	Both
Crash	Evasive Steering								
	Steering			99.8%					
	No Steering			0.2%					
No Crash	Evasive Steering	49.8%		49.8%					
	Steering								
	No Steering			0.4%					

In the near-crash scenarios, evasive steering was performed by the driver in 14.2% of the I-ADAS activation simulations. There was longitudinal driver deceleration and the near-crashes were still avoided (Table 59).

Table 59. Driver Behavior for SV Traversing Straight LTAP/LD Near-Crash Scenarios (Blank Spaces were not Observed)

Outcome		Near-Crash Scenario							
		I-ADAS Not Activated				I-ADAS Activated			
		Accelerate	Decelerate	Neither	Both	Accelerate	Decelerate	Neither	Both
Crash	Evasive Steering								
	Steering								
	No Steering								
No Crash	Evasive Steering						14.2%		
	Steering								
	No Steering		99.5%	0.5%			42.8%	42.9%	

In simulations where SV was turning, I-ADAS never activated. In one-third of the simulations the driver accelerated and evasively steered. In rest of the simulations, the driver did not perform any evasive maneuvers (Table 60).

Table 60. Driver Behavior for SV Turning LTAP/LD Near-Crash Scenarios (Blank Spaces were not Observed)

Outcome		Near-Crash Scenario							
		I-ADAS Not Activated				I-ADAS Activated			
		Accelerate	Decelerate	Neither	Both	Accelerate	Decelerate	Neither	Both
Crash	Evasive Steering								
	Steering								
	No Steering								
No Crash	Evasive Steering	33.2%							
	Steering			66.6%					
	No Steering			0.1%					

3.3.3 LTAP/OD

LTAP/OD simulations in crash scenarios had 100% activation, and two-thirds of the crash scenarios were avoided with I-ADAS alone (Table 61). The crash simulations not avoided were due to the path planning TTC calculation. The intersection was two two-way roads intersecting, so once the vehicle starts to turn and was determined to be a threat there was a limited amount of time to activate I-ADAS and have enough deceleration to avoid the crash.

Table 61. LTAP/OD Outcomes with I-ADAS Only

Outcome	Crash Scenario		Near-Crash Scenario	
	I-ADAS Not Activated	I-ADAS Activated	I-ADAS Not Activated	I-ADAS Activated
Crash	0%	33.3%	0%	0%
No Crash	0%	66.6%	11.5%	88.5%

When LTAP/OD simulations were equipped with a I-ADAS with a driver the driver performs an evasive maneuver (braking or steering) before the vehicle gets within the TTC threshold. All crashes were avoided, and 96.3% of the crash scenarios were avoided with only the driver's behavior (

Table 62).

Table 62. LTAP/OD Outcomes with I-ADAS with Driver

Outcome	Crash Scenario		Near-Crash Scenario	
	I-ADAS Not Activated	I-ADAS Activated	I-ADAS Not Activated	I-ADAS Activated
Crash	0.0%	0.0%	0%	0%
No Crash	96.3%	3.7%	57.8%	42.2%

Most the scenarios where I-ADAS did not activate, an evasive steering maneuver was performed by the driver. (Table 63). For one – third of the SV traversing straight the driver accelerated, the rest of the simulations the driver decelerated (Table 63).

Table 63. Driver Behavior for SV Traversing Straight LTAP/OD Crash Scenarios (Blank Spaces were not Observed)

		Crash Scenario							
Outcome		I-ADAS Not Activated				I-ADAS Activated			
		Accelerate	Decelerate	Neither	Both	Accelerate	Decelerate	Neither	Both
Crash	Evasive Steering								
	Steering								
	No Steering								
No Crash	Evasive Steering	33.0%	66.4%						
	Steering								
	No Steering			0.5%					

In LTAP/OD, all crashes were avoided among simulations of the driver with I-ADAS. In simulations where I-ADAS did activate. Almost all decelerated and accelerated. Most of the simulations that did not have I-ADAS activate evasively steered and had no longitudinal maneuvers (Table 64).

Table 64. Driver Behavior for SV Turning LTAP/OD Crash Scenarios (Blank Spaces were not Observed)

		Crash Scenario							
Outcome		I-ADAS Not Activated				I-ADAS Activated			
		Accelerate	Decelerate	Neither	Both	Accelerate	Decelerate	Neither	Both
Crash	Evasive Steering								
	Steering								
	No Steering								
No Crash	Evasive Steering			61.5%					
	Steering				7.7%				
	No Steering	0.2%			30.6%	1.4%			98.6%

All near-crash LTAP/OD scenarios did not result in a crash, as expected. There were evasive steering maneuvers done by the driver in the simulations where I-ADAS did not activate. Almost three-quarters of simulations with no I-ADAS activation the driver evasively steered and decelerated along the vehicle’s traversal (Table 65).

Table 65. Driver Behavior for SV Traversing Straight LTAP/OD Near-Crash Scenarios (Blank Spaces were not Observed)

		Near-Crash Scenario							
Outcome		I-ADAS Not Activated				I-ADAS Activated			
		Accelerate	Decelerate	Neither	Both	Accelerate	Decelerate	Neither	Both
Crash	Evasive Steering								
	Steering								
	No Steering								
No Crash	Evasive Steering		74.9%	22.4%					88.0%
	Steering								
	No Steering			2.7%				12.0%	

In 68.2% of the simulations where the SV was turning and I-ADAS did not activate, the vehicle traversed with no driver evasive intervention. In 83.6% of the simulations where I-ADAS did activate the driver traversed straight and both decelerated and accelerated throughout the traversal (

Table 66).

Table 66. Driver Behavior for SV Turning LTAP/OD Near-Crash Scenarios (Blank Spaces were not Observed)

		Near-Crash Scenario							
Outcome		I-ADAS Not Activated				I-ADAS Activated			
		Accelerate	Decelerate	Neither	Both	Accelerate	Decelerate	Neither	Both
Crash	Evasive Steering								
	Steering								
	No Steering								
No Crash	Evasive Steering								15.5%
	Steering			68.2%					
	No Steering	0.2%			31.7%	0.8%			83.6%

3.4 Discussion

Overall, the latency of the system and TTC threshold were the biggest contributors to crash avoidance for I-ADAS only simulations. In a turning situation the time the POV is detected by the system is very short causing the smaller TTC threshold and larger latencies to have large effects on the ability to brake in time to avoid the crash. For driver with I-ADAS the sensor parameters had no effect on the collision outcome. The outcome for these simulations was completely determined by what the driver decides to do rather than I-ADAS.

As the field of view increased the number of cases with I-ADAS increased in I-ADAS only simulations. The other parameters, TTC threshold, latency, and range had no effect on AEB activation. The range of the radar showed zero impact on crash avoidance nor the I-ADAS activation. This was most likely due to the object that needed to be detected was lateral for LTAP-

LD scenarios. Near-miss scenarios were avoided, which was expected. Only reason the near-miss scenario could have turned into a crash scenario is if the driver-behavior model predicted that the driver would accelerate at the very last minute. This did not occur because the driver behavior model was trained mostly on normal driving, so the probability of transitioning to acceleration while that close to another vehicle is very small.

In the previous studies, real-world SCP and LTAP/LD crashes were simulated assuming one vehicle in the crash was equipped with I-ADAS. The vehicle was simulated with three sensors, one in the front center and one on each front corner of the vehicle [8], [10]. This differs from this study where the vehicle was only equipped with one camera on the front center of the vehicle which may partly explain the differences in effectiveness. On average, the previous study found 50% of the crashes were avoided with I-ADAS with TTC varying from 1.0 seconds to 3.0 seconds and latency varying from 0 seconds to 0.5 seconds [23]. This study found that 66.7% of crashes were avoided with one vehicle equipped with I-ADAS and a driver. However, this report has crash scenarios that have slower speeds as well as being equipped with a driver behavior model that could potentially aid in the crash avoidance by applying the brake earlier than the TTC threshold.

There were some limitations to these simulations. The I-ADAS TTC calculation was an OpenPass created feature, so those calculations are already compiled and not visible to the user. The TTC used for the driver behavior model is calculated using a simple path planning calculation to determine the intersect point of the vehicles. The intersection point changes based on the current heading and speed and does not account for any acceleration or steering inputs. This may cause I-ADAS to activate earlier than it should. This can cause a limitation for the near-crash scenarios. In the proposed NHTSA tests the near-crash scenarios are not supposed to have I-ADAS activate.

The smallest distance between the vehicles in these near-crash tests is 2 meters, so the smallest calculation changes in TTC can cause a false positive I-ADAS activation. Another limitation is the size of the intersection, the intersection is the one proposed in the NHTSA proposed test matrix. The intersection is two two-way roads intersecting making path planning as well as TTC calculations very difficult due to the intersections size. Ultimately, the size of the intersection limits the amount of time the vehicle has in an LTAP scenario to determine if the other vehicle is a threat or not because the turn occurs so quickly due to the small intersection.

Overall, the simulations with I-ADAS with the driver avoided more crashes than simulations with I-ADAS alone. The driver behavior model was trained on drivers traversing through intersections during primarily normal, non-crash scenarios. The driver was assumed to be attentive in the driver with I-ADAS simulations compared to the I-ADAS only simulations where the driver was assumed to be not attentive. The driver with I-ADAS prevented the crash scenarios that the I-ADAS alone did not prevent. Although, I-ADAS alone did not avoid every crash scenario, the emergency braking can lessen the severity of the crash. I-ADAS did activate in all crash scenarios except LTAP/OD SV turning left scenarios. The driver had different evasive maneuvers for each scenario type. In a portion of SCP simulations, the driver evasively steered. The driver evasively steered to the right and the POV was travelling to the right too. This combination caused the I-ADAS sensors to no longer detect the POV and the crashes were not avoided. In a portion of the LTAP cases that were supposed to have the SV make a left turn, the driver decided to traverse straight instead and accelerate. This driver intervention allowed the imminent crash to be avoided without I-ADAS activation. Perhaps I-ADAS needs to consider the SV driver behavior in addition to the POV position and speed. This can help improve driver acceptance and may actually reduce the

occurrence of I-ADAS activation due to the driver taking action. To predict driver behavior, these I-ADAS systems may benefit from an interior driver monitoring system.

4 CONCLUSIONS

The driver behaviour characteristics for drivers driving through an intersection were found to be different for vehicles in a crash or near-crash in the SHRP-2 dataset compared to the vehicles driving through an intersection in the VT-CAST dataset. The biggest difference was in the maximum deceleration between the crashes and near-crashes and the normal driving encounters. For most crash and near-crash scenarios, the vehicle at-fault had a higher average speed compared to the vehicle not-at-fault. The estimated time to collision also showed differences between normal driving in VT-CAST and the crash and near-crash scenarios in SHRP-2. The estimated time to collision was lower (shorter), as expected, for the crashes and near-crashes vs. normal driving.

The driver behavior model used over 124,000 total intersection encounters including 301 crash and near-crash scenarios. The driver behavior model created in this study has shown that it can be a good predictor of real-world driving in normal driving scenarios, and in crash and near-crash scenarios. The driver behavior model based on normal intersection traversals aided in more crashes being avoided. The driver also decreased the number of false I-ADAS activations in near-crash scenarios by braking prior to the TTC threshold to create a larger distance between the SV and the POV.

The driver behavior model, developed in this study, can give insight into how drivers behave in intersections. Knowing this behavior can assist in the development of I-ADAS as well as improve how I-ADAS can be tested for effectiveness in real-world scenarios. In the development of I-ADAS, the algorithm can be designed to account for driver behaviors, while still accounting for standard test protocols to make the system more effective in real-world scenarios.

This driver behavior model can be applied to an infinite amount of intersection configurations that fall within the encounter types that the models were built for. Knowing how drivers can potentially affect I-ADAS can help with the system design as these systems become more complex. It could also aide in the design of adding automatic evasive steering to the I-ADAS to see how the driver input may impact the effectiveness.

The data in this study could be collected for all types of intersection traversals, which could be used to build an all-encompassing driver behavior model to see how drivers behave in any encounter type that can occur at an intersection.

To conclude, evaluating real-world intersection traversals from crashes, near-crashes, as well as normal driving helps give insight into driver's behavior. This knowledge will help aide in I-ADAS development as well as test protocol development to help with I-ADAS efficacy.

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